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What Role Does Health Play in Enhancing Labour Productivity in Nigeria?

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Abstract

Health status actually influences labour productivity as evidenced by past studies for Nigeria and elsewhere. However, no previous study in Nigeria utilized labour productivity index as a proxy for labour productivity. This study examined the impact of health status on Nigerian labour productivity for the period 1981-2017. For extensive analysis, three health indicators (life expectancy rate at birth, malaria cases and government health expenditure) were utilized. The vector autoregression (VAR) and vector error correction estimate (VECM) frame work were adopted. The result showed that both life expectancy rate and government health expenditure have no significant impact on labour productivity index, however, malaria cases constituted drag to labour productivity index in Nigeria. We recommended that Nigerian government should use policy to increase access to effective treatment of malaria and that government health expenditure for capital goods should be revised up wards in order to provide the necessary health infrastructures for effective health service delivery.

Keywords

Role, Health, labour productivity, Nigeria

JEL Codes: C8, C4, H1, H3, H4

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1. Introduction

There has been growing attention on improving the health of the population among developing countries .This is due to the implications of health on enhancing labour productivity and overall economic performance of nations (Laplagne, Glover and Shomos, 2007). The World Health Organization (1996) defines health as a “state of complete physical, mental and social well-being and not merely the absence of disease or infirmity”. According to Anyanwu *et al.* (1997), health is the ability of an individual to live a socially and economically productive life. The first approach based on the Grossman’s (1972) health capital model assumes that an individual is born with a stock of health that diminishes over time, but can be replenished through the act of health investment. The available health stock of a person produces a stream of healthy time payoffs that determines the individual market (investment) and non-market (consumption) participation in the economy. When this stock diminishes below a certain point, death occurs. In this model, individuals use medicare and their own time to produce "good health". Thus, the health of the individual depends on the amount of time the individual spends and on the investment he or she makes on his/her health.

Improvement in health which improves the quantum of human capital has been identified as a critical catalyst to economic growth and development in macroeconomic literature. Specifically, the neoclassical and endogenous growth models posit that growth in human capital (knowledge) impacts positively on output per worker in the long-run (Romer, 1996). Similarly, Grossman's (1972) human capital model suggests that quality health significantly influences human capital development through the additional working time and utility derived from good health (Grossman, 1972). Good health does not only improve individual's consumption and production in the short-run but also improves returns from investments in productive activities in the long- run (Somi *et al*.; 2009).

Current estimates put the population of Nigeria at 190,886 million (Ahuru, 2019). With an annual population growth rate of 2.6%, Nigeria is projected to be the third most populated nation globally by 2050 (Ahuru, 2009). By the end of 2018, Nigeria’s labour force was put at 90.5 million with the highest labour force population of 17,603,003 in the age group 25-34 (National Bureau of Statistics (NBS), 2018). The labour force participation rate rose from 76.6% by the third quarter of 2017 to 78.3% by the third quarter of 2018 (NBS, 2018). Labour productivity rose from N471.94 in 2011 to N684.43 in 2016, this represents a 45.0% increase in labour productivity over the 6 years and a decline of 4.7% between 2015 and 2016 (NBS, 2018). Nigeria’s huge labour force is an asset in her drive to improve labour productivity and growth (Umoru & Yaqub, 2013).

The health indicators of Nigeria have remained largely below its targets and internationally-set benchmark due to weaknesses inherent in the health system (United Nations Development Programme (UNDP, 2014). According to Data from World Development Indicators, life expectancy rate at birth is 52.1 y ears for males, 54.2 years for females and 53.4 years for both genders. The life expectancy rate was below the global average of 72 years (UNDP, 2018).Evidence from World Development Indicators shows that all four mortality rates (neonatal, infant, under-5 and maternal mortality) have fallen through at a very slow rate. Infant mortality rate was 66.9 per 1,000 live births, neonatal mortality rate was 34.3 per 1,000 live births, and under-five mortality rate was 108.8 per 1,000 live births in 2017. Two main causes of morbidity and mortality among Nigerian adults are HIV/AIDS and malaria (Rolle and Onwuma, 2019). Approximately, 97% of Nigerian populations are at the risk of malaria attack and 1.5% of Nigeria adults aged 15-49 currently live with HIV infection (Nigerian malaria fact sheet, 2011; World Development Indicators, 2018). Current estimates put the tuberculosis incidence rate for Nigeria at 338 per 100,000 (World Development Indicators, 2018). Several other non-communicable diseases such as hypertension, diabetes, coronary heart disease, sickle cell disease, anaemia, mental health, blindness, stroke account for Nigeria's high disease burden (National Strategic Health Development Plan (NSHDP), 2010).

The effect of health on labour productivity has been the subject of various studies in Nigeria. Some studies examined the role of disease-specific conditions on labour productivity (Jimoh, 2005; Rolle & Iseghohi, 2005; Onyema & Nyenke, 2019). Rolle & Iseghohi (2018) utilized time series data to examine the role of malaria on labour productivity, and Jimoh (2005) investigated the effect of malaria on Agricultural productivity using annual time series data. Onyema & Nyenke (2019) investigated the effect of HIV/AIDS on Nigerian per capita income. All three studies reported that disease burden constituted drag to labour productivity in Nigeria. Another set of studies examined the effect of health on labour productivity for specific sectors (Ajani & Ugwu, 2008; Ugwu, 2009; Omonona, Egbetokun & Omidele, 2012). Omonona *et al.* (2012) investigated the effect of health on labour productivity for 120 farmers in Enugu State, Eastern Nigeria. Ajani and Ugwu (2008) examined the effect of adverse health on productivity of farmers in Kainji lake Basin in North-Central Nigeria. All three studies concluded that adverse health negatively influences labour productivity in Nigeria.

All of the studies proxy labour productivity by either per capita income or real GDP; however, none of the studies proxy labour productivity by labour productivity index. Against this backdrop, our task is to investigate empirically the effects of health on productivity in Nigeria using labour productivity index, which we believed is a more accurate measure of labour productivity. The study investigated the effect of the poor health status of Nigerians on its labour productivity index. This endeavour will no doubt exhibit some policy significance as Nigeria battles to catch up its peers in the developing world bracket.

2. Literature review and methodology of research

2.1. Theoretical framework

The endogenous growth model explains that balanced growth is positively influenced by knowledge spillover, human capital (in the form of health and education), research and development (R & D), through their influence on technical progress. Technological progress in this model is therefore endogenized and can be explained by some factors. Based on this model, Lucas (1988) put forward an endogenous growth model where human capital is a major driver of output growth. Lucas (1988) theorized that economic growth Y is a function of capital stock (K), Labour (L) and technological progress (A). The production function may be of the form:

$$Y_t = K_t^{\alpha} A\, L_t^{(1-\alpha)} \qquad (1)$$

Where A (t) L is effective labour with α and 1-α as shares of K and AL respectively in output. Now with the technical progress or labour productivity (A) being entirely explained by the stock of human capital, say, H, that is, human capital increases labour productivity.

$$A = H \qquad (2)$$

Consider an economy where the population does not grow, that is n = 0 (where n is the growth rate of the population), there are constants returns to scale to the produced inputs in both goods and research sectors. Furthermore, Research and Development (R & D) uses labour and the existing stock of human capital, but not physical capital, whereas goods production uses labour, human and physical capital. The production function for labour productivity is given by:

$$A_{(t)} = \beta a_1 L A_{(t)} \qquad (3)$$

And since all physical capital is used to produce goods, goods production is

$$Y(t) = K(t)^{\alpha}[(1 - a1)\,LA(t)]_{1-\alpha} \qquad (4)$$

Where A (t) denotes a derivative of labour productivity with respect to time (that is, A(t) is a shorthand for $\frac{dA(t)}{dt}$; β is a shift parameter (which accounts for all other factors affecting rate of change of labour productivity other than labour and labour productivity), a_1 and $1-a_1$ denote the fraction of labour used in labour productivity and goods production, respectively; and α represents the elasticity of output with respect to capital stock, while L, A, K and Y are labour force, labour productivity, capital stock and output respectively. Notice that time (t) enters the model continuously in line with (the prescription of) the endogenous growth theory. The saving rate is assumed to be constant, so that:

$$K_{(t)} = sY_{(t)} \qquad (5)$$

Equation (4) is important to this study because it introduced capital stock, labour and labour productivity as (macroeconomics) determinants of output. Since model (4) is a mathematical model, it has to be changed to an econometric model by exponentially introducing the error term as thus:

$$Y(t) = K(t)^{\alpha}[(1\text{-}a1)LA_{(t)}]^{1-\alpha}\ e^{u(t)} \qquad (6)$$

Where μt is error term, which entered the model exponentially for two reasons: First, for the model's error term after transformation to follow a normal distribution with zero mean and homoscedastic variance, that is μ -(0, δ), as it is required for valid statistical inference. If μ (t) had entered model (6) multiplicatively such as in Y (t) = K_t [(1-a_1)LA(t)$^{1-a}$ μ(t), it is then the model's log-error that will follow normal distribution, that is in μ ~ N (0,δ^2), in which case μ must follow the log-normal distribution with mean $e^{\frac{\delta 2}{2}}$ and variance $e^{\delta 2}$ ($e^{\delta 2}$-1), which has implications to the statistical inference of the model's findings. Second, $\mu_{(t)}$ entered model (6) exponentially for it to be intrinsically linear (in parameter) regression model because if it had entered additively such as in Y(t) = K(t) ^{a}[(1-a1)LA(t)]$^{1-a}$ + μ(t), there is no way to transform the model so that the transformed model becomes linear in the parameters (Gujarati & Porter,2009). Thus, to show that model (6) is a suitable growth model for this study and to enable the use of linear regression estimation technique such as Vector Autoregression rather than "trial-and-error" or 'iterative' methods of nonlinear regressions, we log-transform model (6) as thus:

$$1nY(t) = 1n[K(t)^{\alpha}[(1-a_1)LA_{(t)}]^{1-\alpha} e^{u(t)} \qquad (7)$$

So,

$$1nY(t) = \alpha 1nK(t) + (1-\alpha)\ln(1-a1) + (1-\alpha)1nL + A_{(t)} + \mu(t)1ne \qquad (8)$$

then,

$$1nY(t) = \alpha 0 + \alpha 1nK(t) + (1-\alpha)1nL + A_{(t)} + \mu(t)\,1ne \qquad (9)$$

$$where\ \alpha 0 = (1-a1)\ln(1-\alpha) = a\ constant,\ \text{And Lne} = 1.$$

Then again, to measure output per man, a measure of labour productivity, we will use per capita income derived in growth model by dividing model (4) by labour, L, as thus:

$$\frac{Y(t)}{L(t)} = \frac{K(t)^{\alpha}[(1-\alpha1)LA(t)]^{(1-\alpha)}}{L(t)} = \frac{Y(t)}{L(t)} = K(t)^{\alpha}[(1\text{-}\alpha1)\,LA\,(t)]^{1-\alpha}[L\,(t)]^{-1} \qquad (10)$$

Then, $$\frac{Y(t)}{L(t)} = k(t)^{\alpha}\ (1-\alpha1)^{1-\alpha}\ A(t)^{1-\alpha}\ L(t)^{1-\alpha-1} \qquad (11)$$

i.e. $$\frac{Y(t)}{L(t)} = k(t)^{\alpha}\ (1-\alpha1)^{1-\alpha}\ A(t)^{1-\alpha}\ L(t)^{-\alpha} \qquad (12)$$

$$y(t) = k(t)^{\alpha}\ (1-\alpha1)^{1-\alpha}\ A(t)^{1-\alpha}\ L(t)^{-\alpha}\ e^{\varpi_t} \qquad (13)$$

Where: y(t) denotes output per man (a proxy for labour productivity), and where ϖt is the error term introduced exponentially into the model for the same reason as in model (6). We divided output by labour as our measure of productivity because output per man or per capita means per head/population. The population of interest here is the population of the working-age and precisely the labour force because Blanchard (1997) opines that people who are not working and are not looking for employment are not regarded as unemployed, hence they are not counted among the labour force. Blanchard (1997) calls these people discouraged workers. Thus, our derivative of the per capita output as a measure of labour productivity in the model (13) is quite a reasonable approximation.

Log-transformation of model (13) yields:

Ln y (t) = $\ln[k(t)^{\alpha} (1-\alpha 1)^{(1-\alpha)} A(t)^{(1-\alpha)} L(t)^{(-\alpha)} e^{\varpi t}]$ (14)

Ln y(t) = αln$K(t)$ + (1-α) InA(t) +$(1-\alpha 1)$ 1n ($(1-\alpha)$ -αlnL(t) +ϖt (15)

Thus, Iny (t) = $\alpha 1$ + (1-α) 1nA (t) +α 1nK (t) + -α1n L (t) +ϖt (16)

Where $\alpha 1 = (1-\alpha 1)$1n (1- α) = a constant, and 1ne = 1

Now, assumes the growth rate of labour to be equal to zero, that is, $\frac{d\ln L(t)}{dt} = \frac{dL(t)}{dt}$ /L(t) = n= 0,

Then the two most interesting models for this study-model (9) and (16)- will reduce respectively to:

$lny(t) = \alpha 0 + (1-\alpha)$LnA (t)+$\alpha lnK + \mu_t$ (17)

And, $lny(t) = \alpha 1 + (1-\alpha)$lnA(t)+$\alpha lnK + \varpi_t$ (18)

Note that transformations that yielded equations (17) and (18) were done also to justify the rationale behind the logging of some variables in this study. Finally, substituting equation 2 or 3 into either 17 or 18, so that human capital H and by consequence, health enters the model, we have:

$lny(t) = \alpha 0 + (1-\alpha)$LnH (t)+$\alpha lnK + \mu_t$ (19)

And, $lny(t) = \alpha 0 + (1-\alpha)$lnH(t)+$\alpha lnK +$ϖt (20)

Thus the equations 19 or 20 will serve as the fundamental equation adopted for this study. It simply shows that human capital in the form of health is an important determinant of labour productivity.

2.2. Model Specification, Data and Econometric Results

2.2.1. A VAR Model of Health Status and Labour Productivity Index

In recent years, there has been extensive use of the powerful tools of vector Autoregression (VAR), which was pioneered by Sims (1980a) in studying economic phenomena, The VAR technique is attractive because it facilitates the study of economic relationships in interdependence; hence all the variables become endogenous. VAR has also been proven to be powerful in analyzing time series data, analysis of both short-run and long-run dynamics, impulse response functions and forecasting error variance decomposition. This study, therefore, adopts this versatile tool to explicate the nature of the relationship that exists between health status and labour productivity index for Nigeria.

In this study, the stationarity state of the variables was examined by carrying out unit root tests. Johansen co-integration test was conducted to see if a long-run meaningful relationship existed between the variables of interest. Dynamic estimation of forecasting Error Variance Decomposition was utilized also. The study posits a 4-variable VAR model in which life expectancy rate, government health expenditure, malaria cases and labour productivity index are simultaneously interrelated. To obtain more meaningful insights, logarithmic transformations of the variables were utilized.

Thus, the VAR model specified is: $\boldsymbol{V_t = \propto + \sum_{i=1}^{k} A_i V_{t-1} + U_t}$, $\boldsymbol{V_t = (LLER, LGHE, LMC, LLPI)}$

$\propto$ = Intercepts of autonomous variables; A_i = Matrix of coefficients of all the variables in the model;

V_{t-1} = Vector of the lagged variables; U_t = Vector of the stochastic error terms.

2.2.2. Data Issues

All the variables of this study are described in this section and their sources disclosed. Health indicators considered in this study include life expectancy rate at birth, government health expenditure, and malaria cases. The variables were obtained from different sources. Malaria cases were obtained from the World Health Organization website and from Sede and Rolle (2017). Government health expenditure was obtained from Central Bank Bulletin (2017). Secondary school enrolment rates, life expectancy rates and labour productivity index were obtained from World Development Indicators (2018).

3.2. Econometric Estimation and Results

3.2.1. Unit Roots Tests

Given that the study utilized time-series data, it is advisable to begin by understanding the stationarity state of the variables employed. To examine if the variables have mean reversion, a unit root test was conducted for all the variables using Augmented Dickey-Fuller (ADF) and Phillip–Perron (P-P) methodology. This approach is widely accepted as the most reliable test of stationarity for time series variables (Iyoha, 2015).

Table 1. Summary of the Unit Root Results

	Augmented Dickey-Fuller				Phillip-Perron			
	With intercept		With Intercept & Trend		With intercept		With Intercept & Trend	
	Levels	Ist diff	Levels	Ist diff	Levels	Ist diff	Levels	Ist diff
LLPI	1.72 (3.68)	5.79(3.68)*	1.68 (4.23)	4.24(5.69)*	1.75(3.63)	5.79(3.63)*	1.72(4.23	5.68(4.24)*
LLER	1.97 (3.63)	1.91 (3.63)	1.82 (4.24)	5.25(4.24)*	2.57(3.62)	1.97(2.95)	0.28(4.23)	5.04(4.24)*
LMC	2.47 (3.64)	7.29(3.65)*	3.53 (4.26)	7.26(4.27)*	2.42(3.65)	8.22(3.65)*	3.52(4.26)	8.04(4.27)*
LGHE	0.79(3.63)	6.86 (3.63) *	2.68 (4.23)	12.51(4.24)*	0.26(3.63)	2.68(4.23)	12.94(3.63)*	12.51(4.24)*

Source: Author Computation

*stationary variables at 1%.

Nb: values in parenthesis are McKinnon critical values

While those outside brackets are the augmented Dickey fuller Statistics

In Table 1, the results of the unit root test are presented. There are two approaches to the test. They are the Augmented Dickey-Fuller test and the Phillip-Perron test. For each of the dimensions, tests are conducted with trend only and with trend and intercept. For both trends only and trends with intercept, analysis is done at levels and first difference. Note that all the economic variables, viz; life expectancy rate at birth, malaria cases, government health expenditure and labour productivity index are homogenous of 1 that is I (1).

3.2.2. Co-Integration Results

For the sake of reasonable policymaking, it is pertinent we consider the relationship among macroeconomic variables in the long-run. If a common stochastic drift exists among the variables such that they move in tandem in the long-run then policy formulation will be reliable based on the perceived relationship among them. Against this backdrop, the Johansen and Juselius co-integration tests were conducted to examine the presence of long-run meaning relationships among the variables. From the test statistic of trace and maximum eigenvalues, the result shows that there are two cointegrating equations among the variables. Hence, we accept the alternative hypothesis which posits that a common stochastic drift exist among the variables used for the analysis. The results are presented in Table 2.

Table 2. Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalues)

Cointegrating vector (LLER, LGHE, LLPI, LMC)		
Null hypothesis	**Trace Statistics**	**Maximum Eigenvalue**
r=0	87.96*	46.65*
r=1	41.30*	36.41**
r=2	4.89	4.86
r=3	0.03	0.03

*Null hypothesis rejected at 5%

Source: Authors Computation

3.3. Pairwise Granger Causality Test

In Table 3, we present the results for the pairwise Granger Causality Test. The result revealed a bicausal relationship between log LPI and log LER. Thus, while log LPI influences log LER, it is in turn influenced by log LER. We can, therefore, infer that the survival rate influence economic progress and it is in turn influence by economic progress. A unidirectional relationship exists between log LER and log GHE. Life expectancy rate influenced government health expenditure, while government health expenditure does not significantly influence life expectancy rate. Finally, unidirectional impact flows from log MC to log GHE and not the other way round. Hence, the impact is from malaria cases to government health expenditure, and not the other way round.

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Table 3. Pairwise Granger causality tests

Direction of causality	Obs.	F-statistics	Remark
LLER → LLPI	35	0.43	Do not reject
LLPI → LLPI	35	2.81***	Rejected
LMC → LLPI	32	039	Do not reject
LLPI → LMC	32	0.29	Do not reject
LGHEXP → LLPI	35	1.85	Do not reject
LLPI → LGHE	35	1.03	Do not reject
LMC →LEXR	32	3.24	Do not reject
LEXP → LMC	32	2.71	Do not reject
LGHE→LLER	35	17.79	Do not reject
LLER → LGHE	35	0.07***	Rejected
LGHE → LMC	32	5.02	Do not reject
LMC → LGHE	32	0.02**	Rejected

Source: Authors' computation.

**Fstatistics significant at 1%; **Fstatistics significant at 5%.*

3.3.1. The Cholesky VAR normality residual tests

One of the requirements of regression model is that the error terms of the observations are normally distributed. The study employed the Cholesky (Lutkepohl) test to ascertain this. The results are presented below.

Table 4. The Cholesky VAR normality residual test

Component	Test criterion	Joint chi-square	Probability
4	**Skewness**	**6.538****	**0.0162**
4	**Kurtosis**	**10.783****	**0.0291**
4	**Jarque-Bera**	**17.321****	**0.0269**

*** Chi-square test significant at 5%.*

Source: Authors' computation

Results from Table 4 show that the residuals are normally distributed as the Skewness, Kurtosis and Jarque-Bera statistics passed the chi-square test at 5%.

3.4. VAR Lag Selection Test

The estimation of a VAR-model requires the use of optimum lag-length in the equation of the model. In this study, the Akaike information criterion (AIC) was used to determine the lag length of the VAR-model.

Table 5. Lag length results of Akaike (AIC), Schwartz and Hannan Quinn Information Criterion

Lags	AIC	SC	HQ
1	**-0.94**	**-0.75**	**- 0.88**
2	**-8.71***	**-7.79 ***	**- 8.41***
3	**-8.74**	**-7.09**	**- 8.19**

Source: Author Computation

This result and that of Schwarz and Hannan-Quinn information criteria are shown in Table 5. The Akaike information criterion (AIC) is minimized for order 2. This implies that the optimal lag length of this study is the order 2.

3.4.1. Estimated Model

The estimated VAR results are presented in Table 6. The coefficient of determination puts at 0.59 revealed that 59% of the variation in log LPI is accounted for by the variation in the collective independent variables (log GHE, log MC and log LER). The adjusted coefficient of determination puts the predictive power of the estimated model at 45%. The Durbin-Watson d statistics puts at 2.1 showed that the error term is free from problem of autocorrelation, hence the efficiency properties of the estimated parameters is guaranteed.

Table 6. Parameter Estimates of Vector Autoregression Model

Variables	Coefficients	t-ratios (s)	Other Statistics
Constant	5.78	3.53**	R^2 = 0.59
LLLPI (-1)	0.38	1.95***	Adjust R^2 = 0.45
LLPI (-2)	-0.11	-0.70	F= 0.45
LGHE (-1)	-0.03	-2.43*	ϸ = 0.00*
LGHE (-2)	0.02	1.39	D-W= 2.1
LLER (-1)	1.97	0.58	
LLER (-2)	- 2.28	-0.65	
LMC (-1)	0.02	0.84	
LMC (-2)	0.04	2.09*	

**/* significant at 5% and 1% respectively.

Source: Author Computation

First and second lagged values of government health expenditure present mixed outcome as to the direction of its influence on labour productivity index. The one time lagged value of government health expenditure has negative and significant effect showing that government health expenditure rather reduces labour productivity index. However, the two time lagged value of government health expenditure though has positive effect, but not statistically significant. This is in support of Eneji *et al*. (2013), Onyema *et al.* (2019) but contradicts those of Umoru & Yaqub (2013).This is expected given that the percentage share of capital health expenditure in the GDP continues to exhibit downward trend, when compared with recurrent health expenditure on health as a percentage of GDP. This shows that Nigeria's government performance in terms of capital inputs is unimpressive (Sede & Ohemeng, 2015). Among Less Developed Countries Nigeria inclusive there is dearth of health infrastructure, hence government health spending should be used in providing and developing health facilities and upgrading the operations of the health system (Novignon *et al*., 2015).

In the same vein, first and second-term lagged values of life expectancy rate have mixed outcome, however none is statistically significant. This contradicts findings by Barro & Salai-martin (1995) and Knowles & Owen (1995), who reported in their studies that life expectancy rate significantly, improve labour productivity. However, it conforms to finding from a Nigerian study (Onyema *et al*.; 2019). Malaria cases have no significant effect on labour productivity index hence no long-run equilibrium relationship exists between malaria cases and labour productivity. This contradicts the report from several Nigerian studies (Alaba & Alaba, 2011; Onwujekwe *et al.;* 2000), who reported that malaria attack is associated with loss days of labour.

3.4.2. Forecasting Error Variance Decomposition

To further examine the short-run dynamic properties of the log LPI, We examined the forecast error variance decomposition (FEVD). Akinbobola (2012) in Ighodaro (2015) believed that the statistical efficiency of the coefficients estimates from Vector Error Correction Model (VECM) cannot be guaranteed, hence most scholars resort to the interpretation of dynamic simulations of Forecasting Error Variance Decomposition (FEVD) and Impulse Response Functions (IRFs). The FEVDs for the log LPI is presented in Table 7. We only presented the FEVD of log LPI because it is the primary thrust for the study.

Table 7. Variance Decomposition Estimates (in percentage)

Period	LLPI	LLER	LMC	LGHE
1	100.00	0.00	0.00	0.00
2	85.00	4.91	0.07	0.07
3	73.91	11.09	0.59	0.59
4	73.28	12.11	0.87	0.87
5	75.99	11.28	0.71	0.71
6	74.36	13.51	0.70	0.70
7	69.95	17.51	0.77	0.77
8	67.29	20.05	0.76	0.76
9	66.42	21.47	0.71	0.71
	65.02	23.42	0.65	0.65

Source: Author computation

In Table 7 the FEVD for the variable log LPI for ten periods is presented. Analysis revealed that the variance of LPI is principally driven by own shock. In the period 1, LPI accounted for 100% of its own variance. However, its variance decreases consistently throughout the period until it peaked at 65.02% by the tenth period. One variable that made significant impact on Log LPI is logLER. By the tenth period, Log LER contributed 23.42% to logLPI. Log MC and LGHE made equal and insignificant contribution to the variance of log LPI, which stood at 0.65% by the tenth period.

Following Johansen and Juselius (1990) and Johansen (1991), a vector of endogenous variables that are homogeneous of order one is analyzed with Vector Error Correction Estimates (VECM). Here all the variables are endogenous and choice of optimum lag is determined by optimal lag selection tests of Ackaike Information Criterion (AIC), Schwartz criterion (SC) and Hannan Quinn (HQ). The results of VECM are presented in Table 7 below.

3.4.3. Estimated Model

Table 8. VECM Results

Variables	Coefficients	t-ratios (s)	Other Statistics
Constant	0.01	0.75	$R^2 = 0.47$
LLLPI (-1)	-0.59	-3.26*	Adj $R^2 = 0.25$
LLPI (-2)	0.08	0.39	F = 2.17
LGHE (-1)	-0.02	-1.91	ƥ = 0.07***
LGHE (-2)	0.01	0.61	D-W = 1.96
LLER (-1)	-3.41	0.77	
LLER (-2)	3.32	0.78	
LMC (-1)	-0.04	-2.17*	
LMC (-2)	1.65	0.98	

**/* significant at 5% and 1% respectively

Source: Authors' computation

In Table 8, the coefficient of determination puts 0.47 showed that 47% of the variation in log LPI is accounted for by variation in the three health indicators (log LER, log GHE, log MC). Given that this is a system equation, the coefficient of determination is commendable. The F-statistics (2.17) with ƥ = 0.07 showed that the entire model is statistically significant; hence the assumption of no significant relationship between the independent variables and the explained variables is rejected at 10%. The Durbin-Watson statistics of 1.96 which is approximately 2 revealed the absence of autocorrelation. Both first and second term lagged values of malaria cases are both negative and statistically significant showing that malaria constitutes a drag on labour productivity in Nigeria. This finding conforms to findings by Jimoh (2005), Rolle and Iseghohi (2018) and Osakede and Lawanson (2016). This is not surprising given the wide spread and frequent bouts of malaria attack on Nigerians. In Nigeria, malaria accounts for absenteeism from work and school among school children. Both victims of malaria and their care givers often forego days of work due to illness associated with malaria attack. Evidence from Alaba & Alaba (2011) reported that the average days lost from malaria attack ranges from 7-11 days and the loss of work hours expressed in monetary terms was put at between $28 and $34 which is lost to every bout of malaria attack. Jimoh (2005) reported that malaria incidence constituted drags on Agricultural productivity for Nigeria. Several Nigerian studies estimated the indirect cost of malaria. Onwujekwe *et al.* (2000) estimated that the cost of treating malaria depletes 2.91% of household monthly income, hence concluded that malaria is a big contributor to the economic burden of diseases in malaria holo-endemic communities. Osakede & Lawanson (2016) estimated that 50% of Nigerian adult population experienced loss in labour contribution due to malaria attack with the indirect cost of about N5, 532.59 ($37.16) and N4, 828.73($ 32.43) per person per day for patient and caregiver respectively.

3.5. Discussions and Policy Recommendations

This paper examined the effect of health on labour productivity through labour productivity index utilizing annual time series data for the period 1981 through 2017. The study revealed that most of the variables that influence economic performance for other countries do not have the potentials for improving Nigerian labour productivity. Specifically, life expectancy rate at birth and government health spending have no significant impact on Nigerian labour productivity. Hence, improving these variables may not yield any economic gain for Nigeria.

Nigeria health spending has no significant effect on labour productivity for a number of reasons. Over the years, Nigeria's health spending has been increasing but the tide has been in favour of recurrent health expenditure. Recurrent health spending is principally incurred on payment of salaries and other administrative health expenses. Attention should be given to quality of government health capital expenditure, particularly on health infrastructure, medical kits and equipment, other healthcare deliverables as against the escalating recurrent health expenditure. The findings have implications for the Nigerian health sector. There is need for Nigerian government to improve its health policy, particularly in the area of health funds, efficient utilization of health resources, ensuring prompt investment in medical equipment and health service delivery. Nigerian government owes it a responsibility to improve the provision of health infrastructure, training of health personnel, immunization and other inoculation services.

The high incidence of malaria remains one of the greatest disease burden plaguing Nigerians, what Sachs called ''the curse of the tropics''. In Nigeria, the costs of malaria treatment is beyond the means of the poorest households and given the reality of repeated bouts of malaria and its effects on household poverty, there is need for the enactment of policies that will increase access to effective treatment of malaria as a priority for the most vulnerable sections of the society. This is particularly urgent with the deployment of the more expensive Artemisin-based combination Therapies (ACTs) in Nigeria. Consequently, efforts should be intensified to formulate policies and programmes to combat malaria.

3.6. Strengths and limitations of the study

The study has two strengths. First, it utilized three health outcomes which yielded deeper insight, unlike previous studies that utilized only one health indicator. Second, the study utilized the versatile technique of vector Auto regression, which addressed possible endogeneity bias. However, the limitation of the study is that the variables used in explaining labour productivity are not exhaustive, as there are other variables beside health outcome that can possibly influenced labour productivity. Nevertheless, the study is not suffering from omission bias.

4. Conclusions

In this study an attempt is made to examine the effect of health status on labour productivity for the period 1981 through 2017. We utilized three health variables which are life expectancy rate at birth, government health expenditure and malaria cases. We specified a vector autoregression model, which accounts for reverse causality among the economic variables utilized in the study. Both augmented Dickey fuller and Phillip- perron tests were used in examining the stationarity state of the variables. The variables were homogeneous of order one. Long-run relationship existed among the variables as evidenced by the Johansen and Juselius cointegration test. The pairwise granger causality revealed a unicausal flows from labour productivity index to life expectancy rate. The FVED revealed that the changes in the variance of labour productivity are largely due to own shock, with life expectancy rate making a modest contribution to the variance of labour productivity index. A-two lagged vector error correction model was estimated having affirmed the robustness of the relevant statistical features of the model through appropriate diagnostic tests. The good-ness-of fit of the model was confirmed at 10% and there is absence of autocorrelation as revealed by the Durbin-Watson statistics. Both life expectancy rates at birth and government health expenditure has no significant impact on labour productivity. However, malaria cases serve as drag to labour productivity due to the wide spread and frequent bout of malaria attacks in Nigeria. It is, therefore, recommended that relevant policies be implemented to combat malaria attack and increase access to effective treatment. Health expenditure on capital goods should be reviewed upward in order to provide needed health infrastructures for effective health service delivery.

Authors' Contribution

RRA conceived the study, undertook the analysis while DO and HAE undertook the write up of part of the manuscript and estimated the models. All three authors read and approved the final manuscript. It was the responsibility of RRA to upload and send to the journal.

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Availability of Data and Materials

The dataset used and analyzed during the current study is available from the corresponding author on reasonable request.

Abbreviation and Acronyms

DALYs: Disability-adjusted life years**;** VARs Vector autoregression: R & D Research and Development; LER: Life Expectancy Rate at birth; GHE: Government Health Expenditure; MC: Malaria Cases; TFP: Total Factor Productivity; ADF: Augmented Dickey-Fuller; VIF: Variance Inflation Factor; AIC: Akaike Information Criterion; SC: Schwartz Criterion; HQ: Hann Quinn; FEVDs: Forecasting Error Variance Decomposition; VECM: Vector Error Correction Model; OECD: Organization for Economic Cooperation and Development.

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