LIFE EXPECTANCY - POVERTY DYNAMICS: AN AUTOREGRESSIVE DISTRIBUTED-LAG (ARDL) APPROACH

[1]Oluranti Grace Aje, [2*]Saheed Busayo Akanni, [1]Azeezat Ayodele O. Adebayo, [1]Ismail Adeyinka Abdulazeez, [3]Ibraheem Tesleem Omowumi and [1]Oladapo Grace Ayanyemi

[1]*Department of Statistics, Federal Polytechnic Ede, Osun State, Nigeria.*
[2]*Department of Statistics, University of Ilorin, Ilorin, Kwara State, Nigeria.*
[3]*Federal College of Agricultural Produce Technology, Kano*
Corresponding author: akannisb2018@gmail.com

Abstract

This study examines the relationship between males' life expectancy at birth (LEM) and poverty (POV), particularly the unilateral relationship from the predictor POV to the dependent LEM. To enhance the robustness of parameter estimations, the Naira-Dollar exchange rate (EXR) was included as a control variable alongside POV. Yearly time series data collected on LEM, POV, and EXR spanning 1981 to 2023 was used in our study. Moreover, to determine the possible presence of short and long-run relationships among these three series, we used the Autoregressive Distributed-Lag (ARDL) model for examining these series. Basic pre-test results of ARDL such as first difference stationary conditions (I(1)s) and lag selection criteria jointly selected the ARDL(1, 3, 2) model as the optimal model for examining the series. Moreover, diagnostic checking on the model's residual showed that it is non-autocorrelated and non-spurious (R^2 (0.999367=) < Durbin-Watson (=2.404865)). The findings established that changes in EXR and POV have an immediate lag on life expectancy, with EXR fluctuations having complex short and long-term effects and POV having significant delayed negative effects. Further findings revealed that the Error Correction Term (ECT) has the correct sign (-0.061242) which indicates a 6.1% adjustment rate back to the long-run equilibrium per period.

Keywords: Life expectancy; Poverty; Short-run Relationship; Long-run Relationship; Autoregressive Distributed-Lag Model.

1.0 Introduction

Life expectancy is a crucial measure of a population's general health and well-being (Muszyńska-Spielauer et al, 2022; Evans & Soliman, 2019). This is because, given the current rates of death, it summarizes the typical lifespan that an individual may anticipate. As such, it is impacted by a broad range of socioeconomic variables, such as living conditions, healthcare and educational access, and income levels (Kennedy et al, 1998; Lantz et al, 1998). Among these, poverty is one of the most important determinants, frequently associated with poor health and a shorter life expectancy **(**Clarke & Erreygers, 2020; Peters et al, 2008**)**. The complex relationship between poverty and life expectancy has attracted a lot of interest from researchers and policymakers since it is essential to comprehend this dynamic to develop solutions that will promote public health and lessen inequality.

Lack of access to opportunities and necessary resources is a hallmark of poverty, which can seriously impair people's capacity to lead healthy lives and, as a result, raise death rates and shorten life expectancies (Garmany et al, 2021). On the other hand, longer life expectancies allow for a more productive workforce and lessen the financial burden of illness, which can have an impact on poverty levels (see Cervellati & Sunde, 2005**)**. This reciprocal link emphasizes how important it is to do a thorough analysis that takes into consideration how poverty and life expectancy interact dynamically throughout time. Moreover, Life expectancy and poverty can also be indirectly impacted by the exchange rate (EXR), another macroeconomic determinant. Exchange rate swings are a major factor in determining a nation's economic stability since they can affect employment rates, inflation, and the cost of necessities. These factors all have an impact on poverty and health consequences. As a result, taking the exchange rate into account when doing the research offers a more comprehensive understanding of the variables influencing life expectancy and the dynamics of poverty. To analyze these relationships, this study employs the Autoregressive Distributed-Lag (ARDL) model, a robust econometric technique suited for exploring both short term and long-term dynamics among time series variables, irrespective of whether they are stationary at level {I(0)}, first difference {I(1)}, or a mixture of both (see Pesaran et al, 2001; Garba et al, 2023). The ARDL approach is particularly advantageous for this study as it allows for the examination of the potential cointegration among life expectancy, poverty, and exchange rate, offering insights into how these variables interact over time. Furthermore, through the use of the ARDL model, this study seeks to provide a detailed understanding of the relationships between life expectancy and poverty by evaluating both the short and long-term effects. By examining these correlations within the framework of a developing nation, the research adds to the wider conversation on how macroeconomic variables impact socioeconomic advancement and public health. The results should help guide more successful initiatives to raise life expectancy and reduce poverty by educating policymakers about the intricate relationships among life expectancy, poverty, and exchange rates. In conclusion, taking into consideration the influence of exchange rate changes, this study explores the dynamics of life expectancy and poverty within the context of the ARDL approach. The study aims to reveal the complex relationships between these important factors through this approach, offering important information for creating economic and health policies that improve population well-being.

Previous studies have focused on public health indicators like life expectancy, or health-growth (i.e. life expectancy-economic growth) nexus. For instance, Aje et al (2024) applied the Autoregressive Integrated Moving Average (ARIMA) model to show that the life expectancy of Nigerian males is expected to increase slightly by 0.64% from 2021 through 2030. Çığşar et al (2024) model the life expectancy of males and females in Türkiye, Singapore, Norway, and China to show that the Constant Share Growth (CSG) model is more suitable than the logistic growth model for estimating life expectancy for overall data and for each gender. Using the endogenous growth theoretical approach and fully modified ordinary least squares (OLS) method, Lawanson & Umar (2021) showed that health contributes positively to economic growth and also mitigates the adverse effect of poverty on economic growth in Nigeria. They also discovered that the minimum threshold of life expectancy of 64.4 years is a health improvement annual benchmark whereas the current annual average of 47.8 years is fundamental. Foreman et al (2018) developed athree-component model of cause-specific mortality to forecast life expectancy, years of life lost, and all-cause and cause-specific mortality for cross countries. Their findings showed that global life expectancy to increase by 4·4 years for men and 4·4 years for women by 2040, but based on better and worse health scenarios, trajectories could range from a gain of 7·8 years to a non-significant loss of 0·4 years for men, and an increase of 7·2 years to essentially no change 0·1 years for women. Also, Cao et al (2020) employed Multiple Linear Regression and Autoregressive Integrated Moving Average (ARIMA) models to examine life expectancy, healthy life expectancy, and Gap series for 195 countries. They projected that life expectancy and healthy life expectancy are likely to increase in most countries and regions while Gap is also expected to expand. Furthermore, Olshansky (2005) examined the effect of obesity on the life expectancy of the U.S. population by calculating the reduction in the rates of death that would occur if everyone whois currently obese were to lose enough weight to obtain an "optimal" BMI, which they defined asa BMI of 24. Their findings indicated a steady rise in life expectancy during the past two centuries may soon end. Through a review study, Seifarth (2012) highlighted biologicalmechanisms that may underlie the sexual dimorphism in life expectancy. They discovered that despite the noted gaps in sex equality, higher body fat percentages, and lower physical activity levels globally at all ages, a sex-based gap in life expectancy exists in nearly every country for which data exist. However, Chetty (2016) used mortality data to estimate race- and ethnicity-adjusted life expectancy at 40 years of age by household income percentile, sex, and geographic area, and to evaluate factors associated with differences in life expectancy. They found that higherincome was associated with greater longevity and differences in life expectancy across income groups increased over time. In a work, Mathers (2015) employed trend analysis to show that lifeexpectancy at age 60 years has increased in recent decades in high-income countries. Woolf & Schoomaker (2019) reviewed the relationships between life expectancy and mortality rates in theUnited States between 1959 and 2017. They discovered that the United States life expectancy increased for most of the past 60 years, but the rate of increase slowed over time and life expectancy decreased after 2014. Torri & Vaupel (2012) examined forecasting life expectancy in an international context for some countries using the ARIMA model, discrete geometricBrownian motion, and discrete model of geometric mean-reverting processes. Levantesi et al. (2022) applied simultaneous forecasting and functional clustering techniques to forecast the multivariate time series of life expectancy at birth of the female populations in some developed and developing countries of the world. They found out that the evolution of developed countries follows a homogeneous pattern and supports the persisting homogeneity within the highlongevity cluster over time. Pascariu et al. (2018) applied the Double-Gap model to forecast the life expectancy at age 0 and the remaining life expectancy at age 65 for some developed countries. His findings established that the model should be considered as a promising available forecasting tool. Using the Li-Lee model, Van Baal et. al. (2016) showed that life expectancy (LE) is likely to increase for all educational groups whereas LE between educational groups will widen. Bennett et al. (2015) examined the future of life expectancy and life expectancy inequalities in England and Wales using Bayesian Spatiotemporal Forecasting techniques. Their findings showed that life expectancy will reach or surpass 81·4 years for men and reach or surpass 84·5 years for women in every district by 2030. Furthermore, Nigri et al. (2021) employed a long short-term memory approach to forecast life expectancy and disparity in Australia, Italy, Japan, Sweden, and the USA. Their predictions were found to be coherent with historical trends and biologically reasonable providing a more accurate portrait of the future life expectancy and lifespan disparity. Levantesi et al. (2022) investigated clustering-based simultaneous forecasting of life expectancy time series through long-term short-term memory neural networks in forty-one (41) countries. Their results showed that the evolution of developed countries follows a homogeneous pattern and supports the persisting homogeneity within the high longevity cluster over time. Rabbi et al. (2018) studied mortality and life expectancy forecasts for nine comparatively high mortality Central and Eastern European (CEE) countries using seven different variants of the Lee-Carter method and the Bayesian Hierarchical Model. Their results revealed that the use of the probabilistic forecasting technique from the Bayesian framework resulted in a better forecast than some of the extrapolative methods but also produced a wider prediction interval for several countries. Kontis et al. (2017) utilized the Bayesian ensemble model to study the future of life expectancy in 35 industrialized countries. Their findings established that life expectancy is projected to increase in all 35 countries with a probability of at least 65% for women and 85% for men. Levantesi et al. (2023) examined the multi-country clustering-based forecasting of healthy life expectancy using multivariate forecasting techniques. Their findings established that the predictive analysis in a multi-population perspective to obtain more accurate information by exploiting the similarities between countries that have shown similar trends. Bergeron-Boucher et al. (2019) investigated the impact of the choice of life table statistics using extrapolative methods. The results show that forecasting based on death rates and probabilities of death leads to more pessimistic forecasts than using survival probabilities, life table deaths, and life expectancy when applying existing models based on linear extrapolation of (transformed) indicators. To the best of our knowledge, no previous studies have examined the relationship between life expectancy and poverty (POV) in Nigeria. This study addresses a gap in the literature by examining the relationship between males' life expectancy at birth (LEM) and poverty (POV), focusing specifically on the directional influence of poverty as a predictor of life expectancy.

2.0 Materials and Methods

Annual time series datasets covering 1981 to 2023 were obtained on the Life expectancy of males at birth (LEM), Poverty (POV), and exchange rates. These datasets were collected from the World Bank Data (2022). Here, the LEM-POV dynamics are explored using EXR as another control variable. For empirical estimation, the model is first stated as equation (1):

$$\mathrm{LEM}_t = \mathrm{f}(\mathrm{POV}_t, \mathrm{EXR}_t) \quad (1)$$

Re-writing equation (1) yields the following Time Series Regression (TSR) equation denoted as equation (2):

$$\mathrm{LEM_t} = \beta_0 + \beta_1\mathrm{POV_t} + \beta_2\mathrm{ERX_t} + \varepsilon_t \qquad (2)$$

Where: $\mathrm{LEM_t}$= LEM at current time *t*, $\mathrm{POV_t}$= POV at current time *t*, $\mathrm{EXR_t}$= EXR at current time *t*, ε_t represent the error term expected to be Normally Independently and Identically Distributed (NIID) with a mean of zero and constant variance {i.e. ε_t~NIID $(0,\delta^2)$},β_0, β_1, and β_2 represent the regression coefficients or parameters to be estimated.

2.1 Autoregressive Distributed-Lag (ARDL) model

The ARDL developed by Pesaran et al (2001) is desirable when the order of integrations of time series variables in a study is either a difference stationary series of order one {I(1)s} or a mixture of level stationary series {I(0)s} and I(1)s. In the ARDL framework, the I(1)s are the only variables that can be assumed as the dependent variables whereas the I(0)s cannot. The I(0)s are mainly proxied as the independent variables.

Based on equation (2), an ARDL specification is given by:

$$\Delta\mathrm{LEM_t} = \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta\mathrm{LEM_{t-i}} + \sum_{i=1}^{n}\alpha_{2i}\Delta\mathrm{POV_{t-i}} + \sum_{i=1}^{n}\alpha_{3i}\Delta\mathrm{EXR_{t-i}} + \partial_1\Delta\mathrm{LEM_{t-1}} + \partial_2\mathrm{POV_{t-1}} + \partial_3\mathrm{EXR_{t-1}} + \varepsilon_{it} \qquad (3)$$

Also, from equation (3), the Error Correction Model (ECM) is of the form:

$$\Delta\mathrm{LEM_t} = \alpha_0 + \sum_{i=1}^{n}\alpha_{1i}\Delta\mathrm{LEM_{t-i}} + \sum_{i=1}^{n}\alpha_{2i}\Delta\mathrm{POV_{t-i}} + \sum_{i=1}^{n}\alpha_{3i}\Delta\mathrm{EXR_{t-i}} + \partial_1\Delta\mathrm{LEM_{t-1}} + \partial_2\mathrm{POV_{t-1}} + \partial_3\mathrm{EXR_{t-1}} + \Upsilon_{1i}ECM_{t-1} + \varepsilon_{it} \qquad (4)$$

Where: α_0 is the constant term, α_{1i} to α_{3i} represent the short-run coefficients, ECM denotes the error correction term and $\varepsilon_t \sim N(0,\delta^2)$ is the white noise error term. The four basic steps in the ARDL modelling are itemized as follows:

Step 1: Unit root analyses

It is essential to ascertain the variables' order of integration before estimating the ARDL model. The variables in the ARDL model can be any combination of I(0) and I(1) and $I(0)$ and I(1), but none of them should be integrated of order 2, that is, I(2). In this study, the ADF tests developed by Dickey & Fuller (1979) have been used to check for the true order of integration of the series.

The null is that the individual series has a unit root. Moreover, the ADF tests the LEM, POV, and EXR series individually by including trend and drift in each test equation as follows

$$\Delta LEM_t = \beta_1 + \beta_2 t + \partial LEM_{t-1} + u_t \tag{5}$$

$$\Delta POV_t = \beta_1 + \beta_2 t + \partial POV_{t-1} + u_t \tag{6}$$

$$\Delta EEXR_t = \beta_1 + \beta_2 t + \partial EEXR_{t-1} + u_t \tag{7}$$

Where: LEM_t, $POV_{t,}$ and $EEXR_t$ are random walks at current period t, β_1= constant term, β_2= trend or time, $\partial = \rho - 1$, u_t= white noise error term, LEM_{t-1}, POV_{t-1} and EER_{t-1} are lagged one term of the LEM, POV and EXR variables. If $\partial = 0$, then $\rho = 1$; which means a time series has a unit root.

Step 2: Optimal lag selection for the best ARDL model

Here, the lags can be selected using any of the selection criteria such as the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), and Hann-Quinn Information Criteria (HQC). According to Burnham and Anderson (2004), the AIC, BIC, and HQC can be computed using the following mathematical relations:

$$\mathrm{AIC(p)} = \mathrm{n}\ln\left(\frac{\hat{\sigma}^2_{\varepsilon_t}}{\mathrm{n}}\right) + 2\mathrm{p} \tag{8}$$

Where: ***n*** is the number of effective observations used to fit the model, ***p*** is the number of parameters in the model, $\boldsymbol{\hat{\sigma}^2_{\varepsilon_t}}$is sum of sample squared residuals.

Of all these selection criteria, AIC is the widely used criterion in the literature when it comes to the ARDL (p, q) model (Liew, 2004).

Step 3: Model estimation

The chosen ARDL (p, q) model will then be estimated based on the number of appropriate lags selected in step 2 above. The estimation procedures will be discussed on a general basis in terms of Y (the dependent variable) and X (vectors of independent variables). In terms of Y and X, equation (3) can be re-specify as

$$\mathrm{Y_t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \mathrm{Y}_{t-i} + \sum_{j=0}^{q} \beta_j \mathrm{X}_{t-j} + \mathcal{E}_t \tag{9}$$

Where Y_t is the dependent variable at current time t, X_t represents the independent variables at time t, $\alpha_{i,}$ and β_j are parameters to be estimated, p and q denote the number of lags for Y and X, $\mathcal{E}_t$ still the same as defined above under (3). According to Kripfganz & Schneider (2023), the Ordinary Least Squares (OLS) can be used to estimate the parameters in (9). For easy estimation, we re-write (9) in vector form as

$$Y = Z\theta + \mathcal{E} \tag{10}$$

Where $Y = (Y_{p+1}, Y_{p+2}, \dots, Y_T)^T$ is a $(T-p) \times 1$ vector of observations for the dependent variable after excluding the initial p observations, $X = (X_{p+1}, X_{p+2}, \dots, X_T)^T$ is a $(T-p) \times (q+1)$ matrix containing lagged values of X up to lag q, Z is the matrix including both lagged values of Y (for the AR terms) and X (for the distributed lag terms), $\theta = (\alpha_0, \alpha_1, \dots, \alpha_p, \beta_0, \dots, \beta_q)^T$ is a $(p+q+1) \times 1$ vector of parameters, $\mathcal{E} = (\mathcal{E}_{p+1}, \dots, \mathcal{E}_T)^T$

Coefficients of the vector of parameters θ are obtained by the OLS estimator $\hat{\theta}$ which minimizes the sum of squared residuals as follows:

$$\hat{\theta} = argmin_\theta (Y - Z\theta)^T (Y - Z\theta) \tag{11}$$

Equation (11) can be reduced to the usual OLS estimator given by

$$\hat{\theta} = (Z^T Z)^{-1} Z^T Y \tag{12}$$

It should be noted that $Z^T Z$ must be invertible for the regression parameters to be estimable in equation (12). Moreover, for the cointegrated series, the ARDL (p, q) model can be re-specify in the Error Correction Model (ECM) as follows

$$\Delta Y_t = \Upsilon(Y_{t-1} - \partial X_{t-1}) + \sum_{i=1}^{p-1} \emptyset_i \Delta Y_{t-i} + \sum_{j-1}^{q-1} \varphi_j \Delta X_{t-j} + \mathcal{E}_t \tag{13}$$

Where Υ represents the speed of adjustment, ∂ is the long-run relationship between Y and X. $\emptyset_i$ and φ_j are short-run dynamic coefficients.

Step 4: Bound testing

After the model estimation, the next step is to test whether there is a long-run relationship (cointegration) between the dependent and independent variables. The ARDL bounds test is based on the F-statistic for the null hypothesis that there is no long-run relationship. If the calculated F-statistic is above the upper bound, reject the null hypothesis (there is a long-run relationship). Moreover, if the F-statistic is below the lower bound, do not reject the null (no long-run relationship). Lastly, if the F-statistic falls between the bounds, the result is inconclusive.

3.0 Results and Discussion

This section presents the results of the Seasonal Autoregressive Distributed Lag (ARDL) model fitted to the Life expectancy at birth for males (LEM), Poverty (POV), and Exchange Rates (EXR) series as discussed in the methodology section.

Table 1: Descriptive Statistics for the macroeconomic time series

Vars	N	Mean	Sd	Min	Max	Skew	Kurtosis
LEM	39	4.73E+00	3.12E+00	4.44E+01	5.35E+01	0.75	-1.09
POV	39	2.39E+13	3.44E+13	1.62E+10	1.16E+14	1.33	0.42
EXR	39	9.41E+01	9.28E+01	6.20E-01	3.07E+02	0.78	-0.29

Table 1 provides descriptive statistics for LEM, POV, and EXR series. For LEM, the average value is 4.73, while the standard deviation is 3.12. Moreover, these statistics suggest considerable variability. The series has a minimum of 44.4 and a maximum of 53.5. It displays light tails (kurtosis of -1.09) and a right-skewed distribution (skewness of 0.75). For the POV series, the average value is 23.9 trillion, and the standard deviation is 34.4 trillion, indicating a great degree of variability. The range is 16.2 billion to 116 trillion. The series has very low tails (kurtosis of 0.42) and a high right skewness (skewness of 1.33). In the case of EXR, the standard deviation is 92.8 and the average exchange rate is 94.1, suggesting a moderate degree of variability. It has a range of 0.62 to 307. With a skewness of 0.78 and a kurtosis of -0.29, the distribution is right-skewed and has somewhat lighter tails.

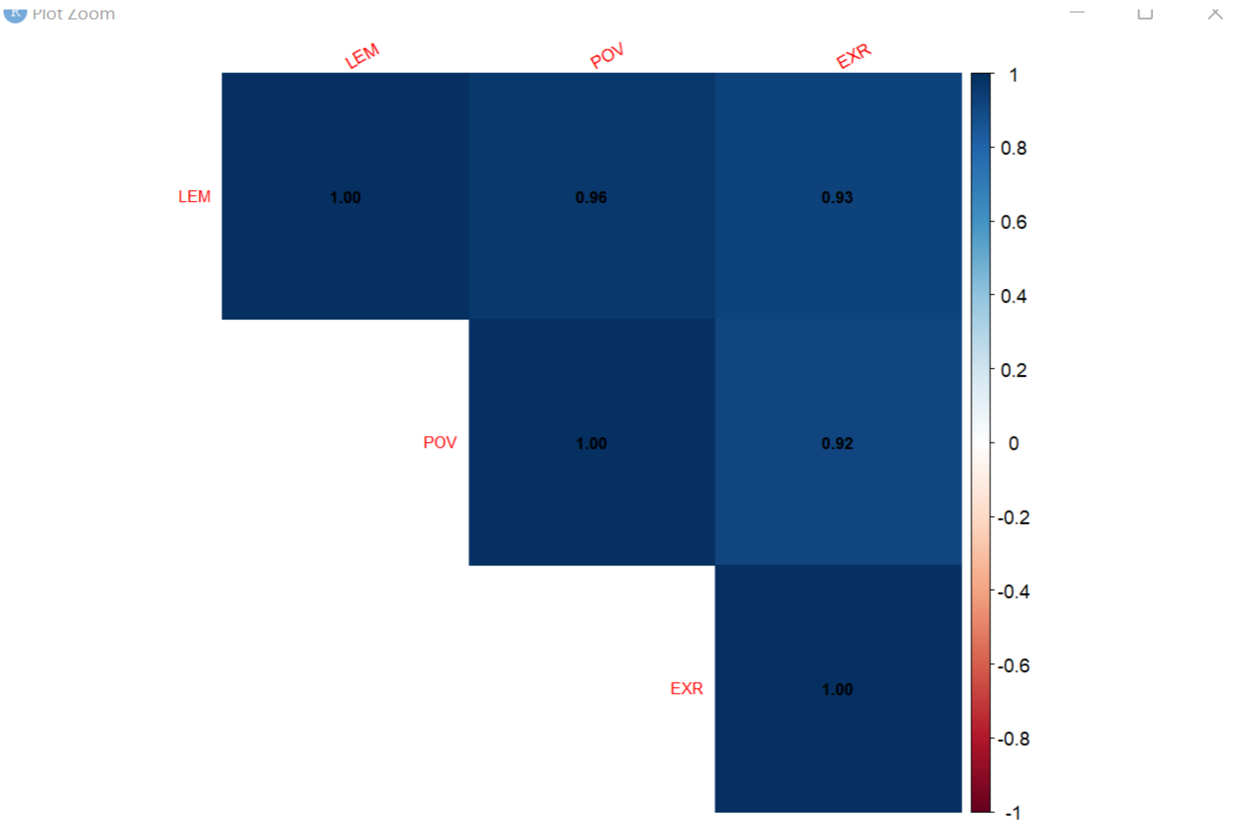

Figure 1: Correlation plot for the LEM, POV, and EXR series

To show the strength of these associations, the heatmap in Figure 1 employs various colors of blue. A higher positive association is found with darker blue hues. The fact that all pair-wise correlations are nearly equal to one suggests that all series have extremely robust positive associations.

Table 2: Correlation matrix for the series

	LEM	POV	EXR
LEM	1		
POV	0.96044	1	
EXR	0.92669	0.91538	1

The macroeconomic time series exhibits a high positive association, as indicated by the correlation matrix in Table 2. The Life Expectancy of Males (LEM) exhibits a strong positive correlation of 0.92669 with the Exchange Rate (EXR) and 0.96044 with Poverty (POV). Furthermore, there is a strong positive correlation (0.91538) between POV and EXR. Strong linear relationships between the series are indicated by this.

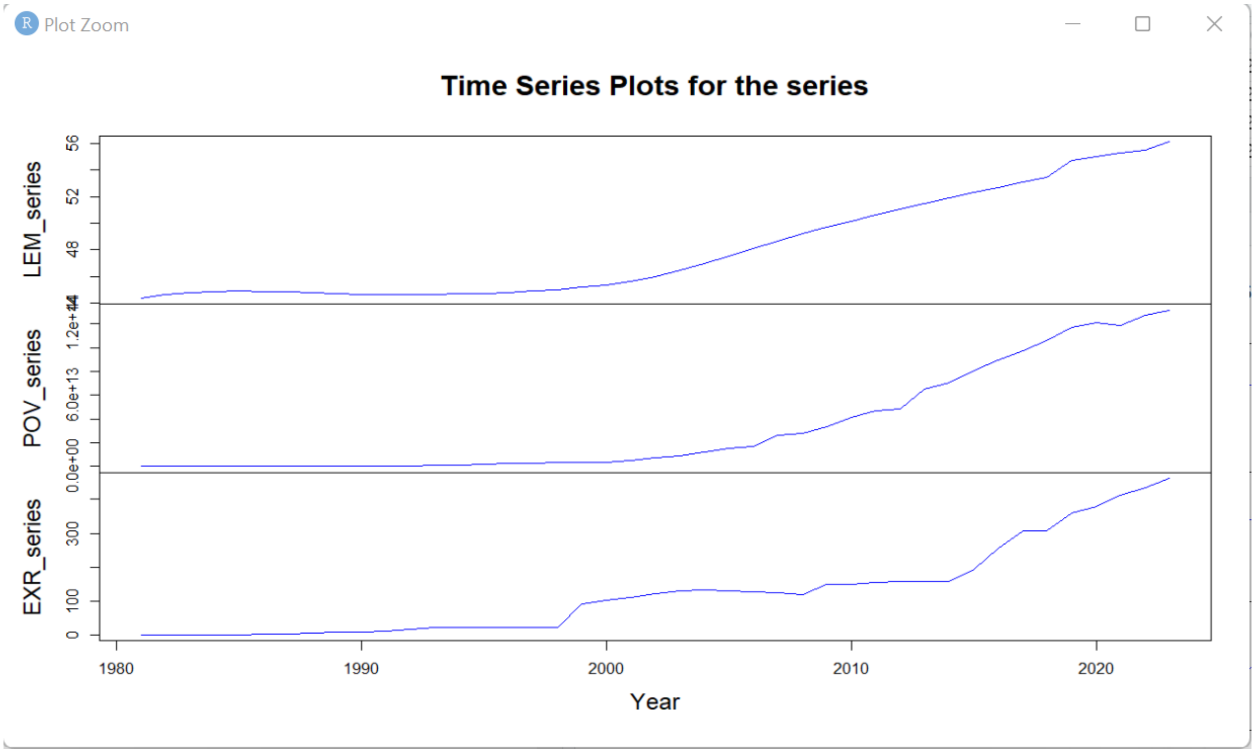

Figure 2: Time series plots for LEM, POV, and EXR series at levels

The time series plot in Figure 2 represents the time series plots for the LEM, POV, and EXR series at the level form. Based on these visualizations, LEM, POV, and EXR exhibit various trends (upward and downward); which are indications of non-stationarity in each of the series. To correctly determine the order of integration of these series, each of the series was subjected to unit root analyses using the Augmented Dickey-Fuller (ADF) and Elliot-Rothenberg-Stock (ERS) tests.

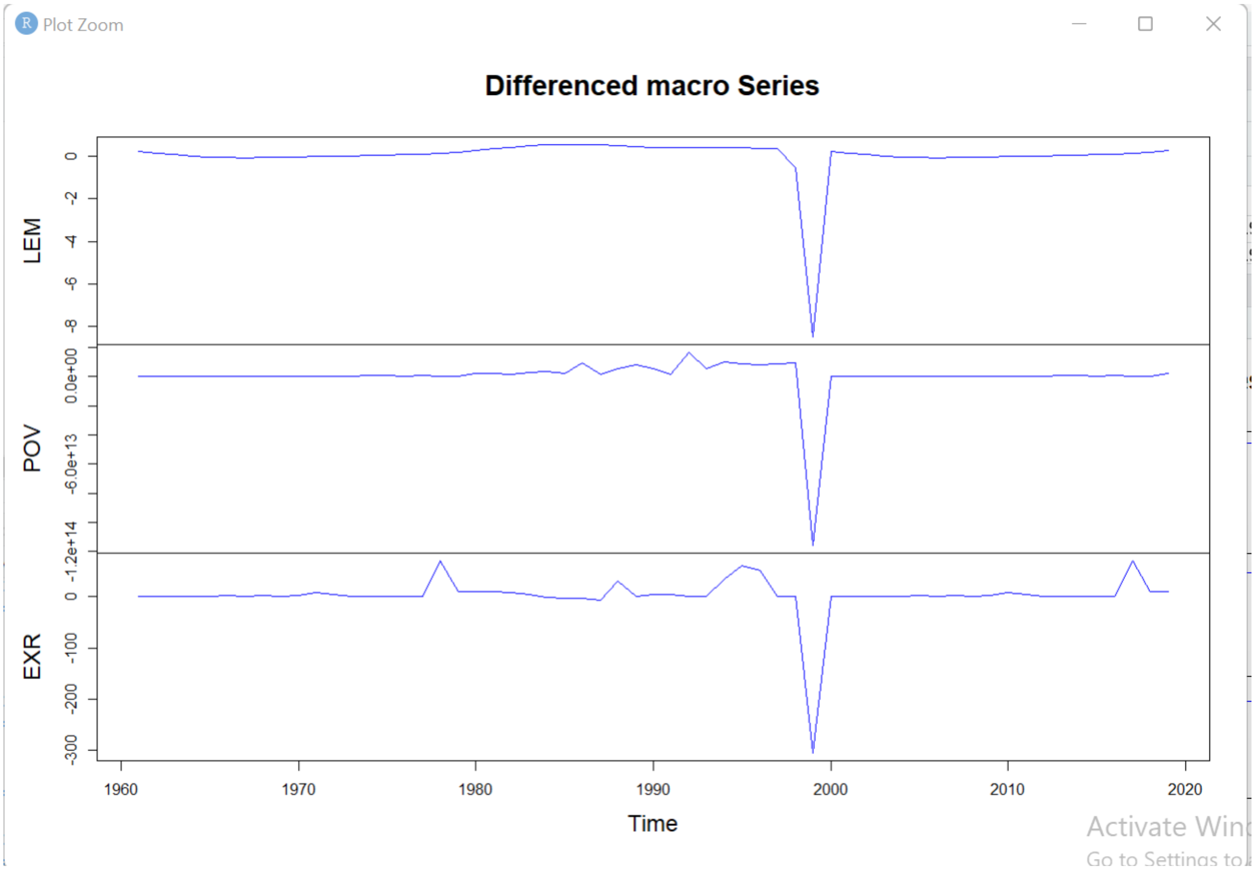

Figure 3: Time series plots of LEM, POV, and EXR series after the first difference

Figure 3 is the time series plots of the LEM, POV, and EXR series after their first differences. As shown in the time series plots, all the series exhibit zero mean and constant variance patterns except for some periods of late 2019 and early 2020 which indicates the coronavirus periods. In other words, they are time-invariant which means that they can now be modelled using any appropriate multivariate time series models depending on whether they are cointegrated or not.

Table 3: Results of ADF tests for LEM, POV, and EXR series

Variable	ADF-statistic	Critical values	P-value	Order of Integration
ADF at Level				
LEM	-0.9675	-3.5208	0.9378	NA
POV	-0.3622	-3.5208	0.9859	NA
EXR	5.12775	-1.9489	1.0000	NA
ADF after the first difference				
LEM	-4.5914	-3.5236	**0.0036*** **	I(1)
POV	-6.3585	-3.5236	**0.0000*** **	I(1)
EXR	-3.6371	-1.9491	**0.0006*** **	I(1)

The results of the stationarity tests in Table 3 further confirmed that truly all the series are difference stationary processes of order one {I(1)s}. This is evident in their p-values which are greater than the chosen level of significance (α= 0.05). The next thing is optimal lag selection for the series for which Table 4 presents the results of the selection criteria for selecting the best orders p and for the ARDL (p, q) model.

Table 4: Selection criteria for selecting the best ARDL (p, q) models

	LEM	POV	EXR	AIC
1	**1**	**3**	**2**	**-53.080*** **
2	1	4	2	-51.325
3	2	3	2	-51.257
4	1	3	3	-51.129
5	3	3	2	-50.863
6	2	4	2	-50.276
7	3	3	3	-49.762
8	2	3	3	-49.522
9	3	2	2	-49.493
10	1	2	2	-48.404
11	2	2	2	-47.809
12	3	4	3	-47.725
13	4	4	4	-44.147
14	1	2	1	-34.518
15	1	1	1	-20.410

Based on the results of optimal lag selection in Table 4, ARDL (1, 3, 2) has been selected as the best model by the selection criterion Akaike Information Criteria (AIC) since it reported the least value of AIC among all other possible orders.

Table 5: Selected model: ARDL(1,3,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LEM(-1)	0.938758	0.038918	24.12122	**0.0000*** **
POV	2.76E-14	6.55E-15	4.209853	**0.0002*** **
POV(-1)	3.48E-15	8.08E-15	0.430632	0.6697
POV(-2)	-2.36E-14	8.24E-15	-2.869109	**0.0073*** **
POV(-3)	-1.60E-14	6.87E-15	-2.325570	**0.0268** **
EXR	0.003387	0.001163	2.912248	**0.0066*** **
EXR(-1)	-0.004204	0.001593	-2.639103	**0.0129** **
EXR(-2)	0.005377	0.001179	4.561874	**0.0001*** **
C	2.696144	1.741435	1.548232	0.1317
R-squared	0.999367	Mean dependent var		48.34528
Adjusted R-squared	0.999204	S.D. dependent var		3.906657
S.E. of regression	0.110251	Akaike info criterion		-1.377002
Sum squared resid	0.376816	Schwarz criterion		-0.997004
Log likelihood	36.54003	Hannan-Quinn criter.		-1.239606
F-statistic	6117.063	Durbin-Watson stat		2.404865
Prob(F-statistic)	**0.000000**			

Significant dynamics between the Life Expectancy of Males (LEM), Poverty (POV), and Exchange Rate (EXR) are revealed by the ARDL(1,3,2) model estimates in Table 5. The highly significant positive coefficient of 0.938758 ($p < 0.001$) for the lag of life expectancy (LEM(-1)) shows that life expectancy values in the past have a significant impact on current values. A direct positive correlation between life expectancy and the current point of view is suggested by the positive and significant coefficient (2.76E-14, $p = 0.0002$). With POV(-2) and POV(-3) having significant negative coefficients (-2.36E-14, $p = 0.0073$ and -1.60E-14, $p = 0.0268$, respectively), the impact turns negative after two and three periods, suggesting a delayed negative influence of poverty on life expectancy. Life expectancy is positively and significantly impacted by the current Exchange Rate (EXR) value (0.003387, p = 0.0066). Exchange rate fluctuations, however, appear to have both short- and long-term effects. The first lag, EXR(-1), has a negative impact (-0.004204, p = 0.0129), whereas the second lag, EXR(-2), has a significant positive effect (0.005377, p = 0.0001) on life expectancy. The model diagnostics demonstrate good performance, and the constant term is not significant. With an R-squared of 0.999367, the model nearly fully accounts for the variation in life expectancy. The model is very significant overall, according to the F-statistic of 6117.063 (p = 0.000000), yet the Durbin-Watson statistic of 2.404865 indicates that there is no significant autocorrelation in the residuals.

Table 6: Error correction estimates from ARDL(1,3,2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COINTEQ*	-0.061242	0.006261	-9.781885	**0.0000*** **
D(POV)	2.76E-14	4.85E-15	5.683624	**0.0000*** **
D(POV(-1))	3.96E-14	4.64E-15	8.535619	**0.0000*** **
D(POV(-2))	1.60E-14	5.47E-15	2.922776	**0.0061*** **
D(EXR)	0.003387	0.001003	3.377565	**0.0018*** **
D(EXR(-1))	-0.005377	0.001011	-5.319190	**0.0000*** **

R-squared	0.864154	Mean dependent var	0.282450
Adjusted R-squared	0.844177	S.D. dependent var	0.266691
S.E. of regression	0.105275	Akaike info criterion	-1.527002
Sum squared resid	0.376816	Schwarz criterion	-1.273670
Log-likelihood	36.54003	Hannan-Quinn criter.	-1.435405
F-statistic	43.25668	Durbin-Watson stat	2.404865
Prob(F-statistic)	0.000000		

* p-values are incompatible with t-Bounds distribution.

Table 6 displays the error correction estimates obtained from the ARDL (1, 3, 2) model, which shows the rate at which the system regains equilibrium following a brief perturbation. With a p-value of 0.0000, the coefficient of the error correction term (COINTEQ*) is -0.061242. This implies that the present era corrects about 6.12% of the previous period's disequilibrium, indicating a gradual systemic adjustment toward long-run equilibrium.

Life expectancy is positively impacted by short-term increases in poverty, as seen by the positive and highly significant coefficient (2.76E-14, p = 0.0000) for the first difference of poverty (D(POV)). Additionally, the lag-first differences, D(POV(-1)) and D(POV(-2)) show positive and significant coefficients (3.96E-14, p = 0.0000 and 1.60E-14, p = 0.0061, respectively), indicating that the short-term benefits of earlier rises in poverty are still being felt.

The Exchange Rate (EXR) exhibits a correlated positive effect on life expectancy (D(EXR)) of 0.003387, p = 0.0018, and a correlated negative impact (-0.005377, p = 0.0000) on life expectancy for the lagged difference (D(EXR(-1))). This suggests that while a one-period lag causes the impact to turn negative, exchange rate hikes initially have a favorable effect in the short run.

With an adjusted R-squared of 0.844177 and an R-squared of 0.864154, the model's diagnostic statistics point to a strong fit, explaining approximately 86.4% of the variation in life expectancy. The Durbin-Watson statistic is 2.404865, and the standard error of the regression is 0.105275, indicating that there are no significant problems with autocorrelation in the residuals. The model as a whole is extremely significant, as indicated by the F-statistic of 43.25668 (p = 0.000000). While the negative and significant error correction term indicates a rather slow adjustment process toward long-run equilibrium, these results highlight the short-term dynamics between life expectancy, poverty, and exchange rates.

Table 7: Bound tests

Test Statistic	Value
F-statistic	21.810614

Table 8: Bounds critical values

	10%		5%		1%	
Sample Size	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
35	2.845	3.623	3.478	4.335	4.948	6.028
40	2.835	3.585	3.435	4.260	4.770	5.855
Asymptotic	2.630	3.350	3.100	3.870	4.130	5.000

* I(0) and I(1) are respectively the stationary and non-stationary bounds.

The Bound test results in Table 7 show an F-statistic of 21.810614, which exceeds the upper bound critical value of 6.028 in Table 8 at the 1% significance level. This strongly indicates the presence of a long-run relationship between the variables in the ARDL model.

4.0 Summary of Findings

The dynamic interactions between the Life Expectancy of Males (LEM), Poverty (POV), and Exchange Rate (EXR) are revealed through the ARDL analysis, providing significant insights. LEM exhibits moderate variability with an average of 4.73 and a right-skewed distribution, while POV shows high variability and a strong positive skew. EXR also displays considerable variation. Strong positive relationships among LEM, POV, and EXR are highlighted in the correlation analysis.

Non-stationarity is confirmed in all three variables through time series analysis, with stationarity achieved after differencing. The ARDL (1, 3, 2) model, which best fits the data, indicates that lagged LEM positively influences current LEM, while POV has a short-term positive effect but a negative long-term impact. Additionally, EXR initially boosts LEM but has complex short-term effects, with both negative and positive impacts depending on the lag. The error correction term indicates a slow adjustment to equilibrium, and the model diagnostics confirm its robustness.

The Bound test supports cointegration, suggesting a stable long-term relationship between the variables. Overall, the findings emphasize the importance of addressing poverty and exchange rate stability in shaping life expectancy outcomes over time.

5.0 Conclusion and Recommendations

This work presents detailed empirical investigations of life expectancy-poverty dynamics in Nigeria using the Autoregressive Distributed-Lag (ARDL) model. This work contributes significantly to the literature on life expectancy by examining both short and long-run impacts of poverty and exchange rates on life expectancy. Our findings show that changes in exchange rates and poverty have an immediate lag on life expectancy, with exchange rate fluctuations having complex short and long-term effects and poverty having significant delayed negative effects.

To enhance public health and economic resilience, policymakers should prioritize addressing poverty and maintaining a stable exchange rate, as these factors can have a significant positive impact on life expectancy in the long term.

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