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Analysis of Mortality Rate in Nigeria

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Abstract:
Mortality Rate in developing Countries remains one of the greatest challenges for monitoring, analyzing and projecting the health situation of the world's population. Because of limited resources, many developing Countries, especially in sub-Saharan Africa lack vital registration systems that could reliably and continuously collect information on Mortality Rate. However, periodic reviews of pattern using mortality models could show new trends and may provide information for the planning of a Country's health care delivery services and a host of other programs. Previous studies have found that the Lee-Carter model works well with adult mortality data. In this current study, effort was made to see the performance of the model on infant and maternal mortality data in Nigeria. A modified version of the Lee-Carter method is used to model sex-combined infant and maternal mortality data of Nigerians aged 15-49 years for maternal mortality and infant mortality for the time periods 1990 to 2013. The model's parameters are estimated using the approach proposed by [1] based on the singular value decomposition technique, while the mortality index is predicted using the approach developed by [13]. The results show that the model follows the mortality pattern very well for most of the ages despite limited data; Forecast values of the mortality index show a gradual decline in mortality from 2014-2025 in Nigeria.

Keywords: *Infant and Maternal Mortality, Age, Lee-Carter model, Nigeria*

1. Introduction

The future of human survival has attracted renewed interest in recent decades. The historic rise in life expectancy shows little sign of slowing, and increased survival is a significant contributor to population ageing. In this context, forecasting mortality has gained prominence. The future of mortality is of interest not only in its own right, but also in the context of population forecasting; on which economic, social and health planning is based. The future provision of health and social security for ageing populations is now a central concern of countries throughout the developing and developed world. This renewed interest in mortality forecasting has been accompanied by the development of new and more sophisticated methods; for a review. A significant milestone was the publication of the Lee-Carter method [1]; although a principal components approach had previously been employed by [2]. The Lee-Carter method is regarded as among the best currently available and has been widely applied [3]; [4]. The Lee-Carter method was a significant departure from previous approaches: in particular, it involves a two-factor (age and time) model and uses matrix decomposition to extract a single time-varying index of the level of mortality, which is then forecast using a time series model. The strengths of the method are its simplicity and robustness in the context of linear trends in age-specific death rates. While other methods have subsequently been developed [5]; [6], the Lee-Carter method is often taken as the point of reference.

In spite of all the policies, declarations, conferences and other efforts aimed at reducing the scourge of maternal deaths across the globe, only modest gains in maternal mortality reduction appear to have been achieved in many countries in the past 20 years [7]. Countries in Africa may have actually lost ground while many developing countries have fallen far short of the standards set by the World Health Organization's initiative on Safe Motherhood. In Nigeria, the Federal Ministry of Health had set Year 2006 as the target year that maternal mortality would have been reduced by 50 percent. However, not only were these targets not achieved but also the maternal health situation in Nigeria is now much worse than in previous years [8]. Past efforts to reduce maternal mortality ratio in Nigeria were concentrated on making direct improvements to the health system. These efforts have not involved enough resources to successfully reduce maternal mortality in the country. In view of this lack of success, reference [9] noted that the high maternal mortality in the country will have to be tackled by generating sufficient political priority to make governments deploy enough resources to successfully reduce maternal mortality in Nigeria.

Maternal and Infant mortality is not an uncommon event in several parts of the developing world. Mothers and children are at the highest risk for disease and death. While motherhood is often a positive and fulfilling experience, for too many women, it is associated with ill health and even death [10]. The death of a woman during pregnancy, labour or pueperium is a tragedy that carries a huge burden of grief and pain, and has been described as a major public health problem in developing countries like Nigeria [11]. Women have an enormous impact on their families' welfare. Deaths of infants/children under five are peculiar and closely related to maternal health. Available evidence indicates that Africa accounts for the highest burden of mortality among women and children in the world [12]. This unhealthy trend has become a matter of great concern, calling for a concerted approach from all and sundry.

2. Data and Method

The study mainly used data extracted from the Nigeria Demographic and Health Survey (NDHS) 2013 national sample survey which provides up-to-date information on basic demographic and health indicators and other background characteristics of the respondents. The NDHS 2013 was implemented by the National Population Commission (NPC) and the final cleaning of the data set was carried out by the ICF data processing specialist and completed in August, 2013. It is a follow-up to the 1999, 2003 and 2008 NDHS surveys. It covers the age-specific mortality rate records of mothers aged 15 to 49 years for the time periods, 1999, 2003, 2008 and 2013 in Nigeria. All NDHS data files are organized by sex, age and time. Population size is given for one-year and five-year age groups. One-year age groups means 1, 2, …, 109, 110+; and five-year age groups means 0, 1-4, 5-9, 10-14, …, 105-109, 110+. Age groups are defined in terms of actual age, for instance, "10-14" extends from exact age 10 to right before the 15th birthday. In this paper, the data we will use is the death rate *period* and the population size is *five-year* age groups. Methods used for analysis include the Singular value decomposition technique using the principal component analysis option. Forecast of the mortality index was done by applying the random walk with drift model. The analysis for this study was done using the *biplot*ad-in in Microsoft Excel 10.0 and Statgraphics 16.1

2.1 The Lee–Carter Model

The Lee-Carter model is a simple bilinear model in the variables x (age) and t (calendar year) defined as;

$\ln m_{xt}$ = $a_x + b_x k_t + \varepsilon_{xt}$ (1)

Where;

m_{xt}: is the matrix of the observed age-specific death rate at age *x* during year *t*. It is obtained from observed deaths divided by population exposed to risk.

a_x: represents the logarithm of the geometric mean of the empirical mortality rates, averaged over the historical data. It describes the average shape of the age profile.

k_t: represents the underlying time trend for the general mortality. It captures the main time trend on the logarithmic scale in mortality rates at all ages. It is also referred to as the mortality index.

b_x: represents the sensitivity of the hazard rate at age *x* to the time trend. It indicates the relative pace of change in mortality by age as k_t varies. It modifies the main time trend according to whether change at a particular age is faster or slower than the main trend.

ε_{xt}: is the residual term at age x and time t. It reflects the age specific influences not captured by the model. Each of ε_{xt} is independent and identically distributed ε_{xt}~ (0, $\sigma 2$).

2.1.1. Merits of the Model

i. It produces an excellent fit to mortality trends;
ii. It is parsimonious in the number of parameters used;
iii. It linearizes mortality trends and thereby adds confidence to extrapolations;
iv. It produces sensible estimates of forecast of uncertainty and the model outperforms other models with respect to its prediction errors.

2.1.2. Assumptions of the Model

i. The model assumes that b_x is invariant (remains constant) over time for all x.
ii. It assumes that k_t is fixed over age-groups for all t.
iii. The practical use of the model assumes that the disturbances ε_{xt} are normally distributed i.e. $\varepsilon_{xt} \sim N$ (0, $\sigma 2$)'

2.2. Estimating the Parameters

The Lee-Carter model unlike most regression formulations is not a common model structure with observed variables on the right-hand side and thus it cannot be fit with simple regression formulations. Hence, the estimation of b_x and k_t cannot be solved explicitly. The *singular value decomposition* (SVD) method was used to find a least squares solution in this study. The Singular Value Decomposition (SVD) is a technique used to decompose a matrix into several component matrices, exposing many of the useful and interesting properties of the original matrix. Ideally, the matrix is decomposed into a set of factors (often orthogonal or independent) that are optimal based on some criterion. In other words, any real *m* x *n* matrix *A* can be decomposed uniquely as:

$A = UDV^T$ (2)

U is *m* x *n* and orthogonal (its columns are eigenvectors of AA^T)

V is *n* x *n* and orthogonal (its columns are eigenvectors of A^TA)

D is *n* x *n* diagonal (non-negative real values called *singular* values)

D = *diag* ($\rho 1$, $\rho 2$, … . , ρn) ordered so that $\rho 1 \geq \rho 2 \geq \cdots \geq \rho n$

(If ρ is a singular value of *A*, it's square is an eigenvalue of A^TA)

The application of the SVD approach follows about 6 steps:

Step: 1. $a_x = \frac{1}{T}\sum_{t=1}^{n} \ln(m_{xt})$

Step: 2. Create a matrix Z_{xt}, for estimating $b_x\ and k_t$, where $Z_{xt} = \ln(m_{xt}) - a_x = b_x k_t$

Step: 3. Apply the Singular Value Decomposition to matrix $Z_{x,t}$, which decomposes the matrix of $Z_{x,t}$, into the product of three matrices: $ULV' = SVD(Z_{x,t}) = L_1\, U_{x1}\, V_{t1} + \ldots + L_X U_{xX} V_{tX}$, where U representing the age component, L is the singular values and V representing the time component.
Step: 4. Select ***Singular Value Decomposition Dialog*** from Biplot in Microsoft Excel, by running the program. k_t is derived from the first vector of the time- component matrix and the first singular value ($k_t = L_1\, V_{t1}$), and b_x is derived from the first vector of the age-component matrix ($b_x = U_{x1}$).
Step: 5. (Lee-Carter) Approximate a new matrix z_{xt} by the product of the estimated parameters b_x and k_t and get $Z\,x_1 t_1 = b_{x1}\, k_{t1}$

$$Z_{x,t} = \begin{pmatrix} z_{x1t1} & z_{x1t2} \cdots & z_{x1tn} \\ z_{x2t1} & z_{xt2} \cdots & z_{x1tn} \\ \ldots & \ldots & \ldots \\ z_{x\wedge t1} & z_{x\wedge t2} & z_{x1tn} \end{pmatrix} b_x \quad (3)$$
$$k_t$$

Where;

$$b_x = \begin{bmatrix} b_0 \\ b_1 \\ \ldots \\ b_n \end{bmatrix} \quad (4)$$

$$k_t = [k_0 \quad k_1 \quad \cdots \quad k_n] \quad (5)$$

Step: 6. Estimate the logarithm of the central death rate
$$\ln(m_{xt}) = a_x + Z_{xt} = a_x + b_x k_t \quad (6)$$
The purpose of using Singular value decomposition is to transfer the task of forecasting an age-specific vector $\ln m_{xt}$ into forecasting a scalar t, with small error. As earlier stated, the model is given by: $\ln(m_{x,t}) = a_x + b_x k_{(t)} + \varepsilon_{x,(t)}$ and we need to estimate a_x, b_x and t.
In order to achieve a unique solution, the following restrictions are used;

$$\sum_{xmin}^{x=m} b_x^2 = 1 \quad - \quad - \quad - \quad - \quad - \quad - \quad (7)$$

$$\sum_{t\,min}^{t=n} k_t = 0: \quad - \quad - \quad - \quad - \quad - \quad - \quad (8)$$

Where $x = 1....$ m age groups and $t = 1......$n calendar years.
To estimate the parameters, choose the values that minimize Q;

$$Q = \sum_{x,t}(a_x + b_x k_t - q_{xt})^2 \quad - \quad - \quad - \quad - \quad (9)$$
Where: $\ln m_{xt}$ and Q are subject to the constraints in (7) and (8) above.
To find values that minimize Q, introduce Lagrange's multipliers; α and β

$$R = Q - \alpha\sum_t k_t - \beta\sum_x b_x^2 \quad - \quad - \quad - \quad - \quad (10)$$
And substitute equation (3.3) into (3.4) and then minimize;

$$R = \sum_{x,t}(a_x + b_x k_t - q_{xt})^2 - \alpha\sum_t k_t - \beta\sum_x b_x^2$$

The first derivative of R in respect of a_x, b_x and t respectively are;

$$\frac{dR}{da_x} = 2\sum_t(a_x + b_x k_t - q_{xt}) \forall\ x \quad - \quad - \quad - \quad - \quad (11)$$

$$\frac{dR}{db_x} = 2\sum_t k_t(a_x + b_x k_t - q_{xt}) - 2\beta b_x \forall\ x \quad - \quad - \quad - \quad (12)$$

$$\frac{dR}{dk_t} = 2\sum_t b_x(a_x + b_x k_t - q_{xt}) - \alpha \forall\ t \quad - \quad - \quad (13)$$

The derivatives are set to equal zero as:

$$\frac{dR}{da_x} = 0, \frac{dR}{db_x} = 0, \frac{dR}{dk_t} = 0$$

To solve equation (3.5);

$2\sum_t(a_x + b_x k_t - q_{xt}) = 0$

$\Rightarrow na_x + b_x \sum_t k_t - \sum_t q_{xt} = 0$

$(\sum_{t\, min}^{t=n} k_t = 0) \Rightarrow na_x - \sum_t q_{xt} = 0$

$$a_x = \frac{1}{n}\sum_t q_{xt}$$
$$a_x = \frac{1}{n}\sum_{t=1}^{n} \ln m_{xt}$$

The estimate for a_x is thus computed as the average over time of the logarithm of the central death, which corresponds to the definition of a_x in section 3.0.

Now define $z_{xt} = q_{xt} - a_x \Rightarrow \sum_t q_{xt} = 0$ *f*or every x.
Equation (7) can now be rewritten as:
$2\sum_x b_x(a_x + b_x k_t - q_{xt}) - \alpha = 2\sum b_x(b_x k_t - z_{xt}) - \alpha$

If we set the new expression of the derivative with regard to *t* equal to zero, we have;
$2\sum_x b_x(a_x + b_x k_t - q_{xt}) - \alpha = 0 \Rightarrow \sum b_x(b_x k_t - z_{xt}) = \frac{\alpha}{2}$

$= k_t \sum_x b_x^2 - \sum_x b_x z_{xt} = \frac{\alpha}{2}$

$$(\sum_{xmin}^{x=m} b_x^2 = 1)$$

$k_t - \sum_x b_x z_{xt} = \frac{\alpha}{2}$ - - - - - - (14)

Taking the sum over‘t’ in the equation (14) above we get,

$$\sum(k_t - \sum_x b_x z_{xt}) = \sum_t \frac{\alpha}{2}$$

$\Rightarrow \sum k_t - \sum_t \sum_x b_x z_{xt} = \sum_t \frac{\alpha}{2}$

$$\left(\sum_{t\, min}^{t=n} k_t = 0\right)$$

$\Rightarrow n\sum_x b_x \sum_t z_{xt} = \frac{m\alpha}{2}$
$\sum_t z_{xt} = 0 \Rightarrow \alpha = 0$

We now have an expression for k_t by putting $\alpha = 0$ in equation (14).
Hence, $k_t = \sum_x b_x z_{xt}$ for every t - - - - - (15)

The constraint for k_t is now fulfilled.

If we substitute the expression $z_{xt} = q_{xt} - a_x$ into equation (12), we obtain;

$$2\sum_t k(a_x + b_x k_t - q_{xt}) - 2\beta b_x = 2\sum_t k_t(b_x k_t - z_{xt}) - 2\beta b_x$$

Setting this equal to zero we have,

$$2\sum_t k_t(b_x k_t - z_{xt}) - 2\beta b_x = 0$$

$b_x(\sum_t k_t^2 - \beta) = \sum_t k_t z_{xt} \forall$ x - - - - - (16)

By taking the square of both sides and summarize over x you get

$$\sum_x (b_x(\sum_t k_t^2 - \beta))^2 = \sum_x (\sum_t k_t z_{xt})^2$$

$\Rightarrow (\sum_t k_t^2 - \beta)^2 \sum_x (b_x)^2 = \sum_x (\sum_t k_t z_{xt})^2$

$$\sum_{xmin}^{x=m} b_x^2 = 1$$

$\Rightarrow (\sum_t k_t^2 - \beta)^2 = \sum_x (\sum_t k_t z_{xt})^2$

(Taking the square root of both sides)

$$\sum_t k_t^2 - \beta = \sqrt{\sum_x (\sum_t k_t z_{xt})^2}$$

$\Rightarrow \beta = \sum_t k_t^2 - \sqrt{\sum_x (\sum_t k_t z_{xt})^2}$ - - - (17)

We are able to get an expression for $b_x$by inserting the equation for β in (17) into equation (16):

$$b_x(\sum_t k_t^2 - \beta) = \sum_t k_t z_{xt}$$

$$(\beta = \sum_t k_t^2 - \sqrt{\sum_x (\sum_t k_t z_{xt})^2}$$

$\Rightarrow b_x(\sum_t k_t^2 - \sum_t k_t^2 + \sqrt{\sum_x (\sum_t k_t z_{xt})^2} = \sum_t k_t z_{xt}$

$\Rightarrow b_x = \frac{\sum_t k_t z_{xt}}{\sqrt{\sum_x (\sum_t k_t z_{xt})^2}} \forall$ x

Hence,

$a_x = \frac{1}{n}\sum_{t=1}^{n} \ln m_{xt}$, $b_x = \frac{\sum_t k_t z_{xt}}{\sqrt{\sum_x (\sum_t k_t z_{xt})^2}}$, $k_t = \sum_x b_x z_{xt}$

2.3. Forecasting Using Arima with Drift

To produce mortality forecasts, Lee and Carter assume that b_x remains constant over time and they use forecasts of k_t from a standard univariate time series model. After testing several ARIMA specifications, they find that a random walk with drift is the most appropriate model for their data. They make clear that other ARIMA models might be preferable for different data sets, but in practice the random walk with drift model for k_t has been used almost exclusively. This model is as follows:

$k_t = k_{t-1} + \mu + \mathcal{E}_t$ - - - - (18)

$\mathcal{E}t \sim N(0, \delta^2)$

Where μ is known as the *drift parameter* and its maximum likelihood estimate is simply $\mu = (k_T - k_1)/(T - 1)$, which only depends on the first and last of the K_t estimates. Then, to forecast two periods ahead, we plug in the estimate of the drift parameter μ and also substitute for the definition of $t-1$ shifted back in time one period:

$k_t = k_{t-1} + \mu + \mathcal{E}_t$ - - - - - (19)

$= (k_{t-2} + \mu + \varepsilon_{t-1}) + \mu + \varepsilon_t$

$= k_{t-2} + 2\mu + (\varepsilon_{t-1} + \varepsilon_t)$

To forecast k_t at time $T + (\Delta t)$ with data available up to period T, we follow the same procedure iteratively (Δt) times and obtain

$kT + (\Delta t) = kT + (\Delta t)\mu + \sum_{i=1}^{(\Delta t)} \varepsilon T + i - 1$ - - (20)

$= kT + (\Delta t)\,\mu + \sqrt{(\Delta t)}\varepsilon_t$

Where the second line is, a simplification made possible by the fact that the random variables ε_t are assumed in this model to be independent with the same variance. The second line indicates that the conditional standard errors for the forecast increase with the square root of the distance to the forecast horizon (Δt). These are conditional standard errors and would be larger if we included estimation uncertainty. From this model, we can obtain forecast point estimates, which follow a straight line as a function of (Δt), with slope μ:

$E[k_T + (\Delta t) \mid k_1, \ldots\ldots k_T] \equiv \mu T + (\Delta t) = (\Delta t)\mu$ - - (21)

The Lee-Carter model for the k's is thus very simple: Extrapolate from a straight line drawn through the first k_1 and last $k_T$points. All other k's are ignored. We now plug these expressions into the empirical and vectorized version of Equation (19) to make a point estimate forecast for log-mortality:

$\mu T + (\Delta t) = m + \beta k_T + (\Delta t)$ - - - - (22)

$= m + \beta\,[k_T + (\Delta t)\mu]$.

3. Summary of Results

We present below a summary of our findings.

	Test critical value				
Variable	1%	5%	10%	ADF	Status
IMR	-3.574446	-2.923780	-2.599925	-3.196158	1(1)
MMR	-3.737853	-2.991878	-2.635542	-4.290664	1(1)

Table 1: Test critical value

In the above unit root test the null hypothesis of a unit root is H0: a = 0 versus the alternative: H1: a < 0. The ADF unit root test result presented above confirms that stationarity was achieved for IMR and MMR at the first difference. The null hypothesis of unit root was not rejected rather the variables, were differentiated at first difference.

Correlations					
				IMR	MMR
MR	Pearson Correlation				.978**
	Sig. (2-tailed)				.000
	N			26	26
	Bootstrap[b]	Bias			.001
		Std. Error			.006
		99% Confidence Interval	Lower		.959
			Upper		.993
MR	Pearson Correlation			.978**	
	Sig. (2-tailed)			.000	
	N			26	26
	Bootstrap[b]	Bias		.001	
		Std. Error		.006	
		99% Confidence Interval	Lower	.959	
			Upper	.993	
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 2: Correlation between MMR and IMR
Source: SPSS Output

In order to explain the relationship between the IMR and MMR, Correlation analysis was adopted and the result shows that the Value 0.978 shows a strong positive correlation between MMR and IMR.

As earlier stated, the Lee-Carter model is given by: $\ln(m_{x,t}) = a_x + b_x k_{(t)} + \varepsilon_{x,(t)}$ and we need to estimate a_x, b_x and k_t. first we need to create a matrix Z_{xt} where $Z_{xt} = \ln(m_{xt}) - a_x = b_x k_t$

$$Z_{xt} = \begin{bmatrix} 0.080658 & -0.004008021 & 0.02429 & -0.159 & -0.42465 & 0.23953 & 0.03459 \\ -0.02429 & -0.121038328 & 0.02429 & -0.001 & -0.42159 & 0.26788 & 0.08121 \\ -0.19601 & 0.041141943 & 0.01309 & 0.466874 & 0.138021 & 0.02327 & 1.09362 \\ -0.34249 & 0.22314355 & 0.10436 & 0 & 0.482426 & 0.09531 & 0.52763 \end{bmatrix}$$

Source: Author's computation

a_x: represents the logarithm of the geometric mean of the empirical mortality rates, averaged over the historical data. It describes the average shape of the age profile. It is estimated as $a_x = \frac{1}{n}\sum_{t=1}^{n} \ln m_{xt}$

a_x=

15-19	-0.12053
20-24	0.03481
25-29	0.010672
30-34	0.076719
35-39	-0.05645
40-44	-0.10884
45-49	-0.43426

Table 3

Source: Author's computation

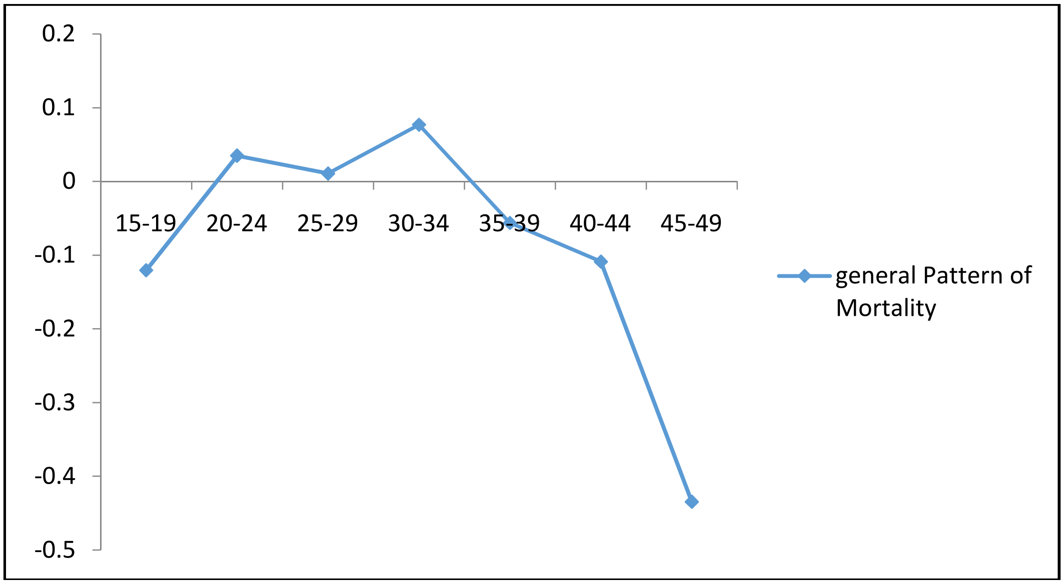

Figure 1: General Pattern of Mortality by Age

The minimum general maternal mortality is found in age 40-45 and the maximum at 30-34. The results show that a_x values are decreasing with increase in age from 30-49. This implies a downward trend in mortality with respect to the age-groups. As shown in Figure 1 above, the younger ages have a higher mortality rate than the older ages

b_x: represents the sensitivity of the hazard rate at age x to the time trend. It indicates the relative pace of change in mortality by age as k_t varies. It modifies the main time trend according to whether change at a particular age is faster or slower than the main trend. b_x is derived from the first vector of the age-component matrix ($b_x = U_{x1}$) after selecting ***Singular Value Decomposition Dialog*** from Biplot in Microsoft Excel, by running the program.

b_x =

15-19	**0.237009469**
20-24	-0.14313339
25-29	*-0.04855694*
30-34	-0.299493
35-39	-0.57840131
40-44	-0.22903242
45-49	0.666544513

Table 4

Source: Output from the Excel biplot 10.

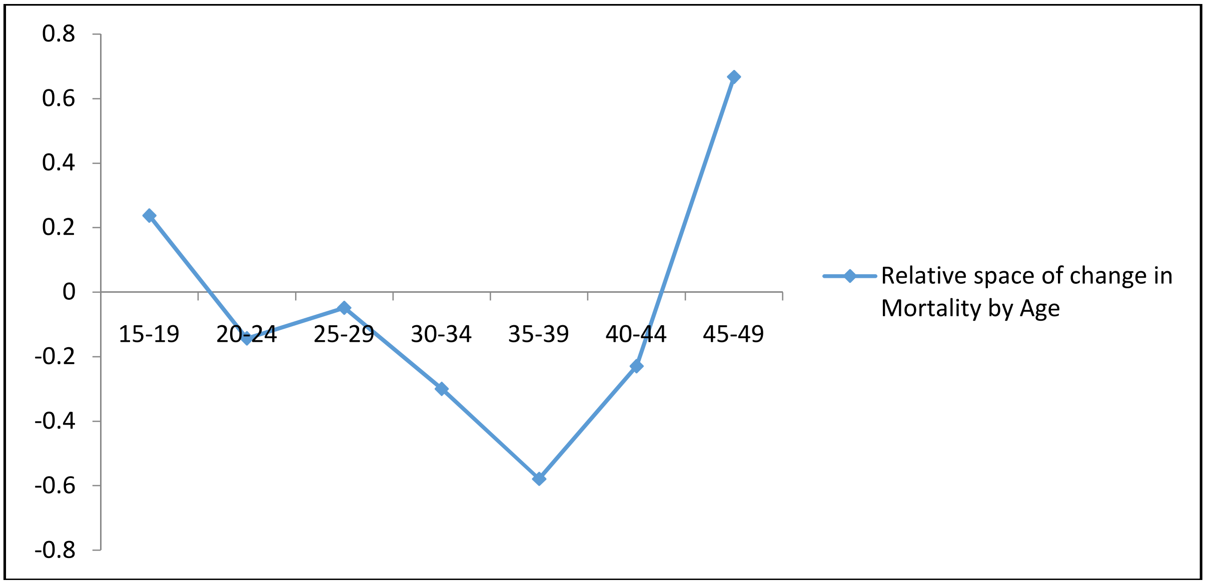

Figure 2: Relative space of change in Mortality by Age
Relative space of change in Mortality by Age

Figure 2 depicts the tendency of mortality at age x to change as the general level of mortality changes. The larger the value of b_x at a particular age-group, the more fluctuant the mortality rate at that age-group as compared to the general level of mortality change. The results obtained shows that persons aged 40-49 have a more fluctuant mortality pattern than other age groups. The relative pace of change is lowest in age group 20-29 as illustrated in Figure 2 above.

$\boldsymbol{k_t}$: represents the underlying time trend for the general mortality. It captures the main time trend on the logarithmic scale in mortality rates at all ages. It is also referred to as the mortality index. k_t is derived from the first vector of the time- component matrix and the first singular value ($k_t = L_1\ V_{t1}$), after selecting ***Singular Value Decomposition Dialog*** from Biplot in Microsoft Excel, by running the program.

k_t =

1999	0.529111317
2003	*0.460943991*
2008	*-0.5884811*
2013	-0.4015742

Table 5
Source: Output from the Excel biplot 10

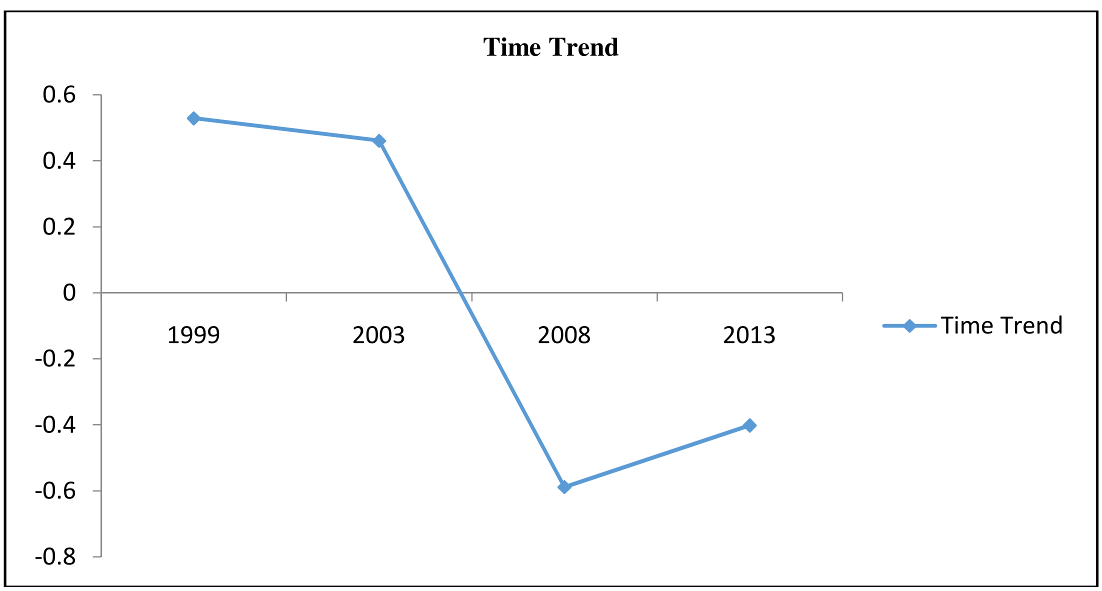

Figure 3: Time Trend for General Mortality

Figure 3 captures the main time trend on the logarithmic scale in death rates at all ages. When k_t values decrease overtime, it signifies a decline in mortality trend as the years' increase. Our findings show a downward trend from 1999 to 2008 and a slight rise from 2008 to 2013 as shown in Figure 3. However, it is important to note that the straight line obtained in Figure 3 from 2003 to 2008 is as a result of the 2-time point nature of the data. It does not necessarily imply that the mortality pattern from 2003-2008 was not a fluctuating one.

Model: Random walk with drift = -0.310229

Period	Data	Forecast	Residual
1.0	0.529111	4.68277E-275	0.529111
2.0	0.460944	0.218883	0.242061
3.0	-0.588481	0.150715	-0.739197
4.0	-0.401574	-0.89871	0.497135

		Lower 99.0%	Upper 99.0%
Period	Forecast	Limit	Limit
5.0	-0.711803	-7.19018	5.76658
6.0	-1.02203	-10.1838	8.13978
7.0	-1.33226	-12.5531	9.88862
8.0	-1.64249	-14.5992	11.3143
9.0	-1.95272	-16.4388	12.5334
10.0	-2.26295	-18.1317	13.6058
11.0	-2.57317	-19.7134	14.567
12.0	-2.8834	-21.207	15.4402
13.0	-3.19363	-22.6288	16.2415
14.0	-3.50386	-23.9903	16.9826
15.0	-3.81409	-25.3004	17.6723
16.0	-4.12432	-26.5661	18.3174

Table 6: Forecast Table for Mortality Index
Source: Statgraphics Output

Table 6 shows the forecasted values for Mortality Index. During the period where actual data is available, it also displays the predicted values from the fitted model and the residuals (data-forecast). For time periods beyond the end of the series, it shows 99.0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 99.0% confidence, assuming the fitted model is appropriate for the data.

4.3. Model Comparison

Data variable: Mortality Index
Number of observations = 4
Start index = 1.0
Sampling interval = 1.0

- Models

(A) Random walk with drift = -0.310229
(B) Constant mean = 2.77556E-17
(C) Invalid model
(D) Simple moving average of 3 terms
(E) Simple exponential smoothing with alpha = 0.2164

Math adjustment:

- Estimation Period

Model	RMSE	MAE	ME
(A)	0.652744	0.492798	1.85037E-17
(B)	0.57735	0.495028	0.0
(D)	0.535432	0.535432	-0.535432
(E)	0.636781	0.532604	-0.024596

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	0.652744					
(B)	0.57735					
(D)	0.535432					
(E)	0.636781					

Source: Statgraphics Output

This table compares the results of three different forecasting models. Looking at the error statistics, the model with the smallest root mean squared error (RMSE) during the estimation period is model D. The model with the smallest mean absolute error (MAE) is model A.

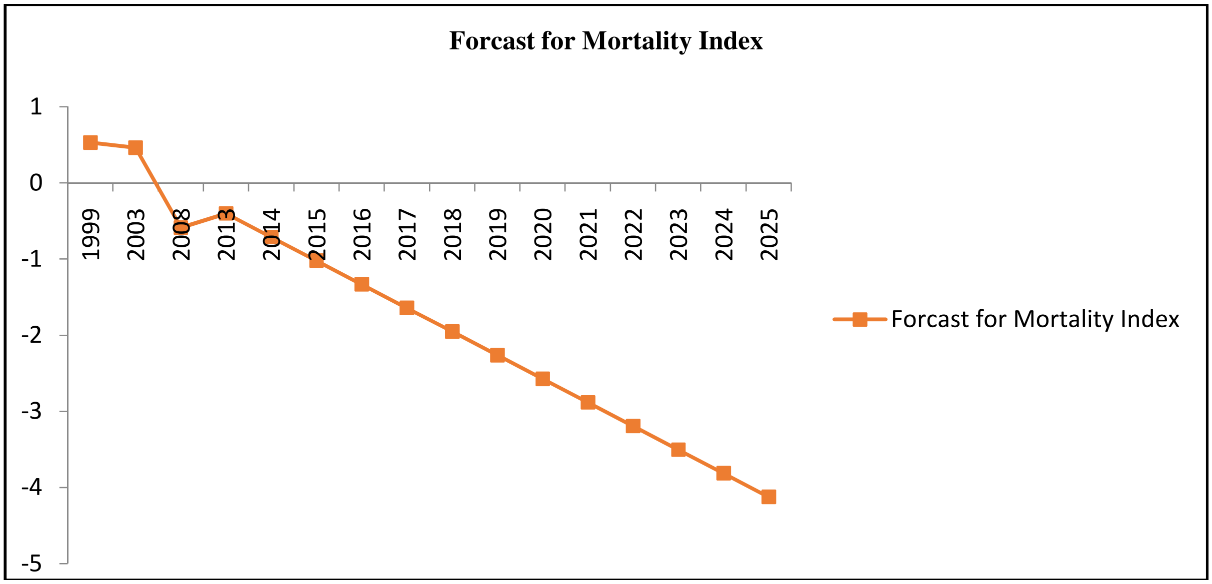

Figure 4: Forecast Plot for Mortality Index

The forecast of the mortality time trend show a gradual decline in mortality from 2013-2025

5. Conclusion

The Lee-Carter model follows the mortality pattern very well for most of the ages despite the limited nature of the data. The forecast of the mortality time trend show a gradual decline in mortality from 2013-2025 as expressed in Figure 4 while the general pattern of mortality shows a downward trend from age 30-49 years all things being equal. We can therefore say that the lee-carter model can be used to model the Nigeria mortality data even when the data available is limited in nature. However, the level of data heterogeneity for which the lee-carter model will give successful result is another issue for discussion.

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