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STATISTICAL ANALYSIS OF CHILD MORTALITY AND ITS DETERMINANTS

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ABSTRACT

Worldwide, childhood mortality rates have decline over the years due majorly to various action plans and interventions targeted at various communicable diseases and other immunizable childhood infections which have been major causes of child mortality, but the situation seems to remain unchanged in sub-Saharan African countries, as approximately half of these deaths occur in sub-Saharan Africa despite the region having only one fifth of the world's children population. Many covariates associated with variations in infant and child mortality are interrelated, and it is important to attempt to isolate the effects of individual variables for proper and effective interventions. This study examined the socio-economic and demographic determinants of child mortality using principal component analysis as a data reduction technique with varimax rotation to assess the underlying structure for nine measured variables, explaining the covariance relationships amongst the correlated variables in a more parsimonious as a way of child mortality modelling in Nigeria. From the analysis and result, two factors component was identified and the total variance explained is 97.25 percent. The result shows that 70.59 percent of the variance was accounted for by the first factor while the second and third factors accounted for 19.9 percent and 6.78 percent respectively. It is particularly instructive to note that more than 97 percent of the variance is accounted for by the first three factors. The first factor which seems to index mother education had a very strong loading on wealth quintile, residence, birth order and zone. The second factor which seemed to index previous birth had high loadings on child sex, birth sex, birth size (weight of the baby at birth in kilogram)and as well as mother's age.

Keywords: Child mortality, Socio-economic and demographic determinants, Mortality rate, Varimax rotation and Principal component analysis.

INTRODUCTION

Population studies remain pivotal effort at understanding the changes in the size, structure and distribution of any geographical area .It provides insights about the changes occurring within the population in term of birth, death, and migration. Thus appropriate indices that would provide information on the population process are often generated and used to measure the standard of living of such geographical entity.

Such indices include Birth Rate, Death Rate and Migration out of which death rate is the most alarming in sub-Sahara Africa due to grossly inadequate health care delivery, ineffective and general poor standard of living in the sub-Sahara Africa unlike the Developed world. Statistics had shown that most Africa countries recorded 2-digits mortality rates for infant and under five years old.

Reliable information from the World Bank (2001, 2002, 2004) showed that countries such as Britain United States, France and Japan had a very low record of Child Mortality Rate of 3/1000 live births, 7/1000 live births, 4/1000 live births and 3/1000 live births respectively as against some sub-Sahara Africa Countries Such as Egypt 25/1000 live births , South Africa 41/1000 live births, Ethiopia 62/1000 live births, Ghana 64/1000 live births, and Nigeria 113/1000 live births (www.dataworldbank.org). Thus, this study intends to look at the Nigeria experience over the years and bring out the major determinant of Child Mortality and the trends exhibited for a period of time with a view to analyzing the principal component of the child mortality for plausible interventions, control and management of the population of children under 5years .The data used in this study was obtained from the Nigeria Demographic and Health Survey (NDHS) 2013 and the annual abstract statistics of the National Bureau of Statistics (NBS) 2013.

BRIEF LITERATURE REVIEW

Determinants of childhood mortality have been viewed from a number of analytical frameworks. This dates back to Mosley *et al.* (1984) and Schultz (1984) who made the distinction between variables considered to be exogenous or socio-economic (i.e. cultural, social, economic, community, and regional factors) and endogenous or biomedical factors (i.e. breastfeeding patterns, hygiene, sanitary measures, and nutrition). The effects of the exogenous variables were considered indirect because they operate through the endogenous biomedical factors while the bio-medical factors were called intermediate variables or proximate determinants because they constitute the middle step between the exogenous variables and child mortality. Empirically, many studies have shown that child mortality is influenced by a number of socio economic and demographic factors such as sex of the child, mother's age at birth, birth order, preceding birth interval among others. For instance, Mondal *et al.* (2009) use the logistic regression model, investigated factors influencing infant and child mortality in Rajshahi District of Bangladesh. Findings revealed that the most significant predictors of neonatal, post-neonatal and child mortality levels are immunization, ever breastfeeding, mother's age at birth and birth interval. In a similar vein, Chowdhury *et al.* (2010) examined the effects of demographic characteristics on neonatal, post neonatal, infant and child mortality also using the logistic regression model. They identified the important predictors of neonatal mortality as breast feeding practice, of post- neonatal period as duration of marriage; order of birth and birth interval and of infant and child mortality as age at marriage, duration of marriage, birth interval, birth order and breast feeding practice. Uddin *et al.* (2009) in their study, investigated child mortality in Bangladesh also using the logistic regression. Results of analysis showed that father's education, occupation of father, occupation of mother, standard of living index, breastfeeding status and birth order were significant determinants of child mortality in Bangladesh. Hong (2006) showed that levels of infant and child mortality in many developing countries remain unacceptably high, and they are disproportionably higher among high-risk groups such as newborn and infant of multiple births. A mother's poor health and poor nutritional status may also have postnatal consequences such as impaired lactation and render her unable to give adequate care to her children (Retherford et al., 1989). Some studies show that child mortality is lower for boys than for girls (Huq *et al.,* 1990; Kabir *et al.,* 1992) while, child mortality has been noted to peak in places where living conditions are lowest (Millard *et al.,* 1990). Kumar *et al.* (2005) used data from the Ethiopia Demographic and Health Survey [EDHS] conducted in 2005 to investigate the predictors of child [0-5 years] mortality in Ethiopia. The cross tabulation technique was used to estimate the predictors of child mortality. Results revealed that birth interval with previous child and mother standard of living index were the vital factors associated with child mortality. Furthermore, Mother's education and birth order were found to have substantial impact on child mortality in Ethiopia. The study concluded that an increase in Mothers' education and improved health care services are significant in reducing child mortality in Ethiopia. Mesike *et al.* (2012) and Mojekwu *et al.* (2011) in their studies examined the environmental determinants of child mortality in Nigeria using principal component analysis and simultaneous multiple regression for child mortality modeling in Nigeria. Estimation from the stepwise regression model showed that household environmental characteristics do have significant impact on mortality as lower mortality rates were experienced in households that had access to immunization, sanitation facilities, good and proper refuse and solid waste disposal facilities, good healthy roofing and flooring materials as well as those using low polluting fuels as their main source of cooking.

THEORY AND METHOD

Principal Component Analysis

Principal components analysis helps to represent and explain the covariance relationships amongst P metrical correlated variable in terms of a much smaller number of uncorrelated variables termed factors (Bartholomew *et al.,* 2002), by taking linear combination of the standardized observables over the specified samples in a more parsimonious way (Leech *et al.,* 2008). This is most useful if one wants to reduce a relatively large number of variables to a smaller number of variables that still capture the same information, as it is much easier to interpret two or three uncorrelated variables than twenty or thirty that have a complicated pattern of interrelationships.

The Outline of PCA

Principal components analysis transforms a set of correlated variables (x's) into a set of uncorrelated components (y's). The principal components are linear combinations of the $X's$ which is written as

$$\begin{cases} y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{p1}x_p \\ y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{p2}x_p \\ \vdots \\ y_p = a_{p1}x_1 + a_{p2}x_2 + \cdots + a_{pp}x_p \end{cases} \quad 1.$$

Each component is a weighted sum of the x's, where the $a_{ij}'s$ are the weights or coefficients, for variable *i* and *j*. Where

$$\sum_{i=1}^{p} a_{ij}^2 = 1 \qquad (j = 1,2,\dots,p)(2).$$

and

$$\sum_{i=1}^{p} a_{ij}a_{ik} = 0 \qquad (j \neq k; j = 1,2,\dots,p;\ k = 1,2,\dots,p)(3).$$

Consequently, the total variance of the y's is equal to the total variance of the x's, that is

$$\sum_{i=1}^{p} var(y_j) = \sum_{i=1}^{p} var(x_i)(4).$$

This means that the total variance does not change; rather variance is redistributed in such a way that the most important component y_1 has maximum variance and therefore, explains the largest proportion of the total variance.

When choosing the number of components, the aim is to retain as small set as possible but at the same time have a significant number that provide good representation of the original data.

The variance of component *j* is the eigenvalue $\lambda_1 \geq \lambda_2,\dots,\lambda_p$. Since the components are derived in order of variance. If the x's are standardized so that the correlation matrix is analysed, the sum of the variances of the x's will be equal to p. Thus the sum of the eigenvalues, the total variance of the y's will be equal to p.

The proportion of total variance explained by component *j* is

$$\frac{\lambda_j}{\lambda_1 + \lambda_2 + \cdots + \lambda_p}(5).$$

The proportion explained by the first k component together is

$$\frac{\lambda_1 + \lambda_2 + \cdots + \lambda_k}{\lambda_1 + \lambda_2 + \cdots + \lambda_p}(6).$$

Variance

Variance is another measure of the spread of data in a data set and the formula is

$$s^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1}(7).$$

Covariance

Covariance is always measured between 2 dimensions. If you calculate the covariance between one dimension and itself, you get the variance. So, if you had a 3-dimensional data set (x,y,z), then you could measure the covariance between th e x and y dimensions, the x and y dimensions and the y and z dimensions. The formula for covariance is

$$Cov(X,Y) = \frac{\sum_{i=1}^{n}(X - \bar{X})(Y - \bar{Y})}{n-1}(8).$$

The covariance Matrix

Recall that covariance is always measured between 2 dimensions. If we have a data set with more than 2 dimensions, there is more than one covariance measurement that can be calculated. For example, from a 3 dimensional data set (x,y,z), you could calculate cov(x,y), cov(x,z) and cov(y,z). In fact, for an n -dimensional data set, you can calculate $\frac{n!}{(n-2)*2}$ different covariance values.

A useful way to get all the possible covariance values between all the different dimensions is to calculate them all and put them in a matrix. The definition for the covariance matrix for a set of data with n - dimensions is

$$C^{n \times n} = \left(c_{i,j}, c_{i,j} = cov\left(Dim_i, Dim_j\right)\right)(9).$$

Where C^{nxn} is a matrix with n rows and n columns and Dim_x is the xth dimension.

For a 3 dimensional data set, using the usual x,y and z dimension. Then, the covariance matrix has 3 rows and 3 columns, and the values are

$$C = \begin{pmatrix} cov(x,x) & cov(x,y) & cov(x,z) \\ cov(y,x) & cov(y,y) & cov(y,z) \\ cov(z,x) & cov(z,y) & cov(z,z) \end{pmatrix}$$

Computing the Principal Components

In computational terms the principal components are found by calculating the eigenvectors and eigenvalues of the data covariance matrix. This process is equivalent to finding the axis system in which the co-variance matrix is diagonal. The eigenvector with the largest eigenvalue is the direction of greatest variation, the one with the second largest eigenvalue is the (orthogonal) direction with the next highest variation and so on. The eigenvectors and eigenvalues are obtained as follows:

Let A be n × n matrix. The eigenvalues of A are defined as the roots of:

$$Determinant(A - \lambda I) = |(A - \lambda I)| \quad 10.$$

where I is the n × n identity matrix. This equation is called the characteristic equation (or characteristic polynomial) and has n roots. Let λ be an eigenvalue of A. Then there exists a vector x such as

$$Ax = \lambda x$$

The vector x is called an eigenvector of A associated with the eigenvalue λ. Notice that there is no unique solution for x in the above equation. It is a direction vector only and can be scaled to any magnitude. To find a numerical solution for x we need to set one of its elements to an arbitrary value, say 1, which gives us a set of simultaneous equations to solve for the other elements. If there is no solution we repeat the process with another element. Ordinarily we normalise the final values so that $x.x^T = 1$. Suppose we have a 3 × 3 matrix A with eigenvectors x_1,x_2,x_3 and eigenvalues $\lambda_1,\lambda_2,\lambda_3$ so:

$$Ax_1 = \lambda_1 x_1 \qquad Ax_2 = \lambda_2 x_2 \qquad Ax_3 = \lambda_3 x_3$$

Putting the eigenvectors as the columns of a matrix gives:

$$A(x_1 x_2 x_3) = [x_1 x_2 x_3]\begin{bmatrix}\lambda_1 & 0 & 0\\ 0 & \lambda_2 & 0\\ 0 & 0 & \lambda_3\end{bmatrix} 11.$$

writing

$$\Phi = [x_1 x_2 x_3] \Lambda = \begin{bmatrix}\lambda_1 & 0 & 0\\ 0 & \lambda_2 & 0\\ 0 & 0 & \lambda_3\end{bmatrix}$$

gives us the matrix equation: $A\Phi = \Phi\Lambda$

We normalised the eigenvectors to unit magnitude, and they are orthogonal, so:

$$\Phi\Phi^T = \Phi^T\Phi = 1$$

which means that: $\Phi^T A \Phi = \Lambda$

and $A = \Phi\Lambda\Phi^T$

Now let us consider how this applies to the covariance matrix in the PCA process. Let Σ be an n x n covariance matrix. There is an orthogonal n x n matrix Φ whose columns are eigenvectors of Σ and a diagonal matrix Λ whose diagonal elements are the eigenvalues of Σ, such that

$$\Phi^T \Sigma \Phi = \Lambda \quad (12)$$

We can look on the matrix of eigenvectors Φ as a linear transformation and transforms data points in the [X,Y] axis system into the [U,V] axis system. In the general case the linear transformation given by Φ transforms the data points into a data set where the variables are uncorrelated. The correlation matrix of the data in the new coordinate system is Λ which has zeros in all the off diagonal elements.

Factor Analysis

The factor analysis model is defined as

$$X = \mu + LF + e \quad (13)$$

where *X* is the p x 1 vector of measurements, μ is the p x 1 vector of means, L is a p x m matrix of loadings, F is a m x 1 vector of common factors and e is a p x 1 vector of residuals. Here, p represents the number of measurements on a subject or item and m represents the number of common factors. F and e are assumed to be independent and the individual F's are independent of each other. The mean of F and e are 0_2, *Cov(F)=I*, the identity matrix, and *Cov(e)*=Ψ, a diagonal matrix. The assumptions about independence of the F's make this an orthogonal factor model.

Under the factor analysis model, the p x p covariance matrix of the data, *X*, is:

$$Cov(X) = LL' + \Psi \quad (14)$$

where L is the p x m matrix of loadings, and Ψ is a p x p matrix of variances of residuals. The i^{th} diagonal element of LL′, the sum of the squared loadings, is called the i^{th} communality. The communality values can be judged as the percent of variability explained by the common factors. The i^{th} diagonal element of Y is called the i^{th} specific variance, or uniqueness. The specific variance is that portion of variability not explained by the common factors. The sizes of the communalities and/or the specific variances can be used to judge the goodness of fit.

RESULTS AND DISCUSSION

Principal component analysis with varimax rotation under factor analysis was conducted to assess the underlying structure of the nine items for the socio-economic and demographic variables of mortality rates. The normality assumptions, as well as the linear relationships between pairs of variables and the variables being correlated at a moderate level were checked.

Table (1) gives the correlations between the original variables and there exist a moderate correlation between the nine socio-economic and demographic variables.

From table 2, communalities show the proportion of each variable's variance that is explained by the principal components, while the initial value of the communality in a principal components analysis is 1. The extraction values in columns indicate the proportion of each variable's variance that can be explained by the principal components. Where variables with high value simplies the variables are well represented in the common factor space.

Total variance explained results in table 3 shows that the components extracted during the principal components analysis is 9 components and the eigenvalues are the variances of the principal components. Because we conducted our principal components analysis on the correlation matrix, the variables are standardized, which means that the each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis, in this case, 9.

Table 1. **Correlation Matrix**[a]

		residence	motheredu	wealthquin	childsex	motherage	birthorder	previousbirth	birthsize	zone
Correlation	residence	1.000	.733	.771	.637	.422	.272	.701	.815	.212
	motheredu	.733	1.000	.625	.849	.837	.683	.698	.567	.373
	wealthquin	.871	.825	1.000	.810	.786	.662	.713	.774	.470
	childsex	.637	.849	.710	1.000	.504	.304	.834	.766	.046
	motherage	.422	.837	.786	.504	1.000	.968	.853	.523	.531
	birthorder	.272	.683	.662	.304	.668	1.000	.700	.303	.613
	previousbirth	.701	.698	.713	.634	.653	.700	1.000	.865	.342
	birthsize	.815	.567	.774	.766	.523	.303	.865	1.000	-.079
	zone	.212	.373	.470	.046	.531	.613	.342	-.079	1.000

a. This matrix is not positive definite.

Table 5. Communalities

	Initial	Extraction
residence	1.000	.800
motheredu	1.000	.970
wealthquin	1.000	.914
childsex	1.000	.987
motherage	1.000	.923
birthorder	1.000	.910
previousbirth	1.000	.958
birthsize	1.000	.976
zone	1.000	.704

Extraction Method: Principal Component Analysis.

In the table 3 below, the column for total contains the eigenvalues. The first component will always account for the most variance (and hence have the highest eigenvalue), and the next component will account for as much of the left over variance as it can, and so on. Hence, each successive component will account for less and less variance and the variance column contains the percent of variance accounted for by each principal component. The cumulative column contains the cumulative percentage of variance accounted for by the current and all preceding principal components. For example, the third row shows a value of 97.251. This means that the first three components together account for 97.251% of the total variance. (Remember that because this is principal components analysis, all variance is considered to be true and common variance. In other words, the variables are assumed to be measured without error, so there is no error variance. From the extraction sums of squared loadings, the three columns of this half of the table exactly reproduce the values given on the same row on the left side of the table. The number of rows reproduced on the right side of the table is determined by the number of principal components whose eigenvalues are 1 or greater.

The scree plot in figure 1 is a plot of eigenvalue against the component number. You can see these values in the first two columns of table 3. From the third component on, you can see that the line is almost flat, meaning the each successive component is accounting for smaller and smaller amounts of the total variance. In general, we are interested in keeping only those principal components whose eigenvalues are greater than 1. Components with an eigenvalue of less than 1 account for less variance than did the original variable (which had a variance of 1) and so are of little use. Hence, you can see that the point of principal components analysis is to redistribute the variance in the correlation matrix (using the method of eigenvalue decomposition) to redistribute the variance to first components extracted.

Component matrix in table 4 contains component loadings which are the correlations between the variable and the component. Since these are correlations whose possible values range from -1 to +1. The component columns are the principal components that have been extracted. As you can see by the footnote in table 4, the two components were extracted (the two components that had an eigenvalue greater than 1). We usually do not try to interpret the components the way that we would factors that have been extracted from a factor analysis. Rather, most people are interested in the component scores, which are used for data reduction (as opposed to factor analysis where you are looking for underlying latent continua).

The reproduced correlations in table 5 contains two tables, the reproduced correlations in the top part of the table and the residuals in the bottom part of the table. The reproduced correlation matrix is the correlation matrix based on the extracted components. You want the values in the reproduced matrix to be as close to the values in the original correlation matrix as possible. This means that you want the residual matrix, which contains the differences between the original and the reproduced matrix, to be close to zero. If the reproduced matrix is very similar to the original correlation matrix, then you know that the components that were extracted accounted for a great deal of the variance in the original correlation matrix, and these few components do a good job of representing the original data. The numbers on the diagonal of the reproduced correlation matrix are presented in the Communalities table in the column labeled Extracted.

The residual aspect of table 5represent the differences between original correlations (shown in the correlation matrix in table 1) and the reproduced correlations which are shown in the top part of table 5.

Table 3. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.354	70.595	70.595	6.354	70.595	70.595	4.955	55.050	55.050
2	1.789	19.872	90.467	1.789	19.872	90.467	3.188	35.417	90.467
3	.611	6.784	97.251						
4	.165	1.831	99.082						
5	.083	.918	100.000						
6	1.265E-16	1.406E-15	100.000						
7	9.184E-18	1.020E-16	100.000						
8	-2.091E-16	-2.323E-15	100.000						
9	-3.470E-16	-3.856E-15	100.000						

Extraction Method: Principal Component Analysis.

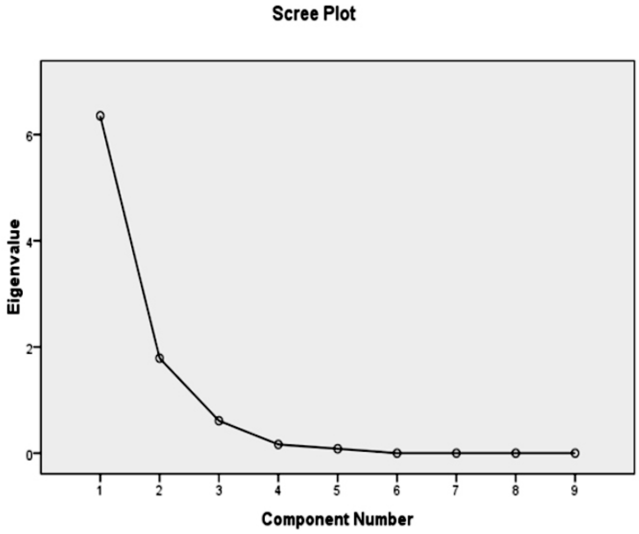

Figure 1. Scree Plot

Table 4. Component Matrix[a]

	Component	
	1	2
motheredu	.985	
previousbirth	.979	
wealthquin	.955	
childsex	.871	-.479
birthsize	.852	-.500
motherage	.847	.453
residence	.801	-.398
birthorder	.710	.637
zone	.407	.734

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Table 5. Reproduced Correlation

		residence	motheredu	wealthquin	childsex	motherage	birthorder	previousbirth	birthsize	zone
Reproduced Correlation	residence	.800[a]	.793	.750	.888	.499	.316	.785	.882	.034
	motheredu	.793	.970[a]	.940	.862	.829	.693	.964	.844	.393
	wealthquin	.750	.940	.914[a]	.813	.827	.704	.935	.794	.418
	childsex	.888	.862	.813	.987[a]	.521	.313	.853	.981	.003
	motherage	.499	.829	.827	.521	.923[a]	.890	.829	.495	.678
	birthorder	.316	.693	.704	.313	.890	.910[a]	.694	.287	.756
	previousbirth	.785	.964	.935	.853	.829	.694	.958[a]	.834	.398
	birthsize	.882	.844	.794	.981	.495	.287	.834	.976[a]	-.020
	zone	.034	.393	.418	.003	.678	.756	.398	-.020	.704[a]
Residual[b]	residence		-.061	.021	.048	-.077	-.044	-.084	-.066	.178
	motheredu	-.061		-.015	-.013	.008	-.010	.034	.023	-.021
	wealthquin	.021	-.015		-.003	-.042	-.041	-.022	-.020	.052
	childsex	.048	-.013	-.003		-.017	-.009	-.019	-.015	.043
	motherage	-.077	.008	-.042	-.017		.078	.025	.028	-.147
	birthorder	-.044	-.010	-.041	-.009	.078		.006	.017	-.143
	previousbirth	-.084	.034	-.022	-.019	.025	.006		.031	-.055
	birthsize	-.066	.023	-.020	-.015	.028	.017	.031		-.059
	zone	.178	-.021	.052	.043	-.147	-.143	-.055	-.059	

Extraction Method: Principal Component Analysis.

a. Reproduced communalities

b. Residuals are computed between observed and reproduced correlations. There are 11 (30.0%) non-redundant residuals with absolute values greater than 0.05.

Conclusively, two factors component was identified and the total variance explained is 97.25 percent. The result shows that 70.595 percent of the variance was accounted for by the first factor while the second and third factors accounted for 19.9 percent and 6.78 percent respectively. It is particularly instructive to note that more than 97 percent of the variance is accounted for by the first three factors. The first factor which seems to index mother education had a very strong loading on wealth quintile, residence, birth order and zone. The second factor which seemed to index previous birth had high loadings on child sex, birth sex, birth size and as well as mother's age.

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