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Forecasting the Real GDP in Nigeria Using Possibilistic Linear Regression Model

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Abstract. This paper presents application of fuzzy linear regression to forecast the real GDP of Nigeria based on macroeconomic indicators including unemployment rate, inflation rate and FDI. A fuzzy linear regression model capable of predicting the real GDP of Nigeria, assuming that residuals are due to system fuzziness is ideal. Based on the empirical results, two fuzzy regression models with threshold values of 0 and 0.5 that can adequately estimate the real GDP of Nigeria are established. Consequently, considering the criteria of interval of possibility and MAPE, the most suitable model is determined.

Keywords: Possibilistic regression, Gross Domestic Product, Membership Functions, Microeconomic Variables, Model.

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1. Introduction

There is no dispute the fact that the growth and stability of a nation's economy lie on its Gross Domestic Product (GDP) as a measure of economic wealth (Anthony and Emediong (2021)) and there are certain macro factors operating in the economic environment that will influence the GDP growth; Inflation, Exchange rate, Foreign exchange reserves, Foreign Institutional Investors, Sensex, Balance of Payments and Fiscal Deficit were also noted (Divya and Devi (2014)).
A number of macroeconomic factors were identified by numerous authors that have impact on GDP: unemployment rate, inflation rate, exchange rate, foreign direct investment, population growth rate, age dependency rate and crude oil exports were identified in Jabaru and Jimoh (2020).
A knowledge of individual effect of the indicators on the real GDP, as well as the best and worst interval that may be achieved based on the indicators may further

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help the analysis of this fundamental indicator. Fuzzy Regression analysis is one of the ideal scientific approaches in this regard. The method, despite capable of modelling the real GDP against related factors, makes it possible to forecast the best and worst possible interval based on predetermined or anticipated values of the related explanatory factors.

Gross Domestic Product forecasting has attracted the attention of many scholars because of its importance in measuring the performance of any economy. The Bureau of Economic Analysis (BEA) gives a clear definition of GDP: Gross domestic product is the value of the goods and services produced by the nation's economy less the value of the goods and services used up in production (Dynan and Sheiner (2018)).

The studies of Anthony and Emediong (2021); Divya and Devi (2014); Dynan and Sheiner (2018); Jabaru and Jimoh (2020); Oyeyemi and Awujola (2014) are few undertakings that evaluated the relationship between GDP and key macroeconomic indicators. The methodology in these studies considers the relationship between GDP and the macroeconomic indicators to be precise or crisp in addition to randomness of the residuals. Such forceful assumption of a crisp relationship may lead to the loss of some vital information (Pandit *et al.* (2021)). Residuals, which are the deviations between the observed and estimated values are sometimes due to indefiniteness of the structure of the system or imprecise observations (Kahraman *et al.* (2006)).

Unlike classical ordinary least squares regression modelling, residuals are assumed to be due system fuzziness in the fuzzy regression concept. The Fuzzy Regression is based on possibility theory introduced in Tanaka *et al.* (1982) and fuzzy set theory described in Zadeh (1965). Fuzzy regression methods have attracted growing interest from researchers in various scientific, engineering, and humanities area due to the ambiguity in real data (Sadi-Nezhad *et al.* (2019)). Furthermore, Fuzzy regression has been widely used in recent years throughout the globe (Ubale and Sananse (2015)). In order to predict the airborne stuck of Baghdad, Alsoltany and Alnaqash (2015) applied the concept of fuzzy regression. The predictors of the airborne in this study are Lead, Zinc, Copper, Iron, Nickel, Chromium and Cadmium. Using fuzzy regression method as the solution method, Akgul *et al.* (2022) examined factors affecting employment in non-life insurance companies. Similarly, Bin Wan Ahmad *et al.* (2022) illustrated the application of fuzzy linear regression to public health data. While Ubale and Sananse (2016), reported that fuzzy regression models can produce better prediction as compared to least square method. Additionally, Akdemir and Tiryaki (2013) studied the relationship between forest fires and meteorological conditions using fuzzy Linear Regression.

Further applications of fuzzy regression were also proposed in Attanayake (2021); Heshmaty and Kandel (1985); Lee *et al.* (2020); Malyaretz *et al.* (2018); Taghizadeh *et al.* (2009); Taheri *et al.* (2020); Tanaka (1987); Tanaka and Watada (1989). In light of the foregoing backgrounds, it is apparent that the application of the fuzzy regression in the recent times has cut across almost all aspects of human endeavours.

Against this backdrop, this research is aimed to explore the effect of Unemployment rate, Inflation rate and Foreign Direct Investment on the basis of the sample data through Fuzzy linear regression analysis in order to obtain a possi-

bilistic real GDP evaluation model.
The rest of the paper is structured as follows: In Section 2, Materials and Method is presented, followed by Results and Discussion in Section 3. Finally, conclusion is provided in Section 4.

2. Materials and Method

2.1 *Fuzzy Linear Regression*

Fuzzy linear regression is a fuzzy type of classical regression analysis in which some elements of the model are represented by fuzzy numbers (Alsoltany and Alnaqash (2015)). The functional relationship between the response and explanatory variables as reported in Tanaka *et al.* (1982) is presented as follows:

$$\tilde{Y} = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_2 + \cdots + \tilde{A}_p x_p \tag{1}$$

In matrix form;

$$\hat{Y} = \tilde{A}X \tag{2}$$

where: $\tilde{Y}$ is the fuzzy output, $X = (x_{0i}, x_{1i}, x_{2i}, \cdots, x_{pi})^T$, p-dimensional crisp input vector, $\tilde{A} = (\tilde{A}_0, \tilde{A}_1, \tilde{A}_2, \cdots, \tilde{A}_p)^T$, fuzzy vector of coefficients presented in the form of a symmetric triangular fuzzy number denoted by $\tilde{A}_j = [c_j, w_j]$ respectively, c_j and w_j are its centre and width, while $x_{0i} = 1$.

2.2 *Determination of Fuzzy Regression Parameters*

A symmetrical fuzzy number A_j denoted as $\tilde{A}_j = [c_j, w_j]$ is defined as $\mu_{A_j}(a_j) = L((a_j - c_j)/w_j), w_j > 0$, where c_j is a centre, w_j is a width and $L(a_j)$ is a shape function of fuzzy number defined by:

i. $L(a_j) = L(-a_j)$,
ii. $L(0) = 1$,
iii. $L(a_j)$ is strictly decreasing function for $a_j \geq 0$,
iv. $\{a_j | L(a_j) \geq 0\}$ is a closed interval.

For each type of A_j, the membership functions are assumed a triangular as shown in Figure 1. By definition, it can be expressed as:

$$\mu_{\tilde{A}_j}(a_j) = \begin{cases} 1 - \frac{|c_j - a_j|}{w_j}, & \text{if } c_j - w_j \leq a_j \leq c_j + w_j \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $w_j > 0$.
To determine the a_j's, we can calculate a_0 and a_2, since $w_0, w_2 > 0$. From Table 1, c_0 = 4.021, c_2 = -0.145, w_0 = 0.116 and w_2 = 0.022.

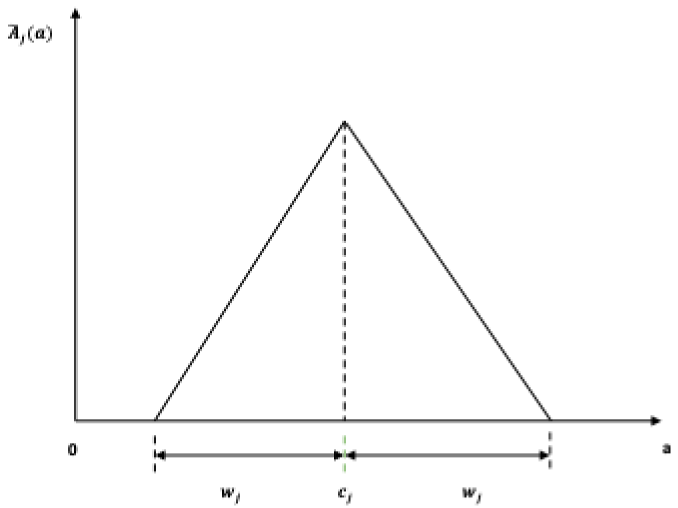

Figure 1: Membership function for the fuzzy parameters $\tilde{A}_j$

According to the extension principle (Zadeh, 1975), the membership function of the fuzzy number $\tilde{y}$ becomes:

$$\mu_Y(y) = \begin{cases} \text{Max}\left(0, 1 - \frac{|y - \sum_{j=0}^{p} c_j x_{ij}|}{\sum_{j=0}^{p} w_j x_{ij}}\right), & \text{if } x_{ij} \neq 0 \\ 1 & \text{if} x_{ij} = 0, y \neq 0 \\ 0 & \text{if} x_{ij} = 0, y = 0 \end{cases} \tag{4}$$

The spread of $\tilde{y}$ is $\sum_{j=0}^{p} w_j x_{ij}$ and the middle value of $\tilde{y}$ is $\sum_{j=0}^{p} c_j x_{ij}$. The membership function for the fuzzy output is presented in Figure 2.

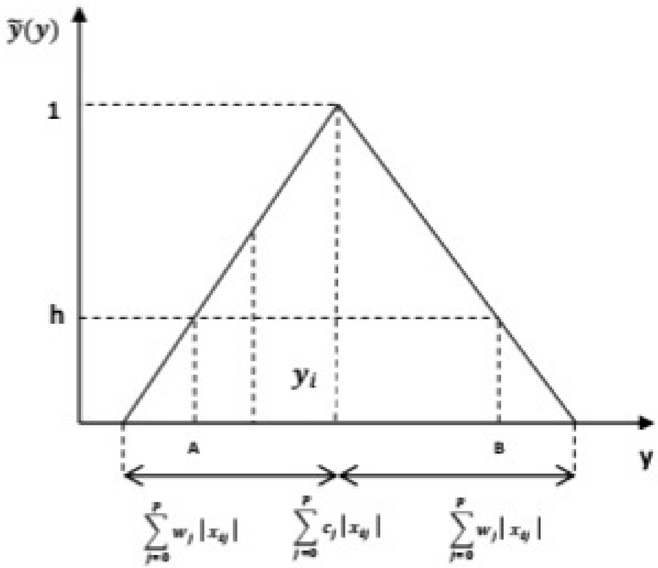

Figure 2: Membership function for the fuzzy output

Objective Function: We seek to find the coefficients $\tilde{A}_j = [c_j, w_j]$ that minimize the spread of the fuzzy output for all data sets. Mathematically, this becomes:

$$\text{Min } S = \sum_{j=0}^{p} w_j|x_{ij}| \tag{5}$$

Constraints: The constraints require that each observation y_i has a threshold value h in the interval (0,1) which is specified by the user of belonging to $\tilde{y}(y)$ (Taghizadeh *et al.,* 2009). This implies,

$$\tilde{y}(y_i) \geq h, \; i = 1, 2, \cdots, n \tag{6}$$

(6) indicates that the fuzzy output should lie between A and B as shown in Figure 2. By substituting (4) into (6), we obtain:

$$1 - \frac{|y - \sum_{j=0}^{p} c_j x_{ij}|}{\sum_{j=0}^{p} w_j x_{ij}} \geq h$$

$$\sum_{j=0}^{p} w_j x_{ij} - |y - \sum_{j=0}^{p} c_j x_{ij}| \geq h \sum_{j=0}^{p} w_j x_{ij}$$

$$\sum_{j=0}^{p} w_j x_{ij} - h \sum_{j=0}^{p} w_j x_{ij} - |y - \sum_{j=0}^{p} c_j x_{ij}| \geq 0$$

$$(1-h) \sum_{j=0}^{p} w_j x_{ij} - |y - \sum_{j=0}^{p} c_j x_{ij}| \geq 0 \tag{7}$$

After simplifying (7), the following constraints are obtained:

$$\begin{aligned} &\sum_{j=0}^{p} c_j x_{ij} - (1-h) \sum_{j=0}^{p} w_j |x_{ij}| \leq y_i, \forall\, i = 1, \cdots, n \\ &\sum_{j=0}^{p} c_j x_{ij} + (1-h) \sum_{j=0}^{p} w_j |x_{ij}| \geq y_i, \forall\, i = 1, \cdots, n \\ &\qquad\qquad\qquad w_j \geq 0, x_{i0} = 1; i = 1, \cdots, n. \end{aligned} \tag{8}$$

Combining (5) and (8), we obtain in compact form the linear programming problem according to Tanaka *et al.* (1982):

$$
\begin{aligned}
&\text{Min S} = \sum_{j=0}^{p} w_j|x_{ij}| \\
\text{s.t} \quad &\sum_{j=0}^{p} c_j x_{ij} - (1-h)\sum_{j=0}^{p} w_j|x_{ij}| \leq y_i, \forall\, i = 1, \cdots, n \\
&\sum_{j=0}^{p} c_j x_{ij} + (1-h)\sum_{j=0}^{p} w_j|x_{ij}| \geq y_i, \forall\, i = 1, \cdots, n \\
&\qquad\qquad w_j \geq 0, x_{i0} = 1; i = 1, \cdots, n.
\end{aligned} \tag{9}
$$

Where, w_j and c_j for $j = 0, 1, \cdots, p$ are unknown variables vectors. Based on the results in (9), the relation in (1) can be rewritten in possibilistic form as follows:

$$\tilde{Y} = (c_0, w_0) + (c_1, w_1)x_{1i} + (c_2, w_2)x_{2i} + \cdots + (c_p, w_p)x_{pi}, \tag{10}$$

$i = 1, 2, \cdots, n$, where n is the number of observations.
This expression makes it possible to forecast the best and worst possible values of $\tilde{Y}$ based on predetermined values of $X = (x_{1i}, x_{2i}, \cdots, x_{pi})$, the related explanatory factors.

3. Results and Discussion

In this section, we converted the Fuzzy Regression (FR) model into linear programming problem as in (9) with threshold levels of $h = 0$ and 0.5 in order to determine the minimal fuzziness of the models. The data related to GDP, unemployment rate, inflation rate and FDI are obtained from Ogosi *et al.* (2022) and shown in the Appendix. The phasic sequence of the empirical results are as follows:
Phase I: Determining the fuzzy parameters: By using Tora Optimization Software (Taha, 2011), a linear programming problem is generated based on the data of the considered macroeconomic factors influencing GDP of Nigeria. The central values and widths of each fuzzy parameter in (1) for $h = 0$ and 0.5 were obtained and presented in Tables 1 and 2 along with the corresponding upper bound (UB) and lower bound (LB), respectively.

Table 1: Central and widths values for fuzzy parameters for $h = 0$

Fuzzy parameters	Centre	Width	UB	LB
A_0	4.021	0.116	4.137	3.906
A_1	1.005	0.000	1.005	1.005
A_2	-0.145	0.022	-0.124	-0.167
A_3	0.376	0.000	0.376	0.376

Table 2: Central and widths values for fuzzy parameters for $h = 0.5$

Fuzzy parameters	Centre	Width	UB	LB
A_0	3.939	0.000	3.939	3.939
A_1	1.121	0.347	1.467	0.774
A_2	-0.137	0.059	-0.077	-0.196
A_3	0.374	0.000	0.374	0.374

The established fuzzy linear regression models for the real GDP ($\tilde{y}$) of Nigeria against the three macroeconomic factors are provided in (11a) and (11b), respectively:

$$\text{GDP}(\tilde{y}) = (4.021, 0.116) + (1.005, 0.000)x_1 + (-0.145, 0.022)x_2 + (0.376, 0.000)x_3 \quad (11a)$$

$$\text{GDP}(\tilde{y}) = (3.939, 0.000) + (1.121, 0.347)x_1 + (-0.137, 0.059)x_2 + (0.374, 0.000)x_3 \quad (11b)$$

(11a) implies real GDP can be suitably predicted when the unemployment indicator is exactly 1.005, index of inflation is between -0.167 and -0.124, and foreign direct investment is 0.376 (see Table 1, columns 4 and 5), whereas (11b) indicates that real GDP can be predicted when the unemployment indicator is between 0.774 and 1.467, index of inflation is between -0.196 and -0.077, and foreign direct investment is exactly 0.374 (see Table 2, columns 4 and 5), respectively.
For both threshold values, 46 iterations were carried out to reach the optimum. The minimum values of the total spreads are 4.077 and 8.242 for $h = 0$ and $h = 0.5$. This means a better prediction can be achieved when $h = 0$ compared to when $h = 0.5$. This is in line with most of the studies in the literature.
Specifically, for $h = 0$ the inflation index has widest interval of possibility (see Table 1), while in Table 2 for $h = 0.5$, the index of unemployment has widest interval of possibility, respectively.
Phase II: Prediction of bounds: Using (11a) and (11b), the best and worst possible real GDP for the considered time range were predicted and the results are shown in Tables 3 and 4. Figures 3 and 4 represents graphical plot of the FR UB and FR LB with the actual real GPD, respectively.

Table 3: Prediction results of FR model for $h = 0$

Year	Actual GDP	FR UB	FR LB	Year	Actual GDP	FR UB	FR LB
2019	4.854	5.114	4.837	2004	4.544	4.676	4.394
2018	4.844	5.037	4.759	2003	4.501	4.694	4.414
2017	4.836	5.120	4.836	2002	4.462	4.689	4.410
2016	4.832	5.086	4.804	2001	4.403	4.588	4.302
2015	4.839	4.839	4.567	2000	4.375	4.635	4.367
2014	4.827	4.940	4.669	1999	4.351	4.618	4.351
2013	4.801	4.873	4.602	1998	4.349	4.395	4.121
2012	4.778	4.898	4.620	1997	4.338	4.477	4.205
2011	4.760	4.944	4.668	1996	4.326	4.422	4.128
2010	4.737	4.869	4.588	1995	4.309	4.309	3.998
2009	4.698	4.925	4.647	1994	4.301	4.608	4.301
2008	4.663	4.900	4.623	1993	4.299	4.545	4.238
2007	4.633	4.896	4.633	1992	4.293	4.484	4.182
2006	4.602	4.847	4.576	1991	4.283	4.507	4.228
2005	4.574	4.820	4.535				

Table 4: Prediction results of FR model for $h = 0.5$

Year	Actual GDP	FR UB	FR LB	Year	Actual GDP	FR UB	FR LB
2019	4.854	5.384	4.629	2004	4.544	4.800	4.258
2018	4.844	5.312	4.548	2003	4.501	4.818	4.278
2017	4.836	5.404	4.619	2002	4.462	4.811	4.275
2016	4.832	5.335	4.604	2001	4.403	4.716	4.164
2015	4.839	4.977	4.567	2000	4.375	4.742	4.242
2014	4.827	5.087	4.522	1999	4.351	4.725	4.226
2013	4.801	4.979	4.475	1998	4.349	4.510	3.992
2012	4.778	5.013	4.487	1997	4.338	4.588	4.079
2011	4.760	5.058	4.536	1996	4.326	4.559	3.985
2010	4.737	4.988	4.588	1995	4.309	4.464	3.844
2009	4.698	5.051	4.514	1994	4.301	4.757	4.149
2008	4.663	5.004	4.497	1993	4.299	4.693	4.087
2007	4.633	4.986	4.516	1992	4.293	4.624	4.036
2006	4.602	4.950	4.451	1991	4.283	4.602	4.099
2005	4.574	4.944	4.398				

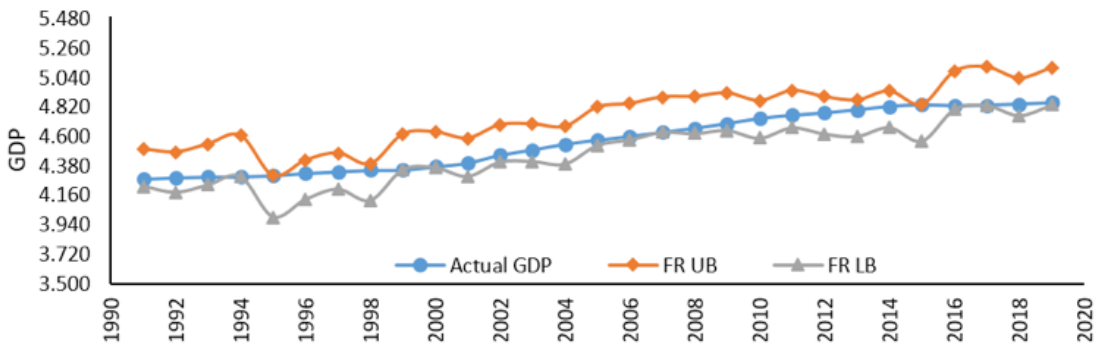

Figure 3: Actual real GDP along with UB and LB resulting from FR model for $h = 0$

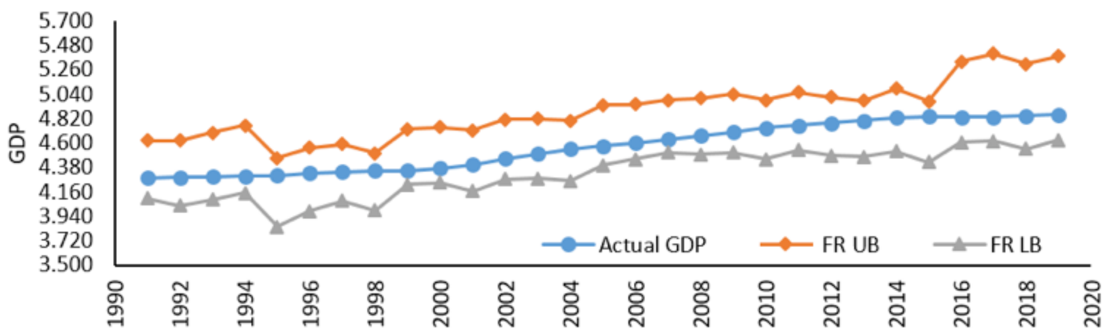

Figure 4: Actual real GDP along with UB and LB resulting from FR model for $h = 0.5$

Phase III: Bound assessment: From Table 3 and Figure 3, as well as Table 4 and Figure 4, it can be observed that the actual GDP values are located within the predicted bounds. However, in Table 3 and Figure 3, the interval of possibility is narrower as compared to Table 4 and Figure 4. Additionally, model adequacy assessment based on Mean Absolute Percentage Error (MAPE) suggests the fitness of the established models as both bounds are within ten percent error,

which is an indication of high accuracy (Akincilar *et al.* (2011); Bakawu et al. (2020)).
Furthermore, the MAPE values for the FR UB and FR LB are (4.047% and 2.131%) for (11a) and (7.151% and 5.307%) for (11b). This shows that the MAPE values for (11a) is smaller than that of (11b). Hence, (11a) could be the suitable model for predicting the future real GDP of Nigeria. This adequacy assessment, tallies with the accuracy of fuzzy regression reported in Malyaretz *et al.* (2018).

4. Conclusion

This study employed a methodology based on fuzzy linear regression capable of predicting the real GDP of Nigeria, assuming that residuals are due to system fuzziness. Based on the empirical results, two fuzzy regression models with threshold values of 0 and 0.5 that can adequately estimate the real GDP of Nigeria are established. Consequently, considering the criteria of interval of possibility and MAPE, the most suitable model is determined.
Future research is focused on comparing the fuzzy linear regression models presented with other available tools. The results of the different methods can be compared with the fuzzy linear regression method.

Declaration

The authors declared to have no conflict of interest in this paper.

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Appendix

Table 5: Data on Macroeconomic Variables: GPD(Y), Unemployment (X_1), Inflation (X_2), and FDI(X_3)

Year	GDP	UNEMPLOYMENT	INFLATION	FDI	Year	GDP	UNEMPLOYMENT	INFLATION	FDI
2019	4.854	0.908	1.057	0.519	2004	4.544	0.579	1.176	0.272
2018	4.844	0.916	1.082	0.301	2003	4.501	0.582	1.147	0.303
2017	4.836	0.924	1.218	0.544	2002	4.462	0.582	1.110	0.276
2016	4.832	0.849	1.195	0.648	2001	4.403	0.577	1.276	0.076
2015	4.839	0.634	0.955	0.486	2000	4.375	0.577	0.841	0.057
2014	4.827	0.659	0.906	0.671	1999	4.351	0.579	0.821	0.000
2013	4.801	0.568	0.928	0.745	1998	4.349	0.575	1.000	-0.523
2012	4.778	0.573	1.087	0.849	1997	4.338	0.575	0.931	-0.328
2011	4.760	0.576	1.035	0.946	1996	4.326	0.576	1.466	-0.301
2010	4.737	0.576	1.137	0.780	1995	4.309	0.575	1.862	-0.469
2009	4.698	0.571	1.099	0.932	1994	4.301	0.575	1.756	0.292
2008	4.663	0.549	1.064	0.913	1993	4.299	0.573	1.757	0.130
2007	4.633	0.553	0.732	0.781	1992	4.293	0.565	1.649	-0.046
2006	4.602	0.562	0.915	0.686	1991	4.283	0.561	1.114	-0.149
2005	4.574	0.573	1.252	0.697					

Source: Ogosi *et al.* (2022)