Journal of Applied Sciences, Information and Computing

Volume 5, Issue 1, June 2024

School of Mathematics and Computing, Kampala International University

ISSN: 1813-3509 https://doi.org/10.59568/JASIC-2024-5-1-08

Predictive stability study of poverty trend in Uganda using selected indicators

[1]Lekia Nkpordee, [2]Juma Ndhokero

[1]Department of Mathematics and Statistics, Kampala International University,
Kansanga, Kampala, Uganda, East Africa
[2]National Agricultural Research Organisation (NARO), Entebbe, Uganda
*Corresponding Email: lekia.nkpordee@kiu.ac.ug
Email: ndhokero@gmail.com

Abstract

This study investigates poverty dynamics in Uganda, employing an extensive stability analysis of different socioeconomic indicators to understand long-term trends and likely drivers of poverty. An eighteen years yearly secondary data from 1992 to 2020 on poverty rates for the selected indicators under review sourced from World Bank site was utilized for all the data analysis. Outcomes from extensive data analysis shows considerable reductions in poverty rates over time, especially in outlying areas of eastern and northern Uganda despite increasing income inequality as suggested by the increasing Gini coefficient. All the metrics have a significant impact on Uganda's poverty rates, with the exception of the poverty headcount ratio, which stands at USD 6.85 per day (2017 PPP) as a percentage of the population. Particularly, the forecasted values also show a fluctuating trend movement, both downward and upward, suggesting possible variability in future poverty rates in Uganda. The necessity to carefully evaluate as well as monitor poverty dynamics to guide policy interventions aimed at reducing poverty is underlined by this information. Additionally, the stability analysis framework suggested in this research provides insights into the viability as well as resilience of Uganda's socioeconomic system in tackling poverty, enabling evidence based policies and interventions in poverty reduction. The study suggests more examination of various other dimensions of poverty and non-monetary indicators of well-being to better our understanding and support better poverty alleviation methods in Uganda along with other similar settings.

Keywords: **Stability Study, Poverty Level, Prediction, Selected Indicators, Regression**

1. Introduction

Uganda, an East African landlocked country, has struggled with poverty for many years in spite of significant economic growth and development efforts. The issue of poverty continues and a great number of individuals live below the poverty line. Sustainable development of Uganda relies upon understanding the dynamics of poverty and applying effective strategies for poverty reduction. This particular research is designed to perform a stability assessment to predict the poverty level of Uganda using selected indicators. The Ugandan economy has averaged 5.4 percent each year during the last decade. Poverty has also fallen significantly because of this relatively high economic growth rate. The Uganda National Household Survey has revealed a lessening in poverty from 38.8 percent to 24.5 percent in the past 8 years alone, based on the Uganda Bureau of Statistics (2020). However, not every region of the nation has had a uniform decline in poverty. Poverty decreased by 15.5 percentage points in rural regions and by 5.3 percentage points in urbanized areas. When comparing local poverty rates, the highest declines have been seen in northern and eastern Uganda (21.7 and 16.8 percentage points, respectively), whereas Western Uganda has seen a fall of 11.1 percentage points.

Although data on poverty rates at the local, state, and federal levels are readily available, little is known about the types of households that have succeeded and the individuals whose standard of living has decreased or stagnated. For instance, are households headed by women doing significantly better or worse? Has the economic growth been shared by households with lower levels of education? In addition to these worries, it's critical to find out whether other measures of living standards also indicate a decline in poverty as measured by per capita spending. Has there been a growth in non-financial indices such as housing quality, access to water and sanitation services, and ownership of consumer goods like motorbikes along with the decline in expenditure-based poverty and radios? Poverty is an interdisciplinary phenomenon which is formed by economic, environmental and social factors. Poverty in Uganda takes numerous forms, including income poverty, food insecurities, Access to essential services and limited educational as well as work opportunities. To tackle these Complexities it's crucial that you identify as well as evaluate key indicators which effectively reflect the dimensions as well as causes of poverty. Different factors which contribute to poverty in Uganda were studied in past research. Growth in the economy, agriculture productivity, healthcare and education accessibility, infrastructure development and governance indicators have all been analyzed in studies which have formed the poverty landscape (Ninsiima, 2020; Okumu & Kizza, 2019). Much more comprehensive approaches that include several indicators and utilize sophisticated analytical methods to anticipate as well as comprehend poverty dynamics are required, though.

According to Kakande (2020), "this is among the largest and quickest reductions in income poverty documented anywhere these days" (p. 237) in her assessment of the trends in poverty. Nevertheless, she claims that economic disparity actually rose and that improvements in living conditions were not distributed equally across the country. According to the most available figures, Uganda's 2009/10 Gini coefficient is 0.4261 (Uganda Bureau of figures, 2020) compared to 0.3641 in 1992 (Appleton, 2021). According to Ssewanyana et al. (2021), almost all of the GDP gains from the 1990s went to the banking and telecommunications sectors. This suggests that the GDP gains were not divided fairly. In an earlier report using data from the UNHS for 2005–06, According to Ssewanyana's (2019) analysis of household welfare, "an increased inequality hurts the "ultra" poor more than the poor." Using UNHS data, Mukwaya et al. (2021) investigate inequality in a much more recent era, from 2005 to 2010. They blame the high proportion of disadvantaged people living in urbanized areas as well as the disparity between urbanized workers in manufacturing and services for the higher levels of inequality.

A number of academics contest the decline in poverty. According to Byekwaso's 2020 research, "the reduction of poverty is a myth." He criticizes the consumption expenditure method of calculating income and contends that a meaningful measure of

 https://doi.org/10.59568/JASIC-2024-5-1-08

living must take asset ownership into account. Although there has been a rapid fall in the rates of poverty, Kakande (2020) acknowledges qualitative research on patterns of poverty that shows a decline in overall well-being. In particular, Kakande shows that there are inconsistent results when reporting on "progress" towards the Millennium Development Goals. The researchers (2016) look at changes in and out of poverty and chronic poverty between 1992 and 2002 using both quantitative and qualitative methodologies. Assets and education were linked to welfare growth, and families that were chronically poor were larger and considerably more likely to be subsistence farmers without any type of pay labor. Similarly, Okidi and McKay (2023) examined panel data from 1992 and 2000 and found that families that had been impoverished for a prolonged period of time had a mean size of six members, compared to four members for families that had never been impoverished. They also acknowledge the value of education and tangible goods.

This study builds upon earlier works by suggesting a stability analysis framework to anticipate the poverty level in Uganda. Stability analysis is a systematic technique for evaluating the longevity and resilience of socio-economic systems (Bhattacharyya et al., 2019). This study seeks to look at long - term trends and tipping points in Ugandan poverty dynamics by integrating stability analysis with poverty prediction. The stability study picks indicators based on significance for evaluating poverty and their accessibility in Uganda. The indicators encompass various aspects of well-being, including income distribution, ability to access essential services, employment opportunities and social safety and environmental sustainability. The stability analysis aims to capture the intricate interplay of variables which determine poverty outcomes by incorporating several indicators. The proposed approach contributes to the existing literature by offering a holistic framework for predicting poverty dynamics in Uganda. This study seeks to enhance our understanding of the systems behind poverty with a range of indicators and advanced statistical techniques. Poverty remains a chronic challenge in Uganda, despite attempts to encourage economic development and growth. This study deals with the need for a comprehensive approach to poverty prediction by employing stability analysis and combining several indicators and also seeks to support evidence based policies as well as interventions to ease poverty in Uganda by providing insights into future trends and possible triggers of poverty.

1.1 Study's Objectives

The particular goals of this research are to:

i. Test for normality and stationarity of the datasets using Anderson-darling and Augmented Dickey Fuller (ADF) test.
ii. Fit the stability regression models.
iii. Validate the model and obtain the shelf life plot for all the indicators (batches).
iv. Generate the futuristic forecast of the poverty trend in Uganda.

2. Materials And Methodologies

This study's scope was centered on stability analysis to forecast Uganda's poverty level utilizing particular indicators. The study examined a number of indicators related to the poverty rate, including the percentage of the urban population living in slums, the income shares held by the next twenty percent, the third twenty percent, the fourth twenty percent, the highest twenty percent, and the percentage of people living below fifty percent of the median income (%), the income shares held by the lowest ten percent and the twenty percent, the poverty headcount ratio at USD 2.15, USD 3.65, and USD 6.85 a day (2017 PPP) (%), the poverty gap at USD 2.15, USD 3.65 and USD 6.85 a day (2017 PPP) (%), and the Gini index, the country of Uganda exhibits a diverse range of poverty trends, which are captured by various measures such as the multidimensional poverty headcount ratio (% of total population), multidimensional poverty intensity, multidimensional poverty index (scale 0 1), poverty headcount ratio at national poverty lines (% of population), survey mean consumption or income per capita, bottom 40% of the population (2017 PPP), and annualized average growth rate in per capita real survey mean consumption or income. For all the data analysis, 18 years of annual data on poverty rates for the chosen metrics under examination from 1992 to 2020 were used. These

 https://doi.org/10.59568/JASIC-2024-5-1-08

Statistics came from the World Bank website. Furthermore, the statistical program MINITAB 21 was used in the research to analyze the data.

2.1 Model Specification
2.1.1 Stability Regression Model
2.1.1.1 Fixed Batch Model Selection

The model selection decides whether the shelf life is dependent upon batch and whether the impact of time is determined by batch. Minitab considers the following 3 models in sequence:

1. Time + Batch +Batch*Time (unequal slopes for batches)
2. Time +Batch (equal slopes and unequal intercepts for batches)
3. Time (the same slopes and intercepts for batches)

The first model is fitted by the analysis when the Batch * Time interaction has significant significance. The analysis can fit the 2nd model when the interaction is minor but the Batch term is essential in the second model. Otherwise, the analysis matches the 3rd model. The test statistic is calculated by dividing the term's sequential mean square by the mean square error. An F-distribution is used in the model selection process to verify the factors. The denominator degrees of freedom in the F distribution are identical to the degrees of freedom for mistakes, and the numerator degrees of freedom are the same as those for the factor. The portion of the F distribution that exceeds the factor's F value is shown by the p-value.

2.1.1.2 Shelf life for the mean response method

Both Boundaries

Take into account which model you adapt to the data in order to streamline the computation of the condition for how and when this study calculates the shelf life.

2.1.1.2.1 The Time*Batch Interaction Model using Time and Batch

This study examines two scenarios to see if it is possible to estimate shelf life in a meaningful way. First, we make sure the mean response is statistically within the given ranges.

$$L+t_{0.95,n-2l}\sqrt{Q_{i,j}}<\hat{\alpha}_i<U-t_{0.95,n-2l}\sqrt{Q_{i,j}} \quad (1)$$

Where

$$\sigma^2=S^2\left(X'X\right)^{-1} \quad (2)$$

$$S^2=\frac{\sum_{j=1}^{n}\sum_{i=1}^{l}\left(y_{ij}-\hat{y}_{ij}\right)^2}{n-2l} \quad (3)$$

I is the total number of levels in a batch
n is the total number of values for the responses
X is the model's design matrix.

Second, we ascertain whether the mean reaction varies over time at a statistically meaningful pace.

$$\left|\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}}\right|\leq t_{cl,n-2l} \quad (4)$$

We then determine if the mean response changes with time in case a significant estimation is present. If one of the subsequent criteria is true, the second condition must be untrue.

Over time, the response diminishes.

$$\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}}<-t_{cl,n-2l} \quad (5)$$

The response increases over time.

$$\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}}>t_{cl,n-2l} \quad (6)$$

We again decide shelf life according to the lower specification cap in case the mean response decreases in time. Otherwise, we go straight to computes the shelf life in comparison with the higher specification limit.

2.1.1.2.2 The Time and Batch Model

To determine whether a meaningful estimation of the shelf life exists, two criteria were assessed. First, we determine whether the mean response is statistically within the given ranges.

$$L + t_{0.95,n-l-1}\sqrt{Q_{i,i}} < \hat{\alpha}_i < U - t_{0.95,n-l-1}\sqrt{Q_{i,i}} \quad (7)$$

Where

$$\{\sigma_{j,k}\}_{i=1,\ldots,l+1=1,\ldots,l+1} = S^2 (X'X)^{-1} \quad (8)$$

$$S^2 = \frac{\sum_{j=1}^{n}\sum_{i=1}^{l}(y_{ij} - \hat{y}_{ij})^2}{n-l-1} \quad (9)$$

I = the total number of levels in a batch

n = the total number of values for the responses

X is the model's design matrix.

Secondly, we ascertain whether there is a statistically significant temporal variation in the mean response.

$$\left|\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}}\right| \le t_{cl,n-l-1} \quad (10)$$

We ascertain if the mean reaction rises or falls with time if a reasonable estimate is available. One of the following conditions is true if the second condition is not true.

Over time, the response declines.

$$\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}} < -t_{cl,n-l-1} \quad (11)$$

The response increases over time.

$$\frac{\hat{\beta}_i}{\sqrt{\sigma_{l+i,l+i}}} > t_{cl,n-l-1} \quad (12)$$

We determined the shelf life in relation to the lower specification limit if the mean reaction gradually drops. If not, a calculation will be made using the shelf life in relation to the upper specification limit.

2.1.1.2.3 The Time-Related Model: In order to ascertain whether a useful estimate of the shelf life existed, we additionally assessed two circumstances. Initially, we ascertained if the average response falls within the statistical bounds of the specification.

$$L + t_{0.95,n-2}\sqrt{Q_{1,1}} < \hat{\alpha} < U - t_{0.95,n-l-1}\sqrt{Q_{1,1}} \quad (13)$$

Where

$$\{\sigma_{j,k}\}_{i=1,2,l=1,2} = S^2 (X'X)^{-1} \quad (14)$$

$$S^2 = \frac{\sum_{j=1}^{n}\sum_{i=1}^{l}(y_{ij} - \hat{y}_{ij})^2}{n-2} \quad (15)$$

I = the total number of levels in a batch

n = the total number of values for the responses

X is the model's design matrix.

Secondly, we assessed if there is a statistically significant temporal variation in the mean response.

$$\left|\frac{\hat{\beta}}{\sqrt{\sigma_{2,2}}}\right| \le t_{cl,n-2} \quad (16)$$

We again looked at whether the mean reaction goes up or down with time to see whether there is a valid estimate. One of the following conditions is true if the second condition is not true.

Over time, the response declines.

$$\frac{\hat{\beta}}{\sqrt{\sigma_{2,2}}} < -t_{cl,n-2} \quad (17)$$

The response increases over time

The shelf life in relation to the lower specification limit will be determined if the mean reaction gradually declines. If not, compute the shelf life using the higher specification limit as a reference.

$\hat{\beta}_i$	=	the batch's slope for i^{th}
I	=	the batch factor's number of levels
n	=	the amount of rows in the dataset
$t_{cl,df}$	=	the values of the inverse cumulative distribution at cl from the t distribution with df degrees of freedom are

 https://doi.org/10.59568/JASIC-2024-5-1-08

$$\frac{\hat{\beta}}{\sqrt{\sigma_{2,2}}} > t_{cl,n-2}$$

presented by the values of n, tcl, and df, respectively (18)

2.2 Adjusted R²

Adjusted R^2 accounts because of the quantity of predictors within your style and can be helpful for evaluating versions with various amounts of predictors. The formula is:

$$R^2_{adj} = 1 - \frac{MS_{Error}}{MS_{Total}} = 1 - \left(\frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2}\right)\left(\frac{n-1}{n-p-1}\right) \quad (19)$$

While the calculations for adjusted $R<^2$ can produce negative values, the zero for these cases are displayed.

2.3 Interval of Prediction

The range in which a fresh observation's expected response is expected to decline. The equation is:

$$\hat{y}_0 \pm t_{(1-\alpha/2, n-p)} \times s(P)$$

$$s(P) = \sqrt{s^2\left(1 + x_0'(x'x)^{-1}x_0\right)} \quad (20)$$

For a given set of predictor values, $\hat{y}_0$ is the fitted response value

α= significance level

n = the quantity of observations

p = total number of terms in the model, if the intercept term is present.

Mean square error, or S^2,

Predictor matrix = x

When the intercept term is present in the model, x_0 is the matrix of supplied predictor values with a column of 1s at the beginning

2.4 Test for Stationarity

2.4.1 Test of Augmented Dickey Fuller (ADF)

The stationarity of the helpful look of daily crude oil prices of Nigeria throughout Russian federation Ukraine was analyzed using the rii root test. In a product test, if the real information simple technique for 1/t has a unit root, the outcome of the check for a certain sample reveals the procedure is stationary (Brooks, 2008). The augmented Dickey fuller model test was put on, it's made as;

$$\Delta x_t = \gamma x_{t-1} + \sum_{j=1} \delta_j \Delta x_{t-j} + \ell_t \quad (21)$$

The lags of ΔY_t “soak up" any powerful structure contained in the dependent variable, to make certain that ε_t not auto correlated. The test statistic just for the Augmented Dickey fuller test is defined as;

$$DF_\gamma = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \quad (22)$$

In all cases where the test statistics are significantly worse than the essential worth, the stationary option is preferred over the null hypothesis of a device root. The test above is valid only ε_t is white noise.

2.5 Tests for Normality

2.5.1 Anderson-Darling Test

The nonparametric action feature (based on the plot points) and the fitting type (based on the chosen distribution) are measured using the Anderson-Darling normality test. The statistic is a squared distance with a higher weight in the distribution's tails. A lower Anderson-Darling coefficient suggests a better fit between the distribution and the data. What makes the Anderson-Darling normalcy test unique is:

H0: There is a normal distribution of the data.

Ha: There is no normal distribution among the data.

Test Statistics: The definition of the Anderson-Darling test statistic is

$$A^2 = -N - \left(\frac{1}{N}\right)\sum (2i-1)\left[\left(\ln C(X_i) + \ln(1 - C(X_{N+1-i}))\right)\right] \quad (23)$$

 https://doi.org/10.59568/JASIC-2024-5-1-08

Where: C is the cumulative distribution function of the normal distribution. X_i is the ordered observations.

2.5.2 The Ryan-Joiner Test

The correlation coefficient that the Ryan-Joiner Test produces shows how your data and its normal scores are related. If the correlation coefficient is close to one, the normal probability plot will be in proximity to your data. If it is less than the given critical value, you reject the null hypothesis of normalcy.

H0: There is a normal distribution of the data.

Ha: There is no normal distribution among the data.

One may compute the correlation coefficient as:

$$R_p = \frac{\sum Y_i b_i}{\sqrt{S^2 (n-1) \sum b_i^2}} \tag{24}$$

Where:

The ordered observations are Y_i.
bi = your ordered data's normal scores
Sample variance (s2)

3. RESULTS

3.1 Normality and Stationary of the Datasets

3.1.1 Normality Test

H0: There is a normal distribution of the data.

Ha: There is no normal distribution among the data.

Table 1: Normality Test of the Actual Datasets

Variable	Mean	St.D	Statistics	P	Decision
Anderson-Darling	36.78	27.44	3.464	<0.005	Not normally distributed
Ryan-Joiner	36.78	27.44	0.968	<0.010	Not normally distributed
Kolmogorov-Smirnov	36.78	27.44	0.129	<0.010	Not normally distributed

The variable is not normally distributed, as indicated by the result in Table 1 above, where each of the three normality test p-values is less than the 0.05 alpha value. As a result, the data was normalized using the Box-Cox transformation.

3.1.2 Stationary Test

Table 2: Augmented Dickey-Fuller Unit Root Test of the Actual Datasets

H0:		Non-stationary data
Ha:		Stationary data
Test Statistic	**P-Value**	**Recommendation**
-3.22932	0.018	The recommendation is -3.22932 0.018 for the test statistic, with a critical value of -2.87801. Level of significance = 0.05 Dismiss the null hypothesis. The data doesn't seem to support differencing; it looks to be stationary.

The information in Table 2 above shows that the actual series is stationary.

Figure 1 below shows that the actual values for relative humidity at 0600 is stationary without differencing.

 https://doi.org/10.59568/JASIC-2024-5-1-08

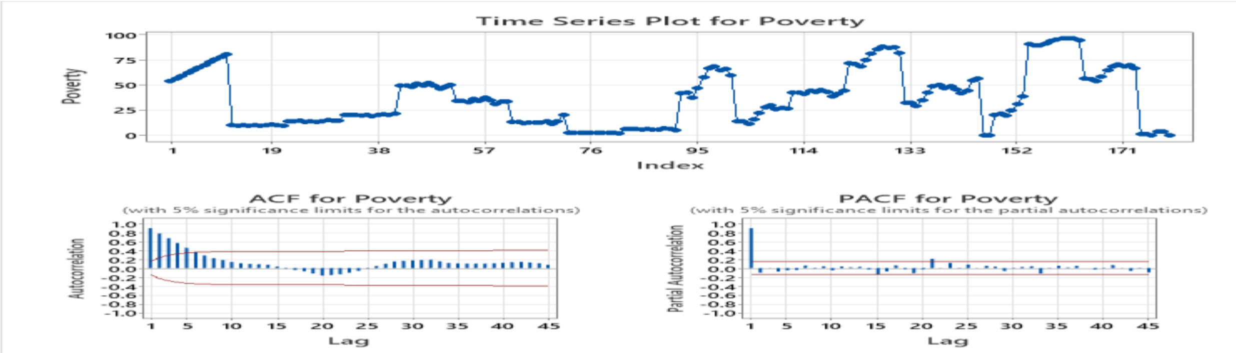

Figure 1: ACF and PACF Plots for Poverty Rates

3.2 Stability Study Analysis

Less than three data point batches were eliminated: Average annual growth rate in real survey mean consumption per capita, or inc, Multivariate poverty headcount ratio (as a percentage of the overall population), Multidimensional poverty intensity (average share of deprivations suffered by), Survey mean consumption or income per capita, poorest 40% of population (2017 PPP), Multidimensional poverty index (scale 0-1) Total population, survey mean consumption or income per capita (2017 PPP $ per d).

Table 4: Factor Data

Factor	Category	Level Count	Levels
Indicator	Fixed	17	Gini coefficient, Income share owned by fourth (20%), highest (10%), highest (20%), lowest (10%), lowest (20%), second (20%), and third (20%) Slum dwellers as a percentage of the total urban population, The percentages of poverty gaps are as follows: poverty headcount ratio at $2.15 per day (2017 PPP) (% of population), poverty headcount ratio at $3.65 per day (2017 PPP) (% of population), and poverty gap at $6.85 per day (2017 PPP) (%),Poverty headcount ratios at $6.85 per day (2017 PPP) and national poverty levels (percentage of population), respectively percentage of the population that makes less than 50% of the median income (%).

Table 4 provides data on seventeen fixed indicators, such as the Gini index, the percentage of people living below 50% of the median income, the income share held by different percentiles, poverty metrics at different income thresholds, and the population living in slums.

Table 5: Model Selection with α = 0.25

Source	DF	Seq SS	Seq MS	F-Value	P-Value
Year	1	503	502.70	58.80	0.000
Indicator	16	119081	7442.57	870.55	0.000
Year*Indicator	16	2096	130.99	15.32	0.000
Error	133	1137	8.55		
Total	166	122817			

Terms in selected model: Year, Indicator, Year*Indicator

Table 5 showed the model selection analysis with α=0.25 revealing significant effects of both the year (F-value = 58.80, $p < 0.001$) and the indicator (F-value = 870.55, $p < 0.001$), together with their interactions (F-value = 15.32, $p < 0.001$) on the dependent variable, with the model causing 503 units of variation for' Year 'and 119,081 for' leading to 2,096 for their interaction, resulting in 122,817 unit total explained variability.

Table 6: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Year	1	1596	1595.62	186.64	0.000
Indicator	16	2171	135.70	15.87	0.000
Year*Indicator	16	2096	130.99	15.32	0.000
Error	133	1137	8.55		
Total	166	122817			

In Table 6 an analysis of variance (ANOVA) reveals that the year and indicator variables play a major role in describing variation in the response variable with most associated p-values under 0.05 indicating statistical significance**.**

Table 7: Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.92392	99.07%	98.84%	98.47%

With an R-squared value of 99.07 percent, the model in Table 7 has a strong explicatory power and indicates that the independent variables account for approximately 99.07 percent of the variability in the dependent variable. However, the modified R-squared and predicted R-squared values can also be large, at 98.84 and 98.47 percent, respectively, indicating the model's robustness and predictive precision.

Table 8: Parameters' Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	757.9	52.7	14.38	0.000	
Gini coefficient	-734	189	-3.88	0.000	83449.65
20% of income is kept by the fourth party.	-679	189	-3.60	0.000	83449.65
Income share owned by the top 10%	-799	189	-4.23	0.000	83449.65
20% of income share is owned by the highest earning group.	-774	189	-4.10	0.000	83449.65
10% of income is controlled by the lowest 10%	-769	189	-4.07	0.000	83449.65
20% of income holders	-782	189	-4.14	0.000	83449.65
The second 20% hold the income share.	-747	189	-3.96	0.000	83449.65
Third 20% of the income share	-702	189	-3.72	0.000	83449.65
Slum dwellers as a percentage of the total urban population	2012	268	7.50	0.000	176911.28
The poverty gap in 2017 was $2.15 per day (PPD)	468	189	2.48	0.015	83449.65
The poverty gap in 2017 was $3.65 per day (PPD)	651	189	3.45	0.001	83449.65
In 2017 PPP, the poverty gap was $6.85 per day (%)	398	189	2.11	0.037	83449.65
The percentage of the people living in poverty is $2.15 per day (PPP, 2017).	1225	189	6.48	0.000	83449.65
Ratio of poverty headcount at $3.65 per day (PPP, 2017) (% of population)	569	189	3.01	0.003	83449.65
Ratio of poverty headcount at $6.85 per day (PPP, 2017) (% of population)	**-181**	**189**	**-0.96**	**0.340**	83449.65
Ratio of poverty headcount to national poverty thresholds (as a percentage of population)	1358	385	3.53	0.001	275925.03
Percentage of the population that makes less than 50% of the median income (%)	-513	189	-2.71	0.008	*

 https://doi.org/10.59568/JASIC-2024-5-1-08

Table 8 displays numerous socioeconomic indicators' parameter coefficients, standard errors, t-values, and p-values along with statistically significant correlations between the indicators and outcome variables. The Gini index, income distribution in various percentiles, the percentage of urban slums, and poverty metrics are important predictors that have a significant impact on the outcome variable. However, care should be taken when interpreting the correlation between the poverty head count ratio at USD 6.85 per day and poverty metrics. This suggests that every metric has a noteworthy impact on Uganda's poverty rates, with the exception of the poverty headcount ratio, which stands at USD 6.85 per day (2017 PPP) as a percentage of the population.

Table 9: Regression Equation

Indicator			Model
Gini coefficient	Poverty	=	24 + 0.0092 Year
20% of income is kept by the fourth party.	Poverty	=	79 - 0.0291 Year
Income share owned by the top 10%	Poverty	=	-41 + 0.0375 Year
20% of income share is owned by the highest earning group.	Poverty	=	-16 + 0.0328 Year
10% of income is controlled by the lowest 10%	Poverty	=	-11 + 0.0068 Year
20% of income holders	Poverty	=	-24 + 0.0151 Year
The second 20% hold the income share.	Poverty	=	10 - 0.0002 Year
Third 20% of the income share	Poverty	=	56 - 0.0208 Year
Slum dwellers as a percentage of the total urban population	Poverty	=	2770 - 1.344 Year
The poverty gap in 2017 was $2.15 per day (PPD).	Poverty	=	1225 - 0.6008 Year
The poverty gap in 2017 was $3.65 per day (PPD).	Poverty	=	1409 - 0.6824 Year
In 2017 PPP, the poverty gap was $6.85 per day (%).	Poverty	=	1156 - 0.5454 Year
Poverty headcount ratio (% of population) at $2.15 per day (2017 PPP)	Poverty	=	1983 - 0.9618 Year
Ratio of poverty headcount at $3.65 per day (PPP, 2017) (% of population)	Poverty	=	1327 - 0.6221 Year
Ratio of poverty headcount at $6.85 per day (PPP, 2017) (% of population)	Poverty	=	577 - 0.2412 Year
Ratio of poverty headcount to national poverty thresholds (as a percentage of population)	Poverty	=	2116 - 1.040 Year
Percentage of the population that makes less than 50% of the median income (%)	Poverty	=	245 - 0.1155 Year

A number of regression equations in Table 9 demonstrate the correlation between different poverty indicators and time. These equations indicate that as time moves on, poverty decreases across income share distributions and poverty spaces at various thresholds, and poverty headcount ratios differ at various income levels, suggesting a positive trend of poverty alleviation as time passes.

Table 10: Fits and Diagnostics for Unusual Observations

Observations	Poverty Rate	Forecast	Resid	Std Resid
94	37.50	47.48	-9.98	-3.75
97	66.70	57.10	9.60	3.47
98	68.70	59.98	8.72	3.19
101	59.40	69.60	-10.20	-4.30
124	68.80	74.89	-6.09	-2.29
131	82.00	89.20	-7.20	-3.03
134	29.30	35.68	-6.38	-2.40
137	48.60	42.51	6.09	2.20
138	50.40	44.55	5.85	2.14
141	45.50	51.38	-5.88	-2.48

 https://doi.org/10.59568/JASIC-2024-5-1-08

173	66.40	71.51	-5.11	-2.15

Table 10 provides fits and diagnostics for anomalous observations, exhibiting the poverty rate, projected values, residuals and standardized residuals of various data points. Negative residuals indicate underestimates of the poverty rate, while positive residuals indicate exaggerations of the poverty rate, while standardized residuals indicate the distance the anticipated values departed from the anticipated ones. The forecasted values in this table demonstrated a fluctuated (downward and upward) trend movement for the poverty rates in Uganda for the coming years.

3.3 Estimating the Shelf Life

1 is the lower standard limit. 5 is the upper standard limit. Shelf life is the amount of time during which at least 50% of responses fall inside specified bounds with a 95% degree of confidence.

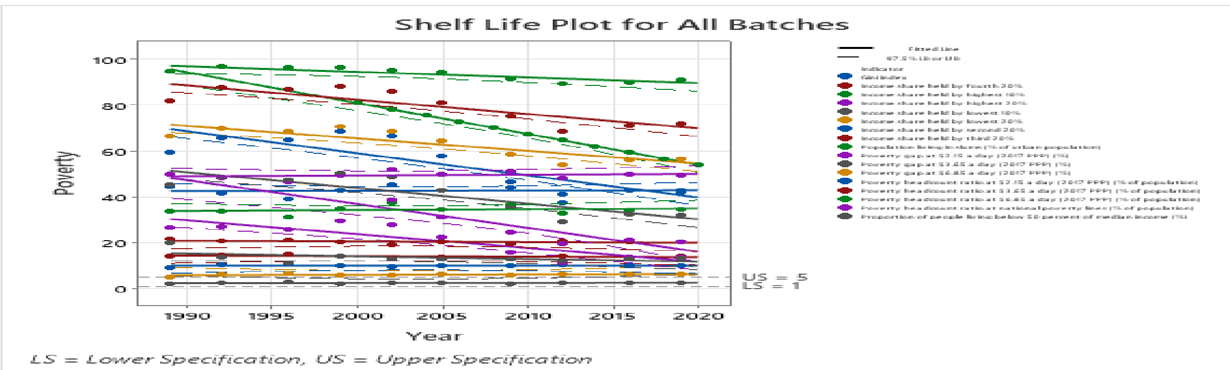

Figure 2: Shelf Life Plot for all Indicators (Batches)

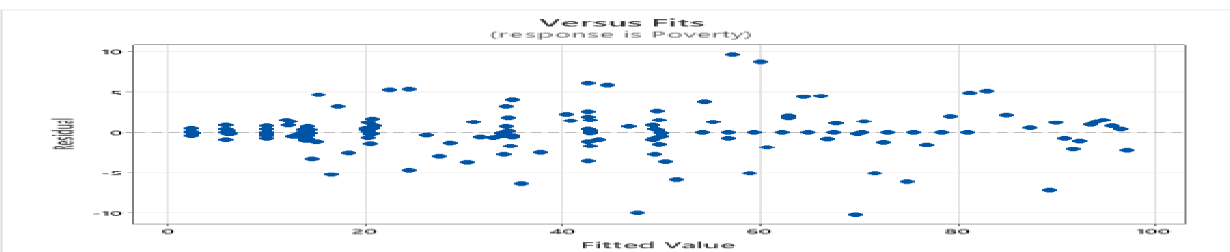

Figure 3: Plot of the Predicted value Against the Residual

4. Discussion

The results presented in Table 10 highlight fits as well as diagnostics for uncommon events in the poverty rate dataset, revealing forecasted values together with residuals as well as standard residuals for a number of data points. The poverty level is underestimated by the positive residuals and also undervalued by the negative residuals, respectively, whereas the standard residuals explain the variance from the anticipated values. Particularly, the forecasted values display a fluctuating trend movement, both downward and upward, suggesting possible variability in future poverty rates in Uganda. The necessity to carefully evaluate as well as monitor poverty dynamics to guide policy interventions aimed at reducing poverty is underlined by this information.

Furthermore, 7, 6, Tables 5, 8 along with 9 present an extensive evaluation of the correlations between different socioeconomic factors and poverty levels in Uganda. The numerous facets of poverty dynamics are exemplified by the substantial impact of indicators like the Gini index, income distribution in different percentiles, percent of urban slum population, and poverty metrics. Additionally, the regression equations in Table 9 depict the evolving nature of poverty over time, indicating a consistent trend to reductions in poverty across various income distributions and poverty

 https://doi.org/10.59568/JASIC-2024-5-1-08

thresholds. The findings contribute to a greater understanding of the sources of poverty and also offer useful information for policymakers as well as practitioners seeking sustainable poverty reduction measures in Uganda.

5. Conclusion

This study's goals were to offer a thorough assessment of Uganda's patterns of poverty and identify potential long-term causes of poverty in the nation. Numerous indices of poverty rates, income distribution, and the capacity to obtain necessary services, among other socioeconomic aspects, were examined in the investigation. Results demonstrated a significant decrease in poverty rates over time, though with differences across various countries and demographic groups. While poverty in cities decreased somewhat, improvements were notable in rural areas, especially
in eastern and north Uganda. Nevertheless, income inequality seemed to have risen despite the general reduction in poverty rates, as demonstrated by the growing Gini coefficient. Additionally, qualitative studies suggested that a lessening in poverty rates might not always result in better general well-being for every part of the population.

Additionally, the stability analysis framework created in this particular study offered insights into the viability as well as resilience of Uganda's socio-economic framework in tackling poverty. The study utilized several indicators and advanced analytical methods to offer a holistic model for predicting poverty dynamics, which could inform evidence based policies and interventions to alleviate poverty. The analysis also stressed the significance of education and asset ownership for reducing poverty, highlighting the need for specific programs to tackle chronic poverty and lack of access to resources. In the future, additional dimensions of poverty might be investigated, which includes multidimensional poverty indicators and indicators of non- financial well - being, to enhance our understanding as well as guide more effective poverty alleviation strategies in Uganda along with other settings.

6. References

[1] Appleton, S. (2021). Changes in poverty and inequality. *In Uganda's recovery. The role of farms, firms, and government*. Eds. Ritva Reinikka and Paul Collier. The World Bank.

[2] Bhattacharyya, S., De Silva, D. G. M. S., & Rahman, M. M. (2019). Stability analysis of socio-economic systems: A review. *Journal of Economic Surveys*, *33*(3), 696–726. https://doi.org/10.1111/joes.12277

[3] Byekwaso, N. (2020). Poverty in Uganda. *Review of African Political Economy*, *37*(126), 517-525.

[4] Kakande, M. (2010) Poverty monitoring. In F. Kuteesa, E. Tumusiime-Mutebile, A. Whitworth, Williamson, T. eds. *Uganda's Economic Reforms: Insider Accounts*. Oxford: Oxford.

[5] Lawson, D, McKay, A. Okidi, J. (2016). Poverty persistence and transitions in Uganda: A combined qualitative and quantitative analysis. *Journal of Development Studies*, *42*(7), 1225-1251.

[6] Mukwaya, P., Bamutaze,Y., Mugarura,S., Benson, T. (2021). Rural-Urban transformation in Uganda. *Paper presented at the IFPRI-University of Ghana Conference*, understanding economic transformation in Sub-Saharan Africa. May 10-11, 2011, Accra, Ghana.

[7] Ninsiima, A. B. (2020). Economic growth, poverty and inequality in Uganda: Evidence from household survey data. *Journal of African Economies*, *29*(3), 321–346. https://doi.org/10.1093/jae/ejz036

[8] Okidi, J., McKay, A. (2023). Poverty dynamics in Uganda : 1992 to 2000. *Chronic Poverty Research Centre Working*, 27. Kampala, Uganda.

[9] Okumu, I. M., & Kizza, J. M. (2018). Governance and income poverty reduction in Uganda: An empirical analysis. *Journal of Public Affairs*, *18*(4), e1784. https://doi.org/10.1002/pa.1784

[10] Ssewanyana, S. (2019). *Growth, inequality, cash transfers and poverty: The Uganda case study*. International Policy Institute for Inclusive Growth.

[11] Ssewanyana, S., Matovu, M., Twimukye, E. (2021). Building on growth in Uganda. *In yes African can: Success stories from a dynamic continent*. Eds. Punam Chuhan-Pole and Manka Angwafo. The World Bank.

[12] Uganda Bureau of Statistics. (2020). *Uganda National Household Survey, 2009/1020. Socio-Economic Module*. The Republic of Uganda.