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ON USING FRACTILE REGRESSION MODELING FOR ECONOMIC VARIABLES

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Abstract: The paper examined the macro–economic variables obtained from the website of the central bank of Nigeria from 1980 to 2020 using Quantile regression (QR). It is an extension of Regression Analysis which gives a thorough investigation of the dataset compared to mean–based regression model. The findings modelled poverty reduction against money supply, government revenue, government expenditure and financial inclusion. The finding revealed that there is presence of outliers at the 75th quantile points and the 25th quantile regression model seems to have reduced outliers. QR is more robust to outliers since it focuses on estimating conditional quantile rather than the mean. By estimating many quantiles, QR offers a more thorough perspective and enables a more sophisticated comprehension of the response variable's conditional distribution.

Keywords: Quantile Regression, Regression Analysis, Poverty Reduction, Money Supply

1. INTRODUCTION

Numerous economic variables impact the complicated phenomena of poverty, which is a continuous worldwide concern. Formulating targeted strategies requires an understanding of the link between economic factors and poverty at various distributional locations. Quantile regression may be necessary because traditional mean–based regression models may not adequately capture the complex impacts across different degrees of poverty. This method enables a more thorough investigation of the effects of changes in the money supply, government revenue, expenditures, and financial inclusion on the decrease of poverty at various percentiles. Using a variety of approaches, earlier research has examined the connection between economic factors and poverty reduction. Despite the widespread use of mean–based regressions, a growing number of research highlights the drawbacks of supposing a consistent influence over the whole distribution. Being a strong substitute that provides information on the heterogeneity of effects, quantile regression has grown in popularity.

[1] presented quantile regression as a method for examining how factors affect various quantiles, they acknowledged that it may be useful in situations where conditional quantiles offer more pertinent data than the mean. Outliers can sometimes dramatically distort the findings of statistical research, while other times, their effects might not be as obvious. Any observation that deviates from the rest of the data is called an outlier, and 10% of data sets typically contain outliers [2]. As stated by [3], these outlier observations can occasionally be unreported and have a significant detrimental impact on the estimations of the response and regressor variables to the regression model. The OLS estimator will perform poorly when there are several outliers in the data or large error in the y–direction, as explained by [4]. In practice, there are some circumstances in which the outliers are not visible. According to [5], masking and swamping issues typically emerge in this situation. The clean observations are regarded as outliers in the swamping problem. On the other hand, with a masking problem, the clean data points are identified as the outliers. The theory and application of robust regression estimators have been the subject of numerous publications in recent years; some of these have been effectively applied in real–world scenarios, while the outcomes still require improvement. These estimators usually involve searching many subsets of the data to fulfill a constrained objective function, or they have nonlinear solutions that demand large computer resources. Several reputable books and articles have covered outliers' diagnostic techniques as well as their corrective procedures [6]. It is crucial for researchers to determine the estimator's efficiency when assessing the accuracy of an estimated regression coefficient due to the behavior of statistical data sets.

This study's main goal is to use quantile regression to predict the link between important economic variables—government revenue, government expenditure, money supply, and financial inclusions and poverty reduction. The research specifically intends to: Examine how the effects of government spending, revenue, money supply, and financial inclusions on poverty reduction fluctuate across different quantiles. In order to capture the impacts at the lower, middle, and higher quantiles.

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2. MATERIALS AND METHODS

A quantile regression model was established to describe the relationship between the decrease of poverty and four independent variables. The 25th, 50th, and 75th percentiles of the distribution are the quantile points that are taken into account.

$$y_t = x_t'\beta_q + e_t \quad (1)$$

$$\sum qe_t + \sum(1-q)e_t \quad (2)$$

Minimize equation (1)

$$e_t = y_t - x_t'\beta_q \quad (3)$$

$$\sum e_t^2 = \sum\left(y_t - x_t'\beta_q\right)^2 \quad (4)$$

$$\beta_q = \frac{\delta Q_q(y/x)}{\delta x_k} \quad (5)$$

3. RESULTS AND DISCUSSION

Poverty Reduction against Money Supply

A scatter plot showing the relationship between the amount of money in circulation and the reduction of poverty is shown in Figure 1. Over a number of years, the data shows a noticeable rising tendency in the money supply. In spite of this general rise, an important finding is that there appears to be a little trend toward a decline in poverty. The graphic highlights a complex interaction between various factors, suggesting that an increase in the money supply generally does not result in a corresponding reduction in poverty.

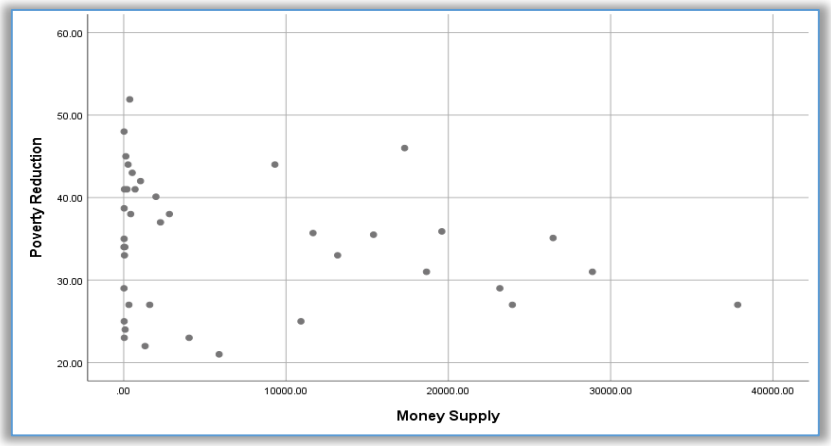

Figure 1: Scatter plot of Poverty Reduction against Money Supply

Poverty Reduction against Government Expenditure

The scatter plot in Figure 2 illustrates the relationship between government spending and the decrease of poverty. It clearly illustrates a pattern in which a rise in government spending corresponds with a decline in poverty alleviation. This discovery raises the possibility of an inverse link between the two variables, suggesting that the rate of reducing poverty may decline as government funding increases.

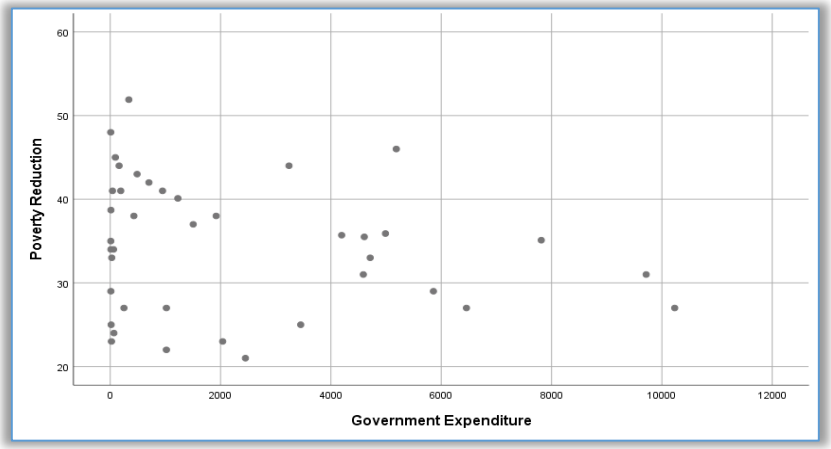

Figure 2: Scatter plot of Poverty Reduction against Government Expenditure

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Poverty Reduction against Government Revenue

A scatter plot demonstrating the relationship between government revenue and the decrease of poverty is shown in Figure 3. The information shows a clear pattern in which government income increases coincide with a decrease in the rate of poverty alleviation. This shows that there is a negative correlation between government revenue and the reduction of poverty, suggesting that increasing government income may not result in a significant decrease in poverty. The intricate relationship between these factors is highlighted by the graphical depiction, which implies that a merely increased government budget does not always equate to a proportionate reduction in poverty.

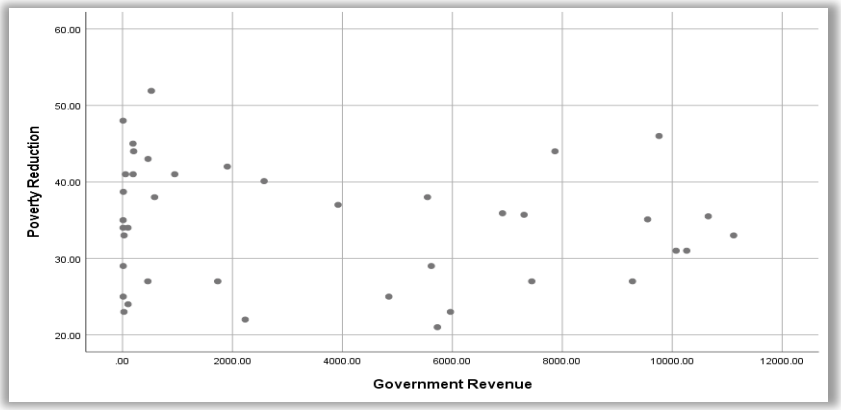

Figure 3: Scatter plot of Poverty Reduction against Government Revenue

Poverty Reduction against Financial Inclusion

A scatter plot showing how financial inclusion and poverty reduction are related is shown in Figure 4. The visual depiction clearly shows a relationship between a little rise in financial inclusion and an elevation in the decrease of poverty. This implies that there is a positive correlation between the two variables, meaning that there is a slight increase in financial inclusion for every effort made to combat poverty. The graphic draws attention to the complex relationships at work and emphasizes how programs aimed at reducing poverty may be dependent on one another in order to advance financial inclusion. The influence on financial inclusion may only be slight, despite the clear positive association.

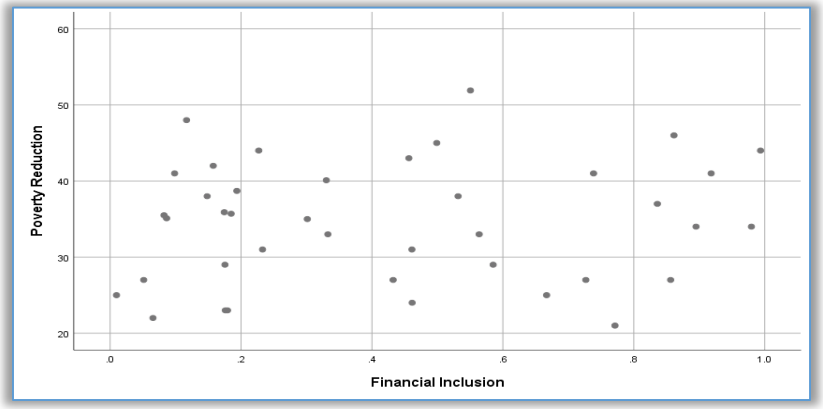

Figure 4: Scatter plot of Poverty Reduction against Financial Inclusion

Quantile Regression Model

The quantile regression for the 25th , 50th and 75th percentile is displayed in table 1 and the following models are included in the fitted model.

— 25th quantile regression Model:

$$\text{Poverty reduction} = 24.5979 - 1.87132e - 0.05\ \text{Money Supply} - 0.00133441\ \text{Government Expenditure} + 0.00105708\ \text{Government Revenue} + 9.57509\text{Financial Inclusion}$$

— 50th quantile regression Model:

$$\text{Poverty reduction} = 37.9171 - 0.000750426\ \text{Money Supply} + 0.00165019\ \text{Government Expenditure} - 1.66529e - 006\ \text{Government Revenue} - 2.02661\ \text{Financial Inclusion}$$

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— 75th quantile regression Model

Poverty reduction

$$= 40.9248 + 2.85014e - 006\text{Money Supply} - 0.00117328\ \text{Government Expenditure} + 8.13298e - 005\text{Government Revenue} + 1.20666\ \text{Financial Inclusion}$$

Table 1: Quantile estimates, using observations 1981–2020

	Tau	Coefficient	Std. error	t–ratio
Const	0.25	24.5979	1.35417	18.1646
	0.5	37.9171	1.95251	19.4197
	0.75	40.9248	2.20380	18.5701
MS	0.25	−1.87132e−005	0.000419538	−0.0446044
	0.5	−0.000750426	0.000604912	−1.24056
	0.75	2.85014e−006	0.000682766	0.00417440
GEX	0.25	−0.00133441	0.00172693	−0.772703
	0.5	0.00165019	0.00248998	0.662734
	0.75	−0.00117328	0.00281045	−0.417471
GRV	0.25	0.00105708	0.000395635	2.67186
	0.5	−1.66529e−006	0.000570446	−0.00291927
	0.75	8.13298e−005	0.000643865	0.126315
FII	0.25	9.57509	2.24162	4.27150
	0.5	−2.02661	3.23209	−0.627030
	0.75	1.20666	3.64807	0.330766

Median depend. var 35.05000 S.D. dependent var 7.936850

4. CONCLUSION

Real–life data on a few macroeconomic indicators was obtained from the 1981–2020 Statistical Bulletin published by the Central Bank of Nigeria. The regression models were formulated using the R program, IBM Statistical Packages for Social Sciences (SPSS), and Number Cruncher Statistical Systems (NCSS). In this study, Poverty Reduction, Money Supply, Government Expenditure, Government Revenue and Financial Inclusion were used for the analysis. The quantile regression model of the 25th percentile shows that government revenue and financial inclusion have a positive effect on the reduction of poverty while money supply and government expenture have a negative effect on poverty reduction. Also, the median regression model of shows that money supply, government revenue and financial inclusion have a negative effect on the reduction of poverty while government expenditure have a positive effect on poverty reduction. The quantile regression model of the 75th percentile shows that government expenditure have effect on poverty reduction while money supply, government revenue and financial inclusion have a positive effect on reduction of poverty. At the 25th percentile characterized by the lowest intercept, the model offers a precise estimate, emphasizing the significance of addressing poverty at the lower end of the socioeconomic spectrum. Strategic enhancement of government revenue and financial inclusion, coupled with judicious management of money supply and expenditures can contribute significantly to alleviating poverty across diverse socioeconomic strata.

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