Multivariate Jackknife Delete-*5* Algorithm On The Effect Of Nigeria Foreign Trade On Foreign Exchange Rates Of Naira (1960-2010).

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Abstract: In this paper we presented the multivariate extension of multiple linear regression using Jackknife techniques in modeling the relationship between m set of responses $Y_1, Y_2, \ldots, Y_m$ and a single set of r regressors $Z_1, Z_2, \ldots, Z_m$. The responses are Oil Import (Y_1), Non-Oil Import (Y_2), Oil Export (Y_3), Non-Oil Export (Y_4) which is classified as Nigeria Foreign Trade, while the regressors are Exchange Rate of US Dollar (Z_1), and Exchange Rate of Pounds sterling's (Z_2) which are classified as Foreign Exchange Rate. We proposed new algorithm for estimating the parameters of multivariate linear regression using the jackknife technique. The results obtained using Jackknife delete-5 algorithm competes favorably with the existing methods. Consequently Time Series approach was adopted for future prediction of the Nigeria Foreign Trade from year 2011 to 2020. Evidently, the time series plot depicts an increase of exchange rate of US Dollar and Pounds Sterling over the years under consideration. Thus, this will definitely affect Nigeria Foreign Trade negatively which could be harmful to the Nigeria's economy.

Keywords: multivariate, Jackknife, delete-*5*, foreign trade, foreign exchange rate, linear regression.

Introduction:

Adebiyi et al [1] estimated the effects of oil price stocks and exchange rate on the real stock returns in Nigeria over 1985-2008 using a multivariate VAR analysis. Variables ranging from real oil prices, real stock returns, and index of industrial production to three types of oil specifications were employed. Also, the study further classified oil price stocks into sub-samples: for a first subsample (1985-1999), for a second sub-sample (2000-2004) and for a third sub-sample (2005-2008). Empirical results showed an immediate and significant negative real stock return on oil price stock in Nigeria. The Granger causality test employed indicated that causation run from oil price stocks to stock returns, implying that variation in stock market is explained by oil price volatility. [6] proposed functional multivariate regression modeling by estimating the model using a regularized maximum likelihood method. This paper presents a multivariate jackknife delete-*5* algorithm on the effect of foreign trade on foreign exchange rates of naira (1960-2010).

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1.0 MATERIALS AND METHODS

1.1 General form of Multivariate Linear Regression Model

According to [5], multivariate linear regression model defines the relationship between m responses $Y_1, Y_2, \ldots, Y_m$ and a single set of r predictors, $Z_1, Z_2, \cdots, Z_r$.

$$\left.\begin{array}{l} Y_1 = \beta_{01} + \beta_{11}Z_1 + \beta_{21}Z_2 + \cdots + \beta_{r1}Z_r + \varepsilon_1 \\ Y_2 = \beta_{02} + \beta_{12}Z_1 + \beta_{22}Z_2 + \cdots + \beta_{r2}Z_r + \varepsilon_2 \\ \vdots \qquad\quad \vdots \qquad\quad \vdots \qquad\qquad\qquad \vdots \\ Y_m = \beta_{0m} + \beta_{1m}Z_1 + \beta_{2m}Z_2 + \cdots + \beta_{rm}Z_r + \varepsilon_r \end{array}\right\} \quad (1)$$

The expectation and variance of error term ε are

$$E(\varepsilon) = E\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix}$$

and

$Var(\varepsilon) = \sigma^2$ respectively.

Let $\left[Z_{j0}, Z_{j1}, \ldots, Z_{jr}\right]$ denote the values of the predictor variables for the j^{th} trial. Let $Y_j = \left[Y_{j1}, Y_{j2}, \cdots, Y_{jm}\right]'$ be the responses, let $\left[\varepsilon_{j1}, \varepsilon_{j2}, \ldots \varepsilon_{jm}\right]$ be the errors for j^{th} trial Thus we have $n \times (r+1)$ design matrix

$$Z_{n\times(r+1)} = \begin{bmatrix} Z_{10} & Z_{11}\cdots & Z_{1r} \\ Z_{20} & Z_{21}\cdots & Z_{2r} \\ \vdots & \vdots & \vdots \\ Z_{n0} & Z_{n1}\cdots & Z_{nr} \end{bmatrix} \quad (2)$$

If we set

$$Y_{(n\times m)} = \begin{bmatrix} y_{11} & y_{12}\cdots & y_{1m} \\ y_{21} & y_{22}\cdots & y_{2m} \\ \vdots & \vdots & \vdots \\ y_{n1} & y_{n2}\cdots & y_{nm} \end{bmatrix} = \left[Y_{(1)} | Y_{(2)} | \cdots | Y_{(m)}\right] \quad (3)$$

$$\beta_{(r+1)\times m} = \begin{bmatrix} \beta_{01} & \beta_{02}\cdots & \beta_{0m} \\ \beta_{11} & \beta_{12}\cdots & \beta_{1m} \\ \vdots & \vdots & \vdots \\ \beta_{r1} & \beta_{r2}\cdots & \beta_{rm} \end{bmatrix} = \left[\beta_{(1)} | \beta_{(2)} | \cdots | \beta_{(m)}\right] \quad (4)$$

$$\varepsilon_{(n\times m)} = \begin{bmatrix} \varepsilon_{11} & \varepsilon_{12}\cdots & \varepsilon_{1m} \\ \varepsilon_{21} & \varepsilon_{22}\cdots & \varepsilon_{2m} \\ \vdots & \vdots & \vdots \\ \varepsilon_{n1} & \varepsilon_{n2}\cdots & \varepsilon_{nm} \end{bmatrix} = \left[\varepsilon_{(1)} | \varepsilon_{(2)} | \cdots | \varepsilon_{(m)}\right] = \begin{bmatrix} \varepsilon'_{(1)} \\ \varepsilon'_{(2)} \\ \vdots \\ \varepsilon'_{(m)} \end{bmatrix} \quad (5)$$

where,

β is the $((r+1)\times m)$ matrix of parameters.

Y is the $(n\times m)$ matrix of the response variables.

ε is the $(n\times m)$ matrix of the errors or the residuals.

Then, the multivariate linear regression model is

$$Y = Z\beta + \varepsilon \quad (6)$$

with

$$E\left(\varepsilon_{(i)}\right) = 0$$

and

$$\operatorname{cov}\left(\varepsilon_{(i)}, \varepsilon_{(k)}\right) = \sigma_{ik} I, \quad \text{i.k=1,2,}\cdots\text{,m}$$

Also, the m observed responses on the j^{th} trial have covariance matrix

$$\sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12}\ldots\sigma_{1m} \\ \sigma_{21} & \sigma_{22}\ldots\sigma_{2m} \\ \vdots & \vdots \quad \vdots \\ \sigma_{m1} & \sigma_{m2}\ldots\sigma_{mm} \end{bmatrix}$$

$$\hat{\beta}_{(i)} = \left(Z'Z\right)^{-1} Z'Y_{(i)}$$

$$\hat{\beta} = \left[\hat{\beta}_{(1)} | \hat{\beta}_{(2)} | \cdots | \hat{\beta}_{(m)}\right]$$
$$= \left(Z'Z\right)^{-1} Z'\left[Y_{(1)} | Y_{(2)} | \cdots | Y_{(m)}\right]$$
$$= \left(Z'Z\right)^{-1} Z'Y \quad (7)$$

Now for any choice of parameter $\beta = \left[b_{(1)} | b_{(2)} | \cdots | b_{(m)}\right]$, the resulting matrix of errors is $Y - Z\beta$. The resulting error sum of squares and cross-product matrix is $\left(Y - Z\beta\right)'\left(Y - Z\beta\right)$

$$= \begin{bmatrix} \left(Y_{(1)} - Zb_{(1)}\right)'\left(Y_{(1)} - Zb_{(1)}\right) \cdots \left(Y_{(1)} - Zb_{(1)}\right)'\left(Y_{(1)} - Zb_{(1)}\right) \\ \vdots \qquad \vdots \\ \left(Y_{(m)} - Zb_{(m)}\right)'\left(Y_{(m)} - Zb_{(m)}\right) \cdots \left(Y_{(m)} - Zb_{(m)}\right)'\left(Y_{(m)} - Zb_{(m)}\right) \end{bmatrix} \quad (8)$$

The selection $b_{(i)} = \hat{\beta}_{(i)}$ minimizes the i^{th} diagonal sum of squares $\left(Y_{(1)} - Zb_{(1)}\right)'\left(Y_{(1)} - Zb_{(1)}\right)$.

Thus, $tr\left[\left(Y - Z\beta\right)'\left(Y - Z\beta\right)\right]$ is minimized by $\hat{\beta}$.

Also, the var$\left[\left(Y - Z\beta\right)'\left(Y - Z\beta\right)\right]$ is minimized by the least squares estimate $\hat{\beta}$. Using the least estimates $\hat{\beta}$, we can obtain the matrix of predicted values as,

$$\hat{Y} = Z\hat{\beta} = \left(Z'Z\right)^{-1} Z'Y \quad (9)$$

and the matrix of the residuals is

$$\hat{\varepsilon} = Y - \hat{Y} = \left[1 - Z\left(Z'Z\right)^{-1} Z'\right]Y \quad (10)$$

Adopting the least squares estimator $\hat{\beta} = [\hat{\beta}_{(1)} | \hat{\beta}_{(2)} | \cdots | \hat{\beta}_{(m)}]$ we obtain the multivariate multiple regression model

$$\underset{(n\times m)}{\hat{Y}} = \underset{(n\times(r+1))}{Z} \cdot \underset{((r+1)\times m)}{\hat{\beta}^{(b)}}$$

1.2 The Proposed Multivariate Jackknife Delete-*d* Algorithm for Estimating the Parameters of

Multivariate Linear Regression Models

Step1. Draw sample $(w_1, w_2, ..., w_n)$ of size *n* randomly from the population and divide the sample into s independent groups each of size *d*.

Step2. Omit first d observation set from full sample at a time and estimate the multivariate linear regression parameters from (*n-d*) sized remaining observations. Thus

$$\hat{\beta} = \left[\hat{\beta}_{(1)} \mid \hat{\beta}_{(2)} \mid \cdots \mid \hat{\beta}_{(m)}\right]$$
$$= (Z'Z)^{-1} Z'\left[Y_{(1)} \mid Y_{(2)} \mid \cdots \mid Y_{(m)}\right]$$
$$= (Z'Z)^{-1} Z'Y$$

$\hat{\beta}_{(i)} = (Z'Z)^{-1} Z'Y_{(i)}$ using the multivariate regression method for each response variable on the predictor variables $\hat{\beta}^{(d_1)}$. See [7-8]

Step3. Omit second d observation set from full sample at a time and estimate the multivariate regression parameters $\hat{\beta}^{(d_2)}$ from (*n-d*) remaining observation set.

Step4. Omit each d of the n observation sets and estimate the multivariate regression parameters as $\hat{\beta}^{(d_k)}$ alternately, where $\hat{\beta}^{(d_k)}$ is the multivariate delete-d regression parameter vector estimated after deletion of K^{th} d observation set from full sample, $k = 1, 2, \ldots, s$;where

$$s = \binom{n}{d}$$

Step5. Obtain the probability distribution $F_{(}\beta^{(d)}{}_{)}$ of delete-d jackknife estimates $\hat{\beta}^{(d_1)}, \hat{\beta}^{(d_2)}, \cdots, \hat{\beta}^{(d_S)}$

Step6. Calculate the jackknife regression parameter estimate which is the mean of the $F_{(}\beta^{(J)}{}_{)}$ distribution as;

$$\bar{\hat{\beta}}^{(multi_{(dd)})} = \frac{\sum_{k=1}^{s} \hat{\beta}^{(d_k)}}{s} \tag{11}$$

Step7. Obtain, the multivariate Jackknife delete-d regression equation

$$\underset{(n\times m)}{\hat{Y}} = \underset{(n\times(r+1))}{\mathrm{Z}} \;.\; \underset{((r+1)\times m)}{\hat{\beta}^{(dd)}} \tag{12}$$

The bias for the multivariate Jackknife delete-*d* parameters estimates

$$bias(\hat{\beta}) = (n-1)(\bar{\hat{\beta}}^{(multi_{(dd)})} - \hat{\beta}) \tag{13}$$

The jackknife standard error; see [3-4].

$$Se\left(\hat{\beta}^{(multi_{(dd)})}\right) = \left[\frac{(n-d)}{\binom{n}{d}} \sum_{k=1}^{s} \left(\bar{\hat{\beta}}^{(multi_{(dd)})} - \hat{\beta}_{(i)}\right)^2\right]^{1/2} \tag{14}$$

$$\text{where } \bar{\hat{\beta}}^{(multi_{(dd)})} = \frac{\sum_{k=1}^{s} \hat{\beta}^{(d_k)}}{\binom{n}{d}}$$

1.3 Data Presentation

The data (see Appendix A) obtained from Central Bank of Nigeria Bulletin 2011 edition is on the Exchange Rate of US Dollar and Pounds Sterling to Nigeria Naira currency and Nigeria foreign trade (Oil Import and Export, Non-Oil Import and Export) from 1960-2010. We intend to obtain the multivariate linear model that describes the relationship between foreign trade and foreign exchange rate of naira per US Dollar and Pounds Sterling.

Let,

$Y_1 =$ Oil import

$\mathrm{Y}_2 =$ Non-oil import

$\mathrm{Y}_3 =$ Oil export

$\mathrm{Y}_4 =$ Non-oil export

$Z_1 =$ Exchange rate of US Dollar

$Z_2 =$ Exchange rate of Pounds Sterling

We shall look at the adequacy of the models at 5% level of significance

$H_0 :$ The models are not adequate $(\beta_{ij} = 0)$

$H_1 :$ The models are adequate $(\beta_{ij} \neq 0)$

The Exiting methods of parameter estimation for model 1-4 are shown in Table 1 and 2

Table 1: Estimation of Multivariate Regression Parameters [5]

Ordinary methods	Model 1 $\hat{Y}_1$	Model 2 $\hat{Y}_2$	Model 3 $\hat{Y}_3$	Model 4 $\hat{Y}_4$
Intercept	-24141.1	-69236.9	-162002.1	-5647.6
Z_1	6692.8	12400.8	-45664.2	600.7
Z_2	-386.7	4459.8	53673.1	384.2

For the models 1-4, the values of multiple R-square are 0.6257, 0.7126, 0.7535 and 0.6431 respectively, Adjusted R-square are 0.6101, 0.7006, 0.7432, and 0.6282 respectively at various P values of

$$5.736\times10^{`-11}, 1.0101\times10^{-13}, 2.541\times10^{-15}$$
$$and 1.823\times10^{-11}$$

respectively. Averagely the R-square is 0.683725; Adjusted R-square is 0.670525 and P-value 2.777×10^{-13}. Since the P-value is less than 0.05, there is enough evidence to reject the null hypothesis and conclude that the models are adequate. We observed that the exchange rates of US Dollar and Pounds Sterling contributed 68% effect on the Nigerian Foreign Trades.

Table 2: Estimation of Existing Multivariate Bootstrap Parameters [8].

Multivariate Bootstrap	Model 1 $\hat{Y}_1^{(b)}$	Model 2 $\hat{Y}_2^{(b)}$	Model 3 $\hat{Y}_3^{(b)}$	Model 4 $\hat{Y}_4^{(b)}$
Intercept	-22876.8	-64926	-155566	-5285.8
Z_1	6292.2	11777.5	-47387	517.99
Z_2	-178.49	4631.7	54485.7	420.37

Table 3: Estimation of the Proposed Multivariate Jackknife Delete-*d*=5 Parameters

Multivariate Jackknife Delete-*d*=5	Model 1 $\hat{Y}_1^{(J_5)}$	Model 2 $\hat{Y}_2^{(J_5)}$	Model 3 $\hat{Y}_3^{(J_5)}$	Model 4 $\hat{Y}_4^{(J_5)}$
Intercept	-23906.6	-68525	-160841	-5593.1
Z_1	6583.5	12175.6	-46193	-23906.6
Z_2	-327.6	4569.6	53948.8	6583.5

The Standard errors of parameters estimation for the models 1-4 are shown in Table 4

Table 4: STANDARD ERROR OF PARAMETER ESTIMATES FOR MODEL 1-4 USING EXISTING METHODS AND MULTIVARIATE DELETE-*d* ALGORTHMS (n=51, B=1000, d=5)

	$\hat{Y}_1$	$\hat{Y}_2$	$\hat{Y}_3$	$\hat{Y}_4$
Existing Method [5]				
Intercept	5880.1	15,958.3	33,385.6	1,174.7
Z_1	802.78	2,178.8	4,558.2	160.33
Z_2	471.41	1,279.4	2,676.6	94.18
Existing Multivariate Bootstrap [8]				
Intercept	420.72	1,197.6	2,271.2	87.11
Z_1	410.71	1,111.9	2,116.99	83.01
Z_2	232.93	624.82	1,225.5	46.39
Proposed Multivariate Delete-5				
Intercept	3.34	9.42	17.66	0.68
Z_1	3.01	8.27	14.95	0.62
Z_2	1.69	4.55	8.42	0.33

Discussion

Table 4 reveals great reduction in standard error for the proposed Multivariate Jackknife delete-5 algorithm when compared with the existing methods. This shows that the proposed algorithm performs better in error reduction and can be used in controlling variation among observations

Prediction Using Proposed Models

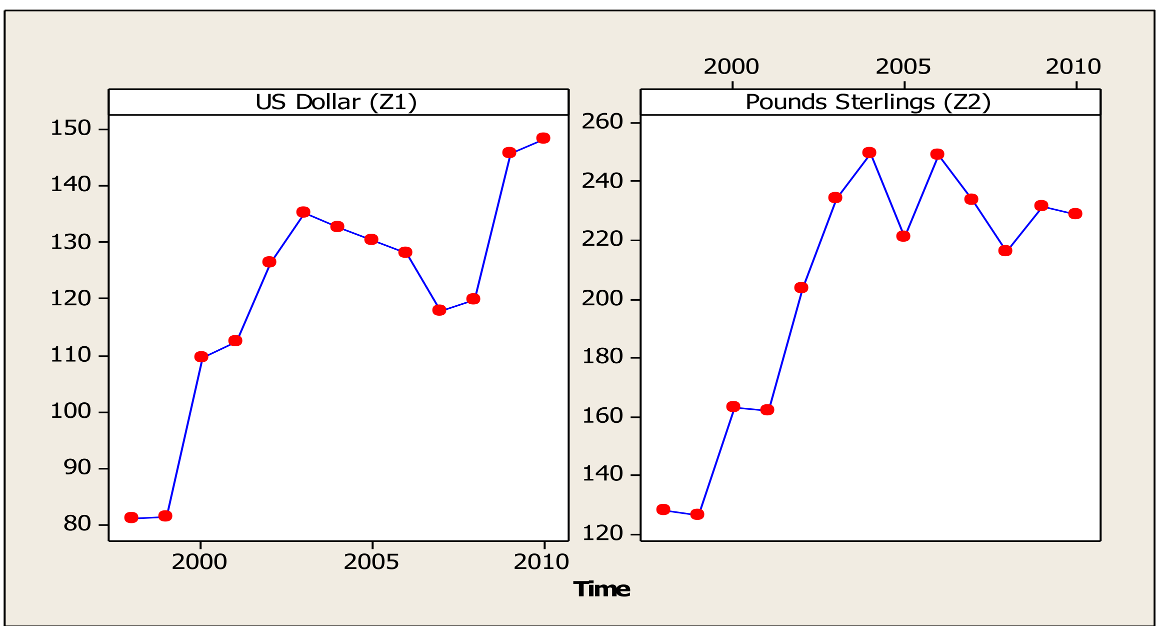

Figure 1: Scatter plot of exchange rate of US Dollar and Pounds Sterling to Naira with respect to time (1998-2010)

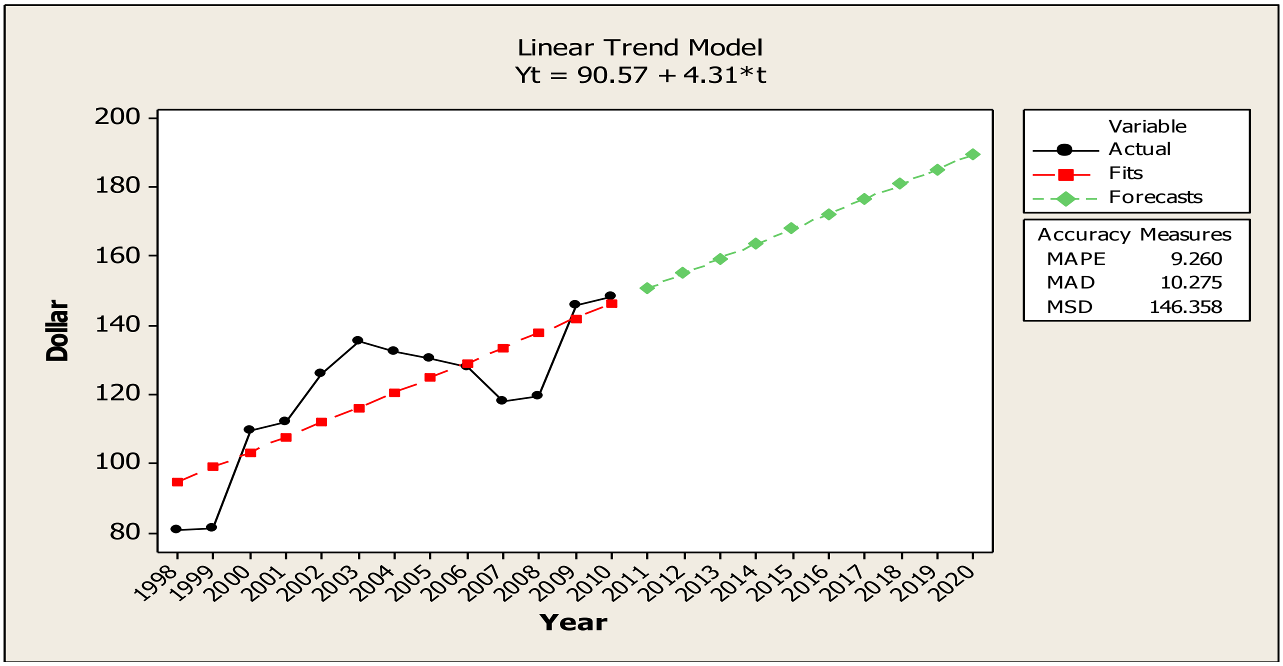

Figure 2: Trend Analysis Plot for US Dollar (1998-2020)

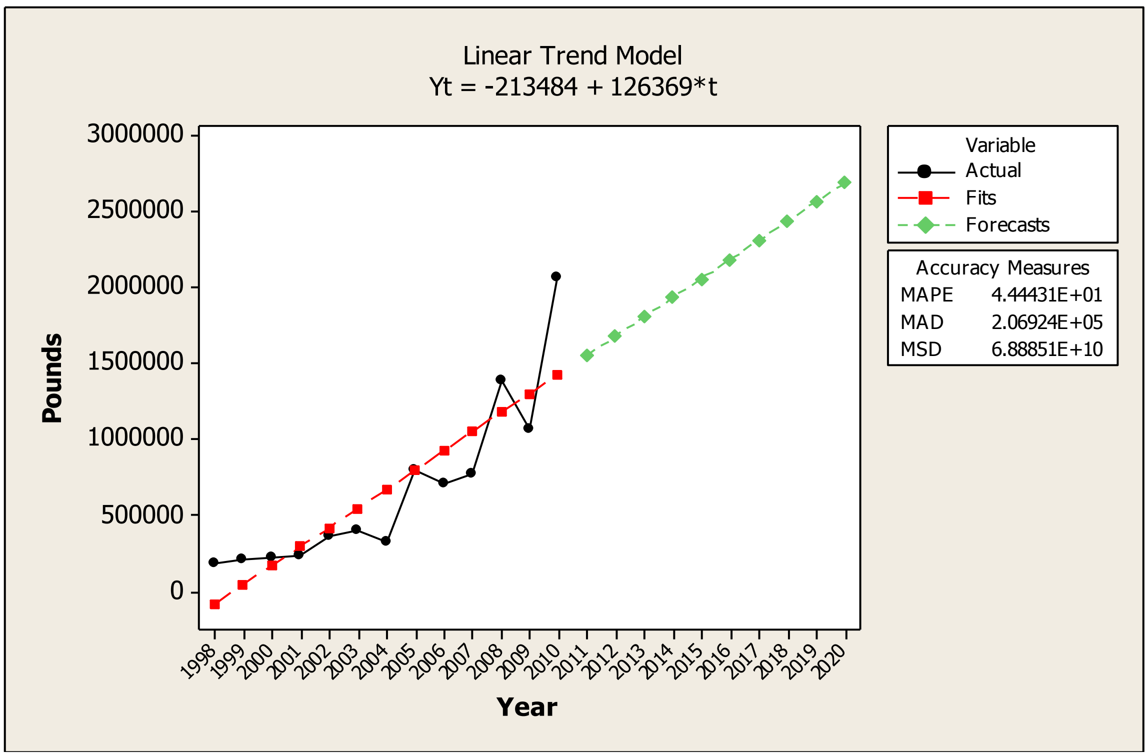

Figure 3: Trend Analysis Plot for Pounds Sterling (1998-2020)

Discussion

The figures 2 and 3 depict increase in the exchange rate of Naira to US Dollar and Pounds Sterling respectively. It is evident that the exchange rates of the currencies were on the high side over the years considered. Using linear model, the predicted values for both US Dollar and Pounds Sterling are as 180naira and 300naira respectively. This might be harmful to Nigeria economy as it is an indication of loss of value of Nigeria currency.

```
Equation   Obs  Parms      RMSE      "R-sq"        F           P
----------------------------------------------------------------------
Z1           13     2       13.15177   0.6399  19.54923  0.0010
Z1           13     2       27.5029    0.6392  19.48608  0.0010
------------------------------------------------------------------------------

             |     Coef.      Std. Err.       t      P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Z1           |
           t |  4.310357  .9748739    4.42   0.001    2.164674    6.45604
       _cons |  90.57119  7.737822   11.70   0.000    73.54036    107.602
-------------+----------------------------------------------------------------
Z2           |
           t |  8.999225  2.038651    4.41   0.001    4.512185   13.48627
       _cons |  140.7688  16.18129    8.70   0.000    105.154    176.3836
```

Thus, the trend equations for future prediction of exchange rates of Us Dollar and Pounds sterling to Naira are

$$Z_1 = 90.57119 + 4.310357t \text{ and}$$
$$Z_2 = 140.7688 + 8.99925t$$

Respectively, since the models are significant at 1% (p-value of 0.0010), then, the values of Z_1 and Z_2 in the nearest future can be computed from the Trend regressions. To determine future values of Z_1 and Z_2, increase the time t from 13 (ie. year 2010) to desirable point, say 14 to 22. This implies predicting the values of US Dollar and Pounds exchange rate to Naira from 2011 to 2020. The result is as shown below

TABLE 5: PREDICTING THE VALUES OF US DOLLAR AND POUNDS EXCHANGE RATE TO NAIRA FROM 2011 TO 2020

Years	**T (time)**	**US Dollar (Z_1)**	**Pounds Sterling (Z_2)**
2011	14	146.606	257.759
2012	15	150.916	266.758
2013	16	155.227	275.757
2014	17	159.537	284.756
2015	18	163.847	293.756
2016	19	168.158	302.755
2017	20	172.468	311.754
2018	21	176.778	320.753
2019	22	181.089	329.753
2020	23	185.399	338.752

The computed values gave the same result as shown in the figures 2 and 3, as the one US Dollar was projected to be the equivalent of 185.399naira in 2020 and 338naira for Pounds Sterling.

The models obtained from Existing method [5] are:

$$\text{Model 1: } Y_1 = -24141.1 + 6692.8Z_1 - 386.7Z_2$$
$$\text{Model 2: } Y_2 = -69236.9 + 12400.8Z_1 + 4459.8Z_2$$
$$\text{Model 3: } Y_3 = -162002.1 - 45664.2Z_1 + 53673.1Z_2$$
$$\text{Model 4: } Y_4 = -5647.6 + 600.7Z_1 + 384.2Z_2$$

The Y_i's can be predicted using the values of Z_1 and Z_2 in Table 5, and the projected values are shown in Table 6.

Table 6: Projection for Oil Import, Non-Oil Import, Oil Export, Non-Oil Export from 2011 - 2020 using the Existing Method [5]

Years	**US Dollar** (Z_1)	**Pounds Sterling** (Z_2)	Y_1	Y_2	Y_3	Y_4
2011	146.606	257.759	856872	2898345	6978070	181449
2012	150.916	266.758	882222	2991932	7264257	187496
2013	155.227	275.757	907572	3085518	7550444	193543
2014	159.537	284.756	932923	3179105	7836632	199590
2015	163.847	293.756	958273	3272692	8122819	205636
2016	168.158	302.755	983623	3366278	8409006	211683
2017	172.468	311.754	1008974	3459865	8695194	217730
2018	176.778	320.753	1034324	3553451	8981381	223777
2019	181.089	329.753	1059674	3647038	9267568	229823
2020	185.399	338.752	1085025	3740625	9553755	235870

B. The models obtained from Existing Multivariate Bootstrap Algorithm [8] are:

$$\text{Model 1: } \hat{Y}_1^{(b)} = -22038.3 + 5732.2Z_1 + 130.998Z_2$$

$$\text{Model 2: } \hat{Y}_2^{(b)} = -62246.3 + 9960.02Z_1 + 5677.7Z_2$$

$$\text{Model 3: } \hat{Y}_3^{(b)} = -151059 - 50960.96Z_1 + 56405.65Z_2$$

$$\text{Model 4: } \hat{Y}_4^{(b)} = -5129.05 + 392.63Z_1 + 492.61Z_2$$

The Y_i's can be predicted using the values of Z_1 and Z_2 in the Table 5, and the projected values are shown in Table 7.

Table 7: Projection for Oil Import, Non-Oil Import, Oil Export, Non-Oil Export from 2011 - 2020 using the Existing Multivariate Bootstrap Algorithm [8]

Years	**US Dollar** (Z_1)	**Pounds Sterling** (Z_2)	Y_1	Y_2	Y_3	Y_4
2011	146.606	257.759	852102	2861427	6916816	179407
2012	150.916	266.758	877988	2955454	7204763	185533
2013	155.227	275.757	903875	3049480	7492710	191658
2014	159.537	284.756	929762	3143506	7780657	197784
2015	163.847	293.756	955648	3237532	8068604	203909
2016	168.158	302.755	981535	3331558	8356552	210035
2017	172.468	311.754	1007422	3425584	8644499	216160
2018	176.778	320.753	1033308	3519610	8932446	222286
2019	181.089	329.753	1059195	3613637	9220393	228411
2020	185.399	338.752	1085082	3707663	9508340	234537

C. The models obtained from the proposed Multivariate Jackknife Delete-5 Algorithm are:

Model 1: $\hat{Y}_1^{(J_{d5})} = -23906.6 + 6583.5Z_1 - 386.7Z_2$

Model 2: $\hat{Y}_2^{(J_{d5})} = -68525.3 + 12175.6Z_1 + 4569.6Z_2$

Model 3: $\hat{Y}_3^{(J_{d5})} = -160841 - 46193Z_1 + 53948.8Z_2$

Model 4: $\hat{Y}_4^{(J_{d5})} = -5593 - 23906.6Z_1 + 6583.5Z_2$

The Y_i's can be predicted using the values of Z_1 and Z_2 in Table 5, the projected values are shown in Table 8.

TABLE 8: Projection for Oil Import, Non-Oil Import, Oil Export, Non-Oil Export from 2011 - 2020 using the Proposed Multivariate Jackknife Delete-5 Method Algorithm

Years	**US Dollar** (**Z_1**)	**Pounds Sterling** (**Z_2**)	Y_1	Y_2	Y_3	Y_4
2011	146.606	257.759	841598	2894343	6973028	-1813485
2012	150.916	266.758	866495	2987947	7259426	-1857285
2013	155.227	275.757	891392	3081551	7545824	-1901085
2014	159.537	284.756	916289	3175155	7832222	-1944884
2015	163.847	293.756	941187	3268759	8118620	-1988684
2016	168.158	302.755	966084	3362363	8405018	-2032483
2017	172.468	311.754	990981	3455967	8691416	-2076283
2018	176.778	320.753	1015878	3549571	8977814	-2120082
2019	181.089	329.753	1040775	3643175	9264212	-2163882
2020	185.399	338.752	1065673	3736779	9550610	-2207682

The negative sign of the values in the column 7 (Y_4) is an indication of reduction in the values of non-oil export from the initial state as a result of depreciation of Nigeria currency. This implies the possibility of great reduction of non-oil export value in some years to come.

3.0 Findings and Conclusion

It is evidently an increase of exchange rate of US Dollar and Pounds Sterling affects Oil import, Oil export, Non-oil import and Non-oil export (Foreign Trade) negatively which could be harmful to the nation's economy. The importance of Foreign Trade to any nation is to increase in the GDP of that Nation, but the reduction in elements of Foreign Trade, definitely, will lead to reduction in the GDP of such nation. Therefore, stability of Foreign exchange rates of US Dollar and Pounds Sterling to Naira should be sustained to a rate that will burst the Nation's economy.

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APPENDIX

A. The data obtained from Central Bank of Nigeria Bulletin 2010 edition on exchange of US Dollar and Pounds to Nigeria naira currency and Nigeria foreign trade from 1960-2010 and shown in the table below.

YEARS	US DOLLAR	POUNDS	OIL (IMPORT)	NON-OIL (IMPORT)	OIL (EXPORT)	NON-OIL (EXPORT)
1960	0.7143	2	26.952	404.83	8.816	330.612
1961	0.7143	2	31.668	413.37	23.09	324.166
1962	0.7143	2	32.966	373.468	34.42	302.652
1963	0.7143	2	37.258	377.916	40.354	338.306
1964	0.7143	2	46.398	461.028	64.112	365.19
1965	0.7143	2	47.876	502.186	136.194	400.58
1966	0.7143	2	22.042	490.666	183.94	384.228
1967	0.7143	2	23.228	417.872	144.772	340.866
1968	0.7143	2	39.642	345.76	73.998	348.12
1969	0.7143	2	42.766	454.616	261.93	374.062
1970	0.7143	1.7114	38.702	717.718	509.622	376.046
1971	0.6955	1.7156	50.4	1028.5	953	340.4
1972	0.6579	1.6289	45.2	944.9	1176.2	258
1973	0.6579	1.6289	41	1183.8	1893.5	384.9
1974	0.6299	1.4795	52.4	1684.9	5365.7	429.1
1975	0.6159	1.3618	118	3603.5	4563.1	362.4
1976	0.6265	1.1317	95	5053.5	6321.6	429.5
1977	0.6466	1.1671	102.2	6991.5	7072.8	557.9
1978	0.606	1.2238	110	8101.7	5401.6	662.8
1979	0.5957	1.2628	230	7242.5	10166.8	670
1980	0.5464	1.2647	227.4	8868.2	13632.3	554.4
1981	0.61	1.2495	119.8	12719.8	10680.5	342.8
1982	0.6729	1.1734	225.5	10545	8003.2	203.2
1983	0.7241	1.1216	171.6	8732.1	7201.2	301.3
1984	0.7649	1.0765	282.4	6895.9	8840.6	247.4
1985	0.8938	1.1999	51.8	7010.8	11223.7	497.1
1986	2.0206	2.5554	913.9	5069.7	8368.5	552.1
1987	4.0179	6.5929	3170.1	14691.6	28208.6	2152
1988	4.5367	8.0895	3803.1	17642.6	28435.4	2757.4
1989	7.3916	12.0695	4671.6	26188.6	55016.8	2954.4
1990	8.0378	16.2419	6073.1	39644.8	106626.5	3259.6
1991	9.9095	17.4955	7772.2	81716	116858.1	4677.3
1992	17.2984	27.8684	19561.5	123589.7	201383.9	4227.8
1993	22.0511	33.2522	41136.1	124493.3	213778.8	4991.3
1994	21.8861	33.4252	42349.6	120439.2	200710.2	5349
1995	21.8861	34.524	155825.9	599301.8	927565.3	23096.1
1996	21.8861	34.7698	162178.7	400447.9	1286215.9	23327.5
1997	21.886	36.2166	166902.5	678814.1	1212499.4	29163.3
1998	81.0228	128.1561	175854.2	661564.5	717786.5	34070.2
1999	81.2528	126.4165	211661.8	650853.9	1169476.9	19492.9
2000	109.55	163.0323	220817.69	764204.7	1920900.4	24822.9
2001	112.4864	161.7534	237106.83	1121073.5	1839945.25	28008.6
2002	126.4	203.7442	361710	1150985.33	1649445.828	94731.85
2003	135.40	234.4	398922.31	1681312.96	2993109.95	94776.44
2004	132.67	249.9925	318114.72	1668930.55	4489472.19	113309.4
2005	130.4	221.2385	797298.94	2003557.39	7140578.92	105955.9
2006	128.27	249.3899	710683	2397836.32	7191085.64	133595
2007	117.968	234.0205	768226.84	3143725.79	8110500.38	199257.9
2008	119.7925	216.4808	1386729.93	3803072.68	9913651.13	247839
2009	146	231.6438	1063544.18	4038990.2	8067233	289152.6
2010	148.455	228.6553	2073579.03	5931795.19	10639417.37	396377.2

Source: Central Bank of Nigeria.

B. *IMPLEMENTATION OF MULTIVARIATE DELETE-d ALGORITHM FOR ESTIMATION OF THE* PARAMETERS OF MULTIVARIATE LINEAR MODEL

```
#part 1:To read data

data=read.table("data(hap).txt", header=T, sep="")

#Part 2

#Run this to get the original estimates

data=data.frame(data)

reg=lm(cbind(y1, y2, y3, y4) ~ x1+x2,data=data)

reg

summary(reg)

#Delete d jacknife algorithm begins here

#d=no of rows to be deleted

#p=no of cols in the data

#data is the data matrix with the first p1 columns

#for the dept vars and the remaining p-p1 cols for the indpt vars

jack.a=function(data,p1,d)

{

p=ncol(data)

n=nrow(data)

u=combn(n,d) #Assign the matrix of all possible combinations to u

output=matrix(0,ncol=p1*(p-p1)+p1,nrow=ncol(u))

y=data[,1:p1] #the responses

x=data[,(p1+1):p] #the covariates

for (i in 1:(ncol(u)))

{

dd=c(u[,i])

yn=y[-dd,] #delete d rows of the independent var

xn=x[-dd,] #delete d rows of the dependent var

reg=lm(formula=yn~xn)

coef=coef(reg)

output[i,]=c(as.vector(coef))

}
```

```
output

}

#Use this part to run

data=data.matrix(data)

run=jack.a(data,2,5)

est=c(mean(run[,1],na.rm=TRUE),mean(run[,2],na.rm=TRUE),mean(run[,3],na.rm=TRUE),mean(run[,4],na.rm=TRUE),mean(run[,5],na.rm=TRUE),mean(run[,6],na.rm=TRUE),mean(run[,7],na.rm=TRUE),mean(run[,8],na.rm=TRUE),mean(run[,9],na.rm=TRUE),mean(run[,10],na.rm=TRUE))

> est1=matrix(est,3,4)

> rownames(est1)=c("Intercept","x1","x2")

> colnames(est1)=c("y1","y2","y3","y4")

> est
```