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Modeling University Student Academic Performance in Nigeria: A Comparison of Seemingly Unrelated Regression Equations (Sure) and Multivariate Regression Techniques

Abdulganiy G. Abdullahi[a], Bamigbala, A. Olateju[b*], Ifeoma Ilochi[a], and Magaji A. Umar[c]

[a]Department of Statistics, Modibbo Adama University, Yola, Adamawa State, Nigeria

[b]Department of Statistics, Federal University Wukari, Taraba State, Nigeria

[c]Department of Mathematics, Jigawa State College of Education Gumel, Nigeria

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ABSTRACT

This study investigates the factors influencing academic performance of students at Modibbo Adama University of Technology, Yola, Adamawa State, using the Seemingly Unrelated Regression Equations (SURE) model. Secondary data were collected from the Department of Statistics and Operations Research, encompassing variables including age at entry, gender, mode of entry, school type, parent occupation, course scores from 100 to 500 level, and CGPA for each session across three student cohorts (2016, 2017, and 2018). The SURE model was employed to analyze three dependent variables: first year CGPA, final year CGPA, and total credit units passed, while accounting for contemporaneous correlation among the error terms. Model selection was conducted using log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The SURE model demonstrated superior performance over multivariate regression, with lower root mean square error values (0.6291, 0.5596, and 3.1884 for first year CGPA, final year CGPA, and total credit passed, respectively). The model explained 55.6%, 60.1%, and 96.0% of the variance in first year CGPA, final year CGPA, and total credit units passed, respectively. JAMB score emerged as the most significant predictor across all three dependent variables ($p < 0.001$), while program type significantly affected all performance measures at the 5% level. Age significantly influenced total credit units passed, and student set significantly affected first year CGPA. Conversely, gender, mode of entry, and number of O-level sittings showed no significant effects on any performance measure. The SURE model effectively captures the interdependencies among different academic performance indicators, with JAMB score serving as the strongest predictor of student success. The findings support the continued use of University Tertiary Matriculation Examination (UTME) scores as a reliable admission criterion for academic programs.

1. Introduction

The Seemingly Unrelated Regression (SUR) framework was developed by Zellner (1962) as a system of p interconnected regression equations. These equations are termed "seemingly unrelated" because when examined individually, their error terms conform to conventional linear ordinary least squares (OLS) specifications. While computing p independent OLS estimations disregards

* Corresponding author. Tel.: +2347066459090
E-mail address: bamigbala@fuwukari.edu.ng (Bamigbala, A Olateju)
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potential error correlations between equations, the interdependence of dependent variables and shared predictor variables across equations may generate "contemporaneous" error correlation among the p equations. Consequently, SUR models find application when multiple equations appear independent but may be interconnected through: 1) identical or zero coefficient assumptions; 2) correlated disturbances between equations; and/or 3) common subsets of explanatory variables. The third characteristic is particularly valuable as it permits each dependent variable to have distinct design matrices while sharing certain predictors. SUR frameworks enable variables to appear in both dependent and independent variable matrices, making them especially relevant for path analytical applications. Despite their utility, SUR models remain underutilized in multivariate analysis.

In econometric theory, the seemingly unrelated regressions (SUR) or seemingly unrelated regression equations (SURE) framework, introduced by Arnold Zellner in 1962 and 1963, along with contributions from Stewart (1980) and Parks (1967), represents an extension of linear regression methodology comprising multiple regression equations with distinct dependent variables and potentially varying sets of exogenous explanatory variables. Each equation constitutes a valid linear regression that can be estimated independently, hence the "seemingly unrelated" designation, though some researchers argue "seemingly related" would be more accurate given the assumed error term correlations across equations. Traditional equation-by-equation estimation using standard OLS produces consistent estimates but typically lacks the efficiency of the SUR approach, which employs feasible generalized least squares with a specialized variance-covariance matrix structure. SUR estimation becomes equivalent to OLS under two specific conditions: when error terms are genuinely uncorrelated between equations (truly unrelated), or when all equations contain identical right-hand-side regressors. The SUR model can be conceptualized as either a restricted general linear model with certain coefficients in matrix B constrained to zero, or as an expanded general linear model permitting different regressors across equations.

Recent developments include Hubert, Verdonck and Yorulmaz's FastSUR algorithm, demonstrating superior performance in simulation studies and outlier detection capabilities using real economic data, particularly within the General Multivariate Chain Ladder (GMCL) framework that utilizes SUR for parameter estimation. Ebukuyo, Adepoju and Olamide (2013) evaluated SUR estimator performance under varying degrees of first-order autoregression using Mean Square Error (MSE) criteria, finding superior performance with autocorrelation coefficients of 0.3 compared to 0.5 across regression equations. Zeebari and Shukur (2012) investigated Least Absolute Deviations (LAD) methodology for ridge-type parameter estimation in SURE models, while El-Dereny and Rashwan (2011) addressed multicollinearity issues through Ridge Regression approaches, though without specifically targeting SUR models under multicollinearity conditions.

The SUR methodology addresses variation across multiple dependent variables rather than single outcomes (Zellner, 2006). Two primary motivations drive SUR implementation: first, achieving estimation efficiency through cross-equation information integration; second, imposing and testing parameter restrictions (Zellner, 1962; Srivastava and Giles, 1987; Fiebig, 2001). Zellner (1962) demonstrated SUR's efficiency advantages over individual equation estimation when disturbance correlations are substantial and explanatory variables exhibit low correlation in two-stage procedures. Significant efficiency gains occur across all sample sizes when $|\rho|>0.3$, where ρ represents the contemporaneous correlation coefficient for equation disturbances.

The aim of this study is to model the academic performance of students in Modibbo Adama University of Technology, Yola, Adamawa State using Seemingly Unrelated Regression Equations (SURE) Model and Multivariate Regression Models. Specifically, this research seeks to investigate the factors influencing academic performance of students at the institution, estimate the parameters associated with student academic achievement, and conduct a comparative analysis of the SURE model output against that of the Multivariate Regression Model. By employing these advanced statistical methodologies, the study aims to provide comprehensive insights into the determinants of academic success while evaluating the relative effectiveness of different modeling approaches in capturing the complex relationships between various predictor variables and multiple dimensions of student academic performance in the Nigerian higher education.

2. Methodology

In this study, data were collected from the secondary source. Data were collected from Department of Statistics and Operations Research of Modibbo Adama University (MAU), Yola. Variables considered include: age at entry, sex, mode of entry, school type, parent occupation, scores of course registered from 100 to 500 level, CGPA for each session etc. Multivariate Regression (MR) Model and Seemingly Unrelated Regression (SUR) Model were used in modeling the factor associated with academic performance of students.

Seemingly Unrelated Regression (Sur) Model

Zellner (1962) developed the Seemingly Unrelated Regression (SUR) estimator for estimating models with $p > 1$ dependent variable that allow for different regressor matrices in each equation ($e.g.\ X_i \neq X_j$) and account for contemporaneous correlation i.e. $E\left(\varepsilon_{it}\varepsilon_{jt}\right) \neq 0$. In order to simplify notation, all equations are stacked into a single equation:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & X_p \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{1}$$

That can be re-written as

$$Y = X\beta + \varepsilon \tag{2}$$

where the $Y = \left(y_1', y_2', \ldots, y_p'\right)$ is a vector of all stacked dependent variables, X is a block diagonal design matrix with the ith design matrix X_i on the ith block, $\beta = \left(\beta_1', \beta_2', \ldots, \beta_p'\right)'$ is the vector of the stacked coefficient vectors of all equation, the total number of parameters estimated for all p sub models is $K = \sum_{i=1}^{p} k_i$ and $\varepsilon = \left(\varepsilon_1', \varepsilon_2', \ldots, \varepsilon_p'\right)$ is vector of the stacked error vectors of all equations.

The same estimates as by separate single-equation OLS estimations can be obtained by an OLS estimation of the entire system of equations, i.e. $\beta^{OLS} = \left(X'X \right)^{-1} X'Y$.

The SUR estimator that accounts for interactions between the single submodels can be obtained by:

$$\beta^{SUR} = \left[X'\Omega^{-1} X \right]^{-1} \left[X'\Omega^{-1} Y \right] \tag{3}$$

Where Ω^{-1} is a weighting matrix based on the covariance matric of the error terms Σ. This covariance matrix $\Sigma = \left[\sigma_{ij} \right]$ has the elements $\sigma_{ij} = E\left(\varepsilon_{in} \varepsilon_{jn} \right)$, where ε_{in} is the error term of the n^{th} observation of the i^{th} equation. Finally, the inverse of the weighting matrix can be calculated by $\Omega = \Sigma \otimes I_N$, where I_N is an $N \times N$ identity matrix and $\otimes$ denotes the Kronecker product. However, as the true error terms ε are unknown, they are often replaced by observed residuals, e.g. obtained from OLS estimates, i.e. $\hat{\varepsilon}_i = Y_i - X_i \beta_i^{OLS}$ so that the elements of the covariance matrix can be calculated by:

$$\hat{\sigma}_{ij} = \frac{\hat{\varepsilon}_i \hat{\varepsilon}_j}{N} \tag{4}$$

Thus, a SUR model is an application of the generalized least squares (GLS) approach and the unknown residual covariance matrix is estimated from the data.

The variance-covariance matrix is given by:

$$\Omega = Var\left(u \right) = \begin{bmatrix} \sigma_{11} I & \sigma_{12} I & \dots & \sigma_{1M} I \\ \sigma_{21} I & \sigma_{22} I & \dots & \sigma_{2M} I \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} I & \sigma_{M2} I & \dots & \sigma_{MM} I \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & \dots & \sigma_{MM} \end{bmatrix} \otimes I = \Sigma \otimes I \tag{5}$$

where I is a unit matrix of order $T \times T$ and $\sigma_{uu'} = E\left(u_{\mu t} u_{\mu' t} \right)$ for $t = 1, 2, \dots, T$ and μ,

$\mu' = 1, 2, \ldots, M$.

In a formal sense we now regard equation (1) and (2) as a single-equation regression model and apply Aitken's generalized least – squares (Aitken, 1934). That ism we pre-multiply both side of (2) by a matrix H which is such that $E(Hu'uH') = H\Sigma H' = I$. In terms of transformed variables, the original variables pre-multiplied by H, the system now satisfies the usual assumptons of the least-squares model. Thus application of least-squares will yield as in well-known, a best linea unbiased estimator, which is

$$b^* = (XH'HX)^{-1} XH'HY = (X'\Sigma^{-1}X)^{-1} X'\Sigma^{-1}Y \tag{6}$$

In constructing this estimator, we need the inverse of Σ which is given by:

$$\Sigma^{-1} = Var^{-1}(u) = \begin{bmatrix} \sigma_{11}I & \ldots & \sigma_{11}I \\ \vdots & \ddots & \vdots \\ \sigma_{11}I & \ldots & \sigma_{11}I \end{bmatrix} = \Sigma^{-1} \otimes I \tag{7}$$

Then the Aitken estimator of the coefficient vector, given in equation (6), is

$$b^* = \begin{bmatrix} b_1^* \\ b_2^* \\ \vdots \\ b_M^* \end{bmatrix} = \begin{bmatrix} \sigma_{11}X_1'X_1 & \sigma_{12}X_1'X_2 & \ldots & \sigma_{1M}X_1'X_M \\ \sigma_{21}X_2'X_1 & \sigma_{22}X_2'X_2 & \ldots & \sigma_{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1}X_M'X_1 & \sigma_{M2}X_M'X_2 & \ldots & \sigma_{MM}X_M'X_M \end{bmatrix}^{-1} \times \begin{bmatrix} \sum_{\mu=1}^{M} \sigma_{1\mu}X_1'Y_\mu \\ \vdots \\ \sum_{\mu=1}^{M} \sigma_{M\mu}X_M'Y_\mu \end{bmatrix} \tag{8}$$

And the variance-covariance matrix of the estimator b^* is easily shown to be $(X'\Sigma^{-1}X)^{-1}$ or

$$Var(b^*) = \begin{bmatrix} \sigma_{11}X_1'X_1 & \sigma_{12}X_1'X_2 & \ldots & \sigma_{1M}X_1'X_M \\ \sigma_{21}X_2'X_1 & \sigma_{22}X_2'X_2 & \ldots & \sigma_{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1}X_M'X_1 & \sigma_{M2}X_M'X_2 & \ldots & \sigma_{MM}X_M'X_M \end{bmatrix} \tag{9}$$

The estimator in equation (7) processes all of the usual optimal properties of Aitken estimators; that is, it is best linear unbiased estimator. Further, with an added normality ssumption, it is also a maximum-likelihood estimator. It is to be noted that equation (6) is identical with estimators provided by single-equation matrix, i.e. if $\sigma_{\mu\mu'} = \sigma_{\mu'\mu} = 0$ for $\mu' \neq \mu$. Also, if $X_1 = X_2 = \cdots = X_M$, equation (7) terms in different equations are correlated $\sigma_{\mu'\mu} = 0$, and these are, as is well-known, the same and when the disturbance terms in different equations are correlated, the estimator in (7) will differ from the single-equation least squares estimators.

If Σ is unknown, as it usually is, it is impossible to use (7) and (8) in practice. What we propose to do is to employ as estimate of $\{\sigma_{\mu'\mu}\}$ in constructing the Aitken estimator. This estimate is,

$$(T-l)\Sigma_e = (T-l)\{s_{\mu'\mu}\} = \{\hat{u}_\mu{}'\hat{u}_\mu\} = \left\{\left(Y_\mu - X_\mu\hat{\beta}_\mu\right)'\left(Y_{\mu'} - X_{\mu'}\hat{\beta}_{\mu'}\right)\right\} \tag{10}$$

Where $\hat{\beta}_\mu$ is the usual single-equation least squares estimator. $\left(X_{\mu'}X_\mu\right)^{-1} X_{\mu'}Y_\mu$. Thus equation (10) is an estimate of the disturbance variance-covariance matrix formed from the single-equation least squares residuals. Given that we have the estimate $\{s_{\mu\mu'}\}$, we can obtain by inversion the matrix $\{s^{\mu'\mu}\}$ the elements of which are employed to form the estimator:

$$b^* = \begin{bmatrix} b_1^* \\ b_2^* \\ \vdots \\ b_M^* \end{bmatrix} = \begin{bmatrix} s_{11}X_1'X_1 & s_{12}X_1'X_2 & \cdots & s_{1M}X_1'X_M \\ s_{21}X_2'X_1 & s_{22}X_2'X_2 & \cdots & s_{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ s_{M1}X_M'X_1 & s_{M2}X_M'X_2 & \cdots & s_{MM}X_M'X_M \end{bmatrix}^{-1} \times \begin{bmatrix} \sum_{\mu=1}^{M} s_{1\mu}X_1'Y_\mu \\ \vdots \\ \sum_{\mu=1}^{M} s_{M\mu}X_M'Y_\mu \end{bmatrix} \tag{11}$$

It will be shown that $b = b^* + 0\left(T^{-1}\right)$, that $T^{1/2}\left(b-\beta\right)$ and $T^{1/2}\left(b^*-\beta\right)$ have the same asymptotic normal distribution, and that the moment matrix of b is:

$$Var\left(b^*\right)=\begin{bmatrix} s_{11}X_1'X_1 & s_{12}X_1'X_2 & \cdots & s_{1M}X_1'X_M \\ s_{21}X_2'X_1 & s_{22}X_2'X_2 & \cdots & s_{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ s_{M1}X_M'X_1 & s_{M2}X_M'X_2 & \cdots & s_{MM}X_M'X_M \end{bmatrix}+0\left(T^{-1}\right) \tag{12}$$

Where $0\left(T^{-1}\right)$ denotes a quantity which is of the order T^{-1} in probability and $0\left(T^{-1}\right)$ denotes terms of higher order of smallness than T^{-1}. The statistical software used in carrying out the analysis is STATA Version 15.

3. Result

This study is based on examining the effect of set (2016, 2017 and 2018), Program (Statistics and Operation Research), gender (male and female), age, mode of entry (UTME, DE, and UTME/Pre-degree), Total Credit Unit Register, Number of O-Level Sittings, and Jamb Score to ascertain whether different dependent variable (namely first year CGPA, Final Year CGPA and Total Credit Passed) had an effect on academic performance of students in the Department of Statistic and Operations Research. For this purpose, we adopt a seemingly unrelated regression equations (SURE) model.

Table 1 present the results of SURE Model on different dependent variables (first year CGPA, Final year CGPA and total credit unit passed). Besides fitting these models, the log-likelihood, Alkaline Information Criterion (AIC) and Bayesian Information Criterion (BIC) was employed. The implies that model 2 was selected as the best model that fit in the data with the lowest BIC and AIC. The model 2 examines the effect of set, Program, gender, age, mode of entry, Total Credit Unit Register, Number of O-Level Sittings, and Jamb Score on different dependent variable (namely first year CGPA, Final Year CGPA and Total Credit Passed) had an effect on academic performance of students as shown in the equation below. Model 1 is such that there is variation in the number of explanatory variables per equation while model 2 is such that all equation have the same explanatory variable.

Model 1

$$TCP = 148.6442 + 0.1302NLS - 13.6701ME + 0.2793TCU + 0.8380S - 5.1893P$$

$$First\ Year\ CPGA = 2.4495 + 0.0254G + 0.3557S - 0.0047A - 0..3973ME + 0.0011JS$$

$$Final\ Year\ CPGA = 8.3641 - 0.1936P + 0.0436S - 0.0281G - 0..0252TCU - 0.0012JS$$

Model 2

$$TCP = 189.6531 - 0.2421S - 5.6194P - 0.1335G - 0.1587A - 0.0267ME + 0.0871TCU - 0.8494NLS - 0.0479JS$$

$$First\ Year\ CPGA = 11.1086 + 0.1770S - 0.2599P - 0.0920G - 0.0137A - 0.0176ME - 0.0370TCU - 0.0162NLS - 0.0022JS$$

$$Final\ Year\ CPGA = 11.9991 - 0.0119S - 0.2712P - 0.0884G - 0.0243A - 0.0182ME - 0.0379TCU - 0.0941NLS - 0.0019JS$$

Key:

TCP = Total Credit Passed

NLS = Number of O-Level Sitting

ME = Mode of Entry (UTME, DE and Pre-degree)

TCU = Total Credit Unit

S = Set (2016, 2017 and 2018)

JS = Jamb Score

G = Gender (Male, Female)

A = Age

P = Program (Statistics, Operations Research)

Table 4.3 shows diagnostic statistics for first year CGPA, final year CGPA and total credit unit passed. The value of the R2 for first year CGPA, final year CGPA and total credit unit passed indicates that 55.6%, 60.1% and 96.0% can be explained by variations in selected independent variables of set, Program, gender, age, mode of entry, Total Credit Unit Register, Number of O-Level Sittings, and Jamb Score. Chi-square value for each dependent variable is higher than its critical value suggesting a good overall significance of the estimated model for all three dependent variables. Therefore, fitness of the model is accepted empirically. Observing the mean root square error (RMSE) for SURE model and Multivariate regression analysis. The mean root square of error of SURE model value showing a smaller value which indicated that SURE model is the best model that fit in the data.

Table 4.2: Model Selection Using Log-likelihood, AIC and BIC

Model	AIC	BIC
Model 1=Multivariate Regression	1269.558	1320.894
Model 2= SURE Model	1005.624*	1082.629*

** Best fit model*

Table 4.3: Seemingly Unrelated Regression (SUR) Model Diagnostic Test for the three dependent variables (First year CGPA, Final year CGPA and Total Credit Passed)

Equation	Parameters	R – Square	P-Value	Root Mean Square Error (RMSE)	
				SURE Model	Multivariate Regression
First Year CGPA	8	0.5563	0.000	0.6291	0.6525
Final Year CGPA	8	0.6009	0.000	0.5596	0.5804
Total Credit Passed	8	0.9600	0.000	3.1884	3.3069

An examination of the result shown on Table 4.4 indicates that the programs had significant effect at 5% on the academic performance of students on their first year CGPA, final year CGPA and total credit passed. This implies that during the period covered in the institution, program to first year CGPA, final year CGPA and total credit passed exerted significant impact on the academic performance of the students. However, set does not have any significant impact on final year CGPA and total credit passed but had significant effect on the first year CGPA of the student.

Also, age had no significant effect on first year CGPA and final year CGPA but had significant impact on the total credit passed. The result indicated that total credit unit registered had significant effect on the academic performance of student at first year CGPA, final year CGPA and total credit unit passed. From the result obtained Jamb score had higher significant effect on the academic performance at the first year CGPA, final year CGPA and total credit passed. However, as can be observed from the result on the Table 4.4, gender, model of entry, number of O-level sittings do not exert any significant effect on first year CGPA, final year CGPA and total credit passed. The coefficient of gender and number of O-level sittings appeared with wrong sign (negative) in all the dependent variables although not significant implying that it does not play any significant role on the academic performance of students.

Table 4.4: Seemingly Unrelated Regression (SUR) Model for first year CGPA, Final year CGPA and Total Credit Passed on set, program, genderm age, mode of entry, total credit unit, number of O-level sittings and jamb score.

Dependent Variable	Independent Variables	Coefficient	Standard Error	Z	P-Value
First Year CGPA	Constant	11.1086	0.8610	12.90	0.000
	Set	0.1770	0.0768	2.31	0.021*
	Program	-0.2599	0.1212	-2.14	0.032*
	Gender	-0.0920	0.1641	-0.56	0.575
	Age	-0.0137	0.0153	-0.89	0.372
	Mode of Entry	0.0176	0.1839	0.10	0.924
	Total Credit Unit	-0.0370	0.0033	-11.05	0.000*
	Number of O-Level Sittings	-0.0162	0.1155	-0.14	0.888
	Jamb Score	-0.0022	0.0004	-4.49	0.000*
Final Year CGPA	Constant	11.9991	0.7660	15.66	0.000
	Set	-0.1191	0.0683	-0.17	0.862
	Program	-0.2712	0.1078	-2.51	0.012*
	Gender	-0.0884	0.1460	-0.61	0.545
	Age	-0.0243	0.0136	-1.78	0.075
	Mode of Entry	-0.0182	0.1636	-0.11	0.911
	Total Credit Unit	-0.0379	0.0029	-12.72	0.000*
	Number of O-Level Sittings	-0.0941	0.1028	-0.92	0.360
	Jamb Score	-0.0019	0.0004	-4.48	0.000*
Total Credit Passed	Constant	189.6531	4.3641	43.46	0.000
	Set	-0.2421	0.3892	-0.62	0.534
	Program	-5.6194	0.6145	-9.14	0.000*
	Gender	-0.1335	0.8320	-0.16	0.872
	Age	-0.1587	0.0779	-2.04	0.042*

	Mode of Entry	-0.0267	0.9323	-0.03	0.977
	Total Credit Unit	0.0894	0.0170	5.12	0.000*
	Number of O-Level Sittings	-0.8494	0.5856	-1.45	0.147
	Jamb Score	-0.0479	0.0025	-19.02	0.000*

4. Discussion of Findings

This study uses Seemingly Unrelated Regression Model (SURE) to investigate effect of set, program, gender, age, mode of entry, total credit unit, number of O-Level sittings, Jamb Score on first year CGPA, final year CGPA and total credit passed. Jamb score were identified as a significant effect of academic performance of student both at first year CGPA, final year CGPA and total credit passed. From the above results, it is clearly seen that University Matriculation Examination (UME) served as a good predictor of the students' performance in their first year results. The result was in line with Omole (1997), who discovered that UME was one of the good predictors of students' performance in the university. In the same vein, Ojerinde and Kolo (2009) discovered that there was a positive relationship between UME and students' First Year Grade Point Average. Also, JAMB examinations could be seen as a standardized examination which is subjected to various levels of judgement to improve its reliability, usability and validity. Equally, the UME is an achievement test in orientation. The finding is also in agreement with that of Ukwuije and Asuk (2011) who reported that UME scores contributed to the students' academic achievements of students in the tertiary institution. The finding of this study agrees with that Omodara (2010) which also reported positive relationships between UME scores and students' academic achievements in the universities. Based on the result age were found as a significant effect on the academic performance of student in the tertiary institution. This result is in line with the finding of Pence and Thornberg (2006) which shows that there exists a positive relationship between age and academic performance while in the finding Kaur, Chung and Lee (2010) found that age does not significantly contribute to academic performance of university students in distance learning. In this study gender were found not significant at the first year CGPA, final year CGPA and total credit passed. This study is in agreement with Borde (1998) which showed that gender did not play a role in academic performance. Another study by Meece and Jones (1996) also revealed that gender differences did not influence students' standardized science test scores.

5. Conclusion

This study successfully employed the Seemingly Unrelated Regression Equations (SURE) model to examine academic performance determinants among students in the Department of Statistics and Operations Research at Modibbo Adama University of Technology, Yola. The research findings demonstrate that the SURE model provides superior analytical capabilities compared to traditional multivariate regression approaches, as evidenced by lower root mean square error values and enhanced model fit statistics. The investigation revealed that JAMB scores constitute the most critical predictor of academic success across all performance dimensions, including first year CGPA, final year CGPA, and total credit units passed.

The study's findings underscore several key insights with significant implications for educational policy and practice. The consistent significance of JAMB scores across all academic performance measures reinforces the examination's role as a reliable predictor of university success. The significant impact of program type on academic performance suggests that disciplinary differences play a crucial role in student outcomes, necessitating program-specific support mechanisms. Additionally, the age effect on total credit units passed indicates that student maturity and life experience may influence academic progression patterns.

Based on these findings, the Federal Government should strengthen support for JAMB by investing in examination quality improvement initiatives and maintaining examination integrity. Universities should prioritize JAMB scores in admission criteria while implementing supplementary assessment mechanisms to capture non-cognitive factors contributing to academic success. Institutions should develop age-sensitive academic advising programs that recognize diverse student needs across different age groups. Furthermore, universities should establish early warning systems utilizing JAMB scores and other significant predictors to identify at-risk students and provide timely interventions. The successful application of the SURE model demonstrates its potential for broader adoption in institutional research, enabling evidence-based decision making in academic policy development and ultimately contributing to enhanced higher education quality in Nigeria.

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