INVESTIGATING THE PREDICTIVE EFFECT OF ADMISSION CRITERIA ON STUDENT ACADEMIC PERFORMANCE IN NIGERIA: USING A LOGIT MODEL

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ABSTRACT

This study aims at investigating the effects of and the predictive capability of admission criteria on students' academic performances in higher institutions. For this, data on results and student's demographic characteristics were collected from the department of Economics, FCE Zaria, Nigeria. In order to capture plausible relationships and deterministic effects between the variables used, the study employed the use of a binary dependent model (logit model). The results from the model estimated showed consistency in the adequacy of the current admission criteria. It also espoused the need for emphasis on UME results rather than WASSCE or NECO results which should be interpreted with caution. Demographic characteristics of students showed better performances from students below 22 years old, feminine and are from the southern region of the country. Thus it was recommended that, the current admission criteria should be maintained as it adequately predicts students' academic performances in higher institutions, but caution should be used when interpreting WASSCE and NECO results of students.

Key Words: *Academic Performance, Academic Criteria, Probability Model*

Introduction

Over the years there has been an increased clamour in developing economies to increase student enrolment in schools, especially with regards to the girl child. This is mainly due to the recognition of qualitative education as one of the major drivers of development and growth. Thus the objective of increasing the literacy level within these economies has been eschewed as one of the millennium development goals and proactively pursued. Respective governments continually allocate vast amount of revenues and resources to programs that will aid in achieving this objective (Salahdeen and Murtala, 2005).

Despite the recorded success in enrolment, the expected level of education outcomes in Nigeria is on the decline. There is evidence to show that student's performances in the senior secondary certificate examination have been on the decline (Adeniyi et al, 2010). Even more worrisome, this exam serves as criteria for continuation of studies in any higher institution in the country. In Nigeria, a student is expected to have a credit score in at least mathematics and English as well as performing within the range of 180-400 in the Universal Matriculation Examination's (UME's) joint administration and matriculation board's exam (JAMB) before getting admitted into an institution of higher learning.

After concluding senior secondary school, students are expected to proceed to institutions of higher learning. The caveat here is that, there are requirements that the students have to fulfil before they are given admission into these institutions of higher learning. The crux of the paper borders on the predictive effects these requirements have on students' academic performance. The postulate is that, for a student to have successfully fulfilled all academic criteria for admission into an institution of higher learning, they must have gained the requisite knowledge, psychology and maturity to perform well in a higher institution. Intuitively, a student who can pass mathematics in the SSCE examination and get a high score in JAMB, all things being equal, will also perform when faced with mathematics in the institution of higher learning. This also follows if the case is reversed for students who do not perform well in the requisite examination. This inkling is based on the realistic premise that the curriculum being tested in the examinations for entry into the higher institutions are closely similar, in content and behavioural expectations, to the curriculum being tested in students first year examinations.

When the number of applicants exceeds the capacity of postsecondary institutions, it must be decided which students are more qualified and most likely to succeed in these institutions. Selection criteria vary from one institution to another and from one country to another, and deciding which criteria are most accurate in predicting academic success in postsecondary institutions is a complex task. Cognitive factors (e.g., JAMB, WASSCE scores), noncognitive factors (e.g., personality traits), and demographic characteristics (e.g., gender, ethnicity, location) are major criteria for the admission decisions in most of the postsecondary institutions around the world.

Nevertheless, future academic success has, traditionally, been predicted from cognitive factors used as the sole criteria of academic success (Pentages and Creedon, 1978). There is already an extensive literature on the type of quantitative and qualitative information that should be used in enrolling students and have come up with consistent set of indicators (King et al 1993). However these indicators are not absolute even though they provide a rule of thumb as a guide for enrolling students in higher institutions. As already indicated, normatively, there should be a direct relationship between students' performances and quality with regards to enrolment into academic institutions and their respective performances and quality in their first year in post-secondary academic institutions.

Empirical studies on academic performances of students in their first year, has shown a disparity from the normative. There were evidences of students who performed above the requisite for enrolment into post-secondary academic institutions, failing in their first year exams (Fleming, 2002; Hoffman, 2002). This has increased the call for admission policies that are not static and dogmatic but reflect the diverse nature of each student. Even though this disparity form the norm can not only be attributed to a flaw in admission criteria, there is a need for further research into the adequateness and the potential for costs saving on admission criteria in enrolling students who will be successful in their post-secondary academic pursuit. The adequateness being inferred to represents the ability of enrolment criteria to select students from the pool, who will successfully meet all requirements of the academic program they are being enrolled into in their respective academic institutions. This adequateness is captured by the predictive ability of the admission criteria in determining students who will be successful in post-secondary academic institutions.

There are costs to both universities and students when student enrolment lacks consistency. If well qualified students are refused admission due to under-estimation of their academic ability, universities are certainly worse off because of the resulting loss of fee income. Indirect social and political costs may also be among the undesirable consequences. On the other hand, students who are not sufficiently qualified but are admitted when their qualifications are over-estimated, risk investing time and considerable financial resources in a programme for which they may be unsuitable and from which they may not reap the opportunities for personal and professional growth they seek to achieve.

In the course of this paper, the following questions will be answered by the findings of the study;

1. Are there any relationships between Academic criteria and Students Academic performances?
2. Do admission criteria predict students' academic performances?
3. Where necessary, what potential improvements exist for academic criteria for higher institutions?

The aim of this paper is not to address the reasons for falling academic outcomes, but to investigate the effect of admission criteria based on academic performance in Senior Secondary Certificate Examination on student's performances when they enrol in a higher institution. Hence, the paper aims to highlight any influence admission criteria can have in academic performances of students when they enrol in a higher institution.

Research Objectives

The following objectives represent the core of the study:

1. Highlight qualitative and quantitative information necessary for adequate academic criteria for higher education academic institutions.
2. Propose possible relationships between Academic criteria and student academic performances using the case study of the research.
3. Espouse for potential improvements in admission criteria into higher educational institutions.
4. Determining the predictive ability of admission criteria on academic performances.

At the conclusion of the study, the postulates provided will give an insight into the relevance and need for a well-structured criteria for student enrolment into higher education institution.

Not limited to relevance, the study will provide a platform from which the curriculum for first year students can be tailored to meet expected behavioural and psychological outcomes given already known performances from academic criteria. Thirdly, for futuristic planning purposes, the findings of the study will provide education stakeholders a guide for curriculum implementation and development. It will guide admissions personnel and decision-makers at the Ministry of Education and other stakeholders in identifying whether WASSCE results are accurate predictors of academic performance of students attending higher education institutions. It might help them in the development of future admission plans and student retention programs.

In carrying out this research, the study limits the scope of our sample size to academic performances of students of the department of economics, Federal College of Education, Zaria, Nigeria. The results to be used comprise the first year results of the current NCE 1, NCE 2, NCE 3 and PRE NCE students. The inclusion of PRE NCE students is for robustness of the study. However, the methodology and findings of this study ensure broad applicability. Also, for the purpose of the research, we will be limiting the study to the use of WASSCE, NECO and UME results. There has been a change over the years on the cut off pass mark that represents success in UME examinations. In 2009 the pass mark was 160 and further reviewed upwards to 180 in 2011. These changes in cut off can affect the reliability and stability of statistical inferences based on the methodology that will be used in the study. To curb this, the study uses an ad hoc cut off marks of 190 and 200 by setting dummy variables for these marks. This will provide a basis for analysis with regards to performance of students below 190, which captures both cut offs of 160 and 180.

Review of Literature

In various educational systems all over the world, conscious efforts are being made to provide quality and quantitative information on intellectual capacity of students for various purposes including enrolment into the next cadre in academic pursuit. In Nigeria, primary school pupils are made to take the National Common Entrance Examinations for enrolment into secondary schools. Similarly, at the conclusion of their secondary education, they are made to take the Senior Secondary Certificate Examination comprising of the West African Senior Secondary Examination (WASSCE) or the National Examination Council (NECO). In addition to these examinations, students also take the Universities Matriculation Examination (UME) of the Joint Admission and Matriculation Board (JAMB), for admission into universities, polytechnics and colleges of education.

In addition to certification of students, a major function of examinations such as WASSCE, NECO and JAMB is to serves as a form of information base from which universities can assess the capacity of prospective students and serve as an entry requirement for admission into educational institutions for advanced studies. Hence the purpose of this research is necessitated on the premise that these entry examinations are adequate and costless in the process of enrolling students into these institutions

In psychometrics, criterion validity refers to a measure of how well one variable or set of variables predicts an outcome based on information from other variables (McDonald, 1999). The gist of criterion validity is to determine the extent to which a test or score can predict future performances or behaviour of an individual. This type of validity is often divided into "concurrent" and "predictive" sub-types of validity. Of paramount importance to this study is the predictive validity. Predictive validity refers to the extent to which any measure can predict future or independent events. These variables are often represented as “intermediate” and “ultimate” criteria. Essentially, the grades students received in high-school math can be used to predict their success in college. Literature shows that research on future academic success can be assessed by two types of predictor variables, namely cognitive and noncognitive predictors. Cognitive predictors refer to the standardized entrance tests such as the JAMB, WASSCE, and NECO. Noncognitive predictors refer to two main attributes: personality characteristics, such as self-motivation, self-directedness, dedication to studies, and social skills; and environment factors, such as size of schools, location of schools, parental education, and socioeconomic status (Klugh and Bierly, 1959; Misanchuk, 1977; Himelstein, 1965; Wolfe and Johnson, 1995; Johnson, 2002; Mulvenon et al., 2002; Barnett et a.,l 2003).

Vast literature already shows that high school grade point averages and standardized test scores, such as the SAT or ACT, are generally significant predictors of student success during their undergraduate studies (Astin et al., 1987; Noble, 1991; Moffat, 1993; Bridgeman et al., 2000; Snyder et al., 2003; Kim, 2002; Kuncel et al., 2004; Ramist et al, 1994; Waugh et al., 1994; Wolfe and Johnson, 1995; Kuncel et al., 2005; Kuncel et al., 2007). However, a substantial bulk of literature suggests that high school GPA more accurately predicts academic success in college than standardized tests or any other factor (Munro, 1981; Lawlor et al., 1997; Peltier et al., 1999; Snyder et al., 2003; Camara and Echternacht, 2000; Tross et al., 2000; Fleming and Garcia, 1998; Fleming, 2002; Hoffman, 2002; Zheng et al., 2002; Gose, 1994). The use of such indicators as a source of information for admitting students into institutions of higher raises the question about their validity in predicting future academic success. The question of sufficiency and adequateness of these indicators in predicting future academic success should be investigated in order to ensure fair admission decisions.

There has been much research already conducted to determine which would be more accurate predictors of future academic success in postsecondary institutions. Some researchers favour cognitive predictors (Noble, 1991; Baird, 1984; Bridgeman et al., 2000; Kuncel et al., 2005; Kuncel et al., 2001; Kuncel et al., 2007), Whereas, other notable scholars favour using noncognitive variables (Pentages and Creedon, 1978; Duran, 1986; Tracey and Sedlacek, 1984; Sedlacek, 2004). Micceri (2001) in his research paper noted that cognitive predictors like high school GPA and standardized test scores are better predictors when other variables such as race, ethnicity, and gender are included because they provide some additional information. Aldeman (1999) was able to show that high school GPA predicted future academic success better than other factors such as the demographic variables of race, gender, or socioeconomic status.

Research Methodology

The study will deviate from the norm with respect to methodology being used in conducting predictive studies. Correlation analysis has been widely used to determine the predictive capability of academic enrolment examinations on post- secondary academic performances. For this research, the statistical method of Limited Dependent Variables (LDV) will be used to espouse possible predictive power of pre-secondary enrolment examinations on post-secondary academic performances in the department of economics, Federal College of Education. The population of the research comprises the results of students from the department of economics, FCE Zaria, Nigeria. These results include both WASSCE or NECO and all results from their program with the department.

From the population, the study focuses on the first year academic performances of students enrolled in the department of economics, FCE Zaria, Nigeria. The intuition for this sample size is based on the need to espouse the predictive capability of WASSCE or NECO in determining students' academic performances at the department of economics. Thus the sample to be used comprises the NCE 1 results of the current NCE1 students, NCE2 students and NCE 3 students. The inclusion of PRE-NCE results will ensure robustness of our inferences.

Limited Dependent Variables

In conventional econometric analysis, the inclusion of dummy variables in capturing qualitative information that is essential to making inferences have been well documented. Dummy variables are normally included in the econometric function to be estimated as one of the independent variables. In using Limited Dependent Variables (LDVs), these dummy variables do not appear as independent variables but as dependent variables in the econometric function. It becomes obvious that the form in which LDVs dependent variables will appear in the form of a 0 – 1 dummy variable, implying that the dependent variables are binary dependent. LDVs are not treated as the conventional econometric techniques. Care has to be taken in interpreting them.

In dealing with dependent variables that are in binary form, the Linear Probability Models (LPMs) are by far the easiest way of dealing with binary dependent variables. The model is based on the probability of an event occurring, Pi is linearly related to a set of explanatory variables X_1. X_2 $X_3 \ldots X_N$

$$P_i = P\,(y_i = 1) = \beta_1 + \beta_2 X_i + \mu_i,\ I = 1, \ldots, N \quad (1)$$[1]

The actual probabilities cannot be observed, so a model is estimated where the outcomes, yi(the series of zeros and ones), would be the dependent variable. This then represents a linear regression model and will be estimated by Ordinary Least Square (OLS) or maximum

[1] β_1 and β_2 represent coefficients to be estimated, X_i is a vector of all possible quantitative and dummy variables+ μ_i is a stochastic random error term.

likelihood estimation. The set of explanatory variables Xi can include quantitative as well as dummy variables or both.

The fitted values from this regression are the estimated probabilities for $y_i = 1$ for each observation *i*. The slope estimates for the linear probability model can be interpreted as the change in the probability that the dependent variable will equal 1 for a one-unit change in a given explanatory variable, holding the effect of all other explanatory variables fixed.
The major problem with LPMs is that there is the possibility of having interpretation problems arising from probability figures that are greater than 1. To curb this problem logit and probit model approaches are able to overcome the limitation of the LPM that it can produce estimated probabilities that are negative or greater than one. They do this by using a function that effectively transforms the regression model so that the fitted values are bounded within the (0,1) interval. For this study, logit models will be used to capture expected relationships.

In a quick overview, logit models are a type of regression used to analyse binomial response variables. It transforms the sigmoid dose-response curve2 to a straight line that can then be analysed by regression through maximum likelihood (Brooks, 2008). logit analysis can be conducted by one of three techniques:

1. Using tables to estimate the logits and fitting the relationship by eye,
2. Hand calculating the logits, regression coefficient, and confidence intervals, or
3. Having a statistical package such as Eviews do it all for you.

Assuming a dependent variable Y is binary, that is, it can take on either 0 or 1. For example, in predictive studies Y can take on the value of 1 to represents the presence of failure in first year examination in post-secondary academic institutions or 0 for students that passed. There will also be a vector of other variables X, which are assumed to influence the outcome of the occurrences in Y. For the purpose of this research, X will include WASSCE or NECO results, and other relevant demographic characterisation that can influence students pass rate or fail rate in their first year in the post-secondary academic institutions. The general form of the logit model is of the form;

$$\Pr(Y = 1 | X) = \Phi(X'\beta) \qquad (2)$$

Where Pr denotes probability, and Φ is the Cumulative Logistic Function (CLF) of the standard normal distribution. The parameters β are typically estimated by maximum likelihood. The logit model can be written as a latent variable model as long as there exist the assumption of an auxiliary random variable;

$$Y^* = X'\beta + \square \qquad (3)$$

[2] A dose–response curve is a simple X–Y graph relating the magnitude of a stressor (e.g. concentration of a pollutant, amount of a drug, temperature, intensity of radiation) to the response of the receptor (e.g. organism under study)

Where □ ~ *N* (0, 1). Then *Y* can be viewed as an indicator for whether this latent variable is positive:

$$Y = \begin{cases} 1 \ if \ Y^* > 0 \ i.e -\epsilon < X'\beta \\ 0 \ otherwise \end{cases} \quad (4)$$

Using the cumulative logistic function Φ (.) to transform the logitit equation ensures that the fitted probabilities of the logit model lies between 0 and 1. Transforming equation (2) with the CLF, Φ (.), provides the specific form of logit model for any random variable Y;

$$f(Y_i) = e^{yi} / 1 + e^{yi} \quad (5)$$

This can be futher elaborated to:

$$f(Y_i) = 1 / 1 + e^{-yi} \quad (6)$$

Note that e represents the exponential in the logit function. The model that will be estimated is a derivative of (6) and will be in the form of;

$$Pi = 1 / 1 + e^{-(\beta1+ \beta2X2i+\ldots+ \beta kXki + \mu)} \quad (7)$$

Where P_i is the probability that the random variable is Y=1. As Yi tends to infinity, e^{-yi} tends to zero and $1/(1 + e^{-yi})$ tends to 1; as Yi tends to minus infinity, e^{-yi} tends to infinity and $1/(1 + e^{-yi})$ tends to 0.

Standard errors and t-ratios can be easily perused from the statistical software used for estimation and hypothesis testing can also be carried out. However, interpretation of the coefficients need slight care. It is tempting, but incorrect, to state that a 1-unit increase in x2i , for example, causes a β2% increase in the probability that the outcome corresponding to yi = 1 will be realised. This would have been the correct interpretation for the linear probability model. However, for logit models, this interpretation would be incorrect because the form of the function is not $P_i = {}_{\beta i} + \beta 2x_i + \mu_i$, for example, but rather Pi = F (X_{2i}), where F represents the (non-linear) logistic function. To obtain the required relationship between changes in X_{2i} and P_i, we would need to differentiate F with respect to X_{2i} and it turns out that this derivative is $\beta_2 F$ (X_{2i}). So in fact, a 1-unit increase in X_{2i} will cause a $\beta_2 F$ (X_{2i}) increase in probability. Usually, these impacts of incremental changes in an Explanatory variable are evaluated by setting each of them to their mean values. These calculated figures are referred to as the marginal effects and are used for making inferences.

For the purpose of this study, a logit model will be used to elicit predictive ability of WASSCE OR NECO results in predicting the academic performances of students in their first year at the department of economics, FCE Zaria. The logit model to be specified will capture the probability of a student not achieving a pass mark at the first attempt:

$$Pr\ (fail) = \Phi\ (\mu,\ D'_s\ d,\ R'_s\ r,\ Y'_s\ y) \quad (8)$$

Where Pr(fail) is our binary dependent variable which captures the probability of a student failing in his first year. This probability will be captured with two variables in the study's analysis: ECO_FAIL and CO, where ECO_FAIL is a dummy variable with 1 representing students who failed the economics course in their first year and 0 for otherwise. CO representing students who have had a carried over course i.e. students with at least one failed course and is represented by the dummy variable CO with 1 representing students with a carryover course and 0 for otherwise. The use of these two variables in capturing students' academic performance in their first year is intuitive. Given the case study of the economics department and the relative similarities between first year course work and entrance / academic enrolment examinations, both variables adequately capture necessary success or failure rates in students' first year. Φ represents the cumulative logistic function that ensures the model's probabilities remain within the band of 0 and 1.

D'_s is a vector of a set of demographic variables relating to students. These demographics include gender, age and state of origin for the students. The students gender is captured with a dummy variable SEX with 1 representing a female student and 0 otherwise, the students ages is also captured by a dummy variable AGE with 1 representing students 22 and below and 0 otherwise, and the students state of origin is captured by a dummy variable LOC with 1 representing students from the northern part of the country and 0 for otherwise. R'_s is a vector of results to be used to predict probability of student's pass or fail rates. The results to be used are WASSCE or NECO and Jamb results of the students. The minimum requirement is 5 credits in WASSCE or NECO for admission into higher institutions. Thus, dummy variables were created for students who got below that minimum and also for those above the minimum. Dummy variables FOUR_C, SIX_C, and SEVEN_C were created to capture students who fall within any of these categories with 1 representing any students in these sets and 0 for otherwise. The minimum criteria five credits will be used as the reference point for analysis. Also, JAMB requirements are also used for admission processes. Thus, the study uses a dummy variable JAMB1 to represent students who scored above 190 in jamb. The minimum criterion for admission is 180. JAMB1 is a dummy variable that takes the value 1 for students who scored 190 and below in the UME examinations and o for otherwise. Y'_s represent time dummy for our sample period. D_Yr10 is the time dummy representing year 2010 with the value of 1 and 0 for any other year. The essence for this time dummy variable is to capture any form of discrepancies other than the effect of WASSCE and NECO on student performances. Such Discrepancies can include; mode of teaching and changes to tutors of the course.
Thus the study will estimate the following econometric equations;

$$\text{ECO\_FAIL} = \alpha_1 + \alpha_2\,\text{AGE} + \alpha_3\,\text{D\_Yr10} + \alpha_4\,\text{FOUR\_C} + \alpha_5\,\text{JAMB1} + \alpha_6\,\text{LOC} + \alpha_7\,\text{SEX} + \alpha_8\,\text{SIX\_C} + \alpha_9\,\text{SEVEN\_C} + \mu \quad (9)$$

$$\text{CO} = \alpha_1 + \alpha_2\,\text{AGE} + \alpha_3\,\text{D\_Yr10} + \alpha_4\,\text{FOUR\_C} + \alpha_5\,\text{JAMB1} + \alpha_6\,\text{LOC} + \alpha_7\,\text{SEX} + \alpha_8\,\text{SIX\_C} + \alpha_9\,\text{SEVEN\_C} + \mu \quad (10)$$

Due to the non-linearity of our model, the computed coefficients cannot be used for interpretation as done in a linear model. The study computes marginal effects on the probability of failure (see equation 7), using the means of each vector of explanatory variable used in the logit model.

Results and Discussions

As already indicated, estimating equations 9 and 10 by a binary dependent model, provides an avenue to capture the predictive capability, in probabilities, of academic criteria on students' first year performances in higher institutions. The binary dependent model used for the analysis is the logit model. Due to its non-linearity, the logit model cannot be interpreted through the conventional methods as espoused in basic econometric analysis. Thus, marginal effects have to be calculated and used as the means of interpreting our findings. To provide clear and concise analysis, the study provides, in this section, correlation analysis between variables being used as well further adequacy tests of the model used.

Using the logit Binary dependent model as specified in equation 9 and 10, tables 1 and 2 show estimation results of the econometric model estimated. First equation 9 is estimated with the following results in table 1.

Dependent Variable: ECO_FAIL

Pr(ECO_FAIL = 1)

Variable (1)	Coefficient (2)	Standard error (3)	Mean (4)	Marginal effects (5)	Probability (6)
AGE	-0.200998	0.321784	0.585761	-0.17	0.5322
D_YR10	-1.341800	0.453534	0.265372	-1.16*	0.0031
FOUR_C	-0.135821	0.502771	0.106796	-0.12	0.7870
JAMB1	1.743185	0.401808	0.585761	1.51*	0.0000
LOC	0.924632	0.579756	0.831715	0.80	0.1107
SEX	-0.880058	0.345866	0.446602	-0.76**	0.0109
SIX_C	1.165301	0.461565	0.527508	1.01**	0.0116
SEVEN_C	-0.385284	0.526462	0.754045	-0.33	0.4643
C	-3.096309*	0.748942	1		0.0000

Table 1: results of estimated model with dependent variable ECO_FAIL showing the coefficients, standard errors, mean of each variable, marginal effects and probabilities. *, **, *** show significance levels at 1%, 5% and 10% respectively.

To arrive at the results in table 3, the following equation was estimated using a logit model;

ECO_FAIL = $\alpha_1 + \alpha_2$ AGE + α_3 D_Yr10 + α_4 FOUR_C + α_5 JAMB1 + α_6 LOC + α_7 SEX + α_8 SIX_C + α_9 SEVEN_C + μ

Out of the eight variables, four of these variables were statistically significant, D_YR10 and JAMB1 at 1% and SEX and SIX_C at 5%. Also, as already stated, the logit model is a non-linear model and the interpretations of the estimated coefficients cannot be used in their raw form. The marginal effects were thus calculated in order to take care of the non-linearity problem true the logistic cumulative function. To do this, equation (7) becomes the reference point.

Having already estimated the logit model, we substitute the values of the coefficients into the equation:

$$Pi = 1 / 1 + e^{-(\beta 1+ \beta 2X2i+\ldots+ \beta kXki + \mu)}$$ [3]

Expanding this equation to fit our estimated equation;

$$Pr\ (ECO\_FAIL) = 1 / 1 + e^{-(\alpha 1 + \alpha 2\ AGE + \alpha 3\ D\_Yr10 + \alpha 4\ FOUR\_C + \alpha 5\ JAMB1 + \alpha 6\ LOC + \alpha 7\ SEX + \alpha 8\ SIX\_C + \alpha 9\ SEVEN\_C + \mu)} \quad (11)$$

Thus to arrive at the marginal effects, substitute the estimated coefficients into equation (11) and multiply these coefficients by their individual means, i.e.

$$Marginal\ Effects = 1 / 1 + e^{-(-3.09 + - (0.20*0.59)\ AGE + (-1.34*0.26)\ D\_Yr10 + (- 0.14*0.11)\ FOUR\_C + (1.74*0.59)\ JAMB1 + (0.92*0.83)\ LOC + (-0.88*0.44)\ SEX + (1.17*0.53)\ SIX\_C + (-0.38*0.75)\ SEVEN\_C + \mu)}$$

Having calculated the marginal effects, to explain each variables individual's effect on the dependent variable, we multiply the calculated marginal effect by the estimated coefficient to arrive at column (5) in table 3. With column 3, the basic interpretations and intuitions of econometric coefficients can now be used. From the four significant variables, JAMB1 has a positive and statistically significant marginal effect of 1.51. The JAMB1 variable is a dummy variable with 1 representing students with a UME score of 190 and below. From the estimation results, it follows that students with a UME score below 190 are more likely to fail economics in their first year. Whereas the students who scored above 190 in UME examinations were more likely to pass economics in their first year. The likelihood of this occurrence is above 100%. In fact, the postulate is that, students who score above 190 in UME will definitely pass economics in their first year, all things being equal. This reflects on the adequacy of UME marks as a reliable source of admission information that can ensure efficient admission process.

Also, the SEX variable from the estimation is statistically significant with a negative sign. The SEX variable is a dummy with 1 representing female students and 0 otherwise. Thus, from the estimated marginal effects, female students are less likely to fail economics in their first year compared to male students. The likelihood of this occurrence is 76%. This is a very high occurrence, indicating that female students had a higher probability compare to male students to pass economics in their first year studies. Thirdly, dummy variables were created to capture the relationships between WASSCE and NECO results and students performances in first year economics. The dummy variables were: FOUR_C, SIX_C, and SEVEN_C, representing students with four credits and below, six credits and below and seven credits and below respectively. Students with five credits and below were not included in the dummy

[3] This equation is the same as equation 7 and it is used to calculate the marginal effects of each coefficient.

variables so as to prevent the problem of a dummy trap. Out of the three dummy variables used for capturing WASSCE and NECO, only FOUR_C and SIX_C were statistically significant at the 5% level but both had different signs. SIX_C dummy variable had a positive sign indicating that students with six credits and below were more likely to fail economics in their first year studies. Whereas, the FOUR_C dummy variable had a negative sign, indicating that students with four credits and below were more likely to pass economics in their first year than students with 5 credits.

This finding is paradoxical and puzzling. Intuitively, one will expect better performances from students who had well above the required minimum qualification (5 credits) as compared to those students who fall below the minimum. A few possible reasons can be put forward for this. It is possible that students who had below the minimum criteria for WASSCE and NECO , consciously decided to engage and dedicate more resources to their study as soon as they got into the institution of higher learning. It's also possible that improvement in academic performances were due to influences from their new lecturers and lecturing techniques, new peers and friends or possibly form the sheer amount of work needed in institutions of higher learning Another possibility for this ironic result is in the difference in grades. Students who had four credits and below in WASSCE and NECO had similar grades in individual subjects as compared with the students with six credits and below. The extra two credit differences between these two sub groups were always in subjects that were not of primary importance to economics as a field of study; Christian religious studies, Arabic, Hausa, Igbo, Islamic Studies, Yoruba.

Another important variable to consider is the location variable, LOC. The variable LOC is a dummy variable with 1 representing students who are from the northern part of the country and 0 for otherwise[4]. The location dummy variable, from the estimation results, is positive and marginally insignificant. Thus all inferences from this variable will be made with an 11% significance level. The results indicate that students from the northern part of the country are 80% more likely to fail economics in their first year as compared to students from the south, all things being equal.

Dummy variable D_YR10 was created to capture any possible difference between the two years from which the sample was drawn form. D_YR10 captures all data from year 2010 and is represented by 1 and the other year (2011) is captured by 0. From the estimation results, D_YR10 is statistically significant and negative. The negative sign shows that students who enrolled in 2010 were more likely to perform better than students who enrolled in 2011. The possible reason for this bias can stem from changes in teaching techniques, changes in teachers and the possibility of the uniqueness of our sample.

[4] The Northern part of the country includes all states in the North east, North central, and North west of Nigeria. The southern part of the country includes all states in the South west, South south and South east.

For robustness, the dependent variable used in the previous estimation will be changed. The new dependent variable will include students who failed economics in their first year and / or another course in their first year. This binary dependent variable will be called CO.

Therefore, the following econometric model will be estimated using the binary dependent logit model;

$$CO = \alpha_1 + \alpha_2 AGE + \alpha_3 D\_Yr10 + \alpha_4 FOUR\_C + \alpha_5 JAMB1 + \alpha_6 LOC + \alpha_7 SEX + \alpha_8 SIX\_C + \alpha_9 SEVEN\_C + \mu$$

The estimation results of the model are reported in Table 2.

Dependent Variable: CO

Pr(CO = 1)

Variable (1)	Coefficient (2)	Standard error (3)	Mean (4)	Marginal effects (5)	Probability (6)
AGE	-0.408300	0.269074	0.585761	-0.28	0.1292
D_YR10	-0.062774	0.303450	0.265372	-0.04	0.8361
FOUR_C	-0.190492	0.437992	0.106796	-0.3	0.6636
JAMB1	1.430992	0.290886	0.585761	0.84*	0.0000
LOC	0.973417	0.433983	0.831715	0.66**	0.0249
SEX	-0.774249	0.278670	0.446602	-0.53*	0.0055
SIX_C	0.714926	0.352153	0.527508	0.48**	0.0423
SEVEN_C	0.024472	0.400741	0.754045	0.01	0.9513
C	-2.209142*	0.565532	1.000000		0.0001

Table 2: results of estimated model with dependent variable CO showing the coefficients, standard errors, mean of each variable, marginal effects and probabilities. *, **, *** show significance levels at 1%, 5% and 10% respectively.

Contents of Table 4 are very similar to those of table 3. The same logit model was used to estimate coefficients of the variables and the marginal effects were measured in the same manner. The only difference is in the definition of the dependent variable used. Instead of using only students who failed economics in their first year, the definition was broadened to include failure by students in any course in their first year studies.

The results from this robust estimation are similar to those from the initial model. JAMB1, LOC, SEX and SIX_C were the significant variables. Unlike the initial model D_YR10 dummy variable was statistically insignificant in this model. A representation of the marginal effects of these two models and how they affect the dependent variables are presented in table 3. It becomes clear that both models are consistent with their postulates on how each independent variable can predict student’s performances; however defined.

Model Comparison

DEPENDENT VARIABLE	ECO_FAIL	CO
AGE	-0.17	-0.28
D_YR10	-1.16*	-0.04
FOUR_C	-0.12	-0.3
JAMB1	1.51*	0.84*
LOC	0.80	0.66**
SEX	-0.76**	-0.53*
SIX_C	1.01**	0.48**
SEVEN_C	-0.33	0.01

Table 3: The marginal effects of the independent variables are presented in this table. It is clear that the signs of the marginal effects are consistent, but the degree of predictive power varies between models. *, **, *** represent significance levels at 1%, 5%, and 10% respectively.

From table 3, the following postulates can be made[5];

1. From AGE variable, students 22 and below are less likely to fail economics or have any failed course in their year one studies, when compared to other students in various age brackets (22 and above) all things being equal.
2. From D_YR10 variable, students who enrolled in 2010 are less likely to fail economics or have any failed course in their first year studies compared to any other year used in the sample with all things being equal.
3. From FOUR_C variable, students with four credits and below in WASSCE and/ or NECO are less likely to fail economics or have any failed course in their year one studies compared to students with the minimum requirement of five credits with all things being equal.
4. From JAMB1 variable, students who scored 190 and below in the UME examinations are more likely to fail economics or have a failed course in their first year studies as compared to students who scored above 190 with all things being equal.
5. From LOC variable, students from the northern part of the country are more likely to fail economics or have a failed course in their first year studies as compared to students from the south with all things being equal.
6. From the SEX variable, female students are less likely to fail economics or have a failed course in their year one studies as compared to the male students with all things being equal.

[5] These postulates are made with a degree of confidence. The probabilities on column (6) in both models, gives the reader an idea of the confidence levels with which these postulates are made.

7. From SIX_C variable, students who had six credits in WASSCE and / or NECO were more likely to fail economics or have a failed course in their first year studies as compared to students with five credits with all things being equal.
8. From SEVEN_C variable, the postulate is not conclusive, Students with seven credits in WASSCE and / or NECO are less likely to fail economics but more likely to have a failed course in their first year studies as compared to students with five credits with all things being equal.

Summary of Findings

Having estimated the loigit model and calculated the marginal effects of each independent variable on the dependent variable, important postulates arise. Two binary dependent variables were used in estimating the logit model; ECO_FAIL and CO. ECO_FAIL represents a proxy for student academic performance in economics in their first year studies> CO variable was included in the analysis to ensure robustness and general applicability of the logit model estimated. From the results, both models were consistent in predicting students performances based on the independent variables used. Of importance to answering the questions of this study, the JAMB1 variable has espoused already known apriori expectations. Intuitively, students who scored high scores (get above the cut off mark of 180) in UME are expected to get admission into higher institutions and also expected to be able to cope with the academic work. JAMB1 variable shows that students who scored lower than 190 in their UME examinations were more likely to fail in economics or have a failed course in their year one studies. This validates the minimum requirement of a UME score of 180 for admission into higher institutions. In fact, from the sample, admitting students with less than 180 in UME examination is akin to admitting students who are already prone to fail in academic work.

Secondly, variables FOUR_C, SIX_C, and SEVEN_C show very important contradictions in our data. These variables represent students who had four credits, six credits and seven credits respectively in WASSCE and/ or NECO examinations. Students with five credits were not included as a dummy variable in order to escape the dummy trap. Thus students with five credits will be used as the basis for interpreting other variables. From the results, students with four credits were more likely to perform better than students with five credits in first year studies, whereas students with six credits were more likely to fail economics or have a failed course as compared to students with five credits. This is in contradiction to apriori expectations. Intuitively, one will expect students with more credits in WASSCE and / or NECO examinations to be more academically ready that students with lower credits. The variable SEVEN_C is even more enlightening, as it provides different postulates when the dependent variables are changed. The results show that students with seven credits were more likely to have a failed course but less likely to fail economics in their first year studies as compared to students with five credits. Reliability of this postulate is in doubt, given that it is not statistically significant and therefore cannot be trusted.

Another important find from the results, stems from the LOC variable. This variable captures student's location, with 1 representing students from the north and 0 otherwise. The results show that students from the north are more likely to fail economics or have a failed course in their first year studies as compared to students from the south. This difference in academic performance is attributed to demographic characterisation of the students.

Lastly, the dummy variable capturing yearly difference; D_YR10 shows that students, who enrolled at the department of economics in the year 2010, were less likely to fail economics or have a failed course in their first year studies as compared to students in other years. The year dummy was included to allow for differences in; average student quality over the sample years, differences in examination rules, examination processes and examination quality.

Conclusions

Higher institutions in Nigeria will continually strive for efficient and adequate means of getting information about prospective students. This needed information is captured in both cognitive and non-cognitive measures. Both measures are equally important to ensuring costs are limited in enrolling students into these institutions of higher learning. Currently, there are some already known admission criteria that exist for students who are interested in enrolling in colleges of education; minimum of five credits (including mathematics and English) and a UME score of 180 and above. The thrust of this research was to determine the predictive ability of this academic criteria.ie, based on these criteria, can we reliably predict who will be successful or not in their academic pursuit?

Using a logit model, the study was able to show that students who had the minimum requirement in UME examinations were successful in year one studies. Also, students who had lower amount of credits as compared to the cut off of five credits in WASSCE and / or NECO examinations were more successful in year one studies. To worsen the contradiction, as the mount of credits gotten increased above the minimum five credits (six credits, seven credits, etc.) students likelihood of failure increased. Finally, the location of the student did matter in determining success or failure. Students from the north were more likely to fail than their counterparts from the south. The results from the analysis do show that, academic criteria can actually predict students' likelihood of being successful or failing in their academic pursuit. To be successful, students who had 4 credits (including Mathematics and English), scored above 180 in UME should be given priority. Demographic information cannot be looked at face value. i.e., it will be irresponsible to advocate that only students from the south should be given priority because they are more likely to be successful according to the data. Hence, other important factors like government policy, environmental and societal needs should take priority over demographic considerations.

Recommendations

From the finding s of the study, the following recommendations can be put forward;

1. The UME minimum criterion of 180 is adequate and limits cost of admitting students into higher institutions. This minimum should be maintained
2. The results of the estimation shows students below the minimum of five credits in WASSCE and/ or NECO performed better than other students above the criterion. This shows that WASSCE and / or NECO results should be interpreted with caution.
3. Demographic characteristics should not be used as a criterion for admitting students, if ensuring success of student in their academics maintains as priority. If demographic characterisations are used, it will contradict cognitive minimum criteria already established.

References

Adelman, C. (1999). *Answers in the tool box: Academic intensity, attendance patterns, and bachelor's degree attainment*. Washington, DC: U.S. Dept. of Education.

Adeniyi, O.S., Araoye, M.A., Amali, E.O., Eru, E.U., Ojabo, C.O., & Alao, O.O. (2010). Effect of Using Combination of O'level Result With JAMB Score on Student Performance in The First Two Years of Medical School in Benue State University, Makurdi. *African J. Biomedical Res.* 13(3), 189 – 195.

Astin, A. W., Korn W., & Green, K. (1987). Retaining and satisfying students. *Educational Record*, *68*(1), 36-42.

Baird, L. L. (1984). Predicting predictability: The influence of student and institutional characteristics on the prediction of grades. *Research in Higher Education, 21*, 261-279.

Barnett, J., Ritter, G. W., & Lucas, C. J. (2003). Educational reform in Arkansas: Making sense of the debate over school consolidation. *Public Policy Working Paper Series*, *2*(1), 1-27.

Bridgeman, B., McCamley-Jenkins, L., & Ervin, N. (2000). *Predictions of freshman grade point average from the revised and recentered SAT I: Reasoning Test* (College Board Rep. No. 2000-1). New York: College Entrance Examination Board.

Camara, W. J., & Echternacht, G. (2000). The SAT I and high school grades: Utility in predicting success in college. *College Board Research Notes* (RN-10). New York: College Board.

Duran, R. P. (1986). Prediction of Hispanics' college achievement. In M. A. Olivas (Ed.), *Latino college students*, 221-245. New York: Teachers College Press.

Fleming, J. (2002). Who will succeed in college? When the SAT predicts Black students' performance. *Review of Higher Education, 25*(3), 281-296.

Fleming, J., & Garcia, N. (1998). Are standardized tests fair to African Americans? Predictive validity of the SAT in Black and White institutions. *Journal of Higher Education*, *69*(5), 471-495.

Gose, B. (1994). Study Says Rigor of High School Coursework is the Best Predictor of College Graduation. *The Chronicle of Higher Education, XLV* (39), A46.

Himelstein, P. (1965). Validities and Inter-correlations of MMPI Subscales Predictive of College Achievement. *Educational and Psychological Measurement, 4,* 1125-1128.

Hoffman, J. L. (2002). The impact of student co-curricular involvement on student success: Racial and religious differences. *Journal of College Student Development, 43*(5), 712-739.

Johnson, J. D. (2002). *Size, excellence, and equity: A report on Arkansas schools and districts*. Athens, OH: Ohio University College of Education.

Kim, M. M. (2002). Historically Black vs. White institutions: Academic development among Black students. *Review of Higher Education, 25*(4), 385-407.

King, B.W., Rasool, J. A., & Judge, J. J. (1994). The relationship between college performance and basic skills assessment using SAT scores, the Nelson Denny Reading Test and degrees of reading power. *Research and Teaching in Developmental Education, 11*(1), 5-13.

Klugh, H. E., & Bierly, R. (1959). The School and College Ability Test and High School Grades as Predictors of College Achievement. *Educational and Psychological Measurement, 4,* 625-626.

Kuncel, N. R., Credé, M., & Thomas, L. L. (2007). A comprehensive meta-analysis of the predictive validity of the Graduate Management Admission Test (GMAT) and undergraduate grade point average (UGPA). *Academy of Management Learning and Education, 6,* 51-68.

Kuncel, N. R., Credé, M., Thomas, L. L., Seiler, S. N., Klieger, D. M., & Woo, S. E. (2005).A meta-analysis of the Pharmacy College Admission Test (PCAT) and grade predictors of pharmacy student success. *American Journal of Pharmaceutical Education, 69,* 339-347.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2004). Academic performance, career potential, creativity, and job performance: Can one construct predict them all? *Journal of Personality and Social Psychology, 86,* 148-161.

Kuncel, N. R., Hezlett, S. A., & Ones, D. S. (2001). A comprehensive meta-analysis of the predictive validity of the Graduate Record Examinations: Implications for graduate student selection and performance. *Psychological Bulletin, 127,* 162-181.

Lawlor, S., Richman, S. & Richman, C. L. (1997). The Validity of Using the SAT as a Criterion for Black and White Students' Admission to College. *College Student Journal. 31*, 507-515.

McDonald, R. P. (1999). *Test theory: A unified treatment.* Hillsdale, NJ: Erlbaum.

Micceri, T. (2001). Facts and fantasies regarding admission standards (Report No. HE034083). Long Beach, CA: Association for Institutional Research.

Misanchuk, E. L. (1977). A model-based prediction of Scholastic Achievement. *Journal of Educational Research, 71*, 30-35.

Moffat, G. K. (1993). *The validity of the SAT as a predictor of grade point average for nontraditional college students*. Paper presented at the annual meeting of the Eastern Educational Research Association, Clearwater Beach, FL. ERIC Document Reproduction Service No. ED 356 252.

Mulvenon, S. W., Stegman, C. E., Ganley, B. J., & McKenzie, S. (2002) *Little Rock School District revisited: Is desegregation working?* Paper presented at the annual meeting of the American Educational Research Association, Chicago.

Munro, B. H. (1981). Dropouts from higher education: Path analysis of a national sample. *American Educational Research Journal*, *18*(2), 133-141.

Noble, J. P. (1991). *Predicting college grades from ACT assessment scores and high school course work and grade information* (Rep. No. ACT-RR-91-3). Iowa City, IA: American College Testing Program.

Peltier, G. L., Laden, R., & Matranga, M. (1999). Student Persistence in College: A review of Research. *Journal of Student Retention. 1*(4), 357-375.

Pentages, T. J., & Creedon, C. F. (1978). Studies of college attrition: 1950-1975. *Review of Educational Research*, *48*, 49-101.

Perfetto, G. (2002). Predicting academic success in the admissions process: Placing an empirical approach in a larger process. *College Board Review*, *196*, 30-35.

Ramist, L., Lewis, C., & McCamley-Jenkins, L. (1994). *Student group differences in predicting college grades: Sex, language, and ethnic groups*. College Board Report No. 93-1. New York: College Entrance Examination Board.

Salahdeen, H.M., & Murtala, A.B. (2005). Relationship between admission grades and performance of students in the first professional examination in a new medical school. *African J. Bio. Res.*, 8:51-57

Sedlacek, W. E. (2004). *Beyond the big test: Noncognitive assessment in higher education*. San Francisco: Jossey-Bass.

Snyder, V., Hackett, R. K., Stewart, M. & Smith, D. (2003). Predicting academic performance and retention of private university freshmen in need of developmental education. *Research & Teaching in Developmental Education, 19*(2), 17-28.

Tracey, T. J., & Sedlacek, W. E. (1984). Noncognitive variables in predicting academic success by race. *Measurement and Evaluation in Guidance*, *16*, 172-178.

Tross, S. A., Harper, J. P., Osher, L. W., & Kneidinger, L. M. (2000). Not just the usual cast of characteristics: Using personality to predict college student performance and retention. *Journal of College Student Development*, *41*(3), 323-334.

Waugh, G., Micceri, T., & Takalkar, P. (1994). *Using ethnicity, SAT/ACT scores, and high school GPA to predict retention and graduation rates* (Report No. HE034024). Orlando, FL: Florida Association for Institutional Research. (ERIC Document Reproduction Service No. ED453704).

Wolfe, R. N., & Johnson S. D. (1995). Personality as a predictor of college performance. *Educational and Psychological Measurement*, *55*(2), 177-185.

Zheng, J. L., Saunders, K. P., Shelley II, M. C., & Whalen, D. F. (2002). Predictors of academic success for freshmen residence hall students. *Journal of College Student Development*, *43*(2), 267-283.