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Modelling the Impact of Continuous Assessment Tests on Final Grade in a Course

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Abstract:
This study is an application of multi-equation system modelling to evaluate the effect of Continuous Assessment (CA) tests on academic performance. Understanding and consequently having good grades in statistics is generally presumed to be a difficult task for many students. Many factors contribute to academic performance, but the concern at the moment is on CA and other extraneous factors. The model was a 2-equation system. The first structural equation expresses final grade as a function of CA, and the second expresses CA as a function of the frequency of conducting CA and class attendance. Two service courses in statistics were used for the study. The results showed the frequency of CA and attendance to be highly significant (P<0.01) in explaining the variation in CA, while, as expected, CA significantly affects the final grades. Estimation of a simple regression of final grade on attendance revealed that attendance was significant (P<0.01) but not when final grade was regressed on both CA and attendance. This disagreement could be attributed to the multicollinearity of CA and attendance. Thus, multi-equation modelling enables the consideration of variables that could further help to improve on CA and, consequently, on the final grade without drawing a wrong inference.

Keywords: *Multi-equation models, academic performance, statistics courses*

1. Introduction

Studies on undergraduates' academic performance have been of interest in education research over the years. Focus varies from socio-economic, demographic, and other factors influencing performance to models for improvements as well as predictions. In Low and Zahari (2012), socioeconomic status was shown to have a greater impact on academic self-concept for female students than male students. It was a study on gender differences in academic achievement using structural equation modelling. In another research, Sharifah et al. (2010), learning engagement was proposed as an addition to motivation in influencing academic achievement. The proposed research method for that model was the structural equation modelling, which was to highlight the complex interactions of motivation in contribution to students' academic achievement. Another study on the effect of motivation on academic performance using structural equation modelling analysis was reported in Kusurkar et al. (2013). Modelling and predicting students' academic performance has also gained attention in research, for example, Migueis et al. (2018), Cortes et al. (2014), Adejo et al. (2018), Shakil Ahamed et al. (2017), Burgos et al. (2017), Palmer (2013). Furthermore, the effect of entrepreneurial interest on academic performance was presented in Osakede et al. (2017) using a study on undergraduate students at the University of Ibadan, Nigeria. The result of this study suggested that engagement in entrepreneurial activity has no significant effect on students' academic performance.

Among other factors found in recent literature on students' academic performance is Information and Communications Technology (ICT) (Basri et al. 2018; Choy and Quek 2016, Han and Yi 2018, Gonul and Solano 2013). The issues raised in these studies include ICT adoption in institutions of learning, an online platform for education, effect of smartphones, and social networking media usage on academic performance. These studies, in most cases, indicated a positive influence of the use of ICT in teaching and learning on proper understanding and academic performance of the students involved.

In particular, this paper focused on statistics courses because of the perceived difficulty for some students in proper understanding and consequent good performance in the course. Improving participation, knowledge, and performance in statistics courses have been of much interest in recent times as a result of this perceived difficulty. Van Es & Weaver (2018) presented the influences of race and sex on introductory statistics education. It was reported that the students' performance varied significantly by sex but not across racial groups. Early intervention through peer tutoring right from the beginning of the semester was said to significantly improve the performance of students in an introductory statistics course in Lunsford et al. (2018). The students were earlier identified to be at risk of not being successful in the class and later had a significantly higher increase in performance than their peers after the early intervention. Another contribution to the literature on statistics education is on the use of projects allowing students to work collaboratively to investigate authentic, familiar problems, for example, Sole and Weinberg (2017). Kalaian and Kasim (2014) earlier gave a meta-Analysis of such projects. Similarly, Fawcett (2017) proposed a set of case-based materials and associated activities for first-year Business undergraduates taking a compulsory course in quantitative methods. A trial of this case-based method in Fawcett suggested that students exposed to the case-based learning process outperform their peers not exposed to the technique.

These studies and others found in literature gave little or no information about the extent of the effect of continuous assessment and classroom attendance on students' academic performance in statistics courses. This is probably arising from the widely held belief that continuous assessment enhances students' learning and performance in a course. However, studies on the influence of "frequency of assessments" on continuous assessment for statistics courses are not yet found in literature. A closely related work on this was presented in Gonul and Solano (2013), consisting of a report on the effect of classroom attendance, web-based course supplements, and homework on academic performance. The frequency of the continuous assessment and the continuous assessment score itself are the additions given in our paper, using results from two statistics courses: one in the first year and the other in the second year in the university. . We designed the empirical study to answer the question: do students actually have better understanding of a course (as measured by final score) with increase in exposure to continuous assessments? It is expected that the more students are exposed to tests, assignments, quizzes, projects and other means of assessing their knowledge of a course, the better their performance in that course. The effect of frequency of continuous assessment and class attendance on continuous assessment score, and in turn, continuous assessment on final score of the students was therefore studied to provide empirical evidence. Specifically, exposure to continuous assessments is the interest here. The rest of the paper is structured as follows. A brief note on multi-equation models is given in section 2, and section 3 contains the theoretical framework and methodology for the study. We present and discussed the result in section 4; while section 5 is the concluding part of the paper.

2. Multi-equation Models

These are models involving systems of equations studied simultaneously as one model. Examples of these models include Simultaneous Equations Models (SEM), Structural Equations Models (SEM), Seemingly Unrelated Regression (SUR) models, Vector Autoregressive Regression (VAR), fully recursive models. Multi-equation modelling has applications in any study involving variables that should be analyzed together in a system of equations. As there are instances in which single equations work ideally having the best fit, other situations arise as well in which multi-equation models provide better information. An example in this regard can be found in Li and Poirier (2003), a study on births inputs and outputs using the simultaneous equations model. Some of the numerous applications of the system of equations are of note here. Tran (1992) presented a multi-equation model of energy consumption in Thailand using m energy share equations for m petroleum products. The use of a multi-equation model enabled the researcher to consider all the products together in a single system of multiple equations. An application of a system of simultaneous equations to study the relationship between physical activities and Body Mass Index (BMI) is also found in Meyer et al. (2016).

Separate equations were written for physical activities and other health behaviours, which were modelled as functions of exogenous variables. These exogenous variables include a vector of instrumental variables that influence BMI only through health behaviours and a vector of other exogenous variables, which may affect health behaviours as well as BMI. The paper was illustrative of the importance of multi-equation modelling in some research situations. Some other applications of multi-equation models can be found in Basri et al. (2017), Kusurkar et al. (2013), Low and Zahari (2012), Sharifah et al. (2010).

The multi-equation model was a choice here because of its flexibility to model interrelationships between academic performance, CA, and other extraneous factors.

2. Theoretical Framework and Methodology

2.1. About the Data

We obtained the data from two service courses in statistics, namely: a 1st year (100-Level) course and a 2nd year (200-Level) course, both taught by the same lecturer for the years included in the data. The 100-level course is a probability course, while the 200-level course is a course designed especially for the students in biological sciences. For the 100-level course, results for three consecutive sessions were available in the format needed for this study, that is, the same lecturer, frequency of Continuous Assessment (CA), and summary of attendance recorded. Similarly, results for only two consecutive sessions satisfied the above criteria for the 200-level course. The data for the three sessions for the 100-level course were combined into one to form Dataset A, while that of the 200-level course is Dataset B.

The variables in the model are the final score, CA score, CA frequency, and class attendance. We describe the measurements of these variables as follows:

- Final Score: this is the total score a student has in the course out of 100. It is the addition of CA and exam scores, e.g., 72
- CA: The CA includes; assignments, tests and quizzes. It is the sum of the scores in all the assessments taken, a total of which is 40, e.g., 26. A note on the CA is that for this study, whatever a student has in the CA is converted to over 40 even when he/she did not partake in all the assessments. For example, if a student only took part in 2 assessment tests of 10 marks each and score 5 and 8, respectively, we convert the total score 13/20 to a percentage of 40. Thus the student's score in CA is 26, that is, (13/20)*40 = 26.

- Frequency of CA: Number of times a student takes part in the assessments. The variation here is two in nature. First, the number of times students take part in the assessment tests varies among the students (by their choice); then, the number of assessment tests/assignments given by the lecturer varies across the years.
- Class attendance: Number of times a student was present in the class.

3.1. Model

A 2-equation model was used for the study to see how the frequency of continuous assessments and class attendance affect total score in continuous assessments and in turn on the final score.
The model for this study was specified as follows:

$$Score = \alpha_1 + \gamma CA + u_{1t}$$
$$CA = \alpha_2 + \beta_{21} CA\ frequency + \beta_{22} Attendance + u_{2t} \quad (1)$$

The matrix of the explanatory variables in the second equation, which is the one with more than one explanatory variable is of full rank; that is, they are not highly correlated.

The first equation of the model is over-identified while the second equation is just-identified; hence, the model is an over-identified 2-equation model. The estimation method was the 2-Stage Least Squares (2SLS). It is a widely used estimation method for simultaneous equation models (Angrist and Imbens, 1995), especially when there are no severe violations of underlying assumptions such as multicollinearity (Olubusoye and Okewole, 2013). The analysis was done in the R statistical package.

4. Results and Discussion

4.1. Descriptive Analysis of the Data

Descriptive analysis using graphs are presented below, suggesting relationships between final score and CA, CA and attendance, and CA and CA frequency. The scatter plots for the first dataset (Figures 1 a, b, and c) indicated positive relationships between final score and CA, CA and CA frequency, and CA versus attendance. The scatter plot for the second dataset (Figures 2 a, b, and c), however, showed a weak relationship between CA and attendance, but the modelling was done all the same to have a clearer picture of the relationship.

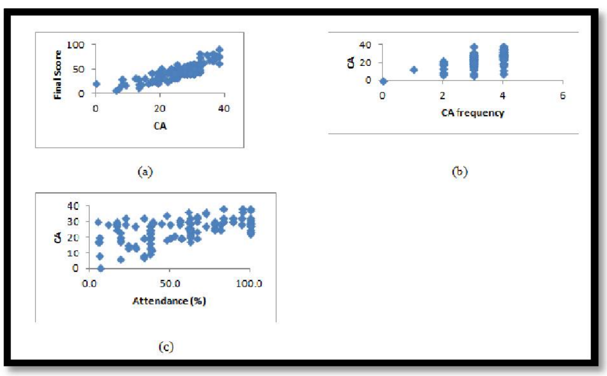

Figure 1: Scatter Plots for Dataset A. (A) Final Score and CA (B) CA and Attendance (C) CA and CA Frequency

The scatter plots indicated a linear relationship between the final score and CA, CA and CA frequency, and CA and attendance. These relationships are more pronounced in dataset A, which is for the first-year students than the data set B, which is for second-year students. The details given by the model is contained in the next section.

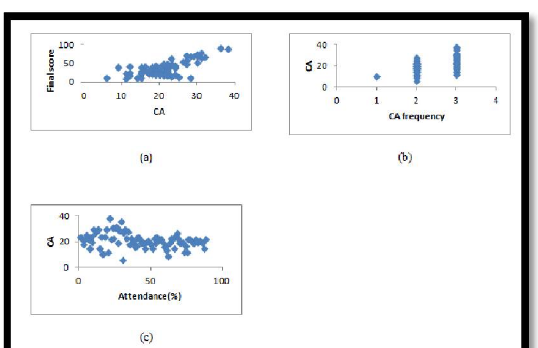

Figure 2: Scatter Plots for Dataset B. (a) Final score and CA (b) CA and CA frequency (c) CA and Attendance

Normal Q-Q plots of Residual for each equation of both datasets showed that the residuals are normally distributed (Fig. 3-6). Similarly, scatter plots of residual with fitted values indicated that the residuals for dataset A are independent and have constant variance. The case of dataset B was however different; the residuals plots showed some indications of interdependence of the residual terms (Fig. 7-10, appendix)

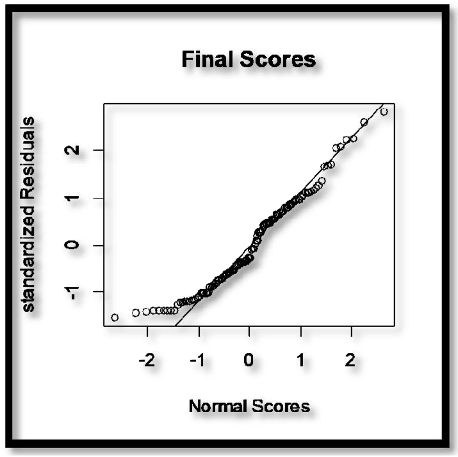

Figure 3: Normal Q-Q Plot of Residuals of First Equation for Dataset A

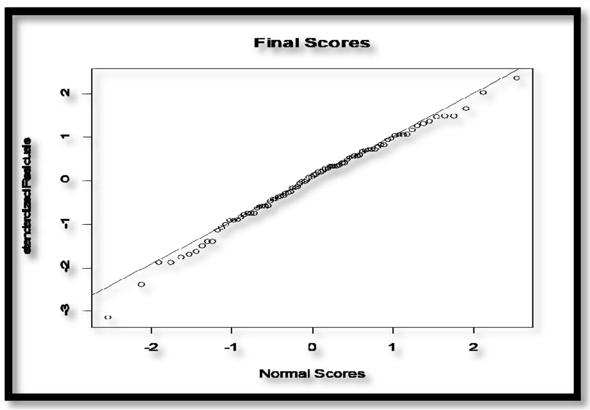

Figure 4: Normal Q-Q Plot of Residuals of Second Equation for Dataset A

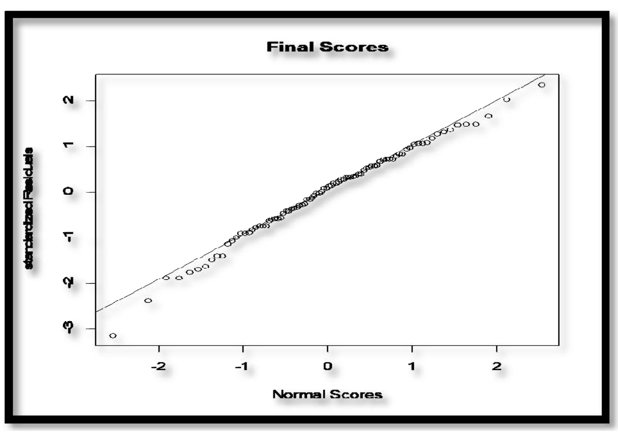

Figure 5: Normal Q-Q Plot of Residuals of First Equation for Dataset B

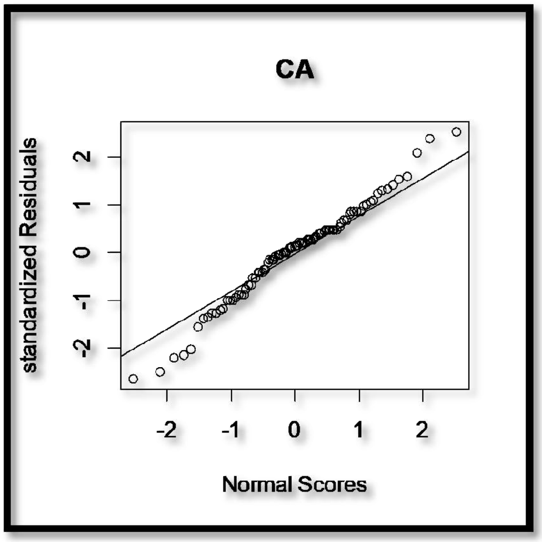

Figure 6: Normal Q-Q Plot of Residuals of Second Equation for Dataset B

4.2. Analysis of the Model

The results showed as expected a positive effect of continuous assessment on academic performance. The Estimate of γ (coefficient of CA) was 1.5812 (P < 0.0001) for dataset A as shown in Table 1 and 4.3326 (P < 0.0001) for dataset B. Likewise, CA frequency showed positive effect on CA scores with for both datasets with β_{21} =5.3512 (P< 0.0001) and 6.1213 (P<0.0001) respectively. We can thus imply that making the continuous assessment more frequent significantly improves performance. The observed difference in performance for the case of small number of assessment and that of larger number of assessments is statistically significant. The students should also take part in all the assessment tests and assignments.

Dataset		variable	Estimate	Std. Error	t value	Pr(>|t|)
A	Equation 1	Intercept	4.6413	4.127529	1.12448	0.26307
		ca	1.5812	0.161659	9.78081	< $2x10^{-16}$
	Equation 2	Intercept	1.0527	2.2505	0.46775	0.64083
		cafreq	5.3512	0.6409	8.34900	$1.514x10^{-13}$
		attend	0.1050	0.0158	6.64094	$9.833x10^{-10}$
B	Equation 1	Intercept	-53.375	12.9607	-4.1182	$8.74x10^{-5}$
		ca2	4.3326	0.6072	7.1353	$2.86x10^{-10}$
	Equation 2	Intercept	4.3359	2.8965	1.4970	0.1381
		cafreq2	6.1213	1.0355	5.9113	$6.856x10^{-8}$
		attend2	0.0333	0.0196	1.6961	0.0935

Table 1: 2SLS estimates of the two equations

Dataset		N	MSE	RMSE	R^2	Adj R^2
A	Equation 1	121	86.379	9.2940	0.638	0.6352
	Equation 2	121	24.794	4.9794	0.531	0.5225
B	Equation 1	88	318.131	17.8362	0.1274	0.1172
	Equation 2	88	22.989	4.7946	0.3063	0.2900

Table 2: Rmse and Other Measures for the System of Equations

Class attendance has been shown in previous studies to improve academic performance significantly; for example, Gonul and Solano (2013). This result was also the case with this study for dataset A (β_{22} = 0.1050, P<0.0001), while it was only significant at the 10% level for dataset B (β_{22} = 0.0333, P<0.1) respectively. This result indicated that the significance of class attendance was stronger for first-year students than second-year students. R^2 for equation 1 was 0.638 and 0.1274 respectively for the two datasets (Table 2), while for equation 2 it was 0.531 and 0.3063, respectively. Some Possible explanations for the disparity in R^2 and significance of class attendance for the two datasets are given here. First, the linear model does not have a good fit for the second dataset, as was also indicated in the scatter plot (Figure 2c).

Furthermore, the omitted variables are more highly significant for the second year students than the first-year of the first dataset (sample size = 121, variation in class attendance = 25.23). This study focused only on the effect of continuous assessment, frequency of continuous assessment, and class attendance on students' performance in statistics service courses. Hence, the size of R^2 is not essential here. Data on other possible variables were not available at the time this study was carried out; this will, therefore, also serve as preliminary results for more extensive modelling. The RMSE of equation 1 for dataset B (17.8362) was higher than that of dataset A (9.294) as a result of the smaller sample size of dataset B. More efficient estimates of the parameters could be obtained with larger sample sizes, as suggested in the literature; for example, Okewole et al. (2011). This result is also a consequence of the absence of other variables that might be more significant for dataset B than dataset A.

Dataset			Estimate	Std. Error	t value	Pr(>|t|)
A	On ca and attend	Intercept	1. 31860	3.06390	0.43	0.668
		ca	1.68414	0.13603	12.38	<2x10^{-16}
		attend	0.01314	0.03370	0.39	0.697
		Intercept	31.4483	2.81075	11.189	<2x10^{-16}
	On attend alone	attend	0.22305	0.04397	5.072	<1.46x10^{-6}
B		Intercept	-18.5977	6.4718	-2.87	0.00512
	On ca and attend	ca2	2..2482	0.2546	8.83	<1.09x10^{-13}
		attend2	0.1221	0.0553	2.21	<0.0300
		Intercept	23.5010	6.0255	3.90	0.00019
	On attend alone	attend2	0.1931	0.0754	2.56	0.0121

Table 3: Linear (Single Equation) Regression of Final Score on Continuous Assessment and Attendance

Application of a model of 2 equations in this study made it possible to have all the explanatory variables of interest together in one model without any adverse effect on estimation due to multicollinearity. Specifically, in the single equation regression of final score on CA and class attendance for dataset A, class attendance was not significant (Table 3), whereas it was significant when considered alone. This is a result of the presence of some collinearity between class attendance and CA with correlation = 0.50 (Table 4). This study is, therefore, another case like Lai and Poirier (2003), where a system of equations is more applicable than a single equation. The model considered the influence of class attendance on the final score through CA by using it as an instrument in the second equation. We have further evidence of this result in the case of low correlation (0.15) between CA and class attendance in dataset B; class attendance had a significant effect on final score even when considered with CA ($P < 0.0300$, Table 3)

	CA & attend		cafreq & attend		CA & cafreq	
Dataset 1	0.50	P=4.083x10^{-9}	0.15	P=0.1036	0.60	P=5.77x10^{-13}
Dataset 2	0.15	P=0.1766	-0.14	P=0.8914	0.53	P=9.72x10^{-8}

Table 4: Correlation coefficients between Pairs of Explanatory Variables in the Model

5. Conclusion

The relationship between continuous assessment, frequency of continuous assessment as well as class attendance and students' performance in two statistics service courses was studied using a 2-equation model. The result indicated that students' performance is better with a higher number of assessment tests/assignments than with fewer numbers. Assessment should be more frequent. Some people may say that they are using 'continuous assessment' whereas they might only be making a small number of assessments prior to the final exam; although they might call this 'continuous' we urge them to increase the number of assessments that they use. Statistics courses will be better embraced and understood when the curriculum is designed to incorporate regular assessments.

Class attendance was also shown to improve students' performance, particularly in the first year significantly. Further studies will give more information for generalization across all levels of undergraduate studies. The application of multi-equation models in this study implied that such models could be used to avoid the problem of multicollinearity. The result also substantiates the fact that students' academic performance might not have the same pattern across levels of undergraduate studies, at least for the first year and second year. Such studied should, therefore, consider the level of education.

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Appendix

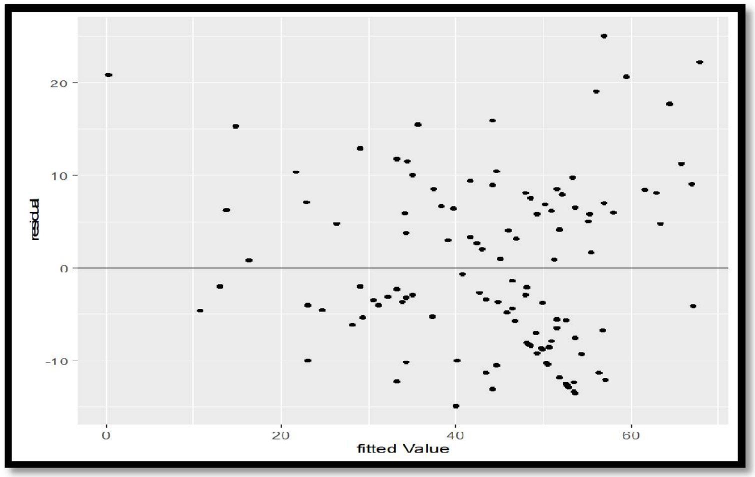

Figure 7: Scatter Plot of Residual of the First Equation for Dataset A

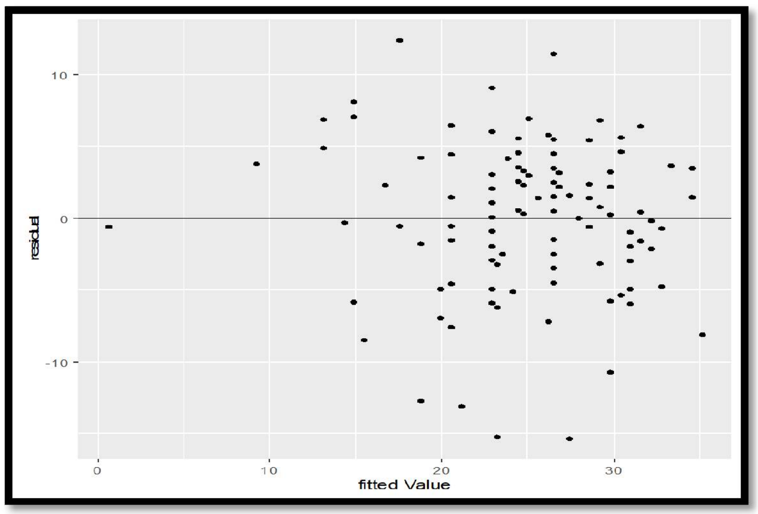

Figure 8: Scatter Plot of Residual of the Second Equation for Dataset A