KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY

(KNUST) KUMASI

INSTITUTE OF DISTANCE LEARNING (IDL)

LONGITUDINAL DATA ANALYSIS OF THE ACADEMIC PERFORMANCE OF CEMBA STUDENTS

CASE STUDY; ACCRA, KUMASI-IDL(KNUST)

This Thesis is presented to Kwame Nkrumah University of Science and Technology in partial fulfillment of the requirement for the award of Masters of Science degree in Industrial Mathematics.

BY

KWABI EMMANUEL

JUNE 2012

DECLARATION

I hereby declare that this submission is my own work towards the Master of Science and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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DEDICATION

This book is dedicated to my late father, E. Y Kwabi and my lovely woman, Rosemond Yaa Korama Boateng.

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I owe my ultimate gratitude to the Almighty God for granting me the knowledge and insight to make this work a success.

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Lastly, I say a big thank you to all my family members for their love and financial support throughout my program and also to all friends, I say God bless you.

ABSTRACT

The purpose of the study is to assess the academic performance of CEMBA students at the Accra and Kumasi centres of institute of distance learning, KNUST. In all about 437 students for the (2009/2010) were considered for the study. Students' semester weighted average (SWA) for three semesters were considered as a dependent variable and their age, sex and centre were considered as explanatory variables. Linear mixed effect model was fitted for the data available using the SAS 9.0 software. It was concluded that the student's academic performance does not depend on their gender. But centre and age were found to be significant. For the start of semester one, on the average Kumasi centre performed better than the Accra centre but the situation changed over the three semesters. Also young students performed better on the average at the start of semester one. The recommendations were that the authorities should have a second look at the facilities at the Accra centre and that the number of the explanatory variables should be widen thus, questionnaire can be designed to look at the attitude of students next time a similar research is been undertaken at the same institute.

Keywords: linear mixed effect models, SWA, SAS and Academic performance.

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CHAPTER 1

1.0 Introduction

This chapter entails the background of the study which captured distance education, students' academic performance and the CEMBA programme. The chapter also covers statement of the problem, purpose of the study, significance of the study, methodology organisation of the study and limitation of the study.

1.1 Background to the problem

From time immemorial, teacher-lecturing/ student-listening was the primary mode of traditional academic education. The delivery system for higher education has been a classroom setting with a professor giving a lecture and students listening and writing notes. Interaction between the professor and student has been viewed as an essential learning element within this arrangement Mickey and Neumann (2003), often referred to as the "sage on the stage." Distance education has been one of the most remarkable events that characterized the delivery of education in the twentieth century. By means of innovative education technologies – radio broadcast, television, audio and video conferencing and the internet – almost all the physical barriers to education have been removed especially in the advanced countries. People can now sit at the comfort of their home and receive formal education. In the continent of Africa in general, and Ghana in particular, this wind of change is yet to be experienced on a large scale. Though it has long been recognized in Ghana that the conventional or traditional campus-based education system can no longer cope with the extremely high demand for higher education (Rev. Prof. E.A Obeng,2007/2008) Typically, distance education is defined as "the planned learning that normally occurs in a different place from teaching and as a result requires special techniques of course design, special instructional techniques, special methods of communication by electronic and other technology, as well as special organization and administrative agreements"

Distance education is education which either does not imply the physical presence of the teacher appointed to dispense it in the place where it is received or in which the teacher is present only on occasion or for selected tasks. It is changing the physical face. That is without doubt, distance education is of the highest relevance and importance to educators, students, and all other stakeholders. It is changing the physical face (i.e., massive buildings) of academic establishments. Students can now learn from the comfort of their homes or offices with no need to commute to campuses. Cutting-edge data are easily accessible on compact discs (CDs), portable personal computers (PCs) have taken the place of instantly obsolete books. Online classrooms and libraries are replacing traditional campus facilities. Rather than requiring students to travel to a specific physical classroom or library, the Internet has facilitated the delivery of (nearly) unlimited learning resources to students. General interest in distance education, which is perceived as a practical choice by many students and education institutions is increasing more and more in parallel with the advances in the information and communication technologies. High motivation level, maturity, and self-discipline are seen as necessary general characteristics of successful students for the achievement of distance education programs and for the continuity of students in the programs Oladejo et al (2010).

Stephen and Francis (2002) looked at the 'priorities and strategies for capacity building in tertiary distance education for human resource development in Ghana'. They explained that the idea of distance education (DE) is not new in Ghana. It was more vibrant two or three decades ago than it is now. It used to be known as correspondence education, an avenue through which a number of workers and professionals upgraded themselves. When the economy of Ghana started deteriorating after independence thus, making it difficult for student-workers to afford the cost of upgrading themselves by this mean of education. The income levels of workers were so low that they could not simply afford to pay their fees and the idea faded out.

However, after some time the idea of using distance education for manpower development resurfaced strongly and this led to the introduction of a number of distance education initiatives including the Modular Teacher Training Programme (MTTP), which was introduced in 1982. This programme was meant to upgrade untrained teachers academically and professionally through some form of distance education. Through this programme 7,537 untrained teachers received professional training and obtained Teachers' Certificate A. However this programme was abandoned because of certain difficulties it faced. Despite the difficulties encountered in the earlier attempts with distance education in Ghana, there was still a strong conviction on the part of the Government of Ghana that distance education is a viable complement to conventional education especially at the tertiary level. This conviction was partly due to the fact that universities were not able to admit even half of qualified applicants due to limited facilities.

Trends in delivery of today's graduate educations programs include distance education, electronic-based instruction, as well as traditional ground-based classes offered in weekend, daytime, and evening formats. Preziosi et al. (2000) stated that "Today, considerable attention is being paid to distance education…and much of the interest in distance education is due to the increasing use of Internet-based instruction." Distance education has been the reality of life for many institutions and adult learners in the past few decades and it is becoming more widespread. There have been many evolutionary changes in distance education mainly brought on by technology and these changes have raised questions pertaining to learning effectiveness across various teaching formats. Researchers agree that much attention has been directed at the number of distance education offerings and delivery mechanisms among institutions as well as to questions of learning equivalency between course and program offerings through various sites and formats. Similarly, accrediting bodies have raised questions of equivalency that range from the resources provided to students in all modalities and the outcomes of student learning. As distance education both nationally and internationally increases in importance, continuous and documented evaluation will continue to be a critical component of process improvement. Of course, the schools offering distance education programs are held accountable for achieving the same level of effectiveness as alternative approaches available to students. Such accountability requires that institutions understand their stakeholders and their needs on a proactive basis in order to deliver superior value to them in today's new and demanding economy. One element of delivering superior value for educational institutions is to assess the achievement of learning outcomes among their students at various sites and to use such results for continuous improvement in order to always have a healthy learning environment for everyone. Mujtaba and Mujtaba (2004).

1.1.2 Students academic performance

According to Willett (1989) as cited by Doran (2005) a basic truism of learning implies that an *individual* student, not a student *group*, has increased in knowledge and skills during a specific period of time. As such, analytical methods concerned with student learning should reasonably reflect this basic principle and consider individual students as the unit of analysis with their growth trajectories employed as outcomes. Thus, when multiple waves of test score data are available, longitudinal analyses of student achievement are more likely to support inferences regarding school and teacher effects than cross-sectional methods of analysis.

Students are the main assets of universities. The students' performance (academic achievement) plays an important role in producing the best quality graduates who will become great leaders and manpower for the country thus responsible for the country's economic and social development. The performance of students in universities should be a concern not only to the administrators and educators, but also to corporations in the labour market. Academic achievement is one of the main factors considered by the employer in recruiting workers especially the fresh graduates. Thus, students have to place the greatest effort in their study to obtain a good grade in order to fulfill the employer's demand. Students' academic achievement is measured by the Cumulative Grade Point Average (CGPA). CGPA shows the overall students' academic performance where it considers the average of all examinations' grade for all semesters during the tenure in university. Many factors could act as barrier and catalyst to students achieving a high CGPA that reflects their overall academic performance.

The Kwame Nkrumah University of Science and Technology also place much emphasis on the performance of its students. The performances of the students are measured through their cumulated grade point averages which show their overall performance and the semester weighted averages. The university now operates on the dual mode. The institute of distance learning takes care of the distance students. Both undergraduate and graduate programs are mounted at the institute. One of the graduate programs is the CEMBA/CEMPA program.

1.1.3 The CEMBA programme

The study focuses on the Commonwealth Executive Master of Business Administration (CEMBA) students. This CEMBA Programme is the outcome of collaboration between the Commonwealth of Learning (COL) and four open universities in South Asia: Allama Iqbal Open University (Pakistan), Bangladesh Open University, Indira Gandhi National Open University (India) and the Open University of Sri Lanka. Established in 2002, the CEMBA Programme is now expanding through partnership with universities in Asia, Africa, the South Pacific and South America. The Commonwealth of Learning aims to empower people with the learning that enables them to be agents of economic and social development. Their goal is to deliver high quality learning and professional development opportunities - with our Commonwealth Partner Universities - that complement existing MBA/MPA programs in the participating countries.

The CEMBA Program is designed for part-time study by busy working professionals, in response to the growing demands for post-graduate level education in business and public administration. The flexible and modular program allows students to choose either Business Administration (MBA) or Public Administration

(MPA) as their major field of study. The minimum completion time for the Commonwealth Executive MBA is two years. Partner institutions in Africa are the Kwame Nkrumah University of Science and Technology of Ghana and the National Open University of Nigeria. Instructional materials for each course were developed by subject experts drawn from various institutions in the Commonwealth. Curriculum developers from universities in Australia, New Zealand, Sri Lanka, India and Canada, wrote original course materials. Other courses were adapted and updated or acquired from existing courses at Indira Gandhi National Open University (IGNOU), the Open University of Hong Kong (OUHK), Charles Stuart University (Australia), and Massey University (New Zealand). Courses are updated regularly, most recently following a comprehensive evaluation by a team led by the University of South Africa. The CEMBA Program has significant representation from the Partner Universities. It is governed by an Executive Governing Board and an Academic Board.

1.2 Statement of the problem

Distance education seems a new idea to most educators of today. However, the concepts that form the basis of distance education are more than a century old. Certainly distance education has experienced growth and change recently, but the long tradition of the field continuous to give it direction for the future. The establishment of different study centres with different facilitators will leave a question of whether the academic performance of students in these centres is the same or almost the same always come to the minds of many. A longitudinal analysis is being used to look at the performance of students based on their semester weighted averages, in the Accra and Kumasi centres of students pursuing CEMBA program at the institute of distance learning KNUST.

1.3 Purpose of the study

The purpose of this study is to find out the prevailing knowledge of students on distance learning who belong to difference study centres through the following:

I. To assess the factors (variables) that affect the performance of students at Accra and Kumasi centres using a random intercept and slope model

II. Use the model in (I) to show whether there is a significant difference between students performance on different study centres

III. To compare the effects of the two centres on academic performance of CEMBA students over the three semesters.

1.4 Methodology

The researcher used a longitudinal data analysis that is, data analysis which involves a continuous observation of the variable, which is semester weighted averages over three semesters in our case. Because of the continuous nature of the data, Linear mixed model is employed. The researcher used only the secondary type of data that is the semester weighted averages for all the three semesters of the final year CEMBA students from both centres including their background information.

1.5 Significance of study

The findings of the study will help the authorities of the tertiary institutions in the country to assess their students' performance over semesters, that is, whether the performance is increasing or decreasing.

The findings of the study will help the institute in particular to assess the performance of their students across different study centres.

The findings of the study will help solve the problem of every student trying to have Kumasi as their centre when it happens that there is no significant difference between the students performance at the two centres.

Lastly, it will contribute to academic discussion and serve as an added source of literature on the issue and to people who might want to carry out further research on the issue of the performance of students on distance learning.

1.6 Organisation of the study

The study will be in five chapters. Chapter 1 will talk about the background of the study, the statement of the study, the purpose of the study, methodology, significant of the study, organisation of the study, limitation and definition of some terms which may have special meanings

Chapter 2 will cover the available literature review that are relevant to the study while chapter 3 will talk about the methods and techniques used. That is the mathematical tool to be used.

The focus on chapter 4 will be on data analysis and modelling.

Chapter 5 which is the last chapter will look at the summary, conclusion and the recommendation of the study.

1.7 Limitation

The study can be universalised due to the fact that it was restricted to the Kumasi and Accra centre of the institute of distance learning KNUST, because of time and financial constraints.

Also, the final year CEMBA students were selected as our sample. This is because their number is large and they would give us large sample size.

CHAPTER 2

LITERATURE REVIEW

According to Oladejo et al. (2004) a lot of researches have been done on students' demographic features and their academic performance For example, for first year programming courses, Jarman et al. (2002) reported that there was a relationship between student learning style and academic performance, while Byrne and Lyons (2001) established that no such relationship exists. Also, Woodley and Parlett (1983) found that previous educational level, gender, age and occupation were associated with persistence and academic performance.

Similarly, it has been established that marital status, gender and financial stability contributed significantly to distance learners' academic performance. Conversely, Chacon-Duque (1985), Wang and Newlin (2002) found that educational level, age, gender, employment status and number of children in the family were not significant predictors of distance learners' academic performance. Based on the findings from above studies on the relationship between socio-demographic characteristics and academic performance, it appears the issue remains inconclusive.

Students are responsible for their own academic gain in college Davis & Murrell (1993). A student's activities can create environments conducive to or detrimental to learning. Previous studies, however, have reported mixed effects of the student's activities on his or her achievement or grades. Rabow, Radcliffe-Vasile, Newcomb, and Hernandez (1992) found that on-campus extracurricular activity was negatively related to the student's grade point average (GPA); yet Camp (1990) reported no significant relationship between activities and a composite measure of achievement in college. Findings are inconsistent even when overall activity is disaggregated into component activities. Although the majority of studies have documented the positive contribution of studying to academic achievement Dickinson & O'Connell, (1990), Fuligni and Stevenson (1995) and to self-assessed gain Davis & Murrell (1993), there are studies that show that the relationship is either nonlinear Nixon & Frost (1990) or non significant Camp (1990). The relationship between the student's interaction with the faculty and academic achievement has received both positive support Davis and Murrell (1993), Hearn, (1985) and no support Pike (1991). Interaction with friends has also been related negatively Fuligni and Stevenson (1995), positively Bemdt, Laychak, & Park (1990), and non-significantly to academic achievement Hatcher, Prus, Englehard, & Farmer, (1991) and satisfaction Pike, (1991). Findings regarding the relationship between achievement and part-time work have been mixed also, including those reporting negative (Fuligni and Stevenson (1995), Stern, McMillion, Hopkins, and Stone (1990) and non significant relationships Davis & Murrell (1993) and Hatcher et al.(1991). Apparently, the reason for these discrepancies is the failure of any single study to assess activity thoroughly. Hence, effects of measured activities are vulnerable to confounding by those of unmeasured activities. Chueng and Kwok (1998) used structural equation modeling to examine the relationship between self-evaluated achievement and a comprehensive measurement of activities. The modeling identifies studying, using elaborative learning strategy, interacting with faculty, interacting with family, interacting with friends, participating in sports, participating in organizations, participating in part-time work, playing indoor games, and using the media. These are the activities that have received only fragmentary examination in earlier studies of academic achievement.

Linda, Martin and Mark (2008) undertook a study on demographic and psychographic variables and their effect on online student success concluded that although researchers did not find significance when examining hope on academic optimism, the researchers report significance regarding age and self-efficacy. Although age may come as no surprise to some educators, one must consider that older students often carry additional responsibilities of marriage, family and work. Younger students might work fewer hours and be able to focus more time and energy to their academic endeavors. As age was found to be significant, universities could consider recruiting older students to serve as mentors to younger students. Oladejo, et. A l(2004) later made the following conclusions according to them, Marital status was found to be a predictor of academic performance. Their finding is in support of studies conducted by Woodley and Parllet (1993) and Powell et al. (1990) that found a significant relationship between marital status and academic performance of distance learners but contradicted those of Chacon-Dugue (1985), Wang and Newlin (2002) and Ergul (2004) that established a negative correlation between marital status of distance learners and their academic performance. Significant relationship between marital status and academic performance as reported in this study might not be unconnected with the fact that both the married and the single distance learners in the program 550 Maruff Akinwale Oladejo, Nelson Adewole IGE, Adenike Omowunmi Fagunwa and Omolara Olubosede Arewa probably had good self-regulation skills that enhanced their study habits, and which in turn, affected their academic performance positively. Also, gender of the students was equally found in their study as a good predictor of academic performance in line with works like those of Adedipe (1986), and Bakare, (2000) which established a significant relationship between gender and academic performance. Employment status also had relationship with academic performance. This finding agreed to some earlier studies which showed that employment issues like nature of occupation, full-time work experience and number of hours employed were related to performance. Employment status is related to academic performance in the present study unlike some cited ones probably because the participants in the study were able to coordinate work schedule and studies effectively.

Darling et al (2005) conducted a longitudinal study concerning extracurricular activities and their results showed that the students who participated in school-based extracurricular activities had higher grades, higher academic aspirations, and better academic attitudes. Students involved in athletics are said to build character, instill a respect for the rules, encourage team-work and sportsmanship, promote healthy competition and perseverance, and provide a sense of achievement. Smoll and Smith (2002)

Norhidayah et al (2009) tried to look at factors influencing performance of students at Diploma level in UiTM Kedah. They found that there are five factors influencing students' performance that are demographic, student attendance, active learning, involvement in extracurricular activities and course assessment. The relationship of independent variables with dependent variables was also examined. The CGPA is used as measurement for student performance. Of all factors, four factors found to be positively related with students CGPA that are demographic, student attendance, active learning and involvement in extracurricular activities whereas course assessment has shown a negative relationship.

Larson, Hansen and Moneta (2006), explained that organized sports also provide an opportunity for initiative, emotional regulation, goal setting, persistence, problem solving and time management which may help to explain association found between sports participation and academic achievement. Although researchers agree that extracurricular activities do, in fact, influence academic performance, Borde (1998) as cited by Larson, Hansen and Moneta (2006), shows that engagements in extracurricular activities are unrelated to students' performance. One study, conducted by the National Educational Longitudinal Study, found that "participation in some activities improves achievement, while participation in others diminishes achievement". This is supported by Kimiko (2005), who found that participation in athletics, television viewing and community service has a positive effect on academic performance while participation in musical performance does not improve academic performance. Involvement in sport activities also have been proven adversely affecting students performance

Various studies had been done and found that peers influence does have impact on student performance Hanushek et. al (2002) Goethals, (2001) Gonzales et. al. (1996) shown that peer influence has more powerful effects than immediate family. Peer support was positively related to students' cumulative grade point average. Wilkinson and Fung, (2002) concluded that; by grouping students in heterogeneous learning ability (low ability students grouped with high ability students) will show an improvement in learning process and outcomes. Top students can positively affect less able students.

Schindler (2003) found that mixing abilities will affect weak students positively however the effect for good students is negative. This is contradicting with Goethals

(2001) who found that students in homogeneous group (regardless of high ability or low ability) perform better than students in heterogeneous group. Giuliodori, Lujan and DiCarlo (2006), covered that with peer interaction, students could increase their ability on solving qualitative problem-solving questions. Peer instruction will also promotes student's participation and improve student's performance.

According to Duvall and Schwartz (2000) on their study on the relationship between academic performance and technology-adept adult students addresses the impart of technology-assisted learning on academic performance among distance learners and their on-campus counterparts. The study further explores the relationship between academic performance and students' technological adaptability. They concluded that, when adjusted for gender (females out-performed males), there were no significant differences in academic performance between distance learners and their on-campus counterparts. The analysis also shows no significant differences in overall academic performance between technology-adept students and those without technological skills. To them, these findings may remove at least some perceived barriers in the decision to initiate distance education programs.

Acadamic attainment is an important parameter in measuring success in students. Observations and reports have shown that success or high acadamic achievement has become herculean task to accomplish by students in recent times, T. D Joseph(2009). In his study he concluded that, there is no significant difference between students acadamic performance and their family size

Cralley (2001), recommended that analyzing whether learner performance was related to age in a distance program. She hypothesized that older learners might perform better than younger ones. But correlation analysis at a 95 percent level of confidence found no correlation significance difference between age and performance.

With few exceptions, students using technology in distance education have similar learning outcomes to students in the traditional classroom setting. Souder (1993) conducted a natural experiment that compared traditional students and distance education students in management of technology master's degree programs. Results indicate that distance learners should not be viewed as disadvantaged in their learning experiences. Further, distance learners can perform as well as or better than traditional learners as measured by homework assignments, exams, and term papers. Equally important, as noted by researchers, is the fact that students in distance learning courses earned higher grades than those in the traditional classroom setting. Conversely, as reported by other researchers, there are no significant differences in grades for distance education students versus traditional students. Freeman (1995), Mortensen (1995) and McKissack (1997). As cited by Souder (1993)

Fillippo B, Antonello M and Lea P looked at a correlated random effects model for longitudinal data with non-ignorable drop-out: an application to university student performance, they concluded that Personal characteristics of students such as sex and place of residence do not have any statistically significant effect on the student performance, they stated that one-period-lagged response variable and the length of the retention at the university affect performance of students in a statistically significant way, And that, two things may be argued. On the one hand, students that show high exam marks in a certain four-month period tend to continue to perform well. This means that students that systematically organize their workload have also a continued high level performance; conversely, students which show bad results in a certain moment of their degree course are probably trapped in a low performance steady state. On the other hand, those who perform better are also those who retain longer in the university; phrased differently, who are likely to conclude the third year of the degree course are those students that show the highest exam results. The educational background, also, is relevant, given that having general high school diploma and showing good high school final marks positively affect the student performance at the university.

Wiesner (1983) as cited by Shelia Tucker (2004) notes that an important question still remaining to be answered, is, “what are the factors that account for student success or failure in distance learning programs”? Is it possible that student learning style preferences have an effect on whether or not students succeed or fail? Students who had learning preferences (that is, strengths) that were not supported were identified by their instructors as being slow or poor achievers. Marshall (1991). According to Sherry (1996), student preference for a particular mode of learning is an important variable in learning effectiveness, and effective learning requires knowledge of learner styles. What may work for one type of learner may not necessarily work for another. Learning style, as defined by Canfield (1992), is the moving component of educational experience that motivates students to perform well. Recognizing the existence of alternate learning styles may be helpful to the instructor in developing a local instructional theory and, according to Owens and Straton (1980), localized theory has a greater prospect of success as opposed to a general instructional theory. According to Dunn, Beaudry, and Klavas (1989), if learning preferences were supported through altering educational conditions to meet learning style preferences, statistically significant improvements in behaviors, grades, and attitudes would be observed. This philosophy can be referred to as "the match of critical learning style factors to environment and instruction" (Marshall, 1991, 226). In addition, there is a relationship between learning style variables and the satisfaction and completion of distance learning programs Thompson (1984); Moore (1976).

According to Urtel, M. G. (2008), in his study on Assessing academic performance between traditional and distance education course formats, concluded that students in a distance education course do not automatically perform equally as well, or even better, than as if they were in a face to face course. This is contrary to earlier studies. In addition, his study suggests that while age is a predictor in enrolling in a distance education versus a face to face course, age is not a predictor in the subsequent academic successes relative to format taken. Specifically, contrary to earlier reports older students do not automatically outperform their younger counterparts in distance education. And in fact, the students who withdrew from a distance education class are about the same age as students who withdrew from a face to face class; this is contrary to previously published assertions.

McDill, E., (1989), Levin, H(1986), B.A Chansarkar and A. Mishaeloudis (2001) as cited by Syed T. H and Kaza N. S(2006) explained the effects of age, qualification, distance from learning place etc. on student performance. The performance of students on the module is not affected by such factors as age, sex and place of residence but is associated with qualification in quantitative subjects. It is also found that those who live near the university perform better than other students. Yvonne Beaumont Walters, kola soyibo,(1998) as cited by Syed T. H and Kaza N. S(2006) further elaborated that student performance is very much dependent on SEB (socio economic back ground) as per their statement, “High school students’ level of performance is with statistically significant differences, linked to their gender, grade level, school elocution, school type, student type and socio-economic background (SEB)."

According to Umar (2010) on his study on "The Effect of Social Factors on Students" Academic Performance in Nigerian Tertiary Institutions, concluded that academic performance is an excellent measure of the transfer of knowledge in modern society. He found out that students' cult is an academic impediment and perhaps an outright evil. Romantic relationships having the highest impact, and may be a psychological barrier to an effective learning process. Excessive sporting activities and involvement in clubs and organizations were found to be a threat, but an insignificant one. All of the research reviews support the hypothesis that student performance depends on different socio-economic, psychological, environmental factors. The findings of research studies focused that student performance is affected by different factors such as learning abilities because new paradigm about learning assumes that all students can and should learn at higher levels but it should not be considered as constraint because there are other factors like race, gender, sex that can affect student's performance. Hansen, Joe B.(2000).

According to Goldstein (1979), as cited by Anderson et al (2006) longitudinal data are used in the research on growth, development, and change. Such data consist of measurements on the same subjects repeatedly over time. To describe the pattern of individual growth, make predictions, and gain more insight into the underlying causal relationships related to developmental pattern requires studying the structure of measurements taken on different occasions. The errors in longitudinal data often exhibit heteroscedasticity and dependence, which call for structured covariance models. Longitudinal data typically possess a hierarchical structure that the repeated measurements are nested within an individual. While the repeated measures are the first level, the individual is the second-level unit and groups of individuals are higher- level units Hox (2000). To take heterogeneity and dependence into account, one must include them as parts of the model Muthen & Satorra, (1989). Because the study was a longitudinal one a Linear Mixed-Effect Regression Model (MRM) is to be employed for the analysis. This is a statistical model that involves both fixed effect and random effects. They are the modified form of a linear regression model.

Variants of mixed-effect regression models(MRMs) have been developed and described under a variety of names: random effects models [Laird and Ware, 19821, variance component models Dempster et al., 19811, multilevel models Goldstein, 1995, hierarchical linear models Raudenbush and Bryk, (2002) two-stage models [Bock, 1989, random coefficient models de Leeuw and Kreft, (1986), mixed models Longford, (1987), Wolfinger, (1993), empirical Bayes models Hui and Berger, (1983), Strenio et al., (1983), and random regression models Bock, (1983), Gibbons et al., (1988). A basic characteristic of these models is the inclusion of random subject effects into regression models in order to account for the influence of subjects on their repeated observations. These random subject effects thus describe each person’s trend across time, and explain the correlational structure of the longitudinal data. Additionally, they indicate the degree of subject variation that exists in the population of subjects.

CHAPTER 3

METHODOLOGY

3.1 Data description

The understanding of student performance is, at present, an issue of increasing concern among academics and policy makers. In this thesis, we try to address empirically this issue at the Institute of Distance learning, KNUST on post graduate students of commonwealth executive masters in business administration students from Accra and Kumasi centers). We used data set from the individual students' records at the Institute of Distance Learning KNUST, in all 435, 433 and 429 students were considered for semester one, semester two and semester three respectively, individual student's semester weighted averages (SWA) was used as the response variable. The SWA is calculated as the summation of all the products of the marks obtained and the number of credit hours for each course divided by the total credit hours. Gender, age and center were treated as the independent variables.

The Table 3.1 shows sample of the data used and how the data was organized.

Table 3.1 sample of data used

id	SWA	Gender	Age	Centre
1	63.50	0	40	0
1	66.33	0	40	0
1	64.85	0	40	0
2	61.75	0	49	0
2	54.80	0	49	0
2	68.50	0	49	0
3	55.25	1	52	0
3	63.00	1	52	0
3	62.50	1	52	0
4	57.25	1	47	1
4	51.40	1	47	1
4	63.25	1	47	1
5	68.25	1	36	1
5	67.00	1	36	1
5	71.50	1	36	1
6	52.25	1	35	0
6	47.60	1	35	0
6	64.00	1	35	0

The coding system for the study is Male =1; Female = 0 and Accra = 0; Kumasi = 1. Because the study is a longitudinal one a Linear Mixed-Effect Model (MRM) is seen as an appreciate tool for the analysis. This is a statistical model that involves both fixed effect and random effects. They are the modified form of a linear regression model.

3.2 Random intercept model

A simple extension of the regression model to allow for the influence of each individual on their repeated outcomes is provided by

$$y_{ij} \ = \ \beta_0 + \ \beta_1 t_{ij} \ + \ v_{oi} \ + \ \varepsilon_{ij} \qquad (3.1)$$

where v_{0i} represents the influence of individual $\boldsymbol{i}$ on his or her repeated observations. Notice that if individuals have no influence on their repeated outcomes, then all of the v_{0i} terms would be equal to 0. However, it is more likely that subjects will have positive or negative influences on their longitudinal data, and so the v_{0i} terms will deviate from 0. We assume that students (subjects) start off, on the average with a certain level of weighted average that is β_0 and then build on it. With this an individual can start on a very high weighed average but as he moves along his average decreases, somebody can also start on a very low weighed average and improve upon it as he moves along and lastly it can also happen that an individual will start on a certain weighted average and maintain it throughout this study.

To better reflect how this model characterizes an individual’s influence on their observations, it is helpful to represent the model in a hierarchical or multilevel form Goldstein (1995), Raudenbush and Bryk (2002). For this, it is partitioned into the following within subjects (or level-1) model,

$$y_{ij} = b_{0i} + b_{1i}t_{ij} + \varepsilon_{ij} \qquad (3.2)$$

and between-subjects (or level-2) model,

$$b_{0i} = b_0 + v_{0i} \qquad (3.3)$$

$$b_{1i} = b_1$$

Here, the level-1 mode l fellows a regression model which indicates that individual $i's$ response at time j is influenced by his or her initial level b_{0i} and time trend, or slope, b_{1i}. The level-2 model indicates that individual $i's$ initial level is determined by the population initial level β_0 plus a unique contribution for that individual v_{0i}Thus, each individual has their own distinct initial weighted average. Conversely, the present model indicates that each individual's slope is the same; all are equal to the population slope β_1. Another way to think about it, is that each person's trend line is parallel to the population trend determined by β_0 and β_1. The difference between each individual's trend and the population trend is v_{0i} which is constant across time. The hierarchical representation shows that just as within subjects (level-1) covariates can be included in the model to explain variation in level-1 outcomes(y_{ij}), between-subjects (level-2) covariates can be included to explain variation in level-2 outcomes (the subject's intercept $\beta_{0i}$and slope β_{1i}). The level-1 model is a within- individuals model and the level-2 model is a between- individuals model Anderson, (2001). Note that combining the within- subjects and between-subjects models yields the previous single-equation, model **(3.1).**

3.2.1 Compound symmetry and intraclass correlation

The random intercept model implies covariance structure which assumes constant variance $\sigma_v^2 + \sigma^2$ over time as well as equal positive correlation $\rho_1 = \sigma_v^2/(\sigma_v^2 + \sigma^2)$ between any two measurements from the same student. This covariance structure is called compound symmetric while the common correlation is term as intraclass correlation. The intraclass correlation measures the degree of association of the longitudinal data within students

3.3 Matrix formulation

A more compact representation of the model is afforded using matrices and vectors. This formulation is particularly useful in summarizing statistical aspects of the model. For this, the MRM for the $n_i \times 1$ response vector y for individuals can be written as

$$\underset{n_i \times 1}{y_i} = \underset{n_i \times p}{X_i} \underset{p \times 1}{\beta} + \underset{n_i \times r}{Z_i} \underset{r \times 1}{v_i} + \underset{n_i \times 1}{\varepsilon_i}$$

With $i = 1 \ldots \ldots \ldots N$ individuals and $j = 1 \ldots \ldots \ldots n_i$ observations for individual i Here, y_i is the $n_i \times 1$ dependent variable vector for individual i, X_i is the $n_i \times p$ covariate matrix for individual i, β is the $p \times 1$ vector of fixed regression parameters, Z_i is the $n_i \times r$ design matrix for the random effects, v_i is the $r \times 1$vector of random individual effects, and $\varepsilon_i$is the $n_i \times 1$ error vector. For example, in the random intercept and slope model we may have

$y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \cdots \\ \cdots \\ y_{in} \end{bmatrix}$ and $X_i = Z_i = \begin{bmatrix} 1 & t_{i1} \\ 1 & t_{i2} \\ \ldots & \ldots \\ \ldots & \ldots \\ 1 & t_{in} \end{bmatrix}$ for data matrices, and $\beta = \begin{bmatrix} \beta_o \\ \beta_1 \end{bmatrix}$ and

$v_i = \begin{bmatrix} v_{0i} \\ v_{1i} \end{bmatrix}$ this is where the model has only one independent variable time(t).

We notice that the model (3.1) has one regression coefficient or independent variable that is the time factor. But the researcher is interested in assessing the influence of covariates, such as treatment group, on the responses across time. For this, covariates that do not change over time (time invariant) or those that vary across measured occasions (time varying) can be added to the model:

$$y_{ij} = \beta_0 + \beta_1 t_{ij} + \beta_2 x_i + \beta_3 x_{ij} + v_{oi} + v_{1i} t_{ij} + \varepsilon_{ij}$$

Here, β_2 is the coefficient for the time invariant covariate x_i, and β_3 is the coefficient for the time varying covariate x_{ij} Interactions between the covariates can be included in the same way as interactions are included into an ordinary multiple regression model. For example, x_i might represent the treatment group that a subject is assigned to (for the course of the study), and x_{ij} might be the treatment by time interaction that is obtained as the product of x_i by t_{ij}. The error terms ε_i are assumed to be normally and conditionally independently distributed with mean 0 and variance σ^2. The error terms are independent conditional on v_{oi} and v_{1i}.

In our case, the independent variables are more than one. We have time, age center and sex as the explanatory variables. Representing this in the form of a matrix gives

$$y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \cdots \\ \cdots \\ y_{in} \end{bmatrix} \quad \text{and} \quad X = \begin{bmatrix} 1 & t_{i1} & a_{i1} & g_{i1} & c_{i1} \\ 1 & t_{i2} & a_{i2} & g_{i2} & c_{i2} \\ 1 & t_{i3} & a_{i3} & g_{i3} & c_{i3} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & t_{in} & a_{in} & g_{in} & c_{in} \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_4 \end{bmatrix} \text{ the } v_i \; and \; Z_i \;\; matrics \; are \; the \; same \; as \; before$$

From matrix X, a,g and c represent age, gender and centre respectively.

3.3 Random intercept and trend model

We release that the random intercept model faces some criticism in the sense that it is not likely that the rate of change across time will be the same for all individuals, it is clear that individuals differ in their time trend. With this, a random intercept and trend model is introduce to allow both the intercept and time trend to vary by individuals. For this, the level one model is maintain as before but the level two model is modified as

$$b_{oi} = \beta_o + v_{oi}$$

$$b_{1i} = \beta_1 + v_{1i}$$

In this model, the $\beta_0 \; and \; \beta_1$ are the population intercept and population slope respectively, v_{0i} is the intercept deviation for individual $i \; and \; v_{1i}$ is the slope deviation for individual i. The ε_{ij} is an independent error term distributed normally with mean 0 and variance σ^2. With two random individual specific effect, the population distribution of intercept and slope deviations is assumed to be bivariate normal $N(0, \Sigma_v), with$ the random effect variance-covariance matrix as

$$\Sigma_v = \begin{bmatrix} \sigma_{v0}^2 & \sigma_{vov1} \\ \sigma_{vov1} & \sigma_{v1}^2 \end{bmatrix}$$

The variance-covariance matrix of the longitudinal data follows the equation $V(y_i) = Z_i \Sigma_i Z'_i + \sigma^2 I_{ni.}$ this is specifically the variance-covariance matrix of the repeated measures given the model covariates X. The variance-covariance matrix is a positive definite one.

In general, a linear mixed effect model is any model which satisfies

$$\begin{cases} Y_i = X_i\beta + Z_i v_i + \varepsilon_i \\ v_i \sim N(0, D) \\ \varepsilon_i \sim N(0, \Sigma_i) \\ v_i \dots\dots.., v_n, \dots\dots\dots \varepsilon_n \qquad independent \end{cases}$$

It follows from the above model that conditional on the random effect v_i Y_i is normally distributed with mean vector $X_i\beta + Z_i v_i$ and with covariance matrix $\Sigma_{i.}$ The v_i is assumed to be normally distributed with mean 0 and covariance matrix D

3.4 Estimation of parameters using restricted maximum likelihood

Laird and Ware, (1982) and Bock, (1989) stated that the estimation of mixed effect models generally uses a combination of two complementary methods. As cited by Dickson and Donald (2006).

This study focuses on the restricted maximum likelihood estimation. To begin with, we consider the case where the variance of a normal distribution $N(\mu, \sigma^2)$ to be estimated based on a sample Y_i, ..., Y_N of N observations. Where the mean μ is known, the maximum likelihood estimation (MLE) for σ^2 equals$\hat{\sigma}^2 = \sum_i (Y_i - \mu)^2/N$, which is unbiased for σ^2. When μ is not known, we get the same expression for the MLE but with μ replace by the sample mean $\overline{Y} = \sum_i Y_i /N$.

$E(\hat{\sigma}^2) = \frac{N-1}{N}\sigma^2$ (3.10)

The above equation (3.18) indicates that the MLE is now biased downward due to the estimation of μ, but an unbiased estimation can be obtained from the above equation as (3.18) $S^2 = \sum_i (Y_i - \overline{Y})^2/(N-1)$ which is the classical sample variance.

To get an unbiased estimate for σ^2 directly without first estimating the μ, can be done as follows. We let $Y = (Y_{1,\ldots\ldots\ldots\ldots} Y_N)'$ denote the vector of all measurements, and let 1_N be N-dimensional vector containing only ones. The distribution of Y is then N ($\mu\ 1_N$, $\sigma^2 I_N$) where I_N equals the N-dimensional identity matrix, let also A represent any N × (N− 1) matrix with N− 1 linear independent columns orthogonal to the vector $1_{N,}$ we then define vector U of N – 1 as $U = A^T Y$ which is called the error contrast. Vector U follows the normal distribution with mean vector zero and covariance matrix $\sigma^2 A^T A$. When we Maximize the corresponding likelihood with respect to the only remaining parameter σ^2 yields $\hat{\sigma}^2 = Y^T A\ (A^T A)^{-1} A^T Y/\ (N-1)$ which can be shown as been equal to equation (3.10) classical The resulting estimator for σ^2 is called the restricted maximum likelihood (REML) estimator since it is restricted to (N− 1) error contrasts. Harville (1974) put down the function for error contrasts. It was later deduced that Harville's function equals

$$L(\alpha) = C\left|\sum_{i=1}^{N} X'_i W_i(\alpha) X_i\right|^{-1/2} L_{ML}(\widehat{\beta}(\alpha), \alpha) \qquad (3.12)$$

Where C is a constant not depending on α, $W_i(\alpha)$ equals $V_i^{-1}(\alpha)$, and where $L_{ML}(\beta, \alpha) = L_{ML}(\theta)$ is the maximum likelihood function. Because $\left|\sum_{i=1}^{N} X'_i W_i(\alpha) X_i\right|$ in (3.12) does not depend on β, it follows that the REML estimators for α and for β can also be found by maximizing the REML likelihood function $L_{REML}(\theta) = \left|\sum_{i=1}^{N} X'_i W_i(\alpha) X_i\right|^{-\frac{1}{2}} \; L_{ML}(\theta)$ (3.13) with respect to all parameters simultaneously (α and β).

3.5 Inference for model parameters

The significance of the model parameters can also be tested to determine their inclusion in the model. Hypothesis testing for the fixed effect parameters $(i.e., \beta)$ generally involves the so-called Wald test (Wald, 1943) as cited by Donald and Dickson (2006). This Wald test uses the ratio of the estimated parameters to their standard errors.

i.e. to test $H_0: \beta = 0$, the Wald test statistic is

$$z = {\hat{\beta}}/{SE}$$

This has an approximately standard normal distribution when $\beta = 0$, the test statistic is compared to the standard normal frequency table to test the null hypothesis that the parameter equal 0. Equivalently, z^2 has an approximately chi-square distribution with one degree of freedom. The p-values are identical in either case.

On the part of the random effect $\mathbf{b_i}$ which reflects on how much the subject-specific profiles deviate from the overall average profile needs to be estimated. Such estimation can be interpreted as residuals which may be helpful for detecting special profiles (i.e. outlying individuals). Also, estimates for the random effects are necessary whenever interest is in prediction of subject-specific evolution. The random effects are assumed to random variables and so the Bayessian techniques would be appropriate. The distribution of the vector Y_i of responses for the *i*th individual condition on that individual's specific regression coefficients b_i is multivariate normal with mean vector $X_i\beta + Z_ib_i$ and covariance matrix Σ_i. Also the marginal distribution of b_i is multivariate normal as before with mean 0 and covariance matrix D. Since the parameters b_i does not depend on the data Y_i the last distribution would be called prior distribution of the parameters b_i. Once observed values y_i for Y_i have been collected, the posterior distribution of b_i is defined as the distribution of b_i conditional on $Y_i = y_i$, can then be calculated.

Apparently, if we denote the density function of Y_i conditional on b_i, and the prior density function of b_i by $f\left(y_i / b_i\right)$ and f (b_i), respectively, we would have the posterior density function of b_i given $Y_i = y_i$ as

$$f(b_i\,|y_i) \equiv f(b_i|Y_i = y_i) = \frac{f(y_i|b_i)f(b_i)}{\int f(y_i|b_i)f(b_i\,)db_i} \qquad (3.14)$$

To make things a bit simple we suppressed the dependence of all above density functions on certain components of θ.Lindley and Smith (1972) and Smith (1973) as cited by Use the theory on general Bayesian linear models to show that (3.14) is the density of the multivariate normal. In most cases b_i is estimated by the mean of this posterior distribution, called the posterior mean of b_i. This estimate is then given by

$$\begin{aligned} \hat{b}_i(\theta) &= E[b_i|Y_i = y_i] \\ &= \int b_i f(b_i|y_i)db_i \qquad (3.15) \\ &= DZ'_i W_i(\alpha)(y_i - X_i\beta), \end{aligned}$$

And the covariance matrix for the corresponding estimator equal

$$var\left(\hat{b}_i(\theta)\right) = DZ'_i\left\{W_i - W_iX_i\left(\sum_{i=1}^{N} X'_iW_iX_i\right)^{-1} X'_iW_i\right\}Z_iD, \qquad (3.16)$$

Where W_i equals V_i^{-1} as before, Laird and Ware (1982) as cited by we notice that equation (3.16) underestimates the variability in$\hat{b}_i(\theta) - b_i$ since it ignores the variation of b_i. The inference for b_i is usually base on

$$var\left(\hat{b}_i\,(\theta) - b_i\right) = D - var(\hat{b}_i\,(\theta) \tag{3.17}$$

as an estimator for the variation in $\hat{b}_i\,(\theta) - b_i$.

CHAPTER 4

DATA ANALYSIS AND RESULTS

4.1 Summary statistics on the data

This chapter deals with the analysis of the data. The students SWA serve as the dependent variable while gender, age, time and centre serves as the independent variables. In the whole a total sample of 1297 observation were used. Out of this, the number of observation for the first semester was 435 that of the second semester was 433 and the third semester was 429. The ages of the students were considered and it was realized that the minimum age was 26 years while the maximum age was 57years. It was also seen that greater percentage of the students fell at age 34, they represented 8.52 percent, the ages with the minimum representation were 26, 52, 53,54,55,56 and 57 they had 0.25 percent each. We also took into account the sex distribution of the students. We observed that the sex status of 36 students was missing. The remaining number was 399 and out of this, females constituted 110 representing 27.57 percent while males constituted 289 representing 72.43 percent. Concerning the centre, 189 students representing 43.45 percent registered at the Kumasi centre while 246 students representing 56.55 percent registered at the Accra centre.

4.2 Exploring the data

One of the major components of a longitudinal data analysis is the exploratory analysis. For a good longitudinal data analysis it must begin by making displays that reveal the patterns important to the scientific question. In this portion of the work, various graphs would be used to explore the sample data. Graphs like the individual profile for the two centres, the individual profile for the various centres, the overall mean for the combine centres and separate centres, how related the SWAs are between various semesters(correlation) and their variances were considered. Knowledge of the individual profiles will inform us to identify general trends within subjects, it may also detect nonlinear change over time and also provides information about the variability at given times. The mean for the two centres will give us the picture of how each centre's entire SWAs behave on the average.

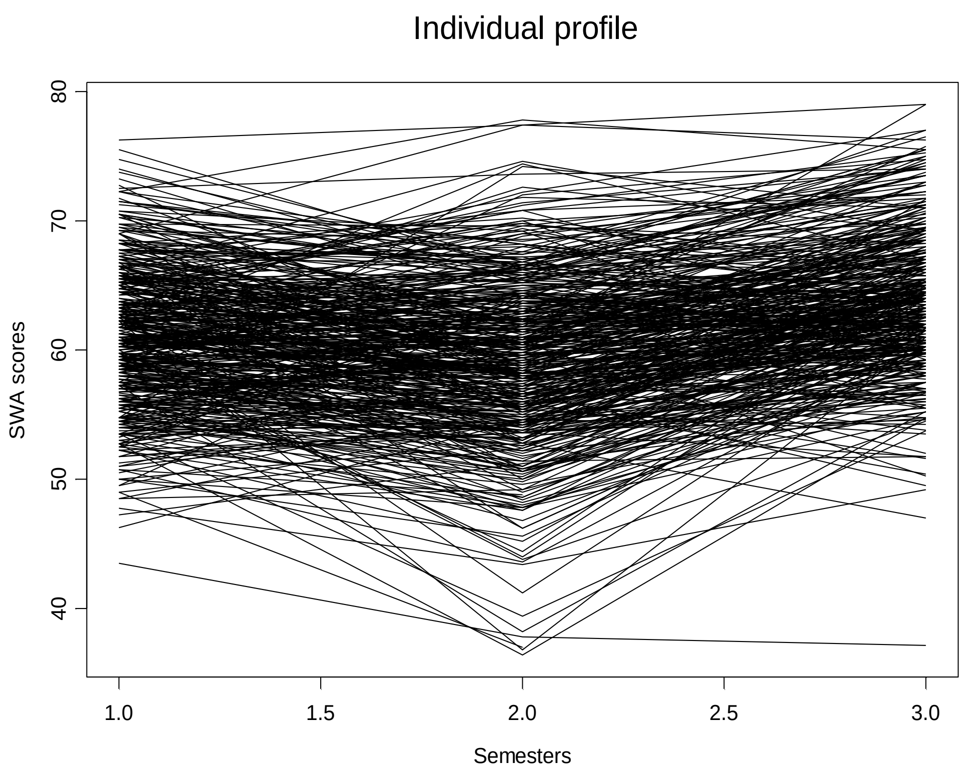

Figure 4.1 shows the individual profile for the two centres combine.

From the figure 4.1 above we observed that some students start on different SWA scores at semester one. The students' SWA ranges between 43 percent and 80 percent. Also, we noticed that some students start with high SWA but the SWA decline in the second semester and rise again in the third semester, other students also begin on a certain SWA improve in the second semester but decline in the third semester. Lastly most students started on an SWA between 55 to 70 percent and maintain it till the third semester.

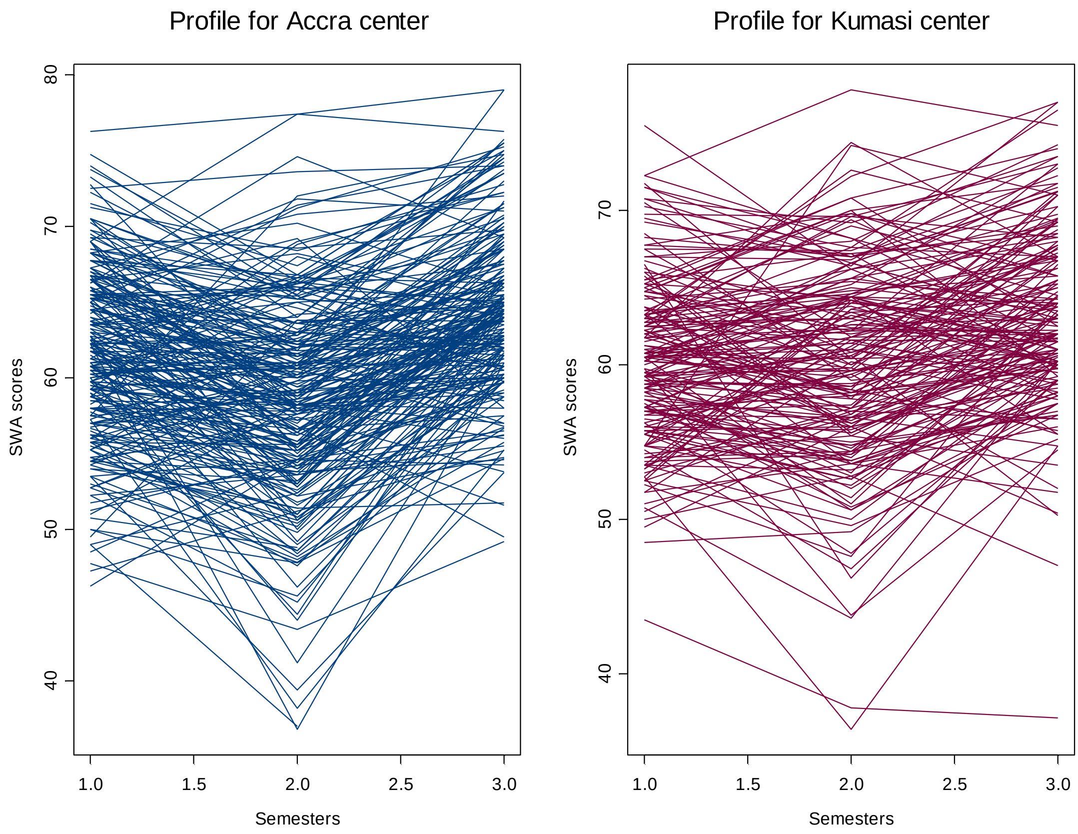

Figure 4.2 shows the individual profile for the two centres separately.

Looking at the profile for the Accra centre, relatively the SWA for some students decreased in the second semester but increased in the third semester. There were very few students who improve upon their SWA from the start till the third semester also most of the students started on SWA between 53 to 70 percent and maintain it till the third semester. The SWAs for the Kumasi centre exhibit almost the same pattern as the Accra centre with few variations.

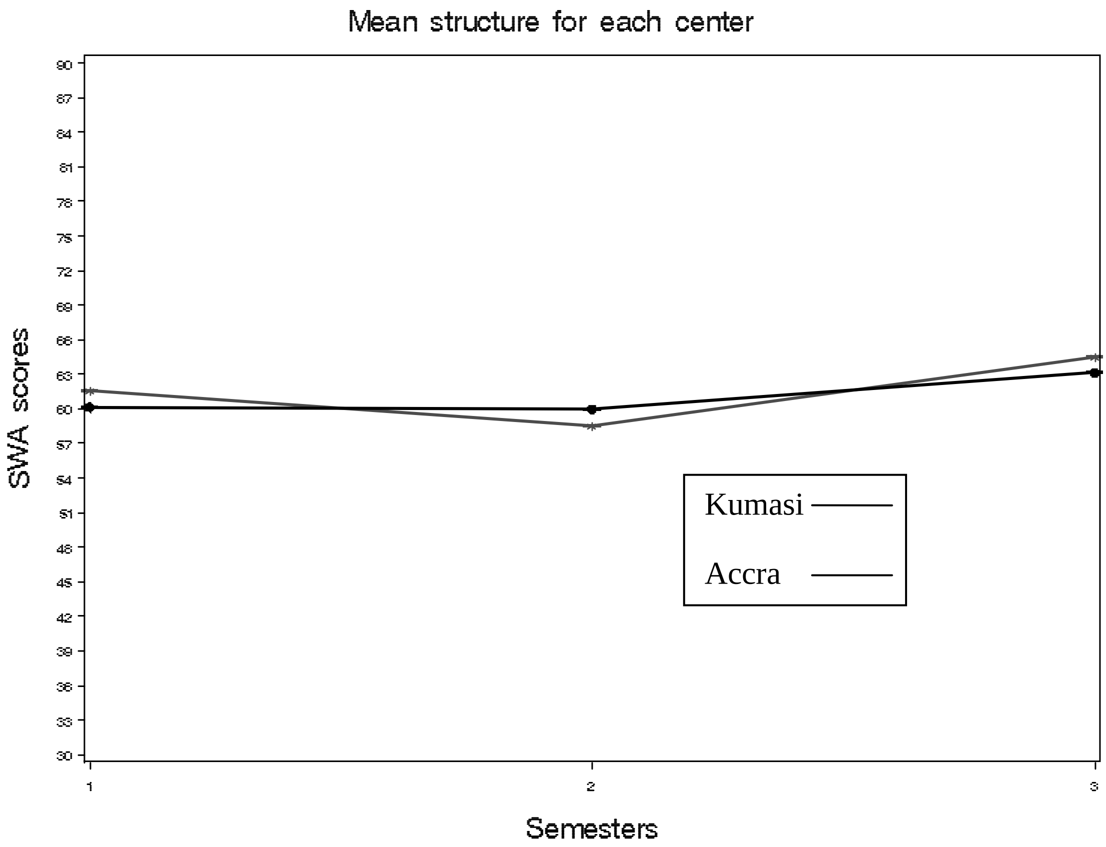

Figure 4.4 shows the mean profile for each centre.

The Accra centre represents the deep line while the Kumasi centre represents the thin line. We observed from Figure 4.4 that, the mean SWA for Kumasi centre is above the mean SWA for the Accra centre at semester one, during the second semester the mean SWA for both centres dropped slightly but the drop in Kumasi was higher than that of Accra, lastly in the third semester, the mean SWA for the Kumasi centre increased relative to the Accra centre, hence the graph of the mean SWA for Kumasi centre is above that of the Accra centre. Generally looking at the overall means, there is a linear trend for the students SWAs across the three semesters. For this reason a linear model may be considered.

Table 4.1 shows the correlation structure of the three time points.

	Swa1	Swa2	Swa3
Swa1	1.0000	0.5499	0.5577
Swa2		1.0000	0.5696
Swa3			1.0000

The general assumption about longitudinal data has been satisfied because we have gotten correlation coefficients which are all above 0.5 . That is, measurements between time points/semesters are correlated. This may mean that a student's SWA for semester two and semester one are linearly related also semester one semester three are linearly related. The variances for the three semesters were also computed as 31.44159, 45.8081and 31.9862 respectively.

Model Formulation

After a thorough exploration of the data it was clear that there is a linear trend between the average students' SWAs. This informed our decision to use the linear mixed model. This model has various forms.

4.3 Random model with no fixed effect

The first model we will fit will be the null model, with this model there is only random variable no fixed effects.

$$SWA_{ij} = v_{oi} + \varepsilon_{ij} \qquad (4.1)$$

$$v_{oi} \sim N(0, \sigma_{bo}^2), \quad \varepsilon_{ij} \sim N(0, \sigma^2)$$

With this model we mean that the students SWAs depend only on their individual random effects.

Table 4.2 covariance parameter estimates

Cov Parm	Subjects	Estimates
UN(1,1)	id	18.7404
Residual		21.6192

The intraclass correlation coefficient (ICC) is computed, the formula is the individual variance divided by the total variance.

$$ICC = \frac{\sigma_v^2}{\sigma^2 + \sigma_v^2}$$

$$ICC = \frac{18.7404}{18.7404 + 21.6192}$$

$$= \ 0.4643$$

This means that the degree of association of the students SWAs is around 46%. It also means that 46% of the variance in the data are attributable to the individuals.

4.4 Random intercept model (with no intercept)

$$SWA_{ij} = \beta_1 age + \beta_2 sex + \beta_3 centre + \beta_4 tme_{ij}\, centre + v_{0i} + \varepsilon_{ij}$$

Effects	Estimates	Standard Error	DF	t Value	PrZ
Age	1.5438	0.03614	789	42.72	< .0001
Sex1	4.1402	1.4102	789	2.94	0.0034
Centre	-2.7185	1.3348	789	-2.04	0.0420
Centre*tme	1.5529	0.2057	789	7.55	< .0001

Table 4.3 shows solution to fixed effects.

The random intercept model with no intercept is considered to assess the effects of the regression parameters. In this model time was allow to vary with centre. That is to assess the impact of study centre over time. According to the t-test conducted it was shown from Table 4.4 that only age is significant. Another test statistic (F- test) was used and the results also confirmed that only age was significant in that model.

4.5 Random intercept model with intercept

$$SWA_{ij} = \beta_0 + \beta_1 age + \beta_2 sex + \beta_3 centre + \beta_4 tme_{ij}\, centre + b_{oi} + b_{1i} tme_{ij} + \varepsilon_{ij}$$

$i = 1, \dots \dots \dots, 435$

$j = 1,2,3$

Effects	Estimates	Standard Error	DF	t Value	Pr > |t|
Intercept	66.4228	1.5206	396	43.68	<.0001
Age	-0.1322	0.04010	789	-3.30	0.0010
Sex1	-0.2198	0.5451	789	-0.40	0.6869
Centre	-3.2608	0.6336	789	-5.15	<.0001
Centre*tme	1.5619	0.2055	789	7.60	<.0001

Table 4.6 solution to fixed effects

Focusing first on the estimated regression parameters, this model shows that on the average students start off with SWA of 66.4228 This value being significant indicates that SWAs are different than zero at the baseline. We realized that on the average students start on a high SWA, drops a little during the second semester and improve in the third semester. Here, we notice that sex is not significant meaning that the students SWAs do not depend on their sex. On the contrary age and centre are significant. The parameter for age is (-0.1322) and this suggest that students SWA reduce by (0.1322) as they grow. In view of this, it means we could drop the sex and have the equation below.

4.6 Final Model

$SWA_{ij} = \beta_0 + \beta_1 centre + \beta_2 age + \beta_3 tme_{ij}\, centre + b_{oi} + b_{1i} tme_{ij} + \varepsilon_{ij}$

Effects	Estimates	Standard Error	DF	t Value	Pr > |t|
Intercept	66.4228	1.5206	396	43.68	<.0001
Centre	-3.2608	0.6336	789	-5.15	<.0001
Age	-01322	0.0401	789	-3.30	<.0010
Centre*tme	1.5619	0.2055	789	7.60	<.0001

Table 4.7 solution to fixed effects

Table 4.7 represent the final model. The solution above means that the students' SWA is a function of time, centre and entry age.

Finally, the estimates for the random effects variance covariance matrix was considered as $a_{11} = 14.2005$, $a_{12} = a_{21} = 0.9794$, $a_{22} = 0.0002$

The figure 14.2005 indicates how much spread there is around the population intercept. The entry 0.0002 represents the spread in slope and lastly the entry 0,9794 represents the degree to which the individual intercept and the slope parameters covary.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5.1 Summary

The study looked at the longitudinal analysis on academic performance of CEMBA at the Accra and Kumasi centres, using their SWAs. The summary statistics and the exploratory data analysis provided a clear picture as to the type of model to be fitted for the data. Upon critical examination of the overall mean performance it was clear that there was a linear trend between the students SWAs for the three semesters and that a linear mixed effect model should be used. The individual profiles for the two centres showed us the trend of each individual academic performance as he or she progresses from semester one to semester three. It was shown that generally students at the Accra centre start on a high SWA dropped at the second semester and later improve on the third semester. There were few cases where students started on low level and increased along the three time period. In other cases also they started on a low SWA, improved upon it during the second semester and dropped again at the third semester. Students at the Kumasi centre exhibited a constant progression in their academic performance, thus, they started with high SWA and increase it throughout or maintain it. Also, there were some students whose SWA dropped at the second semester but eventually increased in the third semester. In other instances, some students started with low SWA increased it at the second semester but fell again in the third semester.

Table 4.1 which, shows the correlation structure indicates that semesters correlate with each other. Thus, semester one and semester two are linearly related, semester one and semester three are also linearly related and lastly semester two and semester three. There was a slight increase in the correlation coefficients but the figures are little above 0.5 which does not show a very strong correlation. But this shows the satisfaction of the compound symmetry assumption which states that there is a constant correlation that is 0.55 The intra class correlation (ICC) which shows the proportion of the data that has been accounted for by the model was computed to be 0.46 which indicates that 46% of the data has been explained by the model.

Several models were fitted, table 4.3 shows that student's age, sex and centre varied with time were significant. When the random intercept model was fitted the age and sex were not seen as being significant. This made us to say that the students SWAs does depend on their age sex and centre but it depends on the centre. The model suggests that at the start of semester one, older students performed better than the younger ones on the average. Also at the start of semester one, students from the Accra centre performed better than the students from the Kumasi centre on the average but when we considered centre over the three semesters we noticed that students at Kumasi centre performed better than their colleagues at Accra centre on the average. This is because the coefficient of the parameter estimates is positive (1.5529). On that same model it was established that males performed better than their female counterparts. Considering the next model which is represented by table 4.4 with this model there was an intercept which indicated that baseline SWA is not zero. The introduction of the intercept changed the first model discussed earlier. In this model age which is significant means that younger students performed better than older students on the average, according to the parameter estimates which is (-0.1322). Also when centre was considered at the start of semester one, it was evident that Accra centre performed better than the Kumasi centre on the average. But when centre was considered over the three semesters, the Kumasi centre performed better than the Accra centre. This model suggests that gender (sex) was not significant at 5% level of significance. This means that students' SWA does not depend on their gender. Final model discussed was table 4.5, in that model we rejected sex because it was found to be insignificant. The model showed that students' SWA is a function of age and centre.

5.2 Conclusion

Upon several exploration and analysis, we made the following conclusions. Student's academic performance depends on their entry age. This is in confirmation of earlier studies by Linda, Martin and Mark (2008) but in contradiction to Syed and Kaza (2006). Also, on the average, students from Kumasi centre performed better than their colleagues from Accra centre over the three semesters 'all things being equal'. In short student's SWA depends on their age and the centre they found themselves. Gender was not significant in determining the academic performance of the CEMBA students.

5.3 Recommendations

We would like to recommend that the Facilitators should encourage group learning so the older students mixed up with the younger ones in order to encourage the older student to also improve upon their academic performance. In addition, the authorities at the institute should have a second look at the facilities at the Accra centre since it was established that students at the Kumasi centre performed better than the Accra centre on the average. Also in the next study on the same topic the number of centres should be increased so as to draw a wider conclusion on the academic performance of students at the institute. Lastly, we would like to recommend that the independent variables should be extended to cover marital status, type of work, and family size in the next study also a questionnaire can be designed to look at the attitude of students.

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APPENDIX A TOTAL DATA

1 SWA	2 SWA	3 SWA	Age	Sex	Centre	Program	sex	centre	program
60.50		68.50	31	Female	ACCRA	CEMBA	0	0	1
63.50	66.33	64.85	40	Female	ACCRA	CEMBA	0	0	1
69.25	68.56	69.77	35	Male	ACCRA	CEMBA	1	0	1
64.50	66.20	68.50	33	Female	ACCRA	CEMBA	0	0	1
61.75	54.80	66.00	49	Female	ACCRA	CEMBA	0	0	1
49.00	52.40	62.00	43	Male	ACCRA	CEMBA	1	0	1
66.50	68.20	65.33	39	Male	ACCRA	CEMBA	1	0	1
60.00	62.00	63.75	39	Male	ACCRA	CEMBA	1	0	1
62.25	55.40	67.25	32	Male	ACCRA	CEMBA	1	0	1
62.00	66.20	74.25	40	Female	ACCRA	CEMBA	0	0	1
55.25	63.00	62.50	52	Male	ACCRA	CEMBA	1	0	1
62.25	57.00	69.25	41	Male	ACCRA	CEMBA	1	0	1
51.75	54.20	56.20	32	Male	ACCRA	CEMBA	1	0	1
56.67	52.60	62.50	43	Female	ACCRA	CEMBA	0	0	1
67.75	61.20	68.50	46	Male	ACCRA	CEMBA	1	0	1
74.75	66.80	75.50	31	Female	ACCRA	CEMBA	0	0	1
57.50	58.60	68.75	32	Female	ACCRA	CEMBA	0	0	1
56.25	53.80	54.60	36	Male	ACCRA	CEMBA	1	0	1
62.25	36.80	61.00	36	Male	ACCRA	CEMBA	1	0	1
54.50	57.40	53.80	34	Male	ACCRA	CEMBA	1	0	1
52.75	47.83	57.50	30	Male	ACCRA	CEMBA	1	0	1
60.75	51.60	60.00	30	Male	ACCRA	CEMBA	1	0	1
56.00	63.80	63.75	33	Female	ACCRA	CEMBA	0	0	1
74.00	65.40	69.75	42	Male	ACCRA	CEMBA	1	0	1
68.25	62.80	75.00	41	Male	ACCRA	CEMBA	1	0	1
52.75	58.20	60.00			ACCRA	CEMBA		0	1
56.00	59.80	67.00	35	Male	ACCRA	CEMBA	1	0	1
67.25	59.00	66.00			ACCRA	CEMBA		0	1
59.75	54.60	64.50	31	Male	ACCRA	CEMBA	1	0	1
65.25	60.00	69.00	32	Male	ACCRA	CEMBA	1	0	1
68.25	57.80	64.25	29	Female	ACCRA	CEMBA	0	0	1
62.25	53.00	66.25	34	Male	ACCRA	CEMBA	1	0	1
63.50	61.40	66.75	36	Male	ACCRA	CEMBA	1	0	1
57.00	54.40	64.75	41	Male	ACCRA	CEMBA	1	0	1
59.75	48.40	59.75	51	Male	ACCRA	CEMBA	1	0	1
63.25	54.20	60.25	45	Male	ACCRA	CEMBA	1	0	1
68.25	65.20	64.25	35	Female	ACCRA	CEMBA	0	0	1
54.50	51.40	51.75	42	Male	ACCRA	CEMBA	1	0	1
65.50	62.20	66.25	31	Male	ACCRA	CEMBA	1	0	1
63.50	57.60	64.25	35	Male	ACCRA	CEMBA	1	0	1

61.25	60.40	58.50	30	Male	ACCRA	CEMBA	1	0	1
59.25	58.20	60.00	40	Male	ACCRA	CEMBA	1	0	1
67.75	64.60	60.75	33	Male	ACCRA	CEMBA	1	0	1
56.75	59.20	60.00	33	Male	ACCRA	CEMBA	1	0	1
51.25	54.60	65.25			ACCRA	CEMBA		0	1
58.75	68.00	64.50			ACCRA	CEMBA		0	1
66.25	74.60	69.25	38	Female	ACCRA	CEMBA	0	0	1
49.50	63.80	62.00	44	Male	ACCRA	CEMBA	1	0	1
58.75	55.60	69.50	49	Male	ACCRA	CEMBA	1	0	1
62.50	66.80	75.50	36	Male	ACCRA	CEMBA	1	0	1
65.75	69.20	58.00			ACCRA	CEMBA		0	1
58.25	65.80	67.50	44	Male	ACCRA	CEMBA	1	0	1
57.50	72.00	74.75			ACCRA	CEMBA		0	1
54.00	53.20	64.00	31	Male	ACCRA	CEMBA	1	0	1
60.25	61.60	58.75	41	Male	ACCRA	CEMBA	1	0	1
63.75	56.40	65.00	30	Female	ACCRA	CEMBA	0	0	1
59.75	59.00	64.75	36	Male	ACCRA	CEMBA	1	0	1
55.25	49.80	62.00	30	Female	ACCRA	CEMBA	0	0	1
66.50	59.00	69.25	32	Female	ACCRA	CEMBA	0	0	1
59.00	44.40	65.00	36	Female	ACCRA	CEMBA	0	0	1
53.50	54.60	59.20	36	Female	ACCRA	CEMBA	0	0	1
50.75	48.80		35	Male	ACCRA	CEMBA	1	0	1
67.75	60.80	79.00	35	Male	ACCRA	CEMBA	1	0	1
64.00	56.80	49.50	42	Male	ACCRA	CEMBA	1	0	1
70.50	65.50	75.50	29	Male	ACCRA	CEMBA	1	0	1
61.25	69.00	72.25	31	Male	ACCRA	CEMBA	1	0	1
60.00	44.00	64.00	36	Male	ACCRA	CEMBA	1	0	1
64.50	61.40	68.50	28	Female	ACCRA	CEMBA	0	0	1
56.25	55.20	59.00	39	Male	ACCRA	CEMBA	1	0	1
59.25	60.80	69.50	40	Male	ACCRA	CEMBA	1	0	1
60.50	50.80	60.75	31	Female	ACCRA	CEMBA	0	0	1
54.75	50.60	59.75	40	Male	ACCRA	CEMBA	1	0	1
58.00	56.60	61.25			ACCRA	CEMBA		0	1
64.00	60.60	65.25	35	Female	ACCRA	CEMBA	0	0	1
62.75	60.60	73.00	44	Male	ACCRA	CEMBA	1	0	1
65.00	71.40	74.00	31	Female	ACCRA	CEMBA	0	0	1
60.75	65.00	60.50	37	Female	ACCRA	CEMBA	0	0	1
66.75	65.20	69.50	32	Male	ACCRA	CEMBA	1	0	1
60.75	63.00	61.75	29	Male	ACCRA	CEMBA	1	0	1
65.00	49.20	63.25	39	Male	ACCRA	CEMBA	1	0	1
69.00	58.60	61.00	40	Male	ACCRA	CEMBA	1	0	1
67.75	66.80	64.00	28	Male	ACCRA	CEMBA	1	0	1
49.00	37.00		28	Female	ACCRA	CEMBA	0	0	1
54.25	50.20	64.00	40	Male	ACCRA	CEMBA	1	0	1

58.00	53.60	64.75	39	Male	ACCRA	CEMBA	1	0	1
69.00	77.40	79.00	38	Male	ACCRA	CEMBA	1	0	1
62.00	58.80	63.75	44	Male	ACCRA	CEMBA	1	0	1
52.75	57.60	62.60	43	Male	ACCRA	CEMBA	1	0	1
70.50	55.20	65.25	49	Female	ACCRA	CEMBA	0	0	1
62.25	60.20	70.00	36	Female	ACCRA	CEMBA	0	0	1
69.50	61.40	65.00	40	Male	ACCRA	CEMBA	1	0	1
62.75	41.20	61.50	35	Male	ACCRA	CEMBA	1	0	1
65.75	60.00	68.75	34	Male	ACCRA	CEMBA	1	0	1
67.75	66.00	63.50	31	Female	ACCRA	CEMBA	0	0	1
63.00	61.80	62.25	31	Male	ACCRA	CEMBA	1	0	1
61.75	54.20	62.75	41	Male	ACCRA	CEMBA	1	0	1
58.00	59.20	65.20	29	Male	ACCRA	CEMBA	1	0	1
65.50	62.00	66.25	50	Male	ACCRA	CEMBA	1	0	1
61.50	54.00	64.50	42	Male	ACCRA	CEMBA	1	0	1
56.00	53.60	56.25	29	Male	ACCRA	CEMBA	1	0	1
66.50	55.00	66.75			ACCRA	CEMBA		0	1
62.25	62.80	70.75	30	Male	ACCRA	CEMBA	1	0	1
64.50	61.00	70.00	55	Female	ACCRA	CEMBA	0	0	1
57.00	59.00	60.50	32	Male	ACCRA	CEMBA	1	0	1
55.50	51.00	65.50	31	Male	ACCRA	CEMBA	1	0	1
64.25	71.20	75.25	27	Male	ACCRA	CEMBA	1	0	1
68.25	63.60	67.75	34	Male	ACCRA	CEMBA	1	0	1
67.25	62.20	68.50	32	Male	ACCRA	CEMBA	1	0	1
54.00	51.40		41	Male	ACCRA	CEMBA	1	0	1
55.25	61.00	62.75	29	Male	ACCRA	CEMBA	1	0	1
62.50	58.20	64.00	31	Female	ACCRA	CEMBA	0	0	1
55.75	53.00	71.67	34	Female	ACCRA	CEMBA	0	0	1
65.50	65.40	59.75	27	Male	ACCRA	CEMBA	1	0	1
66.50	58.00	61.50	32	Male	ACCRA	CEMBA	1	0	1
62.50	46.20	60.25	29	Female	ACCRA	CEMBA	0	0	1
61.75	61.60	66.50	40	Female	ACCRA	CEMBA	0	0	1
61.75	55.60	68.00	36	Male	ACCRA	CEMBA	1	0	1
61.00	63.00	74.75	30	Female	ACCRA	CEMBA	0	0	1
60.00	62.60	67.50	41	Male	ACCRA	CEMBA	1	0	1
71.50	67.40	75.00	36	Female	ACCRA	CEMBA	0	0	1
57.00	57.60	62.50	34	Female	ACCRA	CEMBA	0	0	1
59.25	54.40	65.25	47	Male	ACCRA	CEMBA	1	0	1
50.00	45.60	59.80	46	Female	ACCRA	CEMBA	0	0	1
58.00	57.80	59.67	35	Male	ACCRA	CEMBA	1	0	1
72.25	65.20	71.25	32	Male	ACCRA	CEMBA	1	0	1
66.25	71.80	71.00	32	Male	ACCRA	CEMBA	1	0	1
64.50	62.20	60.75	50	Male	ACCRA	CEMBA	1	0	1
54.50	53.80	64.50	42	Male	ACCRA	CEMBA	1	0	1

51.00	58.20	60.25	38	Male	ACCRA	CEMBA	1	0	1
65.25	62.00	71.50	42	Male	ACCRA	CEMBA	1	0	1
46.25	54.60	56.50			ACCRA	CEMBA		0	1
65.00	58.20	70.25	41	Male	ACCRA	CEMBA	1	0	1
65.25	65.80	74.50	29	Male	ACCRA	CEMBA	1	0	1
58.50	58.20	58.00	33	Female	ACCRA	CEMBA	0	0	1
60.75	55.80	68.50			ACCRA	CEMBA		0	1
59.75	66.60	71.25	30	Female	ACCRA	CEMBA	0	0	1
63.50	64.00	73.75	31	Male	ACCRA	CEMBA	1	0	1
61.00	49.00	58.75	36	Male	ACCRA	CEMBA	1	0	1
60.25	56.60	64.80	32	Male	ACCRA	CEMBA	1	0	1
66.75	60.60	61.25	28	Male	ACCRA	CEMBA	1	0	1
58.00	55.60	68.00	44	Male	ACCRA	CEMBA	1	0	1
63.00	52.80	66.50	30	Female	ACCRA	CEMBA	0	0	1
60.25	61.00	60.75	30	Male	ACCRA	CEMBA	1	0	1
59.75	55.80	62.75	36	Male	ACCRA	CEMBA	1	0	1
57.75		59.00	33	Male	ACCRA	CEMBA	1	0	1
63.25	60.00	64.25	39	Male	ACCRA	CEMBA	1	0	1
55.75	48.20	56.67	32	Male	ACCRA	CEMBA	1	0	1
47.25	51.20	55.20	31	Male	ACCRA	CEMBA	1	0	1
70.25	61.80	75.75	34	Female	ACCRA	CEMBA	0	0	1
68.50	65.80	73.50	28	Male	ACCRA	CEMBA	1	0	1
59.75	58.80	64.00	30	Female	ACCRA	CEMBA	0	0	1
65.50	63.60	64.75	35	Male	ACCRA	CEMBA	1	0	1
61.75	59.60	64.50	27	Male	ACCRA	CEMBA	1	0	1
60.75	60.00	62.50			ACCRA	CEMBA		0	1
68.25	70.20	66.00	38	Female	ACCRA	CEMBA	0	0	1
67.00	62.40	66.25	42	Female	ACCRA	CEMBA	0	0	1
73.25	64.00	74.50	42	Male	ACCRA	CEMBA	1	0	1
54.25	59.80	60.00	39	Male	ACCRA	CEMBA	1	0	1
59.75	64.20	64.75			ACCRA	CEMBA		0	1
63.75	66.60	73.50	35	Male	ACCRA	CEMBA	1	0	1
76.25	77.40	76.25	30	Male	ACCRA	CEMBA	1	0	1
57.75	52.20	62.00	32	Female	ACCRA	CEMBA	0	0	1
57.25	62.00	63.75	37	Male	ACCRA	CEMBA	1	0	1
63.50	65.00	65.75	32	Female	ACCRA	CEMBA	0	0	1
62.75	51.00	65.25	32	Male	ACCRA	CEMBA	1	0	1
58.00	54.80	58.75			ACCRA	CEMBA		0	1
70.50	65.80	61.75	30	Male	ACCRA	CEMBA	1	0	1
64.50	53.20	65.50	44	Male	ACCRA	CEMBA	1	0	1
62.50	60.60	70.25	33	Female	ACCRA	CEMBA	0	0	1
66.50	62.20	61.50	49	Female	ACCRA	CEMBA	0	0	1
62.25	62.40	62.80	34	Male	ACCRA	CEMBA	1	0	1
47.75	43.40	49.20	32	Male	ACCRA	CEMBA	1	0	1

APPENDIX B

Mean SWA: Accra centre

Number	Semester	Mean	Std Dev.
246	1	61.5515	5.7343
244	2	58.5140	6.8372
243	3	64.4922	5.4819

Mean SWA: Kumasi centre

Number	Semester	Mean	Std Dev.
189	1	60.1627	5.3511
189	2	60.0011	6.6019
186	3	63.1649	5.8040

APPENDIX C

Table 4.6, Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	id	14.2005
UN(2,1)	id	0.9794
UN(2,2)	id	0.0002
Residual		20.7592