

AFIT/GOR/ENS/91M-10



THE DEVELOPMENT OF AN OFFICER TRAINING SCHOOL BOARD SCORE PREDICTION METHOD USING A MULTI-BOARD APPROACH

THESIS

Sandra C. Niemi, First Lieutenant, USAF

AFIT/GOR/ENS/91M-10

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THESIS

Presented to the Faculty of the School of Engineering of the Air Force Institute of Technology Air University In Partial Fulfillment of the Requirements for the Degree of Master of Science in Operations Research

> Sandra C. Niemi, B.S. First Lieutenant, USAF

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Abstract

One phase in the Officer Training School (OTS) selection process is meeting a selection board. Recruiting Services (HQ ATC/RS) currently uses a regression model (based on data from one board) to evenly distribute "quality" among the different panels in the selection boards. HQ ATC/RS wanted a method of predicting board scores based on data from multiple boards. This study used the results from eighteen boards and 9215 applicants to develop and validate a multi-board regression model for each of tive application categories.

Comparisons between the two models showed mixed results. In two categories, non-rated operations and technical, the multiboard model explained a higher proportion of the total variance. However, in the other three categories, the single-board model explained significantly more of the total variance. In all but one category, the single-board model had lower prediction errors. Overall, the multi-board model was able to predict board scores well enough to sort the records so that each panel would get approximately the same quality distribution of records.

A discriminant analysis was also performed using the top 33% of the board scores to represent the records that would be selected (the bottom 67% were those that would not be selected). The results showed that the model could not successfully identify the records that would be selected. However, it did a much better job in identifying those that would not be selected.

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THE DEVELOPMENT OF AN OFFICER TRAINING SCHOOL BOARD SCORE PREDICTION METHOD USING A MULTI-BOARD APPROACH

I. Introduction

Background

OTS Selection Process. Officer Training School (OTS) is one of three commissioning programs for the Air Force. Each commissioning source, Reserve Officer Training School (ROTC), the Air Force Academy, and Officer Training School, has its own selection process. Although OTS produces the smallest number of officers, over 1,000 people are considered for entrance in OTS each year. The selection process for OTS consists of three steps: 1) initial screening, 2) meeting the selection board, and 3) final selection. Figure 1 illustrates the selection process.

Initial Screening. The initial screening process consists of interviews with recruiters, taking the Air Force Officer Qualification Test (AFOQT), medical evaluations, and general administrative activities (information-gathering). If a person fails to meet any of the basic qualifications, he/she may apply for a waiver. Once a person is found to be qualified or a waiver(s) is granted, the person will then proceed to the next step in the selection process, the selection board.

According to Air Training Command/Recruiting Services (FQ ATC/RSC), each person applying for OTS may apply in only one of five categories: pilot, navigator, non-rated operations, technical career fields, or non-technical career fields. Selection boards are convened approximately four times per year.



Figure 1. Selection Process

Each board consists of two or more panels in each of the five categories. Three colonels sit on each panel (7:4).

Selection Boards. Every person meeting a board will have a record with all of the pertinent information recorded. (See Appendix B for a sample record.) First, all of the records will be sorted by application category: pilot, navigator, nonrated operations, technical, or non-technical. The number of panels in each category is determined by the number of records in that particular application category.

In order for each panel to receive approximately the same distribution of "good", "fair", and "poor" records, the records are "presorted" using a regression model developed by Headquarters Air Force Military Personnel Center (HQ AFMPC/DPMD). This predicted score serves as a method for rank-ordering all of the records in each application category. The records are then sorted into stacks of ten. The top record would go to the first stack, the next record would go to the second stack, etc. An equal number of stacks are then given to each of the panels (7:4). Any extra stacks are given arbitrarily to the panels.



Figure 2. Board Scoring Procedure

Each colonel will review a stack of ten records and assign a score (0-10) for each record. Then the colonel will pass the

stack to the next colonel. Once a stack has been scored by all three colonels, the total board score is calculated: it is simply the sum of the three scores, so the maximum possible score is a thirty. The scoring procedure is outlined in Figure 2.

Once the total board score has been calculated, the record goes through a "quality control" step. Two separate checks are performed on each record. The first is to check for variations of more than 2.5 points between any two of the three colonel's scores. If the scores vary by more than 2.5 points, the record must be reevaluated. The second check involves calculating the standard deviation for each panel. If the total board score is more than one standard deviation from the predicted score, the record must be reevaluated. Reevaluation means the record will go back to the panel that originally scored it. If the discrepancies cannot be resolved (the colonels stick to their original scores), the board score will stand. Otherwise, the new score will be used (7:4).

Final Selection. When all of the board scores have been finalized, the final selection takes place. At this stage, the Commander of Recruiting Services uses information on the number of candidates needed in each category (pilot, navigator, non-rated operations, technical, and non-technical), quotas, and the board scores of all of the applicants to determine which of the applicants will be selected. Since a single high-ranking individual makes the final selection decision, it is impossible to pinpoint exactly what information is being used to make the

selection decision. It would also be very difficult to adjust the method of selection at this level.

Those individuals who are not selected on their first board will automatically be reapplied for the next board. If the applicant fails to get selected on the next board, he/she must reapply. The person will again be automatically reapplied for the fourth board if he/she fails to be selected at the third board (8). An individual may apply as many times as he/she wishes. The only limitation is an age restriction. However, the person may also apply for an age waiver, if necessary.

The goal of the selection process is to provide a fair and consistent method of determining which applicants will go to OTS. Improvements in the predicted board score would aid this process in two ways. The first is that the records could be more evenly distributed throughout the panels (the quality mix in each stack of ten would more closely resemble the quality mix in any other stack of ten). Currently, ATC uses a matrix score as an indicator of the quality of each stack of ten records. The matrix score is simply the average predicted score for that stack (8). Inevitably, comparisons will be made between the records a colonel is scoring. If every stack contains the same range of "quality," every colonel will be making similar comparisons, and no records will be judged more harshly or leniently based solely on whether the record was placed in a stack of outstanding or below average records.

The second benefit of more accurately predicting the board scores is that the checks and balance system would only return a record for rescoring when the colonels' scores were off (either the scores deviated too much from each other, or the colonels allowed some personal bias to affect their scores). If the predicted score is often inaccurate, records would needlessly be sent back for rescoring, when the real blame was on the prediction not the actual board score.

The current method of predicting the board score is a regression based on the results of a single board. In an effort to validate the model, Recruiting Services used the results from a different board. They found that "the variable weights had changed" (7:4). The measure Recruiting Services is currently using only reflects the outcomes of a single board and does not account for changes that have occurred from one board to another or from one year to another. In order for Recruiting Services to predict the next set of board scores, they need a robust model which includes information which remains constant over the long term, instead of information that may be biased by one given year. The only way to produce such a model is to develop a prediction method using the results from several years and several boards. However, since change is inevitable, the model should be reassessed often using only the most recent data (for example, from the last three to five years).

Objective

It was the objective of this research to develop a method of predicting an applicant's board score based on the individual's application category (pilot, navigator, non-rated operations, technical, or non-technical) using the results from many different boards (these boards would also span several years). This predicted board score was then used to determine the matrix scores which may be used to aid in reducing rater bias.

<u>Sub-objectives</u>. To complete its purpose, the study had to meet the following research objectives:

1. Collect the data and determine if other factors existed which would increase a model's predictive ability.

2. Determine how to accommodate missing data.

3. Determine the relevant factors for predicting board scores.

4. Determine what methods might be used to reduce the board score prediction error.

The literature review, which follows, addresses some of the factors used to predict "success." Some of these factors may also be considered for predicting board scores.

II. Literature Review

Introduction

It is the purpose of this section to review the literature pertinent to personnel selection processes. The primary emphasis will be placed on the use of predictor variables in regression analysis to predict "success". The relevance of certain variables will be discussed. Finally, other selection concerns will be presented.

"An issue of major importance to virtually every business is the ability to predict a priori which applicants will eventually prove to be successful employees" (1:11). If the reference to the Air Force as a "business" can be excused, an important point can be made here. Just like any other organization, the Air Force needs capable people to perform all of the functions within the Air Force. The cost of providing those people is, perhaps, more important now than ever, due to the large cutbacks in the Air Force to hire people who will be able to successfully perform their functions.

Predictor Variables. Data used in predicting job success takes on many different forms: "...application blanks, biographical inventories, interviews, work sample tests, and intelligence, aptitude, and personality tests" (1:11). Asher, Reilly, and Chao have shown that biographical data is highly valid in predicting success (1:11). Bretz points out two major

considerations when selecting variables for a prediction model. The first is the validity of the predictor. Not only does this mean the variable actually reports the information desired, but it also protects an organization in the event of any legal action. the second consideration is the "expected return" or utility of the predictor. A utility analysis may show that although a certain variable does an excellent job in predicting job success, it may be so expensive to obtain that any benefit gained from using this variable (versus using another variable) is lost (1:11-12).

Grade Point Average. One of the more popular prediction variables is grade point average (GPA). This popularity may be based largely on the accessibility of those records and the ease of using numbers in regression analysis. Bretz looked at thirty-nine studies which used GPA as a predictor for some type of adult achievement. The results were very mixed. Not only were the correlations between GPA and adult achievement different in magnitude, many were also different in sign. Eight of the studies showed a negative relationship between GPA and adult achievement (1:13).

Further studies predicting job success from GPA were conducted using meta-analysis (a conglomerate method of analysis). The results indicated that there might be some limited cases where GPA did add predictive power. However, Bretz maintained that there are better predictors of success, regardless of how success is measured. He also points out

several factors that are not included in GPA: difficulty of academic program/individual classes and extracurricular activities. One additional comment was that although general intelligence has been shown to be a good predictor of job success, GPA is not a measure of intelligence (1:10).

Several other studies indicate that at least one of those "other factors" can be compensated for: the educational quality of the school. Senger maintains that there can be vast differences in the general educational quality of a highly competitive technical school (MIT, for example) versus a community college. Additionally, the same GPA from the highly accredited technical school should be worth much more than from the community college (11:13). In a study predicting academic success in a graduate program, Spangler used the Baron School Index (BSI, a measure of the "degree of admissions competitiveness" of different undergraduate institutions) to scale GPA's. His results showed that this conglomerate variable (GPA * BSI) did an excellent job of predicting graduate-level In fact, the addition of the admissions competitive success. rate for the institution increased the correlation between undergraduate GPA and graduate GPA by almost twofold (13:24,48-49).

<u>Training/Experience</u>. Bretz and Giffon discuss the wide use of training and experience in predicting job performance (1:19; 3:131). In fact, Tenopyr and Oeltjen maintain

that almost all organizations that conduct job performance predictions use training and/or experience factors (14:289).

Giffon elaborates on four different methods used for quantifying training and experience: 1) the point method, 2) the grouping method, 3) the task method, and 4) the knowledge, skills, abilities (KSA) method. The point method of measuring training/experience assigns a basic score if a person meets the minimum requirements. For every increment of units (month, year, course hour, etc.) of training or experience over that minimum the person receives points. The grouping method groups applicants based on their "relative qualifications" and assigns that same score for all people in a given group (so the same score will be given to those at the same level of qualification). The task method requires each individual to assess his/her own "level of expertise" on each of a list of tasks. The ratings could reflect the amount of experience in time or the amount of training required before the person could perform the task. Finally, the KSA method uses a list of job elements. Each applicant is rated based on their knowledge, skills, abilities, and other characteristics which relate specifically to each job element (3:131).

Interview. According to N. Schmitt, "Reviews of the employment interview research have generally come to the conclusion that employment interviews (at least as they are commonly practiced in industry and government) lack both validity and reliability" (3:130). Smart discusses methods for improving

the interview process including the expansion of "person specifications." These specifications are requirements that must be met for any person to be successful in a given job. Smart suggests that the list should include twenty to forty different person specifications. In general, he recommends gathering as much information about an applicant as possible (12:47). The problem is then one of quantifying the results and implementing such a system. As suggested by the different methods of measuring training and experience, there are many potential ways to quantify the results. The real problem would be convincing employers (or the Air Force) to use improved interview methods (3:130).

Cognitive Ability Tests. Cognitive ability tests "...are professionally developed objective tests of cognitive skills, that is, aptitude or ability tests. Examples include tests of verbal and quantitative ability, reasoning, spatial and mechanical ability" (4:77). Research shows that although cognitive ability tests are valid predictors of job performance, tests are not predictive of all jobs. Furthermore, as the complexity of the task increases, the validity of the cognitive ability tests increase (4:78).

Smith and Hunter conducted a study in 1981 in which they concluded that 1) cognitive ability tests are valid predictors for all jobs, 2) cognitive ability tests are "...fair for ethnic minorities in that they do not underestimate the expected job performance of minority group members," and 3) large labor cost

savings could be realized through the use of cognitive ability tests for employee selection (4:77).

Assessment Centers.

Assessment centers vary dramatically but typically have in common that applicants participate in a variety of activities, at least some of which are group activities, and are scored by a panel of assessors who have been trained in the evaluation techniques to be used. Common assessment center exercises include leaderless group discussions, preparation and giving of a press briefing, and in-basket exercises (in which applicants are asked to go through paperwork typical to the job, and take the necessary follow-up actions) (3:132).

In addition to predicting managerial performance, assessment centers have been used by See Bray and Campbell to predict leadership in the military (3:132).

Other Selection Concerns. Selecting people to fill positions is a very challenging task. The difficult part is trying to identify what variables give the best indication that a given person will be able to satisfactorily perform the function(s) that are required elements of the position. One of the biggest challenges in the selection process is the number of different types of positions and different people, each with their own array of characteristics. For years, researchers concluded that each situation had to be dealt with individually, creating the need for different "screening" procedures and "validation studies" for every situation (4:76).

McDaniel and Schmidt explain how the "situational specific" mode of conducting personnel selections ended.

The application of improved methods for cumulating research across studies demonstrated that the perceived

situational specificity of selection procedures was illusory and due to random sampling error. The underlying reality was that most personnel selection procedures were effective methods of identifying productive employees, and that their effectiveness was essentially constant across organizational settings (4:76).

Since many different methods used for personnel selection appeared to be working, analysts came up with the idea of combining several methods into one, in the hopes that this multifaceted personnel selection method would do an even better job. In 1976, Glass created his own group of such methods and named this new conglomerate approach "meta-analysis". McDaniel and Schmidt also credit a number of other researchers who have made progress in this field. One particular meta-analysis method developed by Schmidt and Hunter deals specifically with the variation in results. Their medel

...determines the variation attributable to sampling error and to differences between studies in reliability and range restriction, and subtracts that amount from the total amount of variation, yielding an estimate of the true variation across studies. The mean levels of reliability and range restriction are used to correct the mean observed correlation to estimate the true (population) average correlation (4:77).

The problem associated with variables that are restricted in range can be a very serious one. A study conducted by Buckley sought to "evaluate the suitability" of variables used in the selection of graduate students for the Air Force Institute of Technology (AFIT). Unfortunately, the only individuals contained in the database were those who had actually been selected to attend AFIT. As a result, the undergraduate GPA's, Graduate Record Examination (GRE) scores, and other various test results would be contained in a much smaller range than the range for all applicants (2:24).

Summary

In the development of selection processes, two variables make excellent predictors: experience/training and results from cognitive ability tests. GPA, interviews, and assessment centers also have some limited potential. Since the data available for study in certain situations may likely contain only information relevant to the individuals in that group, care must be taken to assure that the proper corrections are made to counter the effects due to any restriction in range.

In a survey of 450 managers, the managers estimated the cost of "...mishiring a \$30,000-per-year employee to be around \$75,000" (12:46). Hunter and Schmidt conservatively estimated an increase in the gross national product of 80 to 100 billion dollars annually if improved selection procedures were implemented throughout the economy (4:79). Imagine the impacts on the economy if the Air Force could implement some improved selection procedures.

III. <u>Methodology</u>

<u>Data</u>

The data used in this analysis is a portion of a database kept at HQ ATC/Recruiting Services. Included are all people who applied to OTS and actually met the selection board at least once (a total of 9215 people from the 8703 board to the 8905 board). Each record in the database includes biographical information, test scores, school information, and other information for each applicant. (A database description is included in Appendix A.)

Any applicant who fails to be selected may reapply (in fact, the person will automatically be reapplied the second time). As a result, many of the applicants have multiple board records. This analysis uses only the results from the last board each person meets. The reason for this is that some of the information is kept for each board (the GPA and highest degree awarded), but most of the information is just updated for subsequent boards. If the database is maintained properly and the updates are indeed entered in the database (which is an assumption that has to be made), then only the most current information would be contained in the database. Therefore the information would apply to the last board the individual met.

Variable Selection

The first step in identifying factors which might play a role in the board score was to look at an actual record. (A sample record can be found in the Appendix B.) The next step was

to look at the ATC/Recruiting Services data base and determine which elements of information that are contained in the individual's record are also captured in the database. Twenty seven variables could be extracted from the database.

There were also many items of information that are included in the records, but either are not contained in the database or cannot be captured in the database. Table 1 lists all items that appear in the actual record that is seen by the board, but are not included in the database (or this analysis).

TABLE 1

RECORD INFORMATION NOT INCLUDED IN THE DATABASE

NEW DATABASE VARIABLES

Number of times applied to commissioning program Violations of civil or military law Sexual preference Schools attended Positions in school organizations Scholarships Athletic participation Hours worked weekly to defray school costs Attendance at industrial/trade schools (duration) Height and weight All GPA's (not just the most current)

OTHER RECORD INFORMATION

Geographic region (home address) Actual major Employment record Additional comments School honors Statement of objective and reasons for desiring an AF commission Pilot questionnaire Resume Flight time worksheet Transcripts The variables are divided into those variables that could (should) be included in the database in some form, and those that cannot be captured. An important point to note is that all of the information listed in Table 1 is not taken into account in this analysis.

Variables such as GPA, AFOQT scores, years of prior service, etc., require no translation because the variables are already expressed in a meaningful numeric form. Table 2 shows these variables that were directly converted to numeric variables.

TABLE 2

				·			
VARIABLE	DESC	<u>RIPTI(</u>	<u>NC</u>				
AFLYHRS	Numb	er of	flying 1	nours			
AFOQT A	Air	Force	Officer	Qualifying	Test	-	Academic
AFOOTN	11	11	11	n 1	H	-	Navigator
AFOOT P	11	11	11	11	11	-	Pilot
AFOOTO	11	11		ti	11	-	Ouantitative
AFOQTV	11	**	11	11	11	-	Verbal
APRYRS	Numb	er of	prior se	ervice years	5		
EVAL1145	Recr	uiter	evaluat	ion			
GPA	GPA	for h	ighest le	evel of educ	catio	n	
GRADE	High	est q	rade atta	ained in pr	ior se	erv	vice
	2	(0,	if non-p	rior service	e)		
LORS COL	Numb	er of	letters	of recommen	ndatio	on	from a colone
LORS GEN	Numb	er of	letters	of recommen	ndatio	on	from a general
LORS TOT	Numb	er of	other le	etters of re	ecomme	end	dation
WAIVS	Numb	er of	waivers	(not includ	ling	age	e waivers)
				•	_	-	•

NUMERIC VARIABLES USED IN ANALYSIS

However, in other cases (marital status, whether or not the person has a private pilot's license, whether or not the person has taken calculus, etc.) some translation must be made. The status of such yes/no variables can be represented by 0 or 1. Note that it does matter which response is assigned the "1". In the case of the APR variable, those who were not prior enlisted should not be punished for not getting all 9's on their last three Airman Performance Reports (APR's). Therefore the question would be if those who were prior service and did not get all 9's would be helped or more likely hurt in their board scores. The DISENRL variable works the same way: only those who had been disenrolled from a commissioning program would be tagged for testing. The MARSTAT, MINOR, and SX variables have all been designed to test whether or not being married, being a minority, or being a female helps or hurts the persons board score. Since the type of degree is given, it would seem appropriate to include some aspect of its relevance to the individual's application category. However, it would be very difficult to break down the degree categories too much because even the application categories are very broad (especially the technical and nontechnical career fields). Therefore the degrees were simply categorized as technical or not. Then the test can be made for whether or not having a technical degree helps/hurts the person's board score in each of the categories. In all other indicator variables, the test is whether or not each of the characteristics captured in the variables helps or hurts the board score. Table 3 shows those variables that were more accurately represented by indicator variables.

TABLE 3

INDICATOR VARIABLES USED IN ANALYSIS

VARIABLE	DESCRIPTION	VALUE
AGEWAIV	Did the person have any waivers?	yes-1 no -0
APR	Did the person have all 9's on their last three APR's?	yes-0 no -0
BACH	Did the person have at least a bachelor's degree?	yes-1 no -0
BACHPLUS	Did the person have more than a bachelor's degree?	yes-1 no -0
CALC	Did the person take calculus?	yes-1 no -0
DISENRL	Was the person ever disenrolled from a commissioning program?	yes-1
MARSTAT	Is the person married?	yes-1
MINOR	Is the person a minority?	yes-1
NOBACH	Did the person have something short of a bachelor's degree?	yes-1 $no -0$
PRIOR	Did the person have prior service time?	yes-1
PRIVLIC	Did the person have a private pilot's license?	yes-1
SX	Is the person a female?	yes-1
т	Did the person have a technical degree?	yes-1 no -0

Missing Data

In several instances, the data base only included responses if they were applicable. For example, the variable APR (all 9's on the last three APR's) only contained an answer if the person was prior service, otherwise the variable was left blank. Using this logic, an assumption was made for a number of variables: if the data was missing, then the person was assumed not to have the characteristic in question. The justification for such an assumption is simple. If the person in question did have some outstanding characteristic, the individual would be certain to have it included in his/her record. By the same reasoning, if there were some negative characteristic (like being eliminated from a commissioning program), the Air Force would be sure to include it. The only drawback of this assumption is that perfeinformation is assumed.

Although this assumption may seem like a big one, it really only assumes that the people involved in information gathering are ensuring that all relevant information is collected and those who deal with the database are keeping it up to date. Additionally, there were so many variables where this assumption had to be applied, that there would have been very few variables (and records) to study if the assumption had not been made. Table 4 lists variables, the possible values for the variables, and the value assigned to missing data.

Regression Analysis

The Statistical Analysis System (SAS), which is a statistical software package, has developed numerous procedures which perform regression analysis. Several of these procedures have been used to select significant variables (PROC STEPWISE), run regression analysis (PROC REG), produce graphs (PROC PLOT), and perform statistical analysis (PROC FREQ and PROC MEANS) (10:401-774; 9:655-1005).

TABLE 4

VARIABLE	VARIABLE RANGES	MISSING VALUES
AFLYHRS	0-4000	0
AFOQT A	0-100	-
AFOQTN	0-100	-
AFOQT_P	0-100	-
AFOQT_Q	0-100	-
AFOQT_V	0-100	-
AGEWAIV	0-2	0
APR	Y/N	Y
APRYRS	0-16	0
BACH	Y/N	-
BACHPLUS	Y/N	-
CALC	Y/N	-
DISENRL	Y/N	N
EVAL1145	0-5	0
GPA	0-4.0	-
GRADE	3-7	0
LORS_COL	0-5	0
LORS_GEN	0-6	0
LORS_TOT	0-9	0
MARSTAT	Y/N	-
MINOR	Y/N	N
NOBACH	Y/N	-
PRIOR	Y/N	-
PRIVLIC	Y/N	-
SX	Y/N	-
Т	Y/N	-
WAIVS	Y/N	0

VARIABLES AND MISSING DATA

Normal Error Model. Regression analysis employs the use of the normal error model. Several assumptions must be made in order to use this particular model: 1) the regression function must be linear, 2) error terms have constant variance, 3) the observations are independent, and 4) the error terms are normally distributed (5:111). These assumptions may be tested using lack of fit tests, residual plots, and Q-Q plots (ordered residual versus residual ranking). The first analytical technique used was regression analysis. The purpose was to determine which of the variables discussed in the previous section were significant in predicting individuals' board scores and how good those predictions were.

In general, linear regression estimates the desired variable, Y, using a linear combination of all of the predictor variables.

 $Y_{predicted} = b_0 + b_1 X_1 + b_2 X_2 + \dots$

The linear combination must minimize the sum of squares of the error: $\Sigma (Y_{actual} - Y_{predicted})^2$.

<u>R-Square</u>. R-square, the coefficient of determination, is a measure of what proportion of the total sum of squares is being explained by the regression function:

 $R^2 = \underline{SSR}$ SSR: Sum of squares regression SSTO SSTO: Sum of squares total (5:422).

Adjusted R-square (coefficient of multiple determination) is a very similar measure, except it takes into account the number of parameters being estimated by the model:

Although R-square and adjusted R-square values are a very convenient way to measure the explanatory capability of the model, they are not the only way to judge a model. Other factors like goodness of fit and prediction error may be even more important. Significance and Lack of Fit Tests. Several tests can be performed to test both the significance of individual variables and the appropriateness of the linear model. The first is called a student t test. This is a test of the significance of each of the variables used in the model. The hypothesis is that the coefficient of a variable is equal to zero (the variable is not significant) unless the t-statistic is greater than a certain threshold. The t-statistic is computed from the following equation:

> $t = b_k$ b_k : estimated coefficient for X_k $s(b_k)$: standard error of b_k (5:278).

The partial F test is similar in that it tests the significance of the individual coefficients. However, there is a notable difference in the approach used. The t test assumes that all other variables are included in the model and the "marginal significance" of the variable in question is tested. This process is repeated until all variables have been tested. The partial F test is used in a step wise approach. The significance of the first variable is tested. If that variable is significant (SAS uses a .15 significance level), the variable is retained in the model. Then the next variable is tested, and if it is significant it is added to the other variables already in the model. This process continues until all variables have been The end result is a model with only those variables that tested. add sufficient explanatory power to the model. The partial Fstatistic is calculated using the sum of squares error for a full model (which includes the variable being tested) and a sum of

squares error for a reduced model (which includes all variables in the model up to that point, except for the variable being tested):

$$F = (\underline{SSE}_{reduced} - \underline{SSE}_{full}) / (\underline{df}_{reduced} - \underline{df}_{full})$$
$$MSE_{full}$$

SSE: Sum of squares error df: Degrees of freedom MSE: Mean square error (5:280).

The overall F test deals with the principle of lack of fit. the test is whether or not the linear model (regression function) does an adequate job of fitting the data. Three assumptions are made for this test: the observations must be 1) independent, 2) normally distributed, and 3) their distributions must have the same variance (5:123). The hypothesis being tested here is that all of the variable coefficients (B's) are equal to zero. If the F-statistic is above a certain level, then this hypothesis may be rejected (which means that the model does adequately fit the data). The F-statistic is calculated according to the following equation:

$$F = MSR$$
 MSR: Mean square regression
MSE MSE: Mean square error (5:131).

Model Development. In order to perform the analysis, the records were first sorted by application category. The following set of procedures was used for each of the five categories (there were five separate models). The first step in the regression analysis was to determine which of the 27 variables added explanatory power to the regression model. The STEPWISE procedure was used for this purpose. Any variable having a
significance level of .15 or higher in the partial F test was included in the model. The next step was to run the regression with those variables. Using the t-statistic, variables not meeting the .15 significance level were removed, one at a time.

Next, several tests were run to ensure compliance with the assumptions of a normal error model. The overall F-statistic was noted at this time (if the F-statistics had shown that models failed the lack of fit test, the assumption of a linear model would have had to be reassessed). In addition, a Q-Q plot was generated to ensure normal distribution of the error terms. Plots of residuals were used to ensure the constant variance and independence of the error terms. Finally, the regression results were compared to the regression results from a study conducted by the Military Personnel Center (MPC). That study used the data from a single board to predict board scores for other boards.

Discriminant Analysis

The SAS procedure DISCRIM uses calibration data to develop a quadratic discriminant function. This function can then be used to classify test data. Since the applicant selection rate was approximately 33%, the top 33% of the board scores will represent group I. This will serve as a surrogate for selection. In each of the categories a slightly different percentage of the applicants will be classified in group I. This results from the fact that the board score is a discrete variable.

One of the assumptions for discriminant analysis is that the data must be multivariate normal. Therefore, the data used in

this analysis consists only of variables with at least some range of numerical values. For this reason, several indicator variables could not be included even though they had statistical significance in the regression models.

The SAS procedure STEPDISC performs the same function for discriminant analysis that STEPWISE does for linear regression. The significance level used for retaining variables was again .15. The STEPDISC procedure was run for each of the five categories, then DISCRIM was used to accomplish an in depth discriminant analysis for each of the categories.

A test of the homogeneity of the within covariance matrices was conducted using the null hypothesis that there was no significant difference between the two matrices. If the test statistic (a chi-square value) was high enough, then the hypothesis would be rejected and the within covariance matrices would be used instead of a pooled covariance matrix.

A board score of 25 was the cut-off for group I for the pilot category. The navigator, technical, and non-technical used a score of 24, and non-rated operations used a score of 23. These board scores were used because they created pools of people that were approximately 33% of their respective categories. Therefore, all of the group I's made up approximately 33% of the total individuals in their respective categories. In order to account for the varying percentage of applicants in group I in each of the application categories, the proportional priors were used. (Table 5 shows the cutoffs for the board scores in group I

and relevant frequency information. Appendix C contains all

board score frequencies.)

TABLE 5

Category	Board Score ¹	Frequency ²	Percent ³
Pilot	25	685	29.3
Navigator	24	379	31.1
Non-rated operations	23	530	32.7
Technical	24	193	33.9
Non-technical	24	684	27.0
¹ Lowest board score i: ² Number of records in ³ Percent of all record	n group I group I ls in group I in	each category	

GROUP I STATISTICS

To validate the discriminant function, records with a SSAN ending in 9 were not included in the calibration data. These records from all five application categories are then classified according to their respective discriminant functions and the results are compared with their "true classifications."

IV. <u>Results</u>

Regression Analysis

Variables. The variables used in the MPC model are very similar to the ones used in this study. However, the programming variable (indicates whether or not the person has taken any computer courses) could not be used because the information did not exist in the database. Additionally, the old model used BACH and MAST for bachelor's and master's degrees. A preliminary test indicated that having a PhD or masters was not as important as distinguishing between having just a bachelor's degree or having additional education beyond a bachelor's degree. The current model includes the variables BACH (which does mean the same as the MPC model) and BACHIPLUS (which does not necessarily mean a masters, but it does indicate that the person has more than just a bachelor's degree).

Pilot. In the Pilot regression, there were some very strong similarities in model variables between the MPC model and the multi-board model run here. Both included GPA, AFOQT_P, and AFOQT_A. However, the new multi-board model also included SX (being female) and PRIVLIC (having a private pilot's license) as main positive factors. It is interesting that having a bachelor's degree was a negative factor in the MPC model, whi'e having more than a bachelors was a definite positive in the new model. One variable in the new model did not have the expected sign. APRYRS is the number of prior enlisted years served.

Since pilots are very expensive to train, and the goal is to keep them around as long as possible, once the money has been spent to train them, they should be kept as long as possible. After some consideration, it seems likely that those individuals who already have some time in would already have made the commitment to stay for twenty years before entering pilot training. Those who enter pilot training without any prior time, might choose to get out after their initial commitment.

TABLE 6

MPC ¹		Multi-Board		
<u>Variable</u>	<u>Coefficient</u>	<u>Variable</u>	<u>Coefficient</u>	
Intercept	0.1162	Intercept	7.8696	
GPA	4.5046	GPA	2.4587	
AFOQTP	0.0715	SX	1.4193	
AFOQTA	0.0358	BACHPLUS	1.0190	
BACH	-1.2883	PRIVLIC	0.9284	
		CALC	0.6573	
		Т	0.4846	
		EVAL1145	0.1739	
		APRYRS	0.0955	
		AFOQT P	0.0481	
		AFOQTA	0.0278	
(Padgett:2)		AFLYHRS	0.0011	

COMPARISON OF VARIABLES: PILOT

<u>Navigator</u>. The navigator category showed fewer similarities between the MPC and multi-board models. In this case only GPA and AFOQT_A were in both regressions. The multiboard regression also included some variables that might not have been available for the MPC study. Both having a private pilot's license (PRIVLIC) and the number of letters of recommendation from generals (LORS_GEN) had large coefficients. Being a minority and having calculus also had fairly large coefficients. Again, the number of years of prior service seemed to be an asset.

TABLE 7

MPC ¹		Multi-Board		
<u>Variable</u>	<u>Coefficient</u>	<u>Variable</u>	<u>Coefficient</u>	
Intercept	6.5801	Intercept	5.7543	
GPA	2.0376	GPA	2.7479	
PGMMING	1.7053	PRIVLIC	2.1306	
AFOQTA	0.0564	LORS GEN	2.0356	
AFOQTN	0.0547	MINOR	0.7676	
BACH	-0.3533	Т	0.4613	
		EVAL1145	0.2521	
		APRYRS	0.2436	
		AFOQT A	0.0447	
		AFOQTP	0.0374	
¹ (Padgett:3) WAIVS		-0.4957		

COMPARISON OF VARIABLES: NAVIGATOR

Non-rated Operations. The non-rated operations category showed no similarities between the two models except for the GPA variable. The variables with the largest impact in the multi-board model were GPA, SX (being a female), T (having a technical degree), and LORS_GEN. The two variables with negative coefficients make sense. If someone who was prior service and did not get all 9's on their last three APR's, then they would not do as well. The more waivers a person had, the more it hurt them.

MPC ¹		Multi-	Multi-Board		
<u>Variable</u>	<u>Coefficient</u>	<u>Variable</u>	<u>Coefficient</u>		
Intercept	9.9249	Intercept	7.5996		
GPA	2.5217	GPA	2.4682		
MAST	0.8056	SX	1.3317		
CALC	0.6304	Т	1.1024		
AFOQTQ	0.0233	LORS GEN	1.0564		
AFOQTV	0.0203	LORSCOL	0.6648		
BACH	-0.2414	MARSTAT	0.5065		
		MINOR	0.4964		
		EVAL1145	0.1593		
		AFOQT A	0.0665		
		AFLYHRS	0.0085		
		WAIVS	-0.5314		
¹ (Padgett:6)		APR	-0.8067		

COMPARISON OF VARIABLES: NON-RATED OPERATIONS

TABLE 8

Technical. Some interesting results came out of the regression for the technical category. Although a factor like GPA was a big player (as would be expected), having a technical degree (T) did not appear to be significant at all. This led to the hypothesis that GPA was the overriding factor. If those individuals who had technical degrees also had lower GPA's, then having the technical degree might be outweighed by the lower GPA. However, an analysis of the technical and non-technical GPA's showed that there is no significant difference (all were within one standard deviation of each other).

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PILOT	N	Mean	<u>Std Dev</u>	<u>Minimum</u>	<u>Maximum</u>
Non-tech Tech	1639 699	2.914 2.913	0.4222 0.4439	1.6700 1.9300	4.000 3.990
NAVIGATOR					
Non-tech Tech	928 291	2.919 2.835	0.4252 0.3993	1.7000 1.9500	4.000 3.950
NON-RATED OPE	RATIONS				
Non-tech Tech	1404 215	3.008 2.788	0.4265 0.4217	1.8400 2.0600	4.000 3.900
TECHNICAL					
Non-tech Tech	403 166	3.057 2.987	0.4403 0.4261	1.9200 2.1200	4.000 4.000
NON-TECHNICAL					
Non-tech Tech	2240 289	3.095 2.949	0.4510 0.4562	1.5500 1.7700	4.000 3.950

GPA COMPARISON FOR TECHNICAL AND NONTECHNICAL MAJORS

Having a background in calculus did help some, but the largest coefficient was on having a private pilot's license. However, the weight of the GPA variable was still higher because PRIVLIC is an indicator variable, so it could only add 4.4183 points while GPA could add as many as 10.29 points. In addition, for every letter of recommendation from a general, the person added 2.6328 to their score, so this variable was also an important player.

Only the GPA variable was common between the MPC and multiboard models, but the real surprise was on the variables associated with highest degree level. In the MPC model, having a master's degree was a strong positive factor. In contrast, the multi-board model showed that not having even a bachelor's degree was significant. (The people who fell into this category were those who were nearly finished with their bachelor's degree, so they would meet the requirement of having the degree before beginning OTS.) Both number of years of prior service (APRYRS) and the number of flying hours (AFLYHRS) seemed to have a negative effect, but this time the number of waivers (WAIVS) had a positive influence (it may be that those with good credentials but who also have waivers end up competing in this category).

TABLE 10

MPC ¹		Multi-Board		
<u>Variable</u>	<u>Coefficient</u>	<u>Variable</u>	<u>Coefficient</u>	
Intercept	4.8560	Intercept	7.5996	
GPA	3.8188	PRIVLIC	4.4183	
PGMMING	2.8330	LORS GEN	2.6328	
MAST	2.1511	GPA	2.5733	
AFOQTQ	0.0651	WAIVS	1.1457	
		NOBACH	1.0618	
		CALC	0.8735	
		AFOQT_A	0.0864	
		AFLYHRS	-0.0251	
¹ (Padgett:4)		APRYRS	-0.1649	

COMPARISON OF VARIABLES: TECHNICAL

<u>Non-technical</u>. The non-technical category is the only one in which every variable found to be significant in the MPC regression, was also significant in the multi-board regression. GPA (again a big player), AFOQT_V, and AFOQT_Q were all in both models. The negative coefficients showed that both the number of regular waivers (WAIVS) and having an age waiver (AGEWAIV) hurt an individual. The surprising coefficient here was the AFOQT_A score, which actually hurt a person. However, the coefficient is not huge (although it still could have an impact of up to -5.39 points) and it is barely significant at the .15 level. This seems to be a category where other factors (more political) come into play. Females, minorities, and those with letters of recommendation from colonels and generals all have a leg up on the competition.

TABLE 11

MPC ¹		Multi-Board			
<u>Variable</u>	<u>Coefficient</u>	<u>Variable</u>	<u>Coefficient</u>		
Intercept	8.3981	Intercept	6.0143		
GPA	2.5863	GPA	2.4792		
AFOQTQ	0.1857	BACHPLUS	1.0758		
AFOQTV	0.0418	LORS GEN	0.9158		
		SX -	0.6749		
		MINOR	0.4489		
		CALC	0.4345		
		LORS COL	0.3589		
		EVAL1145	0.1126		
		AFOQT V	0.0760		
		AFOQTQ	0.0635		
		AFOQT P	0.0130		
		AFOOTA	-0.0539		
		AGEWAIV	-0.4588		
¹ (Padgett:5)		WAIVS	-0.6194		

COMPARISON OF VARIABLES: NON-TECHNICAL

<u>Aptness Assessment</u>. The first requirement of the normal error model is that the function must be linear. Since this model is multi-dimensional, it is impossible to graph the function. Therefore, a graph of the actual versus predicted values was used to give an indication of how well the model fit the data. If the graph showed a linear trend of some sort, then the model must have a reasonable fit. The graphs for the pilot and nontechnical categories were especially good. (The pilot graph is included a Figure 3. See Appendix D for the remaining graphs.)

The model can be shown to satisfy the second and third assumptions of the normal error model. Residual graphs verified that the variance of the error terms was constant. The residual plots for the pilot, navigator, non-rated operations, and nontechnical categories took on a circular shape. (See Figure 4 for the pilot graph, and Appendix E for the remaining graphs.) Although a circular shape indicates that the variance is not constant (it increases and then decreases again), it actually demonstrates an interesting fact. The model did a good job of predicting board scores that are either very high or very low (hence the low residuals at the ends). However, the model did not do as good a job of predicting mid-level board scores, so the residuals and the variance of the residuals were greater. In the technical category, there appeared to be a noticeable decrease in the variance of the residuals. Therefore this model might be improved if a logarithmic transformation of the dependent variable, board score, were used in the regression analysis (see Appendix F for the results of this logarithmic transformation).

Actual					
30.0 +			А	ΑA	AB AA
29.5					
29.0 +				А	А
28.5 +					
28.0 +				A A AA	A A
27.5 +					
27.0 +			A A	ΑΒΑΒ	AAA A
26.5 +					
26.0 +		А	AA AA	BAD AB AB	BAB AA
25.5 +					
25.0 +	A	A A	BAB ACB	ADBBBD BAA	A CAC A
24.5 +					
24.0 +	А		B BAAAB	EADAB ABAA	A A
23.5 +					
23.0 +	AA	AAACB	BBBDBBD	ADAACBBAA	A
22.5 +					
22.0 +	A	A A	AAABBB	AAA ABAAA	
21.5 +		_			
21.0 +	A A	AAA	BAAAA	AA B AA	A
20.5 +	-				-
20.0 +	A	A A A	AAAAC C	A A AA	A
19.5 +					
19.0 +	A AAB	ACA	AB B B	A A	
18.5 +	3 53			0	
	A BA	ВА	AA	C	
17.5 + 17.0 +	λ	אאא א	א א	λ	
17.0 +	А		АА	A	
16.0 +	α α α α	ΔΔΔ	۵		
15.5 +		Δ	л		
15.0 +	А	Δ Δ			
14.5 +			Δ		
14.0 +	А		**		
++ 16	 18	+- 20	22	+24	-+ +- 26
Predicted					

Plot of BDTOT*PREDBD. Legend: A = 1 obs, B = 2 obs, etc.

Figure 3. Predicted vs Actual Board Score (Pilot)



Finally, the normality of the error terms must be substantiated. When ordered residuals are plotted against residual rankings, they should form a straight line if the error terms are normal. In all five categories, the Q-Q plots were, in fact, very close to straight lines. (The pilot Q-Q plot is shown in Figure 5. See Appendix G for the remaining plots.)



<u>R-square</u>. Although the R-square values are not especially high for any of the multi-board regressions, they do indicate that the models have some explanatory power; and there are other ways of measuring the success of this type of model (i.e. prediction results). A comparison of the MPC model R-square values and the multi-board r-square values showed major improvements in three areas: non-rated operations, technical, and non-technical, no change in the navigator category, and a fairly large decrease in the pilot category. The adjusted Rsquare values indicate that the number of variables being used in the models is not excessive--all of the adjusted values are just a little lower than the regular R-square values.

TABLE 12

	MPC ¹	Multi	-Board
	\underline{R}^2	\underline{R}^2	Adj R ²
Pilot	. 47	.320	.316
Navigator	.36	.361	.355
Non-rated Operations	.15	.266	.260
Technical	.14	.239	.226
Non-technical	.14	.316	.313
¹ (Padgett:2-6)			

COMPARISON OF R-SQUARE VALUES

Significance and Lack of Fit Tests. The use of the partial F test to determine which variables should be included in the model (based on each variable's marginal significance), was described in the previous chapter. Once the pool of variables had been narrowed down by the STEPWISE procedure, two other tests were used to test the significance of the individual variables and the overall fit of the model.

The t test was used to ensure that all of the variables included in the model added significance to the model at the .15 significance level. (Any variables not meeting this requirement were dropped one at a time). Then each of the five models was tested for lack of fit using the overall F test. All five models were shown to exhibit no sign of lack of fit. (Refer to Appendix G for the t-statistics, F-statistic, and p-values for all five models.)

Validation. The final, and perhaps the most important test of the multi-board regression model was how well the model actually predicted board scores. The validation group was all individuals whose SSAN ended in nine (they were not included in the regression model). The predicted board scores were calculated for each of the five categories. The prediction error for the multi-board model are all higher, except in the nontechnical category. This result was not unexpected because the MPC model used one board to predict the very next board. The likelihood of any large changes in selection philosophy is much smaller than in the multi-board case. (Table 13 shows the commission of the prediction errors for the MPC and Multi-board models. Other statistics for the prediction error for the Multiboard model can be found in Appendix H.)

TABLE 13

	MPC	Multi	Multi-board	
	<u>Mean</u>	Mean	<u>Std Dev</u>	
Pilot	2.021	2.173	1.632	
Navigator	1.576	2.334	1.734	
Non-rated Operations	2.116	2.797	1.911	
Technical	1.814	3.436	2.711	
Non-technical	3.156	2.848	1.958	
Overall	2.375	2.598		

PREDICTION ERROR COMPARISON

Discriminant Analysis

The test for homogeneity of the within covariances showed overwhelmingly that the within covariance matrices for all five categories were not the same. If the pooled covariance matrix had been used, the discriminant function coefficients would be included in the output. However, these coefficients were not given since the within covariance matrices were used.

The discriminant function was calculated using all records with SSAN's ending in the digits 0-8. These records were then classified into groups based on this discriminant function. Then the validation was done using the remaining records (SSAN's ending in 9). These were also classified into groups. Results from both of these classifications were given in terms of percent of correct classifications and misclassifications.

In all five categories, the percent of group II records (approximately the bottom 67%) that were correctly identified as group II, was quite high. However, the discriminant function did a poor job of classifying group I records as group I. This seemed to indicate that it was much easier to identify those records that should receive lower board scores rather than those that should receive high scores. (Table 14 shows the classification results for the main se, and the test set of records in the pilot category. Appendix I contains the remaining results.)

<u>Main Group</u>					
FROM Group 1 Group 2	TO Group 1 224 115	Percent 32.70 6.96	Group 2 461 1538	Percent 67.30 93.04	Total 685 1653
Total Priors	339	14.50 29.30	1999	85.50 70.70	2338
Error		67.30		6.96	
Validation Gr	roup				
FROM Group 1	TO Group 1 29	Percent 31.52	Group 2 63	Percent 68.48	Total 92
Group 2	16	8.60	170	91.40	186
Total Priors	45	16.19 29.30	233	83.81 70.70	278
Error		68.48		8.60	

TABLE 14

PILOT

CLASSIFICATION RESULTS:

V. <u>Conclusion</u>

This chapter addresses the effectiveness of the methodologies used in this analysis, some points for management consideration, and possible areas for further research.

The regression analysis showed that there are some factors which are very important in the selection board process. GPA seems to be the most universally accepted measure of merit. Other variables representing analytical abilities and flyingrelated activities or abilities also seemed to add explanatory power. The overall power of the regression is somewhat limited. Based on the results of this study, the board scores can be predicted with about 95% certainty to ± 6 points. This means that the capability gained from this study is the ability to classify an individual record in the top, middle, or bottom. Therefore, the records could still be appropriately mixed and sent to the boards to be scored, but double-checking the board score with the predicted score should only be considered for ensuring the board score is in the "ball park" (within one standard deviation of the predicted score may be too tight a restriction).

There may be several factors behind the failure of the discriminant approach to accurately classify applicants in the top 33% or bottom 67%. The first, and most obvious, is that the criteria used to split the individuals into two groups was somewhat arbitrary. The top 33% (and bottom 67%) number was used

because historically, 33% of the applicants are selected. However, this is only a surrogate for selection. If the actual selection/non-selection results were used, discriminant analysis might have proven effective.

The other problem with this approach to discriminant analysis is that many of the factors were not captured in the data, and therefore could not be used in this portion of the analysis--this also includes indicator variables and those factors which are considered in the final selection process.

Recommendations for Management

Two areas of concern may require management consideration. The first deals with the database. If the records are to be kept for just this type of research, then the accuracy and completeness of the data are of paramount importance. Far too many assumptions had to be made concerning missing data. In addition, the reapplication procedures require constant updating of the individuals' paper records as well as the database. This is definitely a potential problem area if the two do not match. Finally, some consideration should be given to the addition of other information to the data base (see Table 1).

The second area concerns the final selection process. Frequency plots of the board scores show an interesting result. If the selection rate is roughly 33% of the applicants, then the cut-off would be at a board score of 23. (Figure 6 shows the distribution of the scores and the cut-off. Appendix J shows the cumulative distribution of scores.) The fact that the line is

drawn right in the middle of the highest frequency of scores is a definite cause for concern. Any shifting of the cut-off line has the potential to impact hundreds of applicants (it is not a situation where a couple of individuals are right above or below the line). Ideally, such a line would be drawn so that it includes the top or bottom tail of such a distribution of scores. The large middle section of scores (from roughly 18-26) represents a large gray area. Traditionally, it is much easier to classify those individuals who should receive very high and very low scores. The most difficult is distinguishing among the more "average" scores. This is why a line drawn right in the middle of these "average" scores should cause concern.

The use of the MPC regression model to double-check scores may be hindering any efforts by the board to distinguish between average and outstanding records. The MPC regression model most likely produces an average board score that is higher than it should be, and any time the board assigns a score that deviates from the predicted score, they are forced to go back and rescore the record. Any time this rescoring occurs, the final resulting score is going to be very close to the predicted score. If any predictive model is used to check the board scores, it should force a mean somewhere in the 15-18 point range (not the 20-24 range).

Recommendations for Further Study

Three areas stand out as potential topics for further research. The first is further regression analysis.



Figure 6. Board Score Frequency Plot

However, instead of using the information from one board or many boards, the emphasis would be on determining how many boards should be used to do the best job of predicting the scores of the next board. To be useful to Recruiting Services (RS), this would require running a new regression for every board using the number of previous boards indicated by the analysis. This approach would appear to do the best job of accomplishing Recruiting Service's objective of accurately predicting the board scores prior to each board.

The second area deals with using discriminant analysis (and possibly logistic regression) to attempt to classify individuals in select/non-select categories. This would indicate exactly what factors are being used in the final selection process.

Finally, on a more general note, determining what factors are currently being used for board scores and selections can be used to verify current selection strategies or to point out potential problems. However, the real problem seems to be one of determining which factors actually predict how well an individual will perform (either in OTS or in the Air Force, itself) once he/she is selected. The emphasis for such a study would be placed on determining what factor(s) best describe how successfully the individual has performed and then finding the factors that most accurately predict this performance.

Appendix A: Alphabetic List of Variables and Attributes

#	Variable	Туре	Len	Pos	Label
83	ACOMMDT	Num	8	314	Date - OTS Commission
84	ADISP	Char	2	322	Disposition Code
85	ADOB	Num	8	324	Date of Birth
86	ADOE	Num	8	332	Date - Enlistment - Actual
87	AELIMDSP	Char	1	340	OTS Eliminee Disposition
88	AELIMRSN	Char	3	341	OTS Elimination Reason
89	AFLYHRS	Num	8	344	Special Qualifications - Flying Hours
12	Α ΓΟ Ο Τ_Α	Num	3	31	AFOQT Percentile Score - Academic
7	AFOQT_FM	Char	1	17	AFOQT Test Form ID
11	AFOQT_N	Num	3	28	AFOQT Percentile Score - Navigator
10	AFOQT_P	Num	3	25	AFOQT Percentile Score - Pilot
14	AFOQT_Q	Num	3	37	AFOQT Percentile Score - Quantitative
13	AFOQT_V	Num	3	34	AFOQT Percentile Score - Verbal
8	AFSC	Char	3	18	DAFSC (Active Duty Only)
15	AFSC1	Char	3	40	AFSC (1st choice or select)
90	AGPA1	Num	8	352	Academic Educ Lvl GPA - Highest
91	AGPA2	Num	8	360	Academic Educ Lvl GPA - 2nd Highest

#	Variable	Туре	Len	Pos	Label
27	ALL9LST3	Char	1	68	Overall 9s Last 3 Ratings
92	APIDBRD	Char	1	368	Program Identity - Applied/Selected Brd
93	APIDSRC	Char	1	369	Program Identity - Source Board
94	APPL	Char	1	370	Private Pilots Liscence
22	APPSTAT2	Char	1	59	Secondary Applicant Status
28	APP_STAT	Char	1	69	Applicant Status (A=AD, N=NPS)
95	APROGHEL	Char	1	371	Program Applying For - Helicopter Pilot
96	APROGMSL	Char	1	372	Program Applying For - Missile Officer
97	APROGNAV	Char	1	373	Program Applying For - Navigator
98	APROGOTH	Char	1	374	Program Applying For - Other
99	APROGPIL	Char	1	375	Program Applying For - Pilot
100	APROGWPN	Char	1	376	Program Applying For - Weapons Officer
101	APRYRS	Num	8	377	Prior Service - TAFMS Length (Years)
102	ARISTAT	Char	2	385	Record ID - Status of Applicant
103	ARITYPE	Char	1	387	Record ID - Program Applying For
16	AVAIL_DT	Char	4	43	Available Date (YYMM)
35	CALCULUS	Char	1	82	Special Qualification - Calculus

#	Variable	Туре	Len	Pos	Label
37	CURRBRD	Num	8	86	Current Board Number (RSO)
9	DEG_TYPE	Char	4	21	Degree Type
32	DISENROL	Char	l	77	Disenrollment from a Commissioning Prog
6	DOBBYYMM	Char	4	13	Date of Birth (YYMM)
18	ETHNIC	Char	1	48	Ethnic Code
24	EVAL1145	Num	3	63	1145 Evaluation (1-5)
1	FIREWALL	Char	l	0	Firewall 9s for Non-Tech Only (Y/N)
36	GRADE	Num	3	83	Military Grade
23	GRADYEAR	Num	3	60	Year of Graduation
33	LORS_COL	Num	3	78	Number of LORs from Colonels
30	LORS_GEN	Num	3	71	Number of LORs from Generals
31	LORS_TOT	Num	3	74	Numbers of Other LORs
39	M1BDNUM	Num	8	102	
41	M1BDSTAT	Char	1	118	Board Status
40	M1BDTOT	Num	8	110	Total Board Score
47	M1DEGLEV	Char	1	145	Degree Level
49	MIGPA	Num	8	147	Grade Point Average
43	M1MATRIX	Num	8	120	Matrix Score for Pilot/Nav
46	M1PANEL	Num	8	137	Panel Number
42	M1PROG	Char	1	119	Program Applying To
44	MISELECT	Char	1	128	Select Status

#	Variable	Туре	Len	Pos	Label
45	MITILT	Num	8	129	Tilt Score for Nav, Tec, Non-Tech
48	M1TRACKR	Char	1	146	Tracking Code
50	M2BDNUM	Num	8	155	
52	M2BDSTAT	Char	1	171	Board Status
51	M2BDTOT	Num	8	163	Total Board Score
58	M2DEGLEV	Chai	1	198	Degree Level
60	M2GPA	Num	8	200	Grade Point Average
54	M2MATRIX	Num	8	173	Matrix Score for Pilot/Nav
57	M2PANEL	Num	8	190	Panel Number
53	M2 PROG	Char	1	172 .	Program Applying To
55	M2SELECT	Char	1	181	Select Status
56	M2TILT	Num	8	182	Tilt Score for Nav, Tec, Non-Tech
59	M2TRACKR	Char	1	199	Tracking Code
61	M3 BDNUM	Num	8	208	
63	M3BDSTAT	Char	1	224	Board Status
62	M3BDTOT	Num	8	216	Total Board Score
69	M3DEGLEV	Char	1	251	Degree Level
71	M3GPA	Num	8	253	Grade Point Average
65	M3MATRIX	Num	8	226	Matrix Score for Pilot/Nav
68	M3PANEL	Num	8	243	Panel Number
64	M3 PROG	Char	1	225	Program Applying To
66	M3SELECT	Char	1	234	Select Status

#	Variable	Туре	Len	Pos	Label
67	M3TILT	Num	8	235	Tilt Score for Nav, Tec, Non-Tech
70	M3TRACKR	Char	1	252	Tracking Code
72	M4 BDNUM	Num	8	261	
74	M4BDSTAT	Char	1	277	Board Status
73	M4BDTOT	Num	8	269	Total Board Score
80	M4DEGLEV	Char	1	304	Degree Level
82	M4GPA	Num	8	306	Grade Point Average
76	M4MATRIX	Num	8	279	Matrix Score for Pilot/Nav
79	M4PANEL	Num	8	296	Panel Number
75	M4 PROG	Char	1	278	Program Applying To
77	M4SELECT	Char	1	287	Select Status
78	M4TILT	Num	8	288	Tilt Score for Nav, Tec, Non-Tech
81	M4TRACKR	Char	1	305	Tracking Code
19	MARITAL	Char	1	49	Marital Status
105	ON156	Num	3	391	Matched ATC 156 to RSO (1=Yes)
104	ONAPPS	Num	3	388	Matched to OTS Apps to RSO (1=Yes)
2	OTSROTC	Char	1	1	Non-select OTS or AFROTC (Y/N)
20	PHYS_DT	Num	8	50	Date of Physical
21	PROMIS	Char	1	58	PROMIS Flag
4	RACE	Char	1	11	Race (C,N,O,X)
29	REVFLAG	Char	1	70	Review Criterion Flag
34	RSOPPL	Char	1	81	Private Pilots License

#	Variable	Туре	Len	Pos	Label
5	SEX	Char	1	12	Sex (M/F)
17	SPONSOR	Char	1	47	Military Sponsor
3	SSAN	Char	9	2	Social Security Number
38	TOTBDMET	Num	8	94	Total Number of Boards Met (RSO)
25	WAIVER1	Char	1	66	Age Waiver
26	WAIVER2	Char	1	67	Other Waiver

Appendix B: Sample Record

(Begins on next page)

APPLICATION FOR TRAINING LEADING TO A COMMISSION
IN THE UNITED STATES AIR FORCE

OMB APPROVAL NO. 0701-0001

h

AUTHORITY 10 U.S.C. 2107, Financial Assistance Program for Specially Sc Camps Implemented by AFR 53-20. Airman Commissioning Programs, and PRINCIPAL PURPOSE. To document evidence of application for consider and voluntary contractual agreement to serve the period specified ROUTINE USE. None. DISCLOSURE IS VOLUNTARY. Failure to furnish the information may resul	elected Members, 10 d AFR 53-27, Officer ation to enter an of t in denial of conside) U.S.C. 9411, Establ Training School-USi flicer training progr eration for training	lishment and Purpos AF (OTS) ram with subsequer leading to a commis	se of Schoo nt commiss ision.	ols and lioning
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(B) When allotted space is insufficient, continue on page 4 of this form. Provide a complete explanation for each item. (Identify each item with the item number)	(F) Include a earned degree	a transcript or ce e reflected in item	ertificate of comp n 10.	pletion fo	r each
 (C) Enter all dates using day, month, and year sequence (i.e., 15 Jan 88). (D) Be certain that you understand and agree to the certification in item 19 prior to signing this application. 	NOTE: Your your home w reappointed, address is us terminate from	home of record i hen you are comi enlisted, inducted ed to determine mactive duty.	is the actual plac missioned, reinsta d, or ordered to ai e travel entitlemi	e designa ted, appo ctive duty ents whe	ited as binted, /. This in you
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Dallas. IX. 75229					
HOME ADDRESS (Home of record) Dallas, Tx. 75229	SERVICING CBPO (I	nclude PAS code)	<u> </u>		
5. LEGAL STATE OF RESIDENCE (AEC# applicants only)	CBPO PHONE NUM	IBERS (Include area	code)	,	
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9 AFOOT SCORES (Only AFTCOs or Unit Commanders are authorized to	enter scores)			57	
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10 E	DUCATION				244
DEGREE(S) EARNED AND YEAR(S) (1) BS-1	988	(2)			
MAJOR SUBJECT(S; (1) Biol	ogy	(2)			
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AF Form 56, SEP 88 PREVIOUS EDITION IS OBSOLETE

PAGE 1 OF 4 PAGES

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18.	IUNDERSTAND AND AGREE THAT:	APPLICANT'S
A.	No promises have been made to me concerning the selection or utilization field of assignment, if selected	469
8.	(Flying or Technical Training Candidates). If I do not complete the course of flying training or all technical training requirements, or formal upgrade or certification training as defined in AFR 36-12, the needs of the Air Force will determine whether or not I remain on active duty. If I remain on active duty, I agree to accept and serve the active duty service commitment(s) associated with withdrawal or elimination from an education or training event, according to AFR 36-51, Table 8	<i>46</i> 4
C .	(OTS Applicants Only) If I am medically disqualified from the career field for which selected. I may be eliminated from OTS unless my academic background and experience can be utilized in another career field.	469
D.	(OTS/AECP Applicants Only). Following: OTS, my initial assignment as a commissioned officer will not be back to my current base of assignment (AFR 36-20)	N/14 56-9
E. 91, 21 al	(OTS/AECP Applicants Only). I am a bonus recipient still serving on a term of enlistment or extension for which the bonus was paid and still due to receive future annual installment payment(s). I understand that on the first class day of OTS/AECP, my future annual installment payment(s) will be suspended. If I am eventually commissioned, I will lose all entitlements to the suspended payments. If I am not commissioned and am returned to enlisted status in my bonus skill, I will begin receiving my installment payments, less a deduction for the time spent in the commissioning program.	MA SES
۶. ۲	(AECP Applicants Only) As a condition of receiving advanced education as defined in Title 10. United States Code, Section 2005. I understand and agree	NING
·	(1) To complete the academic and military requirements specified in AFR 53-20, and to serve on active duty for the period specified in this agreement	N/19 565
۰Ţ.	(2) Should I fail to complete the academic or military requirements of AFR 53-20, or refuse to accept an appointment in the Air Force, if offered, to serve on active duty for the remaining purties of my enlistment contract	N/4 464
	(3) Should I voluntarily or because of misconduct, fail to complete either jieriod of active duty, to reimburse the United States for the percentage of the cost of my education. (The reimbursement amount will be based on the unfulfilled portion of the commitment(s) incurred. Misconduct is any separation effected as a result of action initiated under Air For edirectives governing substandard duty performance (when determined to be within the member's control), una cceptable conduct, moral or professional derelicition or in the interest of national security. This includes sentence by court martial or separation in lieu of court martial.)	NHA S OF
• <u>•</u>	(4) Only the Secretary of the Air Force or designee may excuse me from my obligation to serve on active duty for the period specified in this agreement.	4.1. 505
	(5) A final decree of discharge in bankruptcy under Title 11, United States Code, if obtained within a period of five years after the last day of the specified period which I had agreed to serve, will not release me from my obligation to reimburse the United States as specified in this agreement.	NIA TA
G.	I must serve a minimum of four years of active duty from the date of my entry on active duty as a commissioned officer, or if selected for pilot or helicopter training, eight years from the date of award of aeronautical rating as a pilot or helicopter pilot, or if selected for navigator training, five years from the date of award of aeronautical rating as a navigator.	<i>161</i>
• н.	Upon completion of training, I will accept an appointment as an officer in the Air Force, if offered	469
<u>ا.</u>	If when Lam qualified, for such consideration, Lam considered, for a Regular Air Force appointment, and	969
Ŀ.	(1) A Regular Air Force appointment is tendered and i do not accepit, I may be subject to involuntary separation based on the needs of the Air Force and current policy	56.5
رونی رونی رونی رونی رونی	(2) If, after Lacceptial Regular Air Force appointment, Lidesire to resign my commission and be separated from active duty. I must tender invites resignation under appropriate directives. My separation will be contingent on acceptance of my resignation by the Secretary of the Air Force and may also be contingent upon my accepting a Reserve appointment if Linave not yet fulfilled my military service obligation.	468
19.1	I CERTIFY THAT THE FOREGOING ENTRIES ARE TRUE, CORRECT, AND COMPLETE TO THE BEST OF MY KNOWLEDGE AND BELIEF.	
DAT	Dec 89	
DAT	TYPED NAME AND GRADE OF WITNESS (Active Duty Commander or SIGNATURE USAF Recruiting Interviewing Official (For USAFRS show RIC) WMALL A JEL WAT	4A

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0.	ADDITIONAL COMMENTS OR EXPLANATIONS		ي ور الديني
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PAGE & OF & PAGES

I understand as an Air Force officer I may be required to train and exercise control of, to include actual release of, nuclear weapons in support of the nuclear policy of the United States.

Signature of Applicant

Signature of Interviewing Officer

<u> 3 January 90</u> Dati:

Jan 20
I am submitting my application with the understanding that I am age critical and that if selected and physically qualified I must enter OTS early enough to follow on and enter UPT prior to 27.5 years of age. If the Air Force is unable to place me in the OTS class to facilitate the same, my selection as a pilot would be withdrawn.

EVALUATION OF COMMISSIONING APPLICANTS OMB NO. 0701-0104 Expres 31 January 1997								
AUTHORITY 10 U.S.C. 591, Reserve Components Qui PURPOSE To determine qualifications for training Program (AECP) applicants. To determine qualificate Technicians (ART) ROUTINE USES None Furnishing information is volu a commission or direct appointment	alifications, 10 U.S (g leading to a com ons for direct appoi untary. Failure to fu	59411, Establ Imission of Ol Intment of US Irrish informa	ishment and Pu Kicer Training AFR airmen noi tion may result	rpose of Schools an School (OTS) and I on extended actin in derival of consid	d Camps. Airman Early Co re duty (EAD) an cration for traini	mmissioning d Air Reserve ng leading to		
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I. APPLICANT'S PERSONAL DATA (Applicant m	ust complete. Print	in ink and sta	y within the line	25)		<u> </u>		
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5. HOME ADDRESS AND TELEPHONE NUMBER (Inclu members use unit of assignment)	de Zip code and are	a code) (Militi	ary , 6A.	PROGRAM FOR	RICH APPLYING	<u> </u>		
			68.	# OTS OR AECP, E	ATE (YYMMDD	AVAILABLE		
7. EDUCATION AND EXPERIENCE								
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F. SCHOLARSHIPS	None		<u> </u>					
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AF Form 1145, APR 89 PALVICUS (DITKIN IS UBS.)(11)

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2 November 1989

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To: OTS Selection Board

Subject: Letter of Recommendation for

I am a retired Air Force General Officer with direct personal knowledge of and his family.

I wholeheartedly recommend that the selective for OTS followed by pilot training with the ultimate objective of an F-15 or F-16 flying assignment.

I do not have enough golden words to adequately describe the absolutely superior qualifications of this fine young man. He is:

- The son of an outstanding Air Force Officer.
- An outstanding student (National Dean's List).
- An accomplished pilot (8 different civilian aircraft).
- A highly moral and ethical man.
- A superb athlete including:
 - Quarterback and punter
 - Baseball pitcher
 - Basketball player
 - Skier
 - Tennis player

The Air Force will benefit significantly from sending this fine young man to OTS and UPT. Mark him well - he will someday be a general officer.

Sincerely,

Robert E Chapman

Robert E. Chapman Brigadier General, USAF, Retired

Bill G. Carter State Representative District 91

> Committees: Corrections, Vice Chairman Transportation



Austin Office. P.O. Box 2910 Austin, Texas 78769 512-463-0482 District Office: 7001 Grapevine Huy, Suite 34 F1. Worth, Texas 76180 817-595-0072

TO: Officer Training School Election Board

REF: Letter of Recommendation for

DATE: November 10, 1989

Please accept this letter as my personal endorsement on behalf of the second as a worthy candidate for the U.S.A.F. Officer Training School.

I truly feel he would serve as an outstanding candidate and would prove to be an asset to our country.

After reviewing his resume I think you will agree that he has devoted a lot of time and effort on his endeavors and feels very strong about his career with the Air Force. With the dedication he has expressed I feel he should be given the opportunity to expand and better his career.

Thank you in advance for any consideration you can give during your selection process. In the meantime, please feel free to call if you should require additional information or if I can be of service.

Sincerely,

Bill G. Carter

BGC/ar

cc: Senator Phil Gramm Congressman Pete Geren 12925 Jasoncrest Trail Dallas, TX 75243 10 November 1989

TO: OTS Selection Board

RE:

Dear Sirs,

Terry has expressed to me his desire to become an Air Force Officer and pilot. I know that this means a great deal to him.

I have observed there as he grew from childhood to a young man. As a retired Air Force Officer and pilot, I feel qualified to judge young men on their suitability as officers and pilots: and I can, without reservation, report that the possesses just the qualities that the Air Force expects in its officers and pilots. The is an intelligent, vital young man with the integrity and dedication to become an important contributor as an officer. He possesses the judgement and sharp reflexes that would make him a valued addition to the pilot ranks.

1

should be accorded entrance to the OTS and UPT courses as soon as possible.

Sincerely,

Duby D. Todd Major, USAF (Ret)

REPLY TO

ATTN OF: 14 STU SOD (Capt Wilcox, 343-7595) 28 Oct 89

SUBJECT: Recommendation for to OTS

TO: OTS Selection Brand

1. Recommendation for the upcoming officer Training School Selection Board.

2. The Air Force should not pass the opportunity to have the serve in the Armed Forces. His dedication and hard drive will be an assol to the USAF. Having flown with the first I know he has the natural ability to fly invthing in the air. Getting his private pilots license took minimum time, showing initiative. That is what is needed in the cockpit today. He will be a great Warrior Leader, accepting nothing but the best. I am very happy that will have the opportunity to become ap Air Force officer. Select the without delay and let him be part of the best teat in the world...The United States Air Force.

4

S. I highly recommend to be releated for OTS. He will prove himself over and over again.

DAVID E. WILCOX, Capt, USAF Student, 14 Student Squadron TO: OTS Selection Board SUBJECT: Letter of Reference FROM: Robert McFadden

October 30, 1989

I have known and the first of for fourteen years. During that time, I have seen him grow from a pre-teen with a burning desire to fly to a mature adult with that same burning desire to fly. I have counseled that about the positive and negative aspects of a flying career in both the military and the civilian aviation communities. From 1969 to 1977, I was an Air Force instructor pilot for ATC and a research pilot for AFSC. Since 1978, I have been a commercial airline pilot. Having been in both worlds, I know what it takes to succeed in the aviation career field.

what it takes. After a great deal of consideration and after long periods of selecting a career path, he has chosen the Air Force. He has all the qualities necessary to be an Air Force officer. He is dedicated, goal-oriented, organized, and assertive. He is intelligent, stable, and attentive to detail. The has natural coordination demonstrated over the years through consistent athletic success and flight accomplishments.

I whole-heartedly support the choice to join the ranks of the Air Force officer group. I am particularly proud he chose the Air Force since my memories of the time I spent in the military are fond memories. I highly recommend be selected for the USAF Officer Training School. You will not find a better or more well-suited candidate.

Sincerely U

Robert W. McFadden Formerly Capt., USAF



OBJECTIVE To become an United States Air Force career officer

WORK EXPERIENCE

1989 Flight instructor free-lance for 60 hours

1983-1988 General maintenance duties at an apartment complex

TRAINING AND OTHER EXPERIENCE

Commercial aviation with Ari Ben Aviator. Flight instructor with American Flyers. Certified flight instructor, certified flight instructor instruments and multi-engine flight instructor. Civil Air Patrol Lubbock Chapter for two years. Checked out in eight civilian aircraft with a total of 356 hours.

EDUCATION

Graduated from Texas Tech University in 1988 with a BS degree in Biological Science and a minor in Psychology. Hade the National Dean's List in 1983, Dean's List in 1983 and the Dean's Honor Roll in 1982 and 1983.

ORGANIZATIONS

ALPHA PHI OMEGA National Service Fraternity. Involved in many service activities including blood donor drives. KO SARI Social Fraternity. An elected officer. College Constitutional Revision Committee Civil Air Patrol, Second Lieutenant, pilot, Lubbock, Texas Chapter Boy Scouts of America Trident Society Medical Explorers

ATHLETICS

High School	Baseball - Pitcher/Infielder, All Star Teams, Two Varsity Letters
	Football - Team Captain, Quarterback, All-City Punter, Two Varsity Letters
	Basketball- Guard and Forward, Two Varsity Letters
	Track - 400 Meters, 400 Meter Relay, 1600 Meter Relay, One Varsity Letter
College	Intramural Football, Basketball, Volleyball

PERSONAL

Age: 26	Weight: 185 Height: 6'2"	Marital Status: Single
Hobbies:	Jet Skiing and Snow Skiing	
Other:	Son of a Lieutenant Colonel,	USAF, Retired (Regular
	Air Force)	

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TYPE HOURS	HOURS
Dual	123
Pilot in Command	_290
Cross Country	_207
Night	63
Hood	49
Instrument	12
Solo	26
Total time - Single engine land	_289
Total time - Multi engine land	92
Total time - Other	2
Total Flight Time	_383
TYPE OF AIRCRAFT	/HOURS

3 <u>C-172 / 57 hrs.</u>	6 <u>c-172RG/13 hrs.</u>
2 <u>PA-38 /107 hrs.</u>	5 <u>c-152 / 32 hrs.</u>
1 BE-76 / 92 brs.	4 PA-28 / 40 hrs.

RATINGS

1_Commercial____

2_Single=engine__

3_Multi-engine____

I certify that the above flight times, aircraft type and ratings are correct to the best of my knowledge.

-----Applicant's Signature

01/09/90 Date

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4 Instrument

5<u>Flight Instructor</u>

6 Instrument-Multi

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BS-Bio	logy
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COMPUTING THE GPA			
STRUCTIONS Use the 4-point system $(4=4, P=3, Cr)$ uals two-thirds of one semester hour), include credit hi the grade awarded. If courses were retaken, figure both at wore evoluted, or pass-fail, List each college or univer) to determine the cumulative GPA.	2. D=1, and F=0). Usin ours and quality points 1 grades into the averag 13ity separately: total c	ng AFR 35-25, convert quarter hours to for all courses taken where a grade was e. Do not include credit hours or quality olumns (b) and (c), then, divide the tota	remester hours (one quarter hour received. For incompletes, use an "F" i points for withdrawals, courses I of calumn (b) by the total of colum
NAME OF INSTITUTION (8)		TOTAL CREDIT HOURS	TOTAL QUALITY POINTS
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McMurray College		41	149
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	TOTAL	133	376
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Appendix	<u>C:</u>	Board	Score	Frequencies

(Т	0	t	а	1)
•						

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
7.5	1	0.0	1	0.0
8	3	0.0	4	0.0
8.5	2	0.0	6	0.1
9	4	0.0	10	0.1
9.5	1	0.0	11	0.1
10	2	0.0	13	0.1
10.5	8	0.1	21	0.2
11	12	0.1	33	0.4
11.5	10	0.1	43	0.5
12	16	0.2	59	0.6
12.5	31	0.3	90	1.0
13	45	0.5	135	1.5
13,5	53	0.6	188	2.0
14	81	0.9	269	2.9
14.5	83	0.9	352	3.8
15	132	1.4	484	5.3
15.5	158	1.7	642	7.0
16	410	4.4	1052	11.4
17	506	5.5	1558	16.9
18	643	7.0	2201	23.9
19	690	7.5	2891	31.4
20	871	9.5	3762	40.8
21	763	8.3	4525	49.1
22	825	9.0	5350	58.1
23	950	10.3	6300	68.4
24	896	9.7	7196	78.1
27	757	8.2	7953	86.3
26	569	6.2	8522	92.5
27	307	3.3	8829	95.8
28	118	1.3	8947	97.1
29	30	0.3	8977	97.4
30	238	2.6	9215	100.0

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
9	1	0.0	1	0.0
10.5	1	0.0	2	0.1
12	1	0.0	3	0.1
12.5	2	0.1	5	0.2
14	3	0.1	8	0.3
14.5	8	0.3	16	0.7
15	11	0.5	27	1.2
15.5	15	0.6	42	1.8
16	47	2.0	89	3.8
17	94	4.0	183	7.8
18	149	6.4	332	14.2
19	171	7.3	503	21.5
20	194	8.3	697	29.8
21	194	8.3	891	38.1
22	225	9.6	1116	47.7
23	272	11.6	1388	59.4
24	265	11.3	1653	70.7
25	279	11.9	1932	82.6
26	203	8.7	2135	91.3
27	93	4.0	2228	95.3
28	40	1.7	2268	97.0
29	10	0.4	2278	97.4
30	60	2.6	2338	100.0

Board Score Frequencies (Pilot)

Board	Score	Frequenc	ies (N	avigator)

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
8	2	0.2	2	0.2
10.5	1	0.1	3	0.2
11.5	1	0.1	4	0.3
12.5	2	0.2	6	0.5
13	3	0.2	9	0.7
13.5	2	0.2	11	0.9
14	5	0.4	16	1.3
14.5	10	0.8	26	2.1
15	15	1.2	41	3.4
15.5	13	1.1	54	4.4
16	44	3.6	98	8.0
17	68	5.6	166	13.6
18	81	6.6	247	20.3
19	89	7.3	336	27.6
20	117	9.6	453	37.2
21	114	9.4	567	46.5
22	126	10.3	693	56.8
23	147	12.1	840	68.9
24	154	12.6	994	81.5
25	109	8.9	1103	90.5
26	47	3.9	1150	94.3
27	34	2.8	1184	97.1
28	15	1.2	1199	98.4
29	1	0.1	1200	98.4
30	19	1.6	1219	100.0

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
8.5	1	0.1	1	0.1
9.5	1	0.1	2	0.1
10	1	0.1	3	0.2
10.5	4	0.2	7	0.4
11	1	0.1	8	0.5
11.5	1	0.1	9	0.6
12	6	0.4	15	0.9
12.5	10	0.6	25	1.5
13	14	0.9	39	2.4
13.5	13	0.8	52	3.2
14	24	1.5	76	4.7
14.5	26	1.6	102	6.3
15	37	2.3	139	8.6
15.5	36	2.2	175	10.8
16	113	7.0	288	17.8
17	122	7.5	410	25.3
18	131	8.1	541	33.4
19	120	7.4	661	40.8
20	168	10.4	829	51.2
21	129	8.0	958	59.2
22	131	8.1	1089	67.3
23	148	9.1	1237	76.4
24	127	7.8	1364	84.2
25	97	6.0	1461	90.2
26	84	5.2	1545	95.4
27	40	2.5	1585	97.9
28	16	1.0	1601	98.9
29	4	0.2	1605	99.1
30	14	0.9	1619	100.0

Board Score Frequencies (Non-rated Operations)

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
	 7	1.2	 ?	1.2
11.5	1	0.2	8	1.4
12	1	0.2	9	1.6
12.5	4	0.7	13	2.3
13	5	0.9	18	3.2
13.5	8	1.4	26	4.6
14	8	1.4	34	6.0
14.5	6	1.1	40	7.0
15	9	1.6	49	8.6
15.5	17	3.0	66	11.6
16	25	4.4	91	16.0
17	19	3.3	110	19.3
18	40	7.0	150	26.4
19	34	6.0	184	32.3
20	58	10.2	242	42.5
21	33	5.8	275	48.3
22	50	8.8	325	57.1
23	51	9.0	376	66.1
24	51	9.0	427	75.0
25	34	6.0	461	81.0
26	32	5.6	493	86.6
27	10	1.8	503	88.4
28	6	1.1	509	89.5
29	1	0.2	510	89.6
30	59	10.4	569	100.0

Board Score Frequencies (Technical)

BDTOT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
7.5	1	0.0	1	0.0
8	1	0.0	2	0.1
9	3	0.1	5	0.2
10.5	2	0.1	7	0.3
11	3	0.1	10	0.4
11.5	5	0.2	15	0.6
12	5	0.2	20	0.8
12.5	13	0.5	33	1.3
13	20	0.8	53	2 - 1
13.5	24	0.9	77	3.0
14	31	1.2	108	4.3
14.5	23	0.9	131	5.2
15	41	1.6	172	6.8
15.5	65	2.6	237	9.4
16	140	5.5	377	14.9
17	155	6.1	532	21.0
18	176	7.0	708	28.0
19	212	8.4	920	36.4
20	246	9.7	1166	46.1
21	230	9.1	1396	55.2
22	225	8.9	1621	64.1
23	225	8.9	1846	73.0
24	203	8.0	2049	81.0
25	146	5.8	2195	86.8
26	142	5.6	2337	92.4
27	96	3.8	2433	96.2
28	27	1.1	2460	97.2
29	10	0.4	2470	97.6
30	60	2.4	2530	100.0

Board Score Frequencies (Non-technical)

Appendix D: Predicted vs Actual Board Score

(Navigator)

Plot	of	BDTOT*PR	EDBD.	Lege	nd: A	= 1	l obs	5, E	3 =	2 ob	s, e	etc.
Actual										7		7
30 +										A		А
29 +												
28 +					А		А					
27 +						А					BA	A
26 +		A				A	A A	AAE	3			
25 +			А		AAB	A	DA	ł			А	ВВ
24 +			A		AB	A A	ACAC	C A	A	BA	А	А
23 +	A	А		A	AB	С	BA E	BA		A AA		
22 +			А		A A	A A		A	AB		В	А
21 +			ВАА	А	AA	BA	А		А	А		
20 +			А	AAAA	A I	BA	BA	AA				
19 +			А	A	AAA A		А			А		
18 +			A B AA		AA	А	А	А		А		
17 +		AA	ΑB				A		A			
16 +		А	A AA	A								
15 +	Į	A		ΑB								
14 +				۲.								
16		-+	+	20		+	22		+	 2	 4	+-

Predicted

Predicted vs Actual Board Scores (Non-rated Operations)

Plot of BDTOT*PREDBD. Legend: A = 1 obs, B = 2 obs, etc. Actual! 28.0 +A A 27.5 +27.0 + AA A A 26.5 +A ABAAB AA 26.0 +25.5 +Α Α Α ΑΑΑΑΑΑ 25.0 +A A 24.5 +24.0 +AA A AA AA BA A A 23.5 +AA A B C BAA A A A 23.0 +А 22.5 +A BABBA AA AAA BA A 22.0 +21.5 +A A A BABAAAA 21.0 +20.5 + 20.0 + Α Α Β ΑΑ ΒΑΑ ΑΑ Α ΑΑ Α 19.5 + A A AAA CABA B A A 19.0 +18.5 +AABA AABAAA BA 18.0 + 17.5 +A A AAAA CA A B A 17.0 +16.5 +AAA BAAAA AAAA 16.0 + A A A 15.5 + А ААА 15.0 +14.5 +A AA A A A 14.0 + 13.5 +13.0 +12.5 +12.0 +А 11.5 + 11.0 +10.5 +10.0 + A9.5 + 9.0 + 8.5 + А **16 18 20 22 24 26** Predicted

Predicted vs Actual Board Scores (Technical)



Predicted

Actual								
30.0 +					AAA	А	А	
29.5 +					_	_		
29.0 +					A	A		
28.5 +					7	7	7	
28.0 +					А	A	А	
27.0 +			ז ב	A ARAAAA		Δ		
26.5 +			21 211	5 mbruum		11		
26.0 +		AA	A B A	AA AC A	В		А	А
25.5 +								
25.0 +		А	A AA A	ABAAA C	B AB	А		
24.5 +								
24.0 +		AAA	AB D	AABA BA	A BA	В		
23.5 +								
23.0 +	A	A A	A A BA	AABAC CAA	ł			
22.5 +		`	אם א	\ 		R		
22.0 +	1	τ λ	AD A	AAAD		Б		
21.0 +	;	а а	CABBAZ	AB A	А			
20.5 +	•		0112211		••			
20.0 +	А	АСВА	AD AABO	CCBDABBA	ΒŻ	A		
19.5 +								
19.0 +		AA	BAB AAA	А	А	А		
18.5 +								
18.0 +		AAAA	DCBAA	C CAAC				
17.5 +	~ ~ ~				7			
17.0 +	AA A	A A		AB AA BA	A			
16.5 +	ם מ	в вала	۵۵	вδ				
15.5 +	A A		C A	D A				
15.0 +	А		В					
14.5 +	В	AA AA						
14.0 +				ΑB				
13.5 +	A		AB					
13.0 +	A	A	А					
12.5 +								
12.0 +	A A	A						
11.5 +	2							
11.0 +	A							
I								
	+			+		+	+	
14	16	18	20	22	24		26	

Predicted vs Actual Board Scores (Non-technical)

Plot of BDTOT*PREDBD. Legend: A = 1 obs, B = 2 obs, etc.

Predicted

Appendix E: Residual Plots

(Navigator)



	Plot	of	YRESID*YHAT.	Legend: $A = 1$ obs, $B = 2$ obs, etc.
	7.5			A B A A D B A A C A B B A A B C C ACAA AA B
	5.0			A A B AA B A B B B D C CD A A A B AG K DC D B A AA A ABAI M EC F AA C F E DB J DDDC A A A ABAC HCEI O HEAC A
R	2.5			A A E GACE K DEAA A A B CAAI LBBK A BE A A A BDAI LEFI E CE A A A F DGAJ GACF C C B AC G CHDE RDDD E BA B
e s d u a	0.0	 +		BABC O FACJ J DC B A A B AF L EEBM J CD B A D EABF P IIFD ECAB A ABB-DAAH-T-HGCG-IABAA B AB E GBCE U FDAC EABA A A A DAAI G EI M HCAE CAB A AA
1	-2.5 +	- - - - + - - -		B A CJ NBEI G DC C BA A A A A AABDABH GBFK O DAAB A A A BCCHFCL LACC I C C ACAJABH HCCE I AA A A A A ACCEF E HBDE C A A A A BBBIH K ICAA E BA A A A BAB CGGCCG GC A A
	-5.0			ACC ECDDHCAJ H B A CBABBEDBE DA A AAA ADBCBD A A DABABCBBC B C A EABA BBA A A CAABAAB
	-7.5			A A B B A BA A B B A AAA A A AA B A AA A B A AA B A A A
		 -	10 1	+ 5 20 25 Predicted Value of BDTOT

Residual Plot (Non-rated Operations)





Appendix F: Log Transformation Regression Results (Technical)

Analysis of Variance

Source	e DF	Sum of Squares	Mean Square	F Value	Prob>F
Model Error Total	6 503 509	33.39725 75.76565 109.16290	5.56621 0.15063	36.953	0.0001
	Root MSE Dep Mean C.V.	0.38811 2.14399 18.10214	R-square Adj R-sq	0.3059 0.2977	

Parameter Estimates

		Parameter	Standard	T for HO:	
Variable	DF	Estimate	Error	Parameter=0	Prob > T
INTERCEP	1	3.834260	0.13721321	27.944	0.0001
GPA	1	-0.322987	0.03799875	-8.500	0.0001
AFOQT A	1	-0.010400	0.00093988	-11.066	0.0001
AFLYHRS	1	0.001714	0.00103042	1.663	0.0969
*PRIVLIC	1	-0.412147	0.23476977	-1.756	0.0798
EVAL1145	1	0.016126	0.01062609	1.518	0.1298
*SX	1	-0.107949	0.04866917	-2.218	0.0270

* Indicator variables

PREDICTION ERROR

N	Mean	Std Dev	Minimum	Maximum				
65	0.3327464	0.2943417	0.0265747	1.7042250				



Residual Plot (log Technical)









(Navigator)







Residuaı



Q-Q Plot (Technical)


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Appendix H: Regression / Prediction Error Results

(Pilot)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	11	8362.28321	760.20756	99.516	0.0001
Error C Total	2326	26130.67322	7.63903		
	Root MSE	2.76388	R-square	0.3200	
	Dep Mean C.V.	22.40676 12.33503	Adj R-sq	0.3168	

Parameter Estimates

		Parameter	Standard	T for HO:	
Variable	DF	Estimate	Error	Parameter=0	P > T
τΝΨΈΡΛΕΡ	1	7 869655	0 19950722	15 755	0 0001
ADDADC	1	0.005546	0.45550722	2 117	0.0001
APRIRS	+	0.099346	0.04513243	2.11/	0.0344
EVAL1145	1	0.173891	0.02640054	6.587	0.0001
GPA	1	2.458751	0.13935426	17.644	0.0001
AFOQT A	1	0.027841	0.00374774	7.429	0.0001
AFOQTP	1	0.048135	0.00464340	10.366	0.0001
*PRIVLIC	1	0.928378	0.14141955	6.565	0.0001
AFLYHRS	1	0.001146	0.00023961	4.782	0.0001
*CALC	1	0.657326	0.13311672	4.938	0.0001
*SX	1	1,419295	0.53284456	2.664	0.0078
*BACHPLUS	1	1.018999	0.35098340	2.903	0.0037
*T	1	0.484627	0.13956775	3.472	0.0005

* Indicator variables

PREDICTION ERROR

278 2.1732985 1.6240296	0.0219902	8.7097845

<u>Regression / Prediction Error Results (Navigator)</u>

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model Error C Total	11 1207 1218	5136.32917 9078.98626 14215.31542	466.93902 7.52194	62.077	0.0001
	Root MSE Dep Mean C.V.	2.74262 21.53117 12.73789	R-square Adj R-sq	0.3613 0.3555	

Parameter Estimates

		Parameter	Standard	T for HO:	
Variable	DF	Estimate	Error	Parameter=0	P > T
INTERCEP	1	5.754312	0.67939710	8.470	0.0001
APRYRS	1	0.243617	0.07398384	3.293	0.0010
EVAL1145	1	0.252113	0.04320676	5.835	0.0001
GPA	1	2.747927	0.19680655	13.963	0.0001
AFOQT A	1	0.044723	0.00514397	8.694	0.0001
AFOQTP	1	0.037412	0.00536553	6.973	0.0001
*PRIVLIC	1	2.130650	0.25813735	8.254	0.0001
*CALC	1	0.750541	0.18137081	4.138	0.0001
*MINOR	1	0.767607	0.39675364	1.935	0.0533
LORS GEN	1	2.035595	1.13807531	1.789	0.0739
WAIVS	1	-0.495711	0.32381767	-1.531	0.1261
*T	1	0.461329	0.20711066	2.227	0.0261

* Indicator variables

PREDICTION ERROR

N	Mean	Std Dev	Minimum	Maximum
145	2.3344190	1.7337415	0.0025826	8.0839903

Regression / Prediction Error Results (Non-rated Operations)

Analysis of Variance

		Sum of	Mean	
Source	DF	Squares	Square	F Value Prob>F
Model	12	6315.44543	526.28712	48.413 0.0001
Error	1606	17458.33592	10.87069	
C Total	1618	23773.78135		
	Root MSE	3.29707	R-square	0.2656
	Dep Mean	20.42557	Adj R-sq	0.2602
	c.v.	16.14189		

Parameter Estimates

		Parameter	Standard	T for HO:	
Variable	DF	Estimate	Error	Parameter=0	P > T
INTERCEP	1	7.599636	0.81314546	9.346	0.0001
GPA	1	2.468166	0.19809833	12.459	0.0001
AFOQT A	1	0.066545	0.00464134	14.338	0.0001
AFLYHRS	1	0.008501	0.00308844	2.753	0.0060
*T	1	1.102368	0.24816557	4.442	0.0001
LORS GEN	1	1.056374	0.21208040	4.981	0.0001
*sx [–]	1	1.331728	0.21666022	6.147	0.0001
LORS COL	1	0.664853	0.18158280	3.661	0.0003
*MARSTAT	1	0.506521	0.19088469	2.654	0.0080
*APR	1	-0.806690	0.25299006	-3.189	0.0015
WAIVS	1	-0.531360	0.25470896	-2.086	0.0371
EVAL1145	1	0.159308	0.09912665	1.607	0.1082
*MINOR	1	0.496442	0.34035211	1.459	0.1449

* Indicator variables

PREDICITON ERROR

N	Mean	Std Dev	Minimum	Maximum
177	2.7971218	1.9110768	0.0519215	10.1569195

Regression / Prediction Error Results (Technical)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model Error C Total	9 559 568	2925.57384 9334.03776 12259.61160	325.06376 16.69774	19.468	0.0001
	Root MSE Dep Mean C.V.	4.08629 21.57996 18.93556	R-square Adj R-sq	0.2386 0.2264	

Parameter Estimates

	Parameter	Standard	T for HO:	
DF	Estimate	Error	Parameter=0	P > T
1	6.614265	1.36445403	4.848	0.0001
1	-0.164926	0.06409645	-2.573	0.0103
1	2.573260	0.38991545	6.600	0.0001
1	0.086444	0.00948481	9.114	0.0001
1	0.873485	0.48877385	1.787	0.0745
1	2.632858	0.90477766	2.910	0.0038
1	1.061780	0.50853989	2.088	0.0373
1	1.145752	0.60917044	1.881	0.0605
1	-0.025120	0.00931418	-2.697	0.0072
1	4.418290	1.89917770	2.326	0.0204
	DF 1 1 1 1 1 1 1 1 1	ParameterDFEstimate16.6142651-0.16492612.57326010.08644410.87348512.63285811.06178011.1457521-0.02512014.418290	ParameterStandardDFEstimateError16.6142651.364454031-0.1649260.0640964512.5732600.3899154510.0864440.0094848110.8734850.4887738512.6328580.9047776611.0617800.5085398911.1457520.609170441-0.0251200.0093141814.4182901.89917770	Parameter DFStandard EstimateT for H0: Parameter=016.6142651.364454034.8481-0.1649260.06409645-2.57312.5732600.389915456.60010.0864440.009484819.11410.8734850.488773851.78712.6328580.904777662.91011.0617800.508539892.08811.1457520.609170441.8811-0.0251200.00931418-2.69714.4182901.899177702.326

* Indicator variables

PREDICTION ERROR

N	Mean	Std Dev	Minimum	Maximun
65	3.4361878	2.7108843	0.2359842	10.1759592

Regression / Prediction Error Results (Non-technical)

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model Error	14 2514	12464.56095 26933.93569	890.32578 10.71358	83.103	0.0001
C Total	2528	39398.49664	_		
	ROOT MSE	3.27316	R-square	0.3164	
	Dep Mean C.V.	20.92626 15.64140	Adj R-sq	0.3126	

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	P > T
INTERCEP	1	6.014285	0.57160462	10.522	0.0001
EVAL1145	1	0.112605	0.03292491	3.420	0.0006
GPA	1	2.479181	0.14817933	16.731	0.0001
AFOQT A	1	-0.053941	0.03564603	-1.513	0.1303
AFOQTP	1	0.012978	0.00371784	3.491	0.0005
AFOQTQ	1	0.063558	0.01993085	3.189	0.0014
AFOQT V	1	0.075983	0.02123752	3.578	0.0004
*CALC	1	0.434497	0.15753945	2.758	0.0059
*SX	1	0.674930	0.15736914	4.289	0.0001
*BACHPLUS	1	1.075768	0.33453450	3.216	0.0013
LORS GEN	1	0.915786	0.12905855	7.096	0.0001
LORSCOL	1	0.358931	0.09177405	3.911	0.0001
WAIVS	1	-0.619447	0.19547363	-3.169	0.0015
*MINOR	1	0.448953	0.24123369	1.861	0.0629
*AGEWAIV	1	-0.458792	0.30838051	-1.488	0.1369

* Indicator variables

PREDICTION ERROR

N	Mean	Std Dev	Minimum	Maximum
269 2	2.8484619	1.9582236	0.0146524	8.1976250

Appendix I: Discriminant Analysis Results

(Piiot)

GROUP	Frequency	Weight	Proportion	Prior Probability
1	685	685.0000	0.292985	0.292985
2	1653	1653	0.707015	0.707015

Simple Statistics

Total-Sample

Variable	N	Sum	Mean	Variance	Std Dev
EVAL1145	2338	8532	3.64927	4.85683	2.20382
GPA	2338	6809	2,91247	0.18706	0.43250
AFOQT_N	2338	175903	75.23653	283.22816	16.82938
AFOQTP	2338	186253	79.66339	210.21399	14.49876
AFOQTQ	2338	158795	67.91916	395.34520	19.88329
AFLYHRS	2338	200233	85.64286	71518	267.42940
GRADE	2338	615.00000	0.26305	1.12932	1.06270

GROUP = 1

Variable	N	Sum	Mean	Variance	Std Dev
EVAL1145	685	2838	4.14307	3.52336	1.87706
GPA	685	2127	3.10563	0.19510	0.44170
AFOQT N	685	56179	82.01314	208.71766	14.44706
AFOQTP	685	58735	85.74453	131.89516	11.48456
AFOQTQ	685	51723	75.50803	319.49007	17.87429
AFLYHRS	685	91594	133.71387	129569	359.95629
GRADE	685	224.00000	0.32701	1.42215	1.19254

GROUP = 2

Variable	N	Sum	Mean	Variance	Std Dev
EVAL1115	1653	5694	3.44465	5.26888	2.29540
GPA	1653	4682	2.83242	0.16196	0.40245
AFOQT N	1653	119724	72.42831	287.31765	16.95045
AFOQT P	1653	127518	77.14338	221.08052	14.86878
AFOOTO	1653	107072	64.77435	393.21600	19.82967
AFLYHRS	1653	108639	65.72232	46171	214.87503
GRADE	1653	391.00000	0.23654	1.00636	1.00318

<u>Main Group</u>

	Number	of	Observations	and	Percent	Classified	into	GROUP:
From	GROUP		1			2		Total
	1		224 32.70		(461 67.30		685 100.00
	2		115 6.96		9	1538 93.04	-	1653 100.00
Pe	Total ercent		339 14.50		٤	1999 35.50	-	2338 100.00
I	Priors		0.2930		0	.7070		
			Error Count	Esti	mates fo	or GROUP:		
			1			2	Tota	al
F	Rate		0.6730		0	.0696	0.240	54
I	Priors		0.2930		0	.7070		

Validation Group

Number	of Observations a	nd Percent Classif	ied into GROUP:
From GROUP	1	2	Total
1	29	63	92
	31.52	68.48	100.00
2	16	170	186
	8.60	91.40	100.00
Total	45	233	278
Percent	16.19	83.81	100.00
Priors	0.2930	0.7070	

Error Count Estimates for GROUP:

	1	2	Total
Rate	0.6848	0.0860	0.2614
Priors	0.2930	0.7070	

Discriminant Analysis Results (Navigator)

GROUP	Frequency	Weight	Proportion	Prior Probability
1	379	379.0000	0.310911	0.310911
2	840	840.0000	0.689089	0.689089

Simple Statistics

Total-Sample

Variable	N	Sum	Mean	Variance	Std Dev
GPA	1219	3534	2.89895	0.17684	0.42052
AFOQT P	1219	89230	73.19934	277.34529	16.65369
AFOQTQ	1219	84034	68.93683	346.40898	18.61207
AFLYHRS	1219	28629	23.48564	10822	104.02775
EVAL1145	1219	5075	4.16325	3.39451	1.84242
AFOQT V	1219	85150	69.85234	400.56274	20.01406
APRYRS	1219	339.00000	0.27810	1.27153	1.12762
LORS COL	1219	6.00000	0.00492	0.00819	0.09048

GROUP = 1

Variable	N	Sum	Mean	Variance	Std Dev
GPA	379	1170	3.08741	0.16773	0.40954
AFOQT P	379	29957	79.04222	212.82361	14.58848
AFOQTQ	379	28355	74.81530	272.99225	16.52248
AFLYHRS	379	14652	38,65963	15753	125.50899
EVAL1145	379	1685	4.44591	2.40646	1.55128
AFOQT V	379	28237	74.50396	346.33530	18.61009
APRYRS	379	169.00000	0.44591	2.03080	1.42506
LORS COL	379	1.00000	0.00264	0.00264	0.05137

GROUP = 2

Variable	N	Sum	Mean	Variance	Std Dev
GPA	840	2364	2.81392	0.15787	0.39733
AFOQT P	840	59273	70.56310	284.36550	16.86314
AFOQTQ	840	55679	66.28452	357.24553	18.90094
AFLYHRS	840	13977	16.63929	8462	91.99054
EVAL1145	840	3390	4.03571	3.79133	1.94713
AFOQT V	840	56913	67.75357	411.28723	20.28022
APRYRS	840	170.00000	0.20238	0.91251	0.95525
LORS COL	840	5.00000	0.00595	0.01069	0.10340

<u>Main Group</u>

Number of	f Observations ar	nd Percent Classifi	ed into GROUP:
From GROUP	1	2	Total
1	193 50.92	186 49.08	379 100.00
2	142 16.90	698 83.10	840 100.00
Total Percent	335 27.48	884 72.52	1219 100.00
Priors	0.3109	0.6891	
	Error Count E	Estimates for GROUP	:
	1	2	Total
Rate	0.4908	0.1690	0.2691
Priors	0.3109	0.6891	
Validation Group	<u>0</u>		
Number o	f Observations ar	nd Percent Classifie	ed into GROUP:
From GROUP	1	2	Total
1	21 39.62	32 60.38	53 100.00
n	1 1	01	0.2

2	11	81	92
	11.96	88.04	100.00
Total	32	113	145
Percent	22.07	77.93	100.00
Priors	0.3109	0.6891	

Error Count Estimates for GROUP:

	1	2	Total
Rate	0.6038	0.1196	0.2701
Priors	0.3109	0.6891	

GROUP	Freque	ency We	eight Pro	oportion	Prior Probability
1 2	1	530 530. L089	0000 (1089 (0.327363 0.672637	0.327363 0.672637
		Simple	e Statistics	5	
		Tot	al-Sample		
Variable	N	Sum	Mean	Varianc	e Std Dev
GPA AFOQT_A GRADE LORS_GEN AFLYHRS	1619 1619 1619 1619 1619	4820 110786 1016 185.00000 5276	2.97705 68.42866 0.62755 0.11427 3.25880	0.1920 341.4601 2.7443 0.1729 725.4379	5 0.43824 4 18.47864 8 1.65662 7 0.41589 2 26.93395
			GROUP = 1		
Variable	N	Sum	Mean	Varianc	e Std Dev
GPA AFOQT_A GRADE LORS_GEN AFLYHRS	530 530 530 530 530	1670 39208 535.00000 108.00000 2585	3.15127 73.97736 1.00943 0.20377 4.87736	0.1964 315.3794 4.3118 0.3175 149	0 0.44317 5 17.75893 2 2.07649 7 0.56353 7 38.68972
			GROUP = 2		
Variable	N	Sum	Mean	Varianc	e Std Dev
GPA AFOQT_A GRADE LORS_GEN AFLYHRS	1089 1089 1089 1089 1089	3150 71578 481.00000 77.00000 2691	2.89226 65.72819 0.44169 0.07071 2.47107	0.1681 332.1576 1.8791 0.0970 349.1152	3 0.41004 7 18.22519 8 1.37083 2 0.31148 0 18.68462

Discriminant Analysis Results (Non-rated Operations)

<u>Main Group</u>

Number c	of Observations a	and Percent Classi	fied into GROUP:
From GROUP	1	2	Total
1	127 23.96	403 76.04	530 100.00
2	111 10.19	978 89.81	1089 100.00
Total Percent	238 14.70	1381 85.30	1619 100.00
Priors	0.3274	0.6726	
	Error Count	Estimates for GRO	UP:
	1	2	Total
Rate	0.7604	0.1019	0.3175
Priors	0.3274	0.6726	
Validation Grou	<u>q</u> ı		

Number	of	Observations and	Percent Classified	into GROUP:
From GROUP		1	2	Total
1		15 26.79	41 73.21	56 100.00
2		14 11.57	107 88.43	121 100.00
Total Percent		29 16.38	148 83.62	177 100.00
Priors		0.3274	0.6726	

Error Count Estimates for GROUP:

	1	2	Total
Rate	0.7321	0.1157	0.3175
Priors	0.3274	0.6726	

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Discriminant Analysis Results (Technical)

GROUP	Frequer	ucy Wei	aht Prop	ortion	Prior Probability
GROOT	IICquei		9110 1100	.01 0101	riobability
1	1	193 193.0	000 0.	339192	0.339192
2		376 376.0	000 0.	660808	0.660808
	Sim	mple Statisti	CS		
		Total-Sample			
Variable	N	Sum	Mean	Varianc	e Std Dev
AFOOT A	569	42273	74.29350	345.2816	7 18.58176
GPA -	569	1722	3.02652	0.2220	6 0.47123
LORS_GEN	569	10.00000	0.01757	0.0384	2 0.19602
		GROUP = 1			
Variable	N	Sum	Mean	Variance	Std Dev
AFOQT_A	193	15938	82.58031	213.9427	4 14.62678
GPA	193	612.00300	3.17100	0.2393	0 0.48918
LORS_GEN	193	8.00000	0.04145	0.1024	4 0.32006
		GROUP = 2			
Variable	N	Sum	Mean	Variance	Std Dev
AFOQT_A	376	26335	70.03989	359.9637	4 18.97271
GPA –	376	1110	2.95235	0.1975	7 0.44449
LORS_GEN	376	2.00000	0.00532	0.0053	0 0.07284

<u>Main Group</u>

......

Numper	of Observations a	and Percent Classifie	ed into GROUP:
From GROUF	·]	L 2	Total
1	8 4.15	185 95.85	193 100.00
2	3 0.80	373 99.20	376 100.00
Total Percent	11 1.93	558 98.07	569 100.00
Priors	0.3392	0.5508	
	Error Count	Estimates for GROUP	:
	1	2	Total
Rate	0.9585	0.0080	0.3304
Priors	0.3392	0.6608	
Validation Gro	gin		
Number	of Observations a	and Percent Classifie	ed into GROUP:
From GROUP	1	2	Total
1	0 0.00	29 100.00	29 100.00
2	1 2.78	35 97.22	36 100.00
Total Percent	1 1.54	64 98.46	65 100.00
Priors	0.3392	0.6608	
	Error Count	Estimates for GROUP	:
	1	2	Total

	1	2	Total
Rate	1.0000	0.0278	0.3575
Priors	0.3392	0.6608	

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Discriminant Analysis Results (Non-technical)

GROUP	Frequency	Weight	Proportion	Prior Probability
1	683 1846	683.0000 1846	0.270067	0.270067

Simple Statistics

Total-Sample

Variable	N	Sum	Mean	Variance	Std Dev
AFOQT A	2529	165212	65.32701	442.85624	21.04415
gpa –	2529	7774	3.07410	0.21681	0.46563
LORS GEN	2529	471.00000	0.18624	0.28057	0.52969
EVALI145	2529	10007	3.95690	4.00645	2.00161
LORS COL	2529	866.00000	0.34243	0.62716	0.79193
AFOQT P	2529	144099	56.97865	505.64432	22.48654
WAIVS	2529	112.00000	0.04429	0.11275	0.33579

GRCUP = 1

Variable	N	Sum	Mean	Variance	Std Dev
AFOQT A	683	52082	76.25476	271.33970	16.47239
GPA –	683	2236	3.27343	0.18784	0.43340
LORS GEN	683	205.00000	0.30015	0.48309	0.69505
EVALI145	683	3017	4.41728	2.53090	1.59088
LORS COL	683	264.00000	0.38653	0.72134	0.84932
AFOQT P	683	43962	64.36603	440.92447	20.99820
WAIVS	683	23.00000	0.03367	0.08831	0.29717

GROUP = 2

Variable	N	Sum	Mean	Variance	Std Dev
AFOQT_A	1846	113130	61.28386	445.93456	21.11716
GPA	1846	5539	3.00035	0.20748	0.45550
LORS GEN	1846	266.00000	0.14410	0.19928	0.44641
EVALI145	1846	6990	3.78657	4.44656	2.10869
LORS COL	1846	602.00000	0.32611	0.59170	0.76922
AFOQT P	1846	100137	54.24540	502.16468	22.40903
WAIVS	1846	89.00000	0.04821	0.12179	0.34899

<u>Main Group</u>

Number	of	Observations	and	Percent	Classified	into	GROUP:
From GROUP		1			2		Total
1		284 41.58			399 58.42		683 100.00
2		223 12.08			1623 87.92		1846 100.00
Total Percent		507 20.05			2022 79.95		2529 100.00
Priors		0.2701		(0.7299		
		Error Count	Est	imates :	for GROUP:		
		1			2	Tot	cal
Rate		0.5842		(0.1208	0.24	159

Priors 0.2701 0.7299

Validation Group

Number	of Observations	and Percent Classif	fied into GROUP:
From GROUP	1	2	Total
1	26	54	80
	32.50	67.50	100.00
2	16	173	189
	8.47	91.53	100.00
Total	42	227	269
Percent	15.61	84.39	100.00
Priors	0.2701	0.7299	

Error Count Estimates for GROUP:

	1	2	Total
Rate	0.6750	0.0847	0.2441
Priors	0.2701	0.7299	



Appendix J: Board Score Cumulative Frequency Plot

/*PREG.SAS*/ /*PILOT*/ /*REGRESSION ANALYSIS FROM STEPWISE DISCRIMINANT ANALYSIS PREDICTED VALUES*/ OPTIONS LINESIZE=70 NOOVP; libname sandi 'gor91m:[sniemi.sas]'; DATA rsm; SET sandi.thes; %INCLUDE LASTBD; IF PROGRAM='P'; %INCLUDE LOADVAR; IF BDTOT>24 THEN GROUP=1; ELSE GROUP=2; %INCLUDE KEEPVAR; DATA NEW; SET sandi.thes; **%INCLUDE LASTBD;** IF PROGRAM='P'; %INCLUDE LOADVAR2; IF BDTOT>24 THEN GROUP=1; ELSE GROUP=2; PREDBD=7.869655+.095546*APRYRS+.173891*EVAL1145+2.458751* GPA+.027841*AFOQT A+.048135*AFOQT P+.928378*PRIVLIC+ .001146*AFLYHRS+.657326*CALC+1.419295*SX+1.018999* BACHPLUS+.484627*T: PERROR=ABS (BDTOT-PREDBD); %INCLUDE KEEPVAR2; %INCLUDE DISC; **%INCLUDE PDVAR;** PROC REG DATA=rsm; MODEL BDTOT = APRYRSEVAL1145 GPA AFOQT A AFOQT P PRIVLIC AFLYHRS CALC SX BACHPLUS T; **%INCLUDE APT;** PROC MEANS DATA=NEW; VAR PERROR; PROC PLOT DATA=NEW; PLOT BDTOT*PREDBD;

/*LASTBD.SAS*/

END;

/*READS IN INFO FROM LAST BOARD*/ IF M4BDTOT=MISSING THEN M4BDTOT=0; IF M3BDTOT=MISSING THEN M3BDTOT=0; IF M2BDTOT=MISSING THEN M2BDTOT=0; BDTOT=M4BDTOT; BDSEL=M4SELECT; PROGRAM=M4PROG; DEGLEV=M4DEGLEV; GPA=M4GPA; IF M4BDTOT=0 THEN DO; BDTOT=M3BDTOT; BDSEL=M3SELECT; PROGRAM=M3PROG; DEGLEV=M3DEGLEV; GPA=M3GPA; END; IF M4BDTOT=0 AND M3BDTOT=0 THEN DO; BDTOT=M2BDTOT; BDSEL=M2SELECT; PROGRAM=M2PROG; DEGLEV=M2DEGLEV; GPA=M2GPA; END; IF M4BDTOT=0 AND M3BDTOT=0 AND M2BDTOT=0 THEN DO; BDTOT=M1BDTOT; BDSEL=M1SELECT; PROGRAM=M1PROG; DEGLEV=M1DEGLEV; GPA=M1GPA;

```
/*LOADVAR.SAS*/
/*LOADS VARIABLES, PERFORMS CONVERSIONS*/
LASTSSN=SUBSTR(SSAN,9,1);
IF LASTSSN NE 9;
IF APP STAT='A' THEN PRIOR=1; ELSE PRIOR=0;
IF ALL9LST3='N' THEN APR=1; ELSE APR=0;
IF LORS COL=MISSING THEN LORS COL=0;
IF LORS GEN=MISSING THEN LORS GEN=0;
IF LORS TOT=MISSING THEN LORS TOT=0;
IF APRYRS=MISSING THEN APRYRS-0;
NOBACH=0;
BACH=0;
BACHPLUS=0;
MAST=0:
IF DEGLEV='J' THEN NOBACH=1;
IF DEGLEV='N' OR DEGLEV='O' OR DEGLEV='P' OR DEGLEV='O'
  OR DEGLEV='R' THEN BACH=1;
IF DEGLEV='O' OR DEGLEV='P' OR DEGLEV='Q' OR DEGLEV='R'
 THEN BACHPLUS=1;
IF DEGLEV='P' OR DEGLEV='O' OR DEGLEV='R' THEN MAST=1;
IF RSOPPL='1' THEN PRIVLIC=1; ELSE PRIVLIC=0;
IF AFLYHRS=MISSING THEN AFLYHRS=0;
IF CALCULUS='1' THEN CALC=1; ELSE CALC=0;
IF DISENROL='Y' THEN DISENRL=1; ELSE DISENRL=0;
IF GRADE=MISSING THEN GRADE=0;
IF WAIVER1='1' OR WAIVER1='2' THEN AGEWAIV=1; ELSE AGEWAIV=0;
IF WAIVER2='0' THEN WAIVS=0;
IF WAIVER2='1' THEN WAIVS=1;
IF WAIVER2='2' THEN WAIVS=2;
IF WAIVER2='3' THEN WAIVS=3;
IF WAIVER2='4' THEN WAIVS=4;
IF WAIVER2='5' THEN WAIVS=5;
IF WAIVER2='6' THEN WAIVS=6;
IF WAIVER2=MISSING THEN WAIVS=0;
IF MARITAL='M' THEN MARSTAT=1; ELSE MARSTAT=0;
IF RACE='N' OR RACE='X' THEN MINOR=1; ELSE MINOR=0;
IF SEX='F' THEN SX=1; ELSE SX=0;
GPA=GPA/100;
%INCLUDE MAJOR;
```

/*MAJOR.SAS*/

/*ASSIGNS VALUE FOR TECHNCIAL MAJOR VARIABLE*/

T=0;

IF	DEG_TYPE='OCCB')	THEN	T=1;
IF	DEG_TYPE='OCYY'	I	THEN	T=1;
IF	DEG_TYPE='OYBY'	1	THEN	T=1;
IF	DEG_TYPE='OYRY'	1	THEN	T≈1;
IF	DEG_TYPE='4AYY'		THEN	T=1;
IF	DEG_TYPE='4BYY'	1	THEN	T=1;
IF	DEG_TYPE='4CYY'	1	THEN	T=1;
IF	DEG_TYPE='4DYY'	1	THEN	T=1;
IF	DEG_TYPE='4EYY'	ł	THEN	T≈1;
IF	DEG_TYPE='4FYY'	r	THEN	T=1;
IF	DEG_TYPE='4GYY'	1	THEN	T≈1;
IF	DEG TYPE='4HBY'	1	THEN	T=1;
IF	DEG TYPE='4HYY'		THEN	T=1;
IF	DEG TYPE='4IYY'	ľ	THEN	T=1;
IF	DEG TYPE='4JYY'	I	THEN	T=1;
IF	DEG_TYPE='4LYY'		THEN	T=1;
IF	DEG_TYPE='4MYY'	I	THEN	T=1;
IF	DEG TYPE='4NYY'	,	THEN	T=1;
IF	DEG_TYPE='40BY'	ľ	THEN	T=1;
IF	DEG TYPE='40YY'	I.	THEN	T=1;
IF	DEG TYPE='4QYY'	1	THEN	T=1;
IF	DEG TYPE='4TYY'	r -	THEN	T=1;
IF	DEG TYPE='4UYY'	l	THEN	T=1;
IF	DEG TYPE='4VAX'	t -	THEN	T=1;
IF	DEG TYPE='4VKY'	l.	THEN	T=1;
IF	DEG TYPE='4YYY'	,	THEN	T=1;
IF	DEG TYPE='6BYY'	ł	THEN	T=1;
IF	DEG TYPE='6YYY'	1	THEN	T=1;
IF	DEG TYPE='8HYY'	,	THEN	T=1;
IF	DEG TYPE='8CYY'	1	THEN	T=1;
IF	DEG TYPE='OCYY'	1	THEN	T=1;
IF	DEG TYPE='OYBY'	1	THEN	T=1;

/*KEEPVAR.SAS*/

/*SPECIFIES VARIABLES TO KEEP FOR ANALYSIS*/

KEEP PRIOR APR LORS_COL LORS_GEN LORS_TOT APRYRS EVAL1145 GPA AFOQT_A AFOQT_N AFOQT_P AFOQT_Q AFOQT_V PRIVLIC AFLYHRS CALC DISENRL GRADE AGEWAIV WAIVS MARSTAT MINOR SX NOBACH BACH BACHPLUS BDTOT PROGRAM T LASTSSN GROUP;

/*KEEPVAR2.SAS*/

/*SPECIFIES VARIABLES TO KEEP FOR ANALYSIS OF TEST GROUP*/

KEEP PRIOR APR LORS_COL LORS_GEN LORS_TOT APRYRS EVAL1145 GPA AFOQT_A AFOQT_N AFOQT_P AFOQT_Q AFOQT_V PRIVLIC AFLYHRS CALC DISENRL GRADE AGEWAIV WAIVS MARSTAT MINOR SX NOBACH BACH BACHPLUS BDTOT PROGRAM T LASTSSN PREDBD PERROR GROUP;

```
/*LOADVAR2.SAS*/
/*LOAD VARIABLES FOR TEST GROUP*/
LASTSSN=SUBSTR(SSAN,9,1);
IF LASTSSN EQ 9;
IF APP STAT='A' THEN PRIOR=1; ELSE PRIOR=0;
IF ALL9LST3='N' THEN APR=1; ELSE APR=0;
IF LORS COL=MISSING THEN LORS COL=0;
IF LORS GEN=MISSING THEN LORS GEN=0;
IF LORS TOT=MISSING THEN LORS TOT=0;
IF APRYRS=MISSING THEN APRYRS=0;
NOBACH=0;
BACH=0;
BACHPLUS=0;
MAST=0:
IF DEGLEV='J' THEN NOBACH=1;
IF DEGLEV='N' OR DEGLEV='O' OR DEGLEV='P' OR DEGLEV='O'
 OR DEGLEV='R' THEN BACH=1;
IF DEGLEV='O' OR DEGLEV='P' OR DEGLEV='Q' OR DEGLEV='R'
 THEN BACHPLUS=1;
IF DEGLEV='P' OR DEGLEV='O' OR DEGLEV='R' THEN MAST=1;
IF RSOPPL='1' THEN PRIVLIC=1; ELSE PRIVLIC=0;
IF AFLYHRS=MISSING THEN AFLYHRS=0;
IF CALCULUS='1' THEN CALC=1; ELSE CALC=0;
IF DISENROL='Y' THEN DISENRL=1; ELSE DISENRL=0;
IF GRADE=MISSING THEN GRADE=0;
IF WAIVER1='1' OR WAIVER1='2' THEN AGEWAIV=1; ELSE AGEWAIV=0;
IF WAIVER2='0' THEN WAIVS=0;
IF WAIVER2='1' THEN WAIVS=1;
IF WAIVER2='2' THEN WAIVS=2;
IF WAIVER2='3' THEN WAIVS=3;
IF WAIVER2='4' THEN WAIVS=4;
IF WAIVER2='5' THEN WAIVS=5;
IF WAIVER2='6' THEN WAIVS=6;
IF WAIVER2=MISSING THEN WAIVS=0;
IF MARITAL='M' THEN MARSTAT=1; ELSE MARSTAT=0;
IF RACE='N' OR RACE='X' THEN MINOR=1; ELSE MINOR=0;
IF SEX='F' THEN SX=1; ELSE SX=0;
GPA=GPA/100;
%INCLUDE MAJOR;
```

/*DISC.SAS*/

/*DISCRIMINANT ANALYSIS*/

PROC FREQ DATA=rsm; TABLES GROUP;

PROC DISCRIM DATA=rsm SIMPLE POOL=TEST WCORR TESTDATA=NEW; CLASS GROUP; PRIORS PROPORTIONAL;

/*PROC STEPDISC SIMPLE DATA=rsm; CLASS GROUP;*/

/*PDVAR.SAS*/

VAR EVAL1145 GPA AFOQT_N AFOQT_P AFOQT_Q AFLYHRS GRADE;

```
/*APT.SAS*/
```

/*RESIDUAL PLOTS, K-S TEST, Q-Q PLOT*/ output out=aptness stdp=stderrm 195m=195bm u95m=u95bm stdi=stderrp 195=195bp u95=u95bp p=yhat r=yresid h=hatmatd; proc plot data=aptness; plot yresid*yhat / vref=0; proc univariate data=aptness normal noprint; var yresid; output out=normck n=samsize normal=normtspv; title2 ' APTNESS CHECK FOR NORMALITY '; title3 ' WilkShapiro if N<51 else Kolomogorov-Smirnov '; proc print data=normck; proc rank data=aptness normal=vw; var yresid; ranks resrank; proc plot; plot resrank*yresid;

```
/*PILOT.SAS*/
/*PILOT*/
/*PERFORMS STEPWISE REGRESSION
  GPA ANALYSIS*/
/*2338 OBSERVATIONS 27 VARIABLES*/
/*DEPENDENT VARIABLE BDTOT*/
OPTIONS LINESIZE=70 NOOVP;
libname sandi 'gor91m:[sniemi.sas]';
DATA rsm;
SET sandi.thes;
%INCLUDE LASTBD;
IF PROGRAM='P';
%INCLUDE LOADVAR;
group=1;
%INCLUDE KEEPVAR;
/*PROC FREQ;
  TABLES BDTOT*/;
PROC SORT;
  BY T;
PROC MEANS;
  BY T;
  VAR GPA;
PROC FREQ;
  TABLES LASTSSN;
PROC STEPWISE DATA=rsm;
 MODEL BDTOT = PRIOR APR LORS COL LORS GEN LORS TOT APRYRS
        EVAL1145 GPA AFOQT A AFOQT N AFOQT P AFOQT O AFOOT V
        PRIVLIC AFLYHRS CALC DISENEL GRADE AGEWAIV WAIVS
        MARSTAT MINOR SX NOBACH BACH BACHPLUS T;
```

/*SA.SAS*/

/*CALCULATES MEAN FOR LAST BOARD AND MEAN FOR FIRST, SECOND, THIRD, AND FOURTH BOARDS*/ **OPTIONS LINESIZE=70 NOOVP;** libname sandi 'gor91m:[sniemi.sas]'; DATA rsm; SET sandi.thes; %INCLUDE LASTBD; %INCLUDE LOADVAR3; group=1; %INCLUDE KEEPVAR; DATA ALLREC; SET sandi.thes; %INCLUDE LOADVAR3; KEEP MIBDTOT MIBDNUM M2BDTOT M2BDNUM M3BDTOT M3BDNUM M4BDTOT M4BDNUM; PROC MEANS DATA=rsm; VAR BDTOT;

PROC MEANS DATA=ALLREC; VAR M1BDTOT M2BDTOT M3BDTOT M4BDTOT;

```
/*LOADVAR3.SAS*/
/*INCLUDES ALL RECORDS--ALL SSANS INCLUDED*/
LASTSSN=0;
IF APP STAT='.,' THEN PRIOR=1; ELSE PRIOR=0;
IF ALL9LST3='N' THEN APR=1; ELSE APR=0;
IF LORS COL=MISSING THEN LORS COL=0;
IF LOKE GEN=MISSING THEN LOPS GEN=0;
IF LORS TOT=MISSING THEN LORS FOT=0;
IF APAYRS=MISSING THEN APRYRS=0;
NOBACH=0;
BACH=0;
BACHPLUS=0;
MAST=0;
IF DEGLEN-'J' THEN NOBACH=1;
IF DEGLEV=''' OR DEGLEV='O' OR DEGLEV='P' OR DEGLEV='O'
  OR DEGLEV='R' THEN BACH=1;
IF DEGLEV='O' OR DEGLEV='P' OR DEGLEV='O' OR DEGLEV='R'
  THEN BACHPLUS=1;
IF DEGLEV='P' OR DEGLEV='Q' OR DEGLEV='R' THEN MAST=1;
IF RSOPPL='1' THEN PRIVLIC=1; ELSE PRIVLIC=0;
IF AFLYHRS=MISSING THEN AFLYHRS=0;
IF CALCULUS='1' THEN CALC=1; ELSE CALC=0;
IF DISENROL='Y' THEN DISENRL=1; ELSE DISENRL=0;
IF GRADE=MISSING THEN GRADE=0;
IF WAIVER1='1' OR WAIVER1='2' THEN AGEWAIV=1: ELSE AGEWAIV=0;
IF WAIVER2='0' THEN WAIVS=0;
IF WAIVER2='1' THEN WAIVS=1;
IF WAIVER2='2' THEN WAIVS=2;
IF WAIVER2='3' THEN WAIVS=3;
IF WAIVER2='4' THEN WAIVS=4;
IF WAIVER2='5' THEN WAIVS=5;
IF WAIVER2='6' THEN WAIVS=6;
IF WAIVER2=MISSING THEN WAIVS=0;
IF MARITAL='M' THEN MARSTAT=1; ELSE MARSTAT=0;
IF RACE='N' OR RACE='X' THEN MINOR=1; ELSE MINOR=0;
IF SEX='F' THEN SX=1; ELSE SX=0;
GPA=GPA/100;
```

%INCLUDE MAJOR;

/*ALL.SAS*/

/*CALCULATES MEAN BOARD SCORES FOR EACH INDIVIDUAL BOARD*/

OPTIONS LINESIZE=70 NOOVP; libname sandi 'gor91m:[sniemi.sas]';

DATA ALLREC; SET sandi.thes;

IF M1BDNUM=8905 THEN BDTOT=M1BDTOT; ELSE IF M2BDNUM=8905 THEN BDTOT=M2BDTOT; ELSE IF M3BDNUM=8905 THEN BDTOT=M3BDTOT; ELSE IF M4BDNUM=8905 THEN BDTOT=M4BDTOT; ELSE BDTOT=MISSING; KEEP M1BDTOT M1BDNUM M2BDTOT M2BDNUM M3BDTOT M3BDNUM M4BDTOT M4BDNUM BDTOT;

PROC MEANS; VAR BDTOT; /*TBDFREQ.SAS*/

/*CREATES BOARD SCORE FREQUENCY GRAPHS*/

OPTIONS LINESIZE=70; libname sandi 'gor91m:[sniemi.sas]';

DATA BDS;

INPUT BDSCORE FREQ PERCENT CUMFREQ CUMPERC;

CARDS;

7.5	1	0.0	1	0.0
8	3	0.0	4	0.0
8.5	2	0.0	6	0.1
9	4	0.0	10	0.1
9.5	1	0.0	11	0.1
10	2	0.0	13	0.1
10.5	8	0.1	21	0.2
11	12	0.1	33	0.4
11.5	10	0.1	43	0.5
12	16	0.2	59	0.6
12.5	31	0.3	90	1.0
13	45	0.5	135	1.5
13.5	53	0.6	188	2.0
14	81	0.9	269	2.9
14.5	83	0.9	352	3.8
15	132	1.4	484	5.3
15.5	158	1.7	642	7.0
16	410	4.4	1052	11.4
17	506	5.5	1558	16.9
18	643	7.0	2201	23.9
19	690	7.5	2891	31.4
20	871	9.5	3762	40.8
21	763	8.3	4525	49.1
22	825	9.0	5350	58.1
23	950	10.3	6300	68.4
24	896	9.7	7196	78.1
25	757	8.2	7953	86.3
26	569	6.2	8522	92.5
27	307	3.3	8829	95.8
28	118	1.3	8947	97.1
29	30	0.3	8977	97.4
30	238	2.6	9215	100.0

; PROC PLOT DATA=BDS; PLOT FREQ*BDSCORE; PLOT CUMFREQ*BDSCORE; PLOT PERCENT*BDSCORE; PLOT CUMPERC*BDSCORE;

```
/*LOGTREG.SAS*/
/*REGRESSION FROM STEPWISE
  PREDICTED VALUES*/
OPTIONS LINESIZE=70 NOOVP;
libname sandi 'gor91m:[sniemi.sas]';
DATA rsm;
SET sandi.thes;
%INCLUDE LASTBD;
IF PROGRAM='T';
%INCLUDE LOADVAR;
IF BDTOT>23 THEN GROUP=1; ELSE GROUP=2;
LNBDTOT=LOG(30-BDTOT);
%INCLUDE KEEPVARL;
DATA NEW;
SET sandi.thes;
%INCLUDE LASTBD;
IF PROGRAM='T';
%INCLUDE LOADVAR2;
IF BDTOT>23 THEN GROUP=1; ELSE GROUP=2;
PREDBD=3.83426-.322987*GPA-.0104*AFOQT A+.001714*
  AFLYHRS-.412147*PRIVLIC+.016126*EVAL1145-
  .107949*SX;
LNBDTOT=LOG(30-BDTOT);
PERROR=ABS (LNBDTOT-PREDBD);
%INCLUDE KEEPV2L;
/*%INCLUDE DISC;
%INCLUDE TDVAR;*/
PROC REG DATA=rsm;
  MODEL LNBDTOT = GPA AFOQT A
        AFLYHRS PRIVLIC EVAL1145 SX;
%INCLUDE APT;
PROC MEANS DATA=NEW;
  VAR PERROR;
PROC PLOT DATA=NEW;
 PLOT LNBDTOT*PREDBD;
```

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