



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**AN ANALYSIS OF THE EFFECT OF QUANTITATIVE
AND QUALITATIVE ADMISSIONS FACTORS IN
DETERMINING STUDENT PERFORMANCE AT THE U.S.
NAVAL ACADEMY**

by

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September 2004

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REPORT DOCUMENTATION PAGE			Form Approved OMB No. 0704-0188
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.			
1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE September 2004	3. REPORT TYPE AND DATES COVERED Master's Thesis	
4. TITLE AND SUBTITLE: An Analysis of the Effect of Quantitative and Qualitative Admissions Factors in Determining Student Performance at the U.S. Naval Academy			5. FUNDING NUMBERS
6. AUTHOR(S) LT Barton L. Phillips, USN			
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A			10. SPONSORING/MONITORING AGENCY REPORT NUMBER
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.			
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			12b. DISTRIBUTION CODE A
13. ABSTRACT (maximum 200 words) This thesis analyzes the effect of quantitative and qualitative factors used in the admissions process at the Naval Academy in determining student performance of candidates admitted. In determining student performance, graduation, Order of Merit, cumulative academic QPR, cumulative military QPR, and striper selection are used as performance outcome measures. The data is from Naval Academy graduation year groups 1995 through 2001. The analysis separates the Naval Academy's Whole Person Multiple into quantitative and qualitative inputs. The Candidate Multiple (CM) is the quantitative input to the admissions process derived from a statistical based scoring model anchored in proven high school performance measures such as SAT and high school GPA. The Recommendations of the Admissions Board (RAB) is the qualitative input awarding points for subjective traits not captured in the CM or from various other subjective measures such as student interviews and essays. This research highlights the properties of the two admissions factors and the estimated impact on student performance. The results show student performance increased as CM and RAB increased, revealing the importance of a combined quantitative and qualitative admissions process and emphasizing the qualitative input as the value added to the admissions process providing the increased predictability of student success.			
14. SUBJECT TERMS U.S. Naval Academy, admissions, Whole Person Multiple, Candidate Multiple, Recommendations of the Admissions Board, SAT, student performance			15. NUMBER OF PAGES 101
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT UL

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THE U.S. NAVAL ACADEMY**

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Submitted in partial fulfillment of the
requirements for the degree of

**MASTER OF SCIENCE IN LEADERSHIP AND HUMAN RESOURCE
DEVELOPMENT**

from the

**NAVAL POSTGRADUATE SCHOOL
September 2004**

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This thesis analyzes the effect of quantitative and qualitative factors used in the admissions process at the Naval Academy in determining student performance of candidates admitted. In determining student performance, graduation, Order of Merit, cumulative academic QPR, cumulative military QPR, and striper selection are used as performance outcome measures. The data is from Naval Academy graduation year groups 1995 through 2001. The analysis separates the Naval Academy's Whole Person Multiple into quantitative and qualitative inputs. The Candidate Multiple (CM) is the quantitative input to the admissions process derived from a statistical based scoring model anchored in proven high school performance measures such as SAT and high school GPA. The Recommendations of the Admissions Board (RAB) is the qualitative input awarding points for subjective traits not captured in the CM or from various other subjective measures such as student interviews and essays. This research highlights the properties of the two admissions factors and the estimated impact on student performance. The results show student performance increased as CM and RAB increased, revealing the importance of a combined quantitative and qualitative admissions process and emphasizing the qualitative input as the value added to the admissions process providing the increased predictability of student success.

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ACKNOWLEDGMENTS

Thanks to my wonderful wife, Jessica, for her support and patience.

To Buzz and Steve, Thanks for the encouragement, inspiration and your devoted perseverance.

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I. INTRODUCTION

A. BACKGROUND

The United States Naval Academy has a long history of being one of the most highly selective universities in the country. They receive thousands of applications a year and ultimately reduce the number to roughly 1,250 highly competitive candidates who raise their right hand on Induction Day to join the Brigade of Midshipmen. This impressive process of admissions is geared for admitting highly qualified students who are well rounded and are most likely to achieve success at the United States Naval Academy. But what sets the United States Naval Academy apart from other highly selective colleges and universities is that the United States Naval Academy must also find those who are motivated for service in the United States Navy and Marine Corps.

The Naval Academy must carefully review the applicants and admit only those candidates who are most likely to succeed as students at the Naval Academy and who will serve honorably and dutifully in the fleet after they graduate. With this larger vision of service in mind, the Admissions Board must admit the most qualified candidates and these candidates must also fit the institution and its needs. To find the most qualified candidates it starts with an exhaustive admissions package submitted by the candidates. This package provides information about the candidate on all aspects of their educational experience in easily quantifiable measures or measures that are easily normalized into quantifiable data. The admissions board tallies all of the candidates' qualifications into what is referred to as the Candidate Multiple. This multiple is based on a weighted algorithm where all the applicant data that can be quantified is plugged in. The selected weights and factor are based on many years of selecting quality candidates to the Naval Academy and ultimately producing Navy and Marine Corps officers. The algorithm computes the Candidate Multiple and this is the first tier of qualification established by the Admissions Board. The candidate must have a minimum Candidate Multiple to be considered by the Admissions Board for review.

Once it has been determined that the candidate has met minimum qualification and is fully medically qualified, the Admissions Board reviews the applicant's package in

its entirety. Upon review of the package, if the Admissions Board sees something noteworthy about the candidate that is not captured by the quantitative data, it may award a Recommendation of the Admissions Board (RAB) which consists of raw points that are added to the Candidate Multiple.

The Candidate Multiple and the RAB points are summed to create the Whole Person Multiple. The Whole Person Multiple is the score that determines whether a candidate is considered fully qualified and ultimately competitive for appointment to the Naval Academy. The Whole Person Multiple captures observable traits, like SAT scores and high school grade point average, as well as capturing unobservable traits, like a strong teacher recommendation, an outstanding personal essay or possibly a challenging experience requiring persistence and perseverance above and beyond that of the average candidate. This method provides a holistic approach to find the candidates to fill the ranks of the Brigade of Midshipmen that will go on to serve in the Navy and Marine Corps. The Admissions Board at the Naval Academy has thousands of qualified applicants each year who go through the admissions process resulting in a historical graduation rate of approximately eighty percent which ultimately provides candidates who were successful Midshipmen and they continue to serve our country with honor in the Armed Forces, the government and in our local communities.

B. PURPOSE

The purpose of this research is to examine the role of the Recommendations of the Admissions Board (RAB) scores in providing value added to the admissions process in predicting which applicants are best suited for the Naval Academy. The RAB has played a vital role in the overall admissions process and is the final opportunity for the Admissions Board to award points to an applicant. These extra points are something the Admissions Board, after a comprehensive review of the individual package, awards the candidate for mostly unobservable traits. This research will attempt to validate the Admissions Boards statistical-based scoring model and the value added of the RAB score to the predictive power of the model. The study will use indicators of success of admitted applicants, such as, graduation and order of merit.

The following research questions are examined by this thesis.

1. How does the Admissions Board utilize the RAB in the admissions process?

RAB's are awarded to candidates who the Admissions Board feels have demonstrated exceptional potential for leadership and future success at the Naval Academy through various subjective measures such as determination, character, and experience. These subjective measures are characterized as unobservable traits, as they are not captured by the quantitative measures included in the Candidate Multiple. The RAB captures those unobservable traits and adds points to the Candidate Multiple to create the Whole Person Multiple.

2. Using a multivariate regression modeling approach, can we model the determinants of the RAB and validate the value it adds to the admissions process?

Using the available data, which includes the graduation outcome of each midshipman and other selected performance measures, we will develop a model to predict an applicant's success and to validate the RAB as a predictor of that success.

C. METHODOLOGY

We have obtained historical data from the Office of Institutional Research at the Naval Academy representing candidate admissions data from the classes of 1995 through 2001. Following the discussion of descriptive statistics, we build a regression model of the role of RAB scores as a predictor of success at the Naval Academy. Using various measures of success we attempt to validate the RAB as a predictor of student success.

D. ORGANIZATION OF STUDY

Chapter II reviews prior studies of the admissions process at selective college and universities. With the rise in applicants trying to enter colleges and universities, admissions officers have been speaking out and trying to find a way to handle all of the applications and to keep the institutions' needs in line with student demands. This balance lends itself to maintaining humanistic aspects of college admissions while finding ways to streamline the application evaluation process. Not only is streamlining the admissions process a challenge for current admissions officers but finding a way to

maintain diversity on the campus has also been an extremely complex nut to crack. This search for a balance, guides our literature review, which surveys different admissions theories, processes and opinions.

Chapter III presents the quantitative data obtained from the Naval Academy's Office of Institutional Research for cohorts 1995 through 2001. This chapter discusses descriptive statistics of the data sample. From the data, measurable traits emerge that can be used in the regression analysis. We will explain the performance measures we have chosen to use in the validation process. Based on the statistical scoring model of the Naval Academy admissions process, we then conduct a regression analysis to validate the RAB as a predictor of success at the Naval Academy. Chapter IV analyzes the results of the regression model and validates the RAB as a predictor of success at the Naval Academy.

Chapter V concludes the study and evaluates the value added of RAB scores in the Naval Academy's statistical-based admissions process. This chapter will also provide recommendations based on the results of the study to the Admissions Board as well as lay out options for future studies in this area.

II. LITERATURE REVIEW

A. INTRODUCTION

The continuing efforts of admissions officials to create an admissions process that balances the subjectivity and humanistic factors with the use of quantitative data in selecting applicants has been a strategic battle for years within highly selective U.S. colleges and universities. During the last decade the admissions processes for highly selective college and universities have been feeling the pressure from the public because of a dramatic increase in the total number of applicants, particularly from the “Baby Boom Echo, the large cohort of children of the Baby Boomers,” (Long, 2003) and numerous other admissions-related issues that have been in the front lines of the press. Naturally, officials have been pressured to discuss implications and impacts of recent events and trends in their admissions arena.

The Supreme Court ruling in June of 2003, upheld race-based admissions in defense of affirmative action which “carefully circumscribed authorization to continue a practice that almost all consider valuable.” (Bok, 2003) It was this ruling that has admissions officials re-examining their own admissions policies to ensure they continue to further minority enrollment. In seeking minority enrollment, selective colleges and universities continually look for ways to identify minority students who have qualities and traits that are predictors of success at their institutions. “It is under these conditions that racial preferences in higher education have been attacked most severely as the country debates how to distribute access to competitive, four year colleges.” (Long, 2003) This affects the screening process to find those minority students and it is evolving into investigating factors beyond the standardized test scores and high school grade point averages. Because of a growing gap in minority achievement on standardized test scores and a lower average high school grade point average for minorities, the student essays and interviews are making strong cases as well as teacher and guidance counselor recommendations in helping to predict minority success.

In addition to affirmative action and diversity issues facing admission officials, the admissions system is becoming chaotic.

The system has become chaotic because it is overloaded. Changes in demographics, technology, and society have saddled the most selective colleges with more applicants than they know how to handle. More applicants mean an even higher rate of rejections, which makes a college statistically more 'selective.' Perversely, this makes it all the more attractive to the next crop of applicants and the cycle goes on. (Fallows et al., 2003)

With the increase in the number of applicants in a chaotic system, the pressure on the admissions process increases. These highly selective colleges and universities must choose which of the applicants will receive one of the limited slots. With the increased competition and pressure, the burden lies on the admissions board to choose wisely, and to offer entry to those students who they feel will succeed at their institution as well as meet the needs of the school, while simultaneously meeting the needs of the students.

The admissions process for highly selective college and universities has traditionally been a topic held very close to the vest, until recently. Admissions officers have become more open and willing to talk about their experiences as well as weaknesses in the arena of the admissions system. Academic journal articles, forums and editorials are exposing many of the issues the admissions officials face and what solutions are being proposed to fix them. With all this exposure, college admissions officers are feeling the increasing pressure from the growing college bound high school senior population.

Over time, the range of qualifications necessary to be considered for admittance to a highly selective college or university has become more complex. Admissions officers now use both quantitative and qualitative indicators to screen applicants. The quantitative measures include such factors as standardized test scores and normalized high school grade point averages. The most prolific of the measures are the SAT and ACT, both of which are standardized tests that are administered to high school juniors nationwide. These standardized tests have grown in value over the years and have become somewhat of a cornerstone in the admissions process. They also have enabled admissions processes to use quantitative models to screen applicants. However, highly selective colleges and universities are starting to realize that admitting well rounded students requires more than admitting those scoring in the top percentile on the

standardized tests and with the highest grade point averages. The change we are seeing today is the movement toward an increased use of a mixed approach which includes both qualitative and quantitative measures to capture the attributes of the well rounded student.

B. QUANTITATIVE MODELS OF A QUALITATIVE ADMISSIONS PROCESS

Sadler and Hammerman (1999) discuss how quantitative models for selecting Harvard Graduate School applicants can save time, reduce bias and strengthen their graduate program. This study illustrates how quantitative modeling is “used to predict a reasonable cut-off for selection of candidates who should be considered in the next stage.” (Sadler and Hammerman, 1999) The importance of this research to us is the use of both quantitative modeling, as well as qualitative subjective measures to predict which candidates advance to the next stage.

Harvard’s graduate admissions process is different from most undergraduate admissions processes because of the composition of the board, which includes both faculty and students. In addition, the mindset of the board is different from most undergraduate programs because the doctoral student is seen as a long term investment by the university. The admissions process at the Harvard Graduate School of Education may not be an exact match to the Naval Academy’s process because USNA does not have students on the board of admissions. However, both processes are similar in that they view the admissions decision as a long term investment. For example, the Naval Academy must select young men and women to ultimately serve in careers as officers in the US Navy and Marine Corps.

The Saddler and Hammerman (1999) study was conducted over a five-year period “characterizing a three-stage admissions process that relies heavily on judgments of quality based in complex data.” In the first stage, individual members read the admissions packages and rate each candidate. In the second stage the candidates are discussed by the committee and rated through group consensus. In the third stage, the candidates are compared and each case is decided. (Sadler and Hammerman, 1999)

This three-step process uses quantitative modeling but relies heavily on a subjective review of each candidate's admissions package, which includes prior success history, recommendations and test scores. The subjective review looks to extract a "candidate's potential for educational leadership, depth of educational ideas, match with the program's strengths and resources, and motivation for embarking on a doctoral program." (Sadler and Hammerman, 1999) This subjective review extracts traits that are not captured in any statistical based model. This identification of the traits that match the ideals of the institution is the very same thing that is captured by the RAB at USNA. The Harvard Graduate School of Education admissions board uses the quantitative models to narrow the field of candidates and then reviews the packages and searches for desirable traits that predict career success. The Naval Academy Admissions Board brings the same value added to their statistical based scoring model. Once the quantitative model has narrowed the candidate field, the Board extracts the desirable traits and quantifies those traits by awarding additional points to the Candidate Multiple.

The overall concepts and findings of the Harvard study are worthwhile and pertinent to the study of the RAB at the Naval Academy admissions process. Saddler and Hammerman show that even though quantitative models are used, the subjective identification of the institutionally desired traits demonstrated by the candidate keeps the focus on the human aspect of the admissions process. The study illustrates the value of combining the strengths of quantitative modeling with a largely qualitative admissions process.

The Harvard admissions process is "viewed as an opportunity to match the resources and needs of a school with an applicant's interests and talents, impressions and intuitions must substitute for the comfort of numerical scores." (Sadler and Hammerman, 1999) Similarly, the Naval Academy admissions process is viewed as an opportunity to match the resources and needs of the institution with a candidate's interest and talents, where impressions and intuitions are the value added to the admissions process and quantified in the form of a RAB, which is added to the statistical based scoring model. The RAB will never substitute for the overall numerical scoring model but it certainly is that little bit extra that could push the board to accept candidates with lower scores.

C. SEEKING DIVERSITY: HOW DO WE STRENGTHEN DIVERSITY AT HIGHLY COMPETITIVE CAMPUSES?

In June 2003, there were two Supreme Court case decisions that involved diversity issues at the University of Michigan. The ruling upheld one admission policy and turned down another. In the case the Supreme Court upheld, it ruled that the law school's admissions policy that "had compelling interest in enrolling a racially diverse student body because of educational benefits that diversity provides. The majority said that the law school's race-conscious admissions policy was an acceptable means of achieving that diversity because it considered race as just one of several factors in evaluating each individual." (Schmidt, 2003) In the case that was not upheld, the Supreme Court ruled that the admissions policy relied primarily on a statistical-based scoring system that was "too formulaic and mechanistic, and treated whole groups of applicants differently based solely on their race. Because the policy was not 'narrowly tailored' to achieving educational diversity it violated the Constitution's equal-protection clause and Title VI of the Civil Rights Act of 1964, which prohibits racial discrimination by any institution, public or private, that receives federal funds." (Schmidt, 2003) The theme the Supreme Court was ruling on was that race needed to be "evaluated flexibly" and not used by treating individuals as members of a particular racial grouping. Beginning with the freshman class entering in the fall of 2004, university officials say they will "instead consider race in a more 'holistic' way." (Cavanagh, 2003) The new University of Michigan's undergraduate admissions policy is serving as a "harbinger of admissions overhauls...where administrators are seeking to craft legally defensible affirmative action plans of their own." (Cavanagh, 2003)

College admissions officials read the Supreme Court rulings as allowing race-based admissions in higher education as long as they institute a more comprehensive evaluation system, which measures the abilities of each applicant on an individual basis. The challenge for the college and universities comes in the manner of how do they identify the qualified minorities that are seeking admission to their respective university.

Universities can also seek new ways to identify minority high-school students with personal qualities that would allow them to overcome modest grades and test scores and succeed in college. The problem is not, as some liberal critics continue to assert, that minority scores are

artificially low because of cultural bias in the tests. In fact, the reverse is true: Standardized tests consistently over-predict the academic performance of minority students in college and professional school. Even so, tests and high-school records are far from infallible; many minority students can do much better than their prior records would predict. If admissions committees could identify more of those young people, larger numbers of poor and minority students could gain access to selective colleges. (Bok, 2003)

D. THE IMPLICATIONS OF TRADITIONAL MEASURES: SAT, GPA, STUDENT ESSAYS, INTERVIEWS, COUNSELOR STATEMENTS.

The standardized test has been under scrutinized by statisticians and researchers for years as they have been trying to find the appropriate fit into admissions process. Keller, Crouse, and Trushiem (1994) published a study that explored the effect of the SAT on admissions and the results suggest that the SAT has more of an effect on the composition of a freshman class than it does the academic outcomes of the class. “The fact that the SAT has compositional effects means that most colleges probably ignore the SAT scores of some applicants to balance the composition of their freshman class. They must do this when they consider financial need and affirmative action in their admissions.” (Keller et al., 1994) “The compositional effects of the SAT could increase the number of engineering majors, but decrease the number of education, human resources, nursing, and physical education majors. It could also decrease female and black admissions.” (Keller et al., 1994)

Standardized tests scores alone should not be the sole factor in which an admissions decision is made. Carole Veir (1990) presented a paper at the Annual Meeting of the University Council of Educational Administrators discussing how to identify potential leaders through pre-admittance assessment. In her paper, she explains how the Leadership Assessment Center process utilized at the University of Texas at Austin selects students for the Educational Administration Leadership Program. The assessment center was finding that they were admitting students who did not possess the ability, personality or potential to be leaders for the schools. After studying and reviewing their admissions process they were finding that they were admitting students based on their standardized test scores. There was no humanistic or subjectivity in the admission process. From that point on the Leadership Assessment Center learned that “a

good GRE score alone does not denote potential for leadership, but rather potential to succeed in graduate programs.” (Veir, 1990) This realization turned them back to their admissions process and they “determined that program admission should be determined by multiple sources of evidence that include much more information than these standard measures, which provide little information about the most essential aspects of the ability to be a school leader and survive a rigorous graduate program with a strong focus on communication and interpersonal skills, leadership and decision-making procedures.” (Veir, 1990)

Even today as the admissions process moves towards goals of an increasingly diverse student body, the effect of standardized test scores is still an issue of debate. But as the debate continues, admission officials are seeking the appropriate balance of quantitative data through standardized tests and elusive data on more subjective measures. “Admissions committees, particularly at these types of institutions [highly selective], take into account a wide variety of criteria, and some of these factors are likely to be subjective measures not easily captured in analysis. For example, many schools require student essays and recommendations from teachers. Moreover, extracurricular activities and leadership experiences are also important influences in application decisions.” (Long, 2003)

Some officials are more holistic in nature looking for that distinguishing attribute that the applicant will contribute to the institution. “As an admissions officer, I looked for clues to character. What has the student done to overcome obstacles? In what ways has the student distinguished herself? These items can be revealed in ways that could be much more student-centered and efficient.” (Sjogren, 2004)

In a paper to the Association for Institutional Research in 1989, Kanarek discusses how Willingham (1985) found that “‘productive flow through’ in high school ‘purposeful, continuous commitment to certain types of activities versus sporadic efforts in diverse areas’ was the best predictor of overall success. He notes, however, that ‘extracurricular productivity’ is not a substitute for academic qualification.” In contrast, she also notes that Trushiem and Middaugh (1987) “found that personal qualities were not related to the prediction of freshman grades.” He also suggests that the collection of

personal data is an inefficient and an unjustifiable contribution to the prediction of freshman grades. So the bottom line is determined by the characteristics the Admission Board is searching for in their student body. Are they screening for leaders and decision makers, or are they screening to predict freshman grade point averages? The concentration and focus of the Admissions Board is critical to what data is collected and how it is weighed in the process.

In addition to the data collection, the interview process and “developing regional alumni interviewing committees is another way institutions have managed to meet more students face-to-face.” (Greene et al., 2003) “As long as they are conducted sensitively, interviews can be an important part of a holistic admissions process.” (Greene et al., 2003)

III. DATA AND METHODOLOGY

A. DATA SOURCE

This study draws on data obtained from the Office of Institutional Research at the Naval Academy. The dataset contains candidate application information, such as demographics and high school performance as well as midshipmen performance information. Using cohorts entering for graduation years between 1995 and 2001 yields a total of 8,299 individual records, 6,495 of which are graduate records. From the 6495 individual graduate records, 65 individual records were removed leaving 6,430 individual cases for estimating the order of merit, academic QPR and military QPR outcome measures. For estimating the striper selection outcome, 90 individual graduate records were removed from the 6,495 individual graduate records for missing data. Figure 1 represents the total number of cases (accepted applicants) by graduating class year in the data sample.

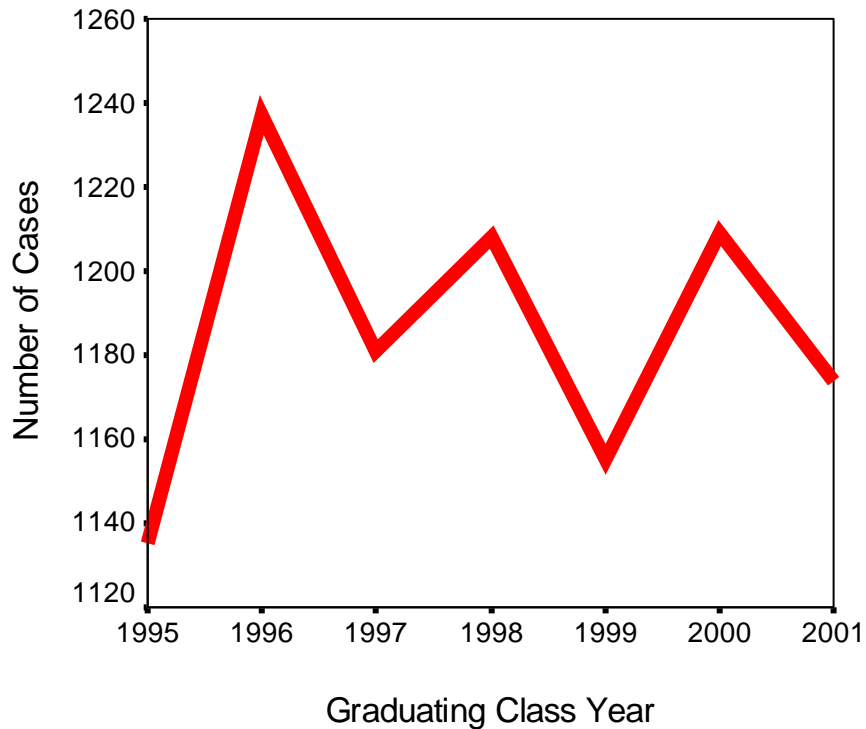


Figure 1. Number of Accepted Applicants in Each Graduation Year

The Office of Institutional Research does not maintain information on candidates who do not attend the Naval Academy. The data set did not contain information for candidates who were offered an appointment and opted not to attend the Naval Academy or for candidates who were not offered an appointment. This is important to keep in mind as all results of the study are based on accepted applicants rather than the full population of total applicants.

B. METHODOLOGY

To examine the relationship between qualitative judgments of the Admissions Board (RAB) and accepted applicant performance at USNA, this study follows several steps. The explanatory and dependent variables are identified and defined based in information in the dataset received from the USNA Office of Institutional Research. The independent variables and the development of the multivariate regression models were based on the types of performance measures chosen for the study.

This section on methodology is divided into two parts: (1) method of analysis; (2) outcome performance variables. Several factors are considered in defining the independent and dependent variables used in this study. These include: how to categorize the variables (dichotomous, categorical, or continuous); correlations between explanatory variables; and the possibility of using interaction variables.

Linear and logistic multivariate regressions are used to analyze relationships between the selected performance (outcome) measures and the subjective judgments of the Admissions Board (RAB). For this phase, several dependent variables are selected as outcome performance measures. These include: graduation (**Grad**); order of merit (**Pctloom**); cumulative academic quality point ratio (**Cumaqpr**); cumulative military quality point ratio (**Cummqpr**); and striper selection (**Stripers**).

1. Method of Analyses

We will address the modeling analyses primarily focusing on the groups which we could consider a trade off in overall performance for diversity. The regression models will use two types of multivariate estimation techniques to quantify the relationships between the RAB and the selected performance measures. Standard Ordinary Least Squares (OLS) regression analysis is used for models where the dependent variables are

continuous, such as **PctIROOM**, **Cumaqpr**, and **Cummqpr**. Logistic (Logit) regression analyses are used for binary dependent variables, in our case **Grad** and **Stripers**. Descriptions of the OLS regression and the Logit regression models are included in the following two subsections.

a. General

Linear multivariate regression analysis is used for a number of reasons. First, multiple regression techniques can be applied to a data set where the independent variables are somewhat correlated with one another and with the dependent variables to varying degrees. Second, multiple regression uses several independent variables to predict the dependent variable. Third, the result of the estimated regression model is an equation that represents the best prediction of a dependent variable from several (continuous or dichotomous) independent variables. The regression equation takes the following form:

$$Y' = A + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + e \quad (1)$$

Where Y' is the predicted of the dependent variable, A is the Y intercept, the X s represent the various independent variables, the B s are the coefficients of each of the independent variables to be estimated, and e is the stochastic error term. The estimated intercept and coefficients are used to predict the values of the dependent variables for all observations in the sample. A different Y' value is predicted for each observation as a result of inserting the subject's own X values into the equation.

The goal of the regression is to estimate the β values, called coefficients, for the independent variables that minimize the difference between the Y values predicted from the equation and the Y values obtained by measurement. That is, ordinary Least Squares techniques minimize deviations between predicted and obtained Y

values and optimize the correlation between the predicted and obtained Y values for the data set. (See Tabachnick, Barbara G. Using Multivariate Statistics, 4th ed. Ch5, p111-112)

In cases where a clear (binary) division can be made between successful performance and lower performance, such as graduation (**Grad**) or selection to a leadership position that rates wearing stripes (**Stripers**), linear probability, probit, and logit models can all be used. While all these techniques are appropriate when estimating a relationship between a set of explanatory variables and a dichotomous (binary) dependent variable, this study uses the logit regression model. The logit model has neither assumptions about the distribution of the predictor variables nor do the predictors have to be normally distributed, linearly related, or of equal variance within each group. The predictors can be a mix of continuous, discrete and dichotomous variables. Also, the estimated logit model cannot produce negative predicted probabilities.

Because the logit model is non-linear, the equations used to describe the outcomes are slightly more complex than those for the OLS multiple regressions. The outcome variable, \hat{Y} , is the probability of having one outcome or another based as a nonlinear function of the best linear combination of predictors: with two outcomes:

$$\hat{Y}_i = e^u / 1 + e^u$$

where \hat{Y}_i is the estimated probability that the i th case ($I=1, \dots, n$) is in one of the categories and u is the usual linear regression equation:

$$u = A + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

with constant A , coefficients β_j , and predictors X_j for k predictors ($j = 1, 2, \dots, k$). This linear regression equation creates the logit or log of the odds:

$$Ln (\hat{Y} / 1 - \hat{Y}) = A + \sum \beta_j X_{ij}$$

The linear regression equation is the natural log (ln) of the probability of being in one group divided by the probability of being in the other group. The goal is to

find the best linear combination of predictors to maximize the likelihood of obtaining observed outcome frequencies. The most complex and best fitting model includes the constant, all predictors, and perhaps interactions among predictors. (See Tabachnick, Barbara G. Using Multivariate Statistics, 4th ed. Ch5, p517-519)

b. Modeling Specifications

(1) Multiple Regression Analysis. We have constructed a series of regression models by adding explanatory variables to each additional regression to understand and illustrate the relationship of the RAB to the given performance measure. The baseline regression model includes independent variables for gender (**Female**), minority groups (**Aframer**, **Hispanic**, and **Othrace**), athletic recruit status (**Recblchp**), and nomination source (**Nomprvp**, **Nomqalt**, **Nomenrtc**, and **Nomsupe**).

The second step in the modeling adds candidate multiple (**Cmthous**) to the regression as an independent variable. This is an important step in the analysis because we now account for the candidate multiple in the regression and its relationship to the performance measure.

The third step adds the variable representing the RAB (**RAB500**) to the regression model. We begin to see the impact the Admission Board has once they have been afforded the opportunity to review each candidate's package and award RAB's to the candidate.

The fourth step adds a variable to the regression model that interacts the RAB score and the candidate multiple (**RABCM**). This is to test for any interaction effect between the RAB and the candidate multiple.

The fifth and final step of our regression model checks for non-linearity by adding the squared candidate multiple variable (**CMThSqr**) to the model. Also, the interaction variables between RAB score and the four distinct quartiles of the candidate multiple (**RABLO58**, **RAB5861**, **RAB6165**, **RAB65HI**) are added. In this regression, we have removed the RAB * Candidate Multiple (**RABCM**) interaction variable. The steps of the regression model and the sequence in which the independent variables are entered into the model is summarized in Table 1 below.

Table 1. Multiple Regression Models

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	x	x	x	x	x
Ethnicity					
African American (Aframer)	x	x	x	x	x
Hispanic (Hispanic)	x	x	x	x	x
Other Minority (Othrace)	x	x	x	x	x
Athletic Status					
Blue Chip (Reblchp)	x	x	x	x	x
Nomination Source					
President & VP (Nomprvp)	x	x	x	x	x
Qualified Alternate (Nomqalt)	x	x	x	x	x
Enlisted & NROTC (Nomenrtc)	x	x	x	x	x
Superintendent USNA (Nomsupe)	x	x	x	x	x
CM & RAB					
CM/1,000 (Cmthous)		x	x	x	x
CM ² (CMTHSqr)		x	x	x	x
RAB/500 (RAB500)			x	x	
Interactions					
CM/1000 * RAB/500 (RABCM)				x	
Interactions Non-linear					
(RABLO58)					x
(RAB5861)					x
(RAB6165)					x
(RAB65HI)					x

Note: ‘x’ indicates variable included in model.

(2) Logit Regression Analysis. The dichotomous dependent variables graduate (**Grad**) and striper selection (**Stripers**) are estimated using a logit model. We follow the same five-step process in our logit model as we do for our OLS models discussed above. The input of the independent variables and interaction variables in this same process once again allows us to measure the impact of each independent variable. The independent variables used in our logit models for our two dichotomous dependent variables are the same as summarized in Table 1.

2. Outcome Performance Measures

The outcome performance measures are chosen to parallel research found in the literature regarding admissions and performance of the admissions process. Several

dependent variables are selected as outcome performance measures, including: graduation (**Grad**), percentile order of merit (**Pctloom**), cumulative academic quality point ratio (**Cumaqpr**), cumulative military quality point ratio (**Cummqpr**), and striper selection (**Stripers**) and are discussed in detail in the following sections below. Table 2 contains descriptive statistics for the outcome performance measures.

Table 2. Outcome Performance Measure Descriptive Statistics

OUTCOME PERFORMANCE MEASURES	N of Cases	Mean	Std Dev.	MIN	MAX
Graduate (Grad)	8299	0.78	0.4120	0	1
Percentile of OOM (Pctloom)	6430	50.05	0.3600	1	100
Cumulative AQPR (Cumaqpr)	6430	2.93	0.0059	2	4
Cumulative MQPR (Cummqpr)	6430	3.18	0.0039	2.1	3.99
Selected for Striper Billet (Stripers)	6305	0.19	0.0050	0	1

*From the 6495 graduate cases, 65 cases were removed for missing data.

** From the 6495 graduate cases, 90 cases were removed for missing data

a. Graduation (Grad)

Grad is a dichotomous variable with 1 representing whether or not a candidate graduated from the Naval Academy and 0 representing a non-graduate. For this variable, we included delayed graduates as well. The over-arching criterion is whether or not the candidate completed the course of study and was awarded a diploma from the Naval Academy. Figure 2 charts the mean graduation rate by each graduating class year in the study.

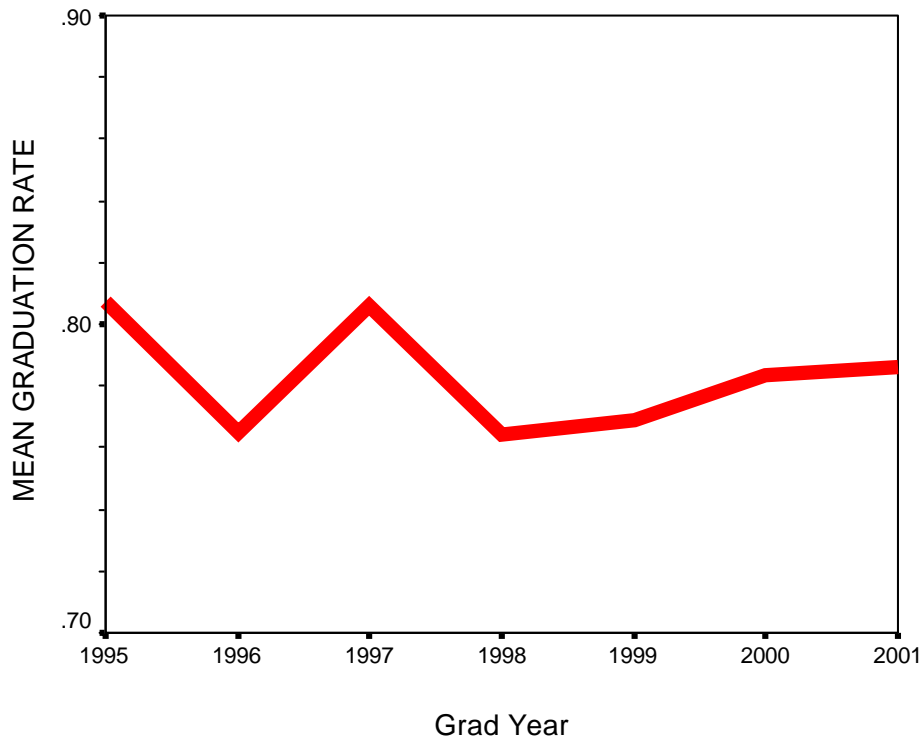


Figure 2. Mean Graduation Rate by Graduation Year

b. Percentile Order of Merit (Pctloom)

This variable represents the percentile ranking of each candidate in the graduating class. The raw Order of Merit is the sum of cumulative performance measures calculated to determine class ranking upon graduation. The measure contains universally weighted information to include academic grades, conduct grades, military performance grades, and physical readiness tests. The variable used in this study, however, is derived from stacking and ranking the raw Order of Merit (**OOM**) into a new variable (**ROOM**) which represents the stacked rankings of only graduating midshipmen. The variable (**ROOM**) is then divided by the number of members in each graduating class. This stacked ranking is done because members of the class that did not graduate may have held an order of merit position thus affecting the graduating member's final order of merit performance measure. Our goal is to see how successfully graduating members performed. When interpreting this performance measure, the estimated

coefficient represents an impact on percentile order of merit, not individual spots a candidate will move up or down. Note the Mean of the variable (Pctloom) should equal 50 by definition.

c. Cumulative Academic Quality Point Ratio (Cumaqpr)

This is a continuous variable representing the cumulative academic grade point average the candidate achieved while at the Naval Academy. This grade point average measure includes only academic courses of study. Figure 3 charts the mean cumulative academic QPR by each graduating class year. The evident rising trend in academic performance indicates that there could be increased academic grade inflation for successful cohorts in our study. Though we should not dismiss that this inflation exists, we will not attempt to prove or disprove the existence of the inflation. To account for the inflation we include class year dummy variables in the regression models as independent variables when analyzing cumulative academic QPR (**Cumaqpr**).

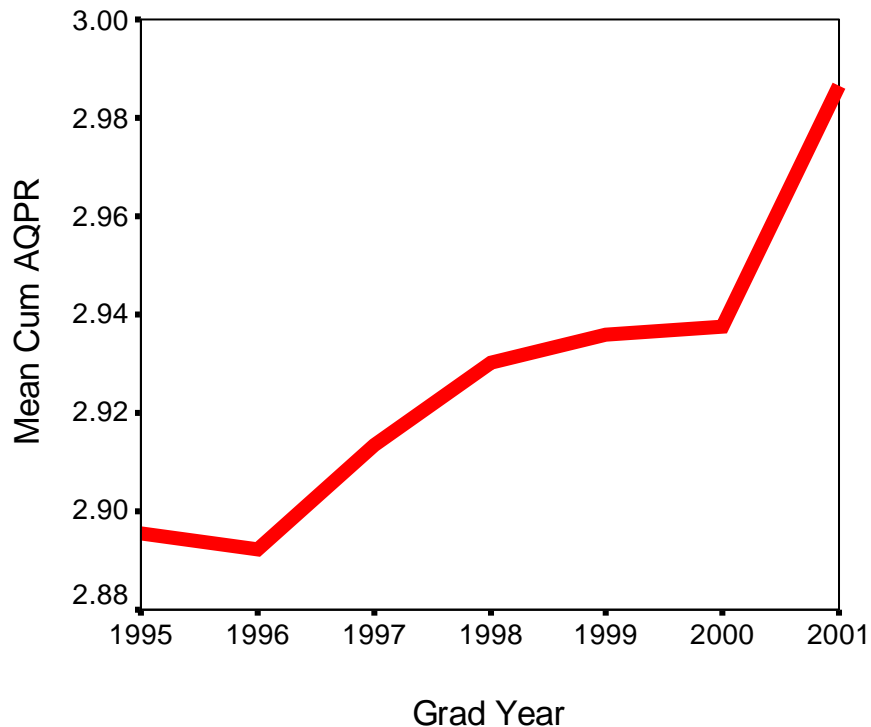


Figure 3. Mean CUMAQPR by Graduation Year

d. Cumulative Military Quality Point Ratio (Cummqpr)

This is a continuous variable representing the cumulative military grade point average the candidate achieved while at the Naval Academy. This grade point average includes military courses of study as well as conduct and military performance grades throughout the four years at USNA. It is evident in Figure 4 that there is a downward trend in the cumulative military QPR for the cohorts in this study. This very well could stem from a deliberate lowering of military grade inflation during the graduating class year cohorts of our study. We will not attempt to prove that this deflation exists, but it is pointed out as it affects our performance measures when we compare the entire data sample. For this reason we have included the class year dummy variables as independent variables in the models analyzing cumulative military QPR (**Cummqpr**).

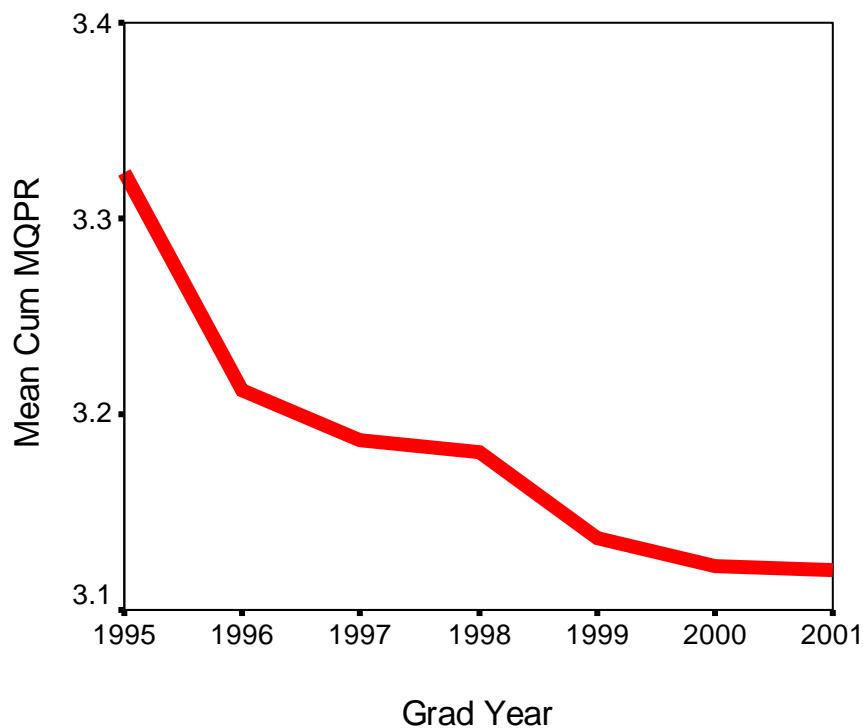


Figure 4. Mean CUMMQPR by Graduation Year

e. Striper Selection (Stripers).

This is a dichotomous variable with 1 representing whether the candidate was selected for a leadership position within the Brigade of Midshipmen that was awarded three stripes or more. Three stripes and above represents unit commanders (company, battalion, regimental, brigade), command staff (battalion, regimental, and brigade), as well as varsity sports team captains. Because stripes are awarded each semester to the midshipmen, the (**Stripers**) dependent variable accounts for the candidate's highest rank, three stripes or above, during the two semesters students are eligible for stripes. This choice to use three stripes and above was made because in order to earn three stripes or above the midshipmen are subjectively selected by the active duty leadership at the Naval Academy.

Figure 5 charts the striper selection rate by graduation year. Note the decrease in mean striper selection rate from graduating class year 1995 to 1997. The number of "striper" billets in the Brigade of Midshipmen is a fixed number each year. The selection rate can vary due to differing class sizes but the decrease in the chart is mostly accounted for by a significant decrease in the number of available striper billets from grad year 1995 to 1997 as there was a change in the organizational structure of the Brigade of Midshipmen from 36 companies to 30 companies. This affected the number of available striper billets to fill as there was a loss of six company commanders (equating to twelve lost leadership striper positions) and the loss of a Battalion staff (equating to approximately 20 to 25 lost leadership striper billets). Once this transition was complete, the number of available striper billets to award remains constant between 1998 and 2001. We note this because it certainly affects our striper selection rate over the entire data sample. Once again because of the impact of class size, we will include the class year dummy variables in the model to account for this changing rate of striper selection.

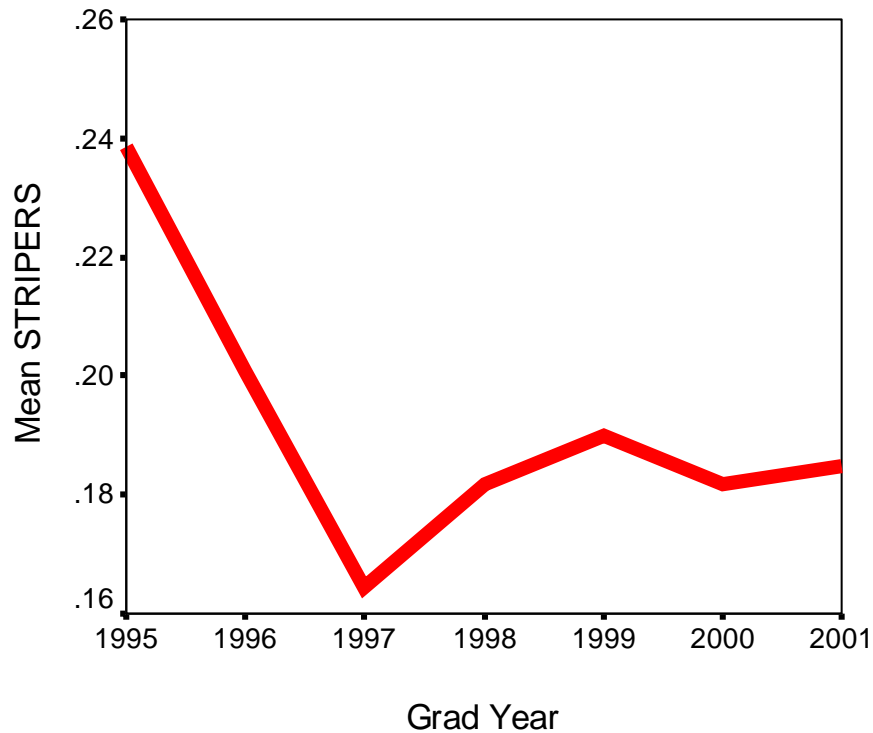


Figure 5. Mean Striper Selection Rate by Graduation Year

3. Independent Variables

a. Diversity Groups

This section examines the various demographic groups that may be given special consideration by the Admissions Board. An analysis of these groups will help to explain the function of the RAB and show that the value added of the RAB to the admissions process stems from its use as a diversity tool and as predictor of success.

This section addresses why these demographic groups are considered special by the Academy and analyzes any performance gaps between these diversity groups and the rest of the sample in the study. The literature review has identified certain groups that have the greatest potential for being treated differently by admissions boards across the country, including females, racial and ethnic minorities, as well as recruited athletes. In addition, groups that are specific to the Naval Academy admissions process that have potential to be treated differently are those that receive a special nomination from sources that include enlisted Navy and NROTC nominations, military legacy

nominations from the President and Vice President of the United States, Superintendent of the Naval Academy nominations, and the qualified alternate category nominated from the Admissions Board.

To completely grasp the scope and enormity that these special groups introduce to the Admissions Board when reviewing applications, we have compiled Table 3 that sums the maximum possible number of accepted applicants that fall into a special consideration category. This table does not double count any case that could fall into multiple categories. For example, out of the 8,299 accepted applications for this period, 1,273 were female applicants leaving only male applicants for counting 1,315 ethnic minority cases. Once females and ethnic minority applicants have been accounted for, 1,003 are blue chip athletes. So if the applicant is not female, is not an ethnic minority or a blue chip athlete, they still could be considered in one of the nomination categories. The following table sums the number of cases that could potentially be considered a special category by the Admission Board and surprisingly 67.5% of all accepted applicants were in at least one special consideration group when their admissions package was reviewed by the Admission Board.

We must understand that not only are the majority (67.5%) of all accepted applicants in this study in a group that could receive special consideration, some of these special consideration groups have a gap in observed performance based on high school performance, standardized test scores and the other performance measures that are captured in the candidate multiple. In analyzing these gaps, the candidate multiple sets the stage of our methodology as it is the initial performance measure calculated for every candidate.

We use t-tests and anova-tests as appropriate, to analyze differences in performance for the demographic groups. We run these tests on the groups using the candidate multiple as the measure. Identifying differences in the performance of each group will help us understand the dynamics of the RAB and how it is used as a universal diversity tool and some cases to overcome observed performance gaps.

Table 3. Number and Percentage Of Diversity Groups By Class Year

	1995		1996		1997		1998		1999		2000		2001		Total by group	
Female	145	12.8 %	168	13.6 %	166	14.1 %	190	15.7 %	193	16.7 %	198	16.4 %	213	18.1 %	1273	15.3 %
Minority	193	17.0 %	197	15.9 %	158	13.4 %	209	17.3 %	191	16.5 %	172	14.2 %	195	16.6 %	1315	15.8 %
Blue Chip	154	13.6 %	142	11.5 %	165	14.0 %	134	11.1 %	138	11.9 %	137	11.3 %	133	11.3 %	1003	12.1 %
Nomination	236	20.8 %	269	21.7 %	368	31.2 %	281	23.3 %	270	23.4 %	298	24.6 %	292	24.9 %	2014	24.3 %
Total by Grad Year	728	64.1 %	776	62.7 %	857	72.6 %	814	67.4 %	792	68.6 %	805	66.6 %	833	71.0 %	5605	67.5 %
Total Accepted by Grad Year	1135		1237		1181		1208		1155		1209		1174		8299	

(1) Gender. The trend in female entrants over the year groups in this study have remained relatively stable and consistent. Figure 6 illustrates the number of cases in the data sample by gender delineated by year group. Figure 7 charts the candidate multiple mean by gender.

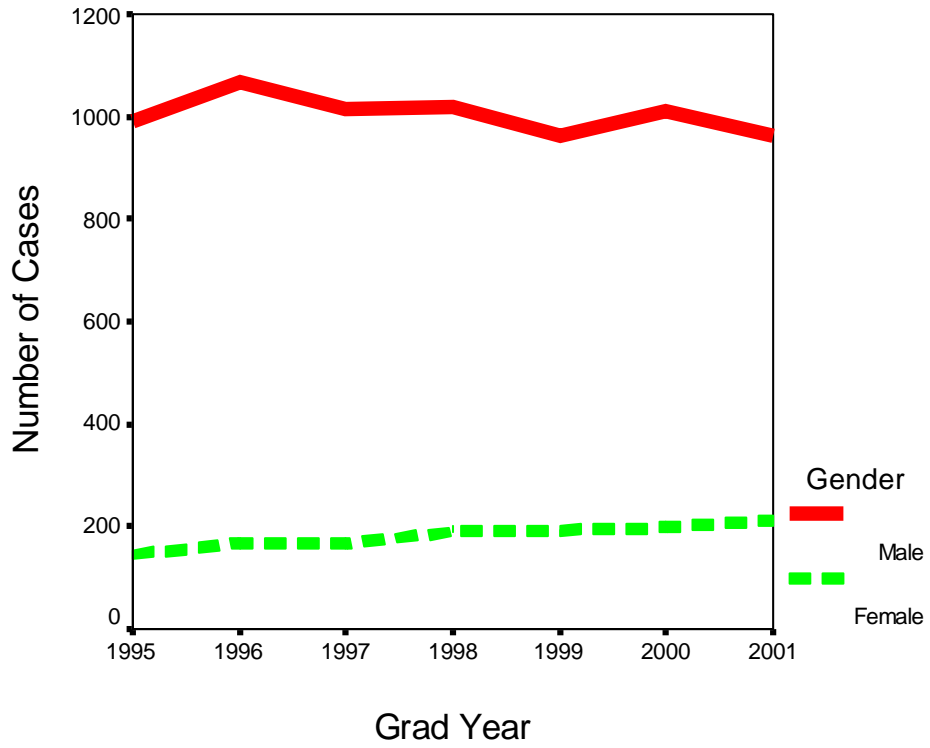


Figure 6. Number of Cases by Gender and Graduation Year

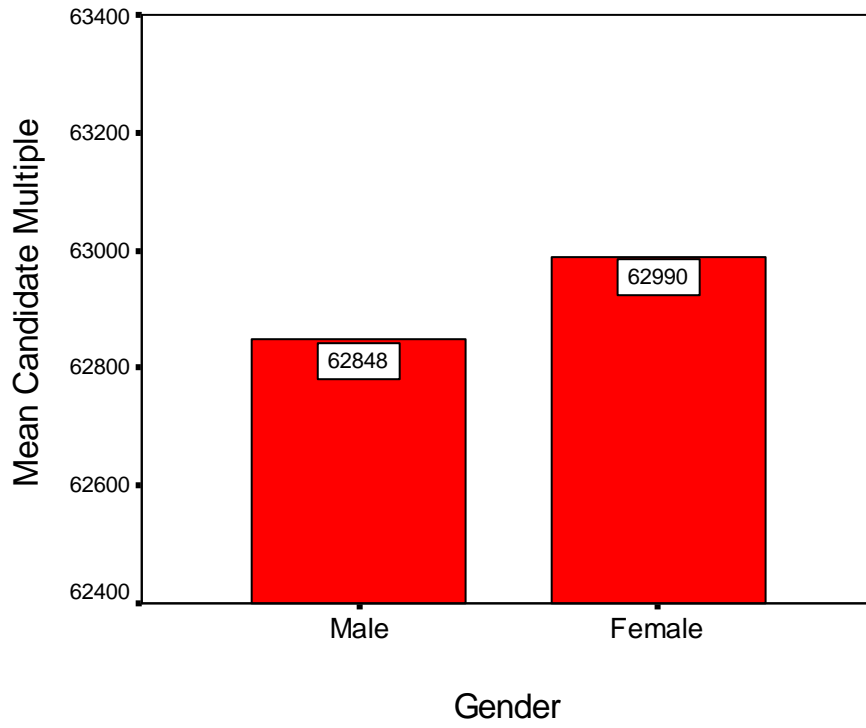


Figure 7. Mean Candidate Multiple by Gender

Accepted female applicants to the Naval Academy have a slightly higher candidate multiple mean (differing by only 142 points) but the difference is not significant (t value = .95, p = .340). This leads us to believe that females were not treated differently in the admissions process as they do not have any significant difference in past performance.

(2) Racial and Ethnic Minority Groups. Figure 8 illustrates the number of cases in each respective minority group in the data set by graduating class year. The trend in minority entrants has remained relatively stable. (The scale on the chart in Figure 8, leads you to believe that the cases numbers for each year are not stable. The cases in minority groups account for 10% to 18% of the class that have approximately 1,200 total cases.)

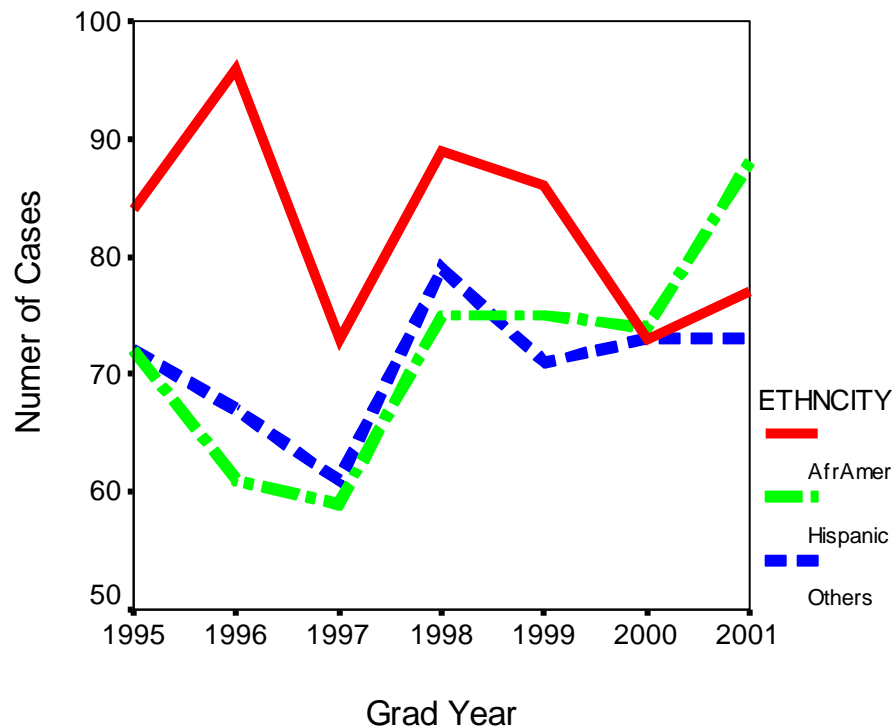


Figure 8. Number of Cases in Minority Groups by Graduation Year

Figure 9 shows that African American candidates have a considerably lower mean candidate multiple as compared to other candidates. The mean candidate multiple varies from 63,401 for whites, to 62,869 for the other minority races,

60,965 for Hispanic and 58,307 for African American candidates. A one way ANOVA resulted in an F value of 240.53 (Sig. level of <.001) indicating the candidate multiple scores differ significantly across the groups.

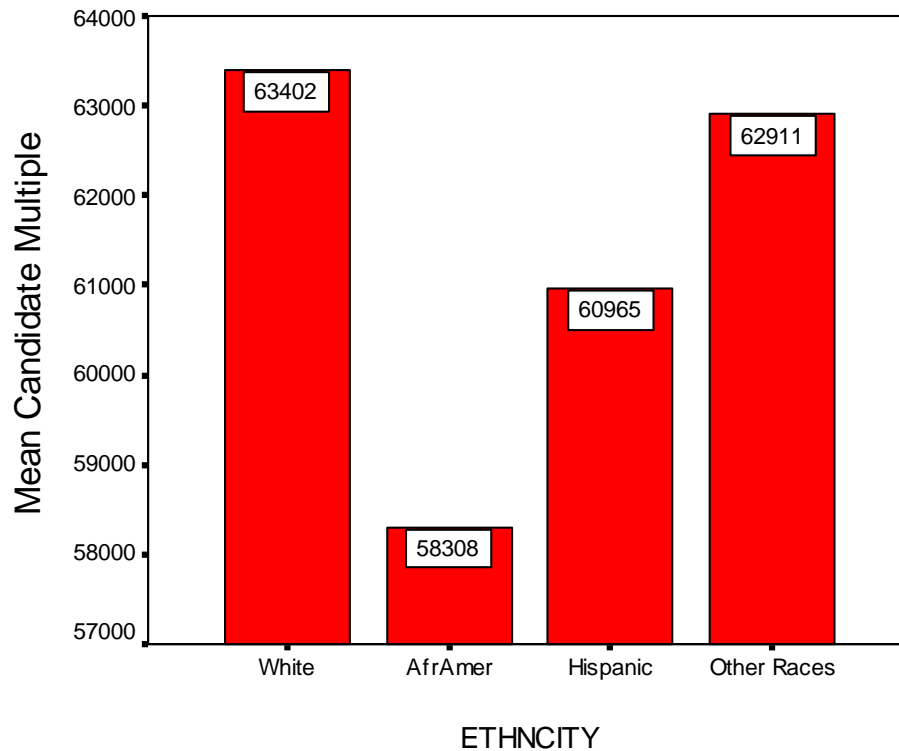


Figure 9. Mean Candidate Multiple of Minority Groups by Graduation Year

The difference in mean candidate multiple scores clearly indicate a gap in initial qualifications and observed performance coming out of high school for African American ethnic group. This gap in candidate multiple scores lead us to believe that on average an African American candidate may be treated differently by the Admission Board if they are to overcome the candidate multiple gap. This study will focus on the Recommendations of the Admissions Board (RAB) and how the RAB affects performance at the Naval Academy. The importance of this relationship is critical to this study because we show that once candidate multiple is accounted for, the RAB becomes a strong predictor of success. By accounting for race and ethnicity in the analyses, we will see how the RAB may act as an equalizing factor for candidates with

lower candidate multiples as well as a performance predictor across the full scale of candidate multiples. Because the RAB is a subjective measure awarded to the candidates on an individual basis once their admissions packages have been completely reviewed, it appears to be used to reward unobservable traits that the Admissions Board finds important and critical to the candidate's success at the Naval Academy.

(3) Nomination Sources. Peculiar to the Naval Academy admissions process, the nomination source also provides an opportunity for the Admissions Board to reward a particular group of applicants. Figure 10 displays the trend in awardees by nomination source by class year.

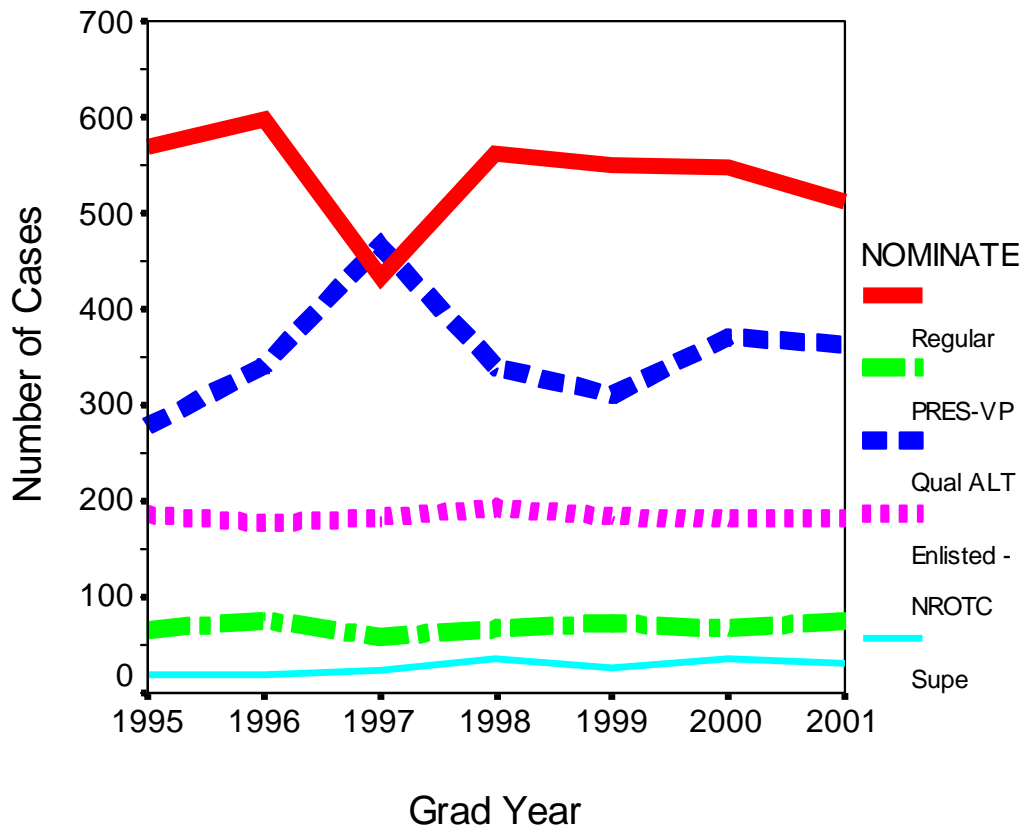


Figure 10. Number of Cases in Each Nomination Source by Graduation Year

Figure 11 shows that candidates entering from active duty service as enlisted sailors and NROTC candidates have a considerably lower Candidate Multiple. Not only are enlisted/NROTC candidates considerably lower, the highest mean candidate multiple is for the Senator and Congressional nominations, which in our study is

considered a “regular” nomination source. The means vary from 64,524 for the Senator and Representative nominees to 58,864 for the enlisted and NROTC candidates. An ANOVA resulted in an F value of 399.34 (Sig. level of <.001). Once again, we have identified a group with a considerable gap in observed prior performance thus, the active duty enlisted and NROTC candidates that are offered an appointment to the Naval Academy must possess unobservable traits that the Admissions Board awards in the form of the RAB in the admissions process. Table 4 shows the mean SAT scores and RAB points awarded by nomination source.

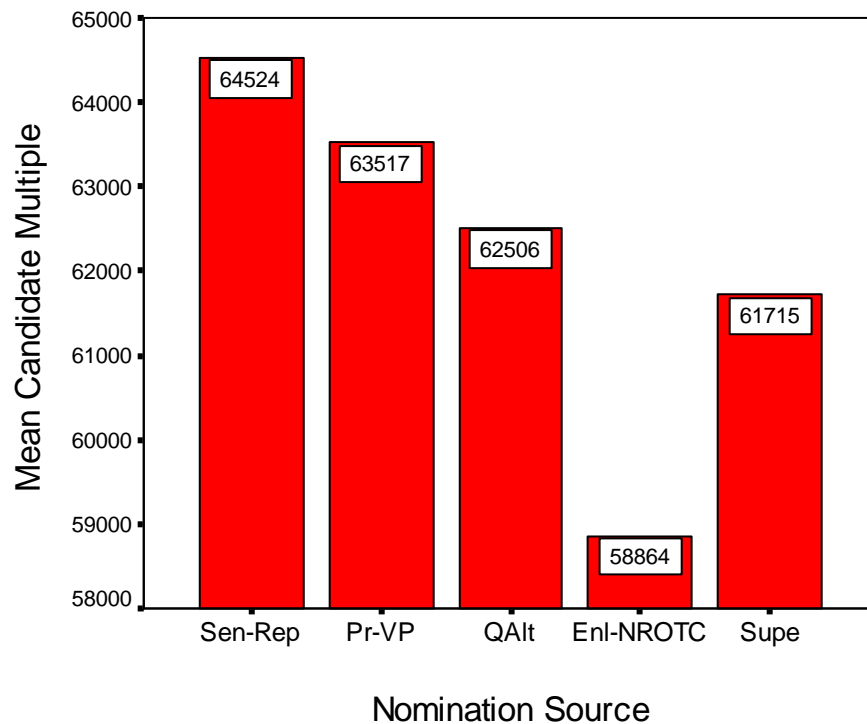


Figure 11. Number of Cases in Each Nomination Source by Grad Year

Table 4. Mean SAT and RAB Scores by Nomination Source

	N	Mean SAT-M	Mean SAT-V	Mean RAB
Senator & Representative	3768	671	649	1097
President & VP	484	662	637	1533
Qualified Alternate	2470	656	633	1462
Enlisted -ROTC	1285	620	597	2325
Superintendent	189	636	612	1693

(4) Athletic Recruit Status. Recruited athletes are clearly a group that may receive special treatment. We have chosen the Blue Chip Athlete to concentrate on in this study because these athletes are recruited all over the country to participate in a specific NCAA DIV I varsity sports program. For most schools around the country this is a sensitive topic for the Admissions Board as they try to balance advancing the athletic program with student performance in the classroom. The Blue Chip athlete who applies to the Naval Academy must also possess academic strengths and the candidate multiple is the tool to highlight the prior performance of applicants. The number of cases of Blue Chip athletes is charted by graduation year in Figure 12.

Figure 13 shows why athletic recruit status is a delicate topic among the nation's Admissions Boards. The non-recruits have a higher candidate multiple than recruited athletes. The difference is 4,128 (*t-value* = 35.9; $P < .001$).

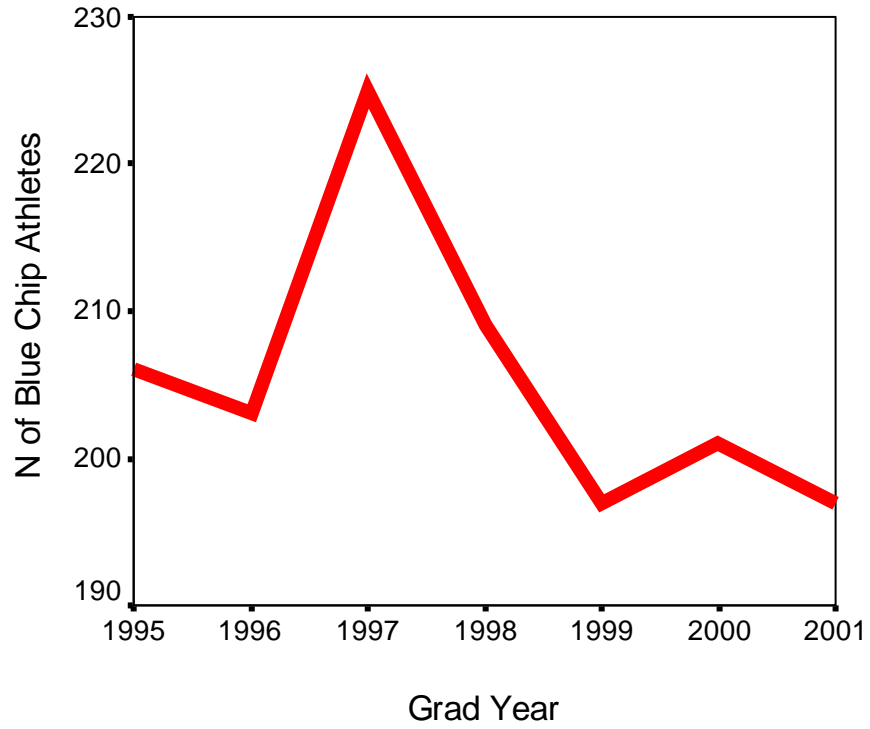


Figure 12. Number of Cases of Blue Chip Athletes by Grad Year

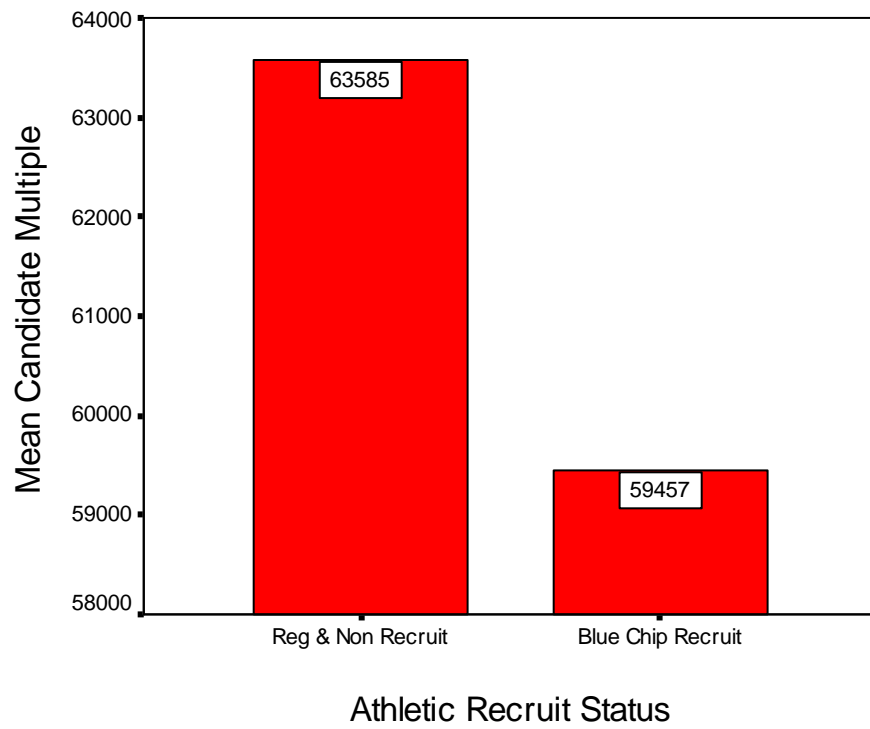


Figure 13. Mean Candidate Multiple by Athletic Recruit Status

Having a complete understanding of the initial candidate multiple of the various special groups shows why the Admission Board may need to take special action to assist these groups. For the Admissions Board, the search for diversity and quality is where the subjective RAB adds its value in the admissions process. By seeking diversity and admitting candidates in groups that traditionally have a lower candidate multiple, the Admission Board is taking the chance of lowering the overall quality of the candidates admitted, in terms of performance, but also recommending and admitting candidates that they expect to rise to the challenge and perform to the standards of the Naval Academy due to desirable unobserved traits discovered during the admissions process.

b. Defining Diversity Groups as Independent Variables

This study divides the independent variables into five categories: basic demographic data; recruit athletic status; nomination sources; candidate multiple (CM); and Recommendations of the Admissions Board (RAB). Individual variables in each category are discussed at length in the sections below.

(1) Basic Demographic Data. The demographic data consists of gender and race/ethnicity. These independent variables are included in the regressions because of the likelihood that gender and race/ethnicity are treated differently and could be considered for the award of additional RAB points during the admissions process. The variables are defined as follows:

(i) ***Female***. This is a dichotomous variable where 1 represents a female, and 0 otherwise.

(ii) ***African American (AFRAMER)***. This is a dichotomous variable where 1 represents the candidate's race as an African American, and 0 otherwise.

(iii) ***Hispanic (Hispanic)***. This is a dichotomous variable where 1 represents the candidate race as a Hispanic, and 0 otherwise.

(iv) ***Other Minority (Othrace)***. This is a dichotomous variable where 1 represents the candidate race as minority other than African American or Hispanic, such as Asian American, Filipino, Native American, Native

Hawaiian/Pacific Islander, Puerto Rican, as well as if the candidate indicated “other” as their race on the application form, otherwise the variable is 0.

(2) Recruit Athletic Status. The athletic status is also used as independent variable because this category could also be seen as group that would benefit from the award of RAB points.

(i) *Blue Chip Recruited Athlete (Rechlchp)*. This is a dichotomous variable where 1 represents the candidate was considered a “blue chip” recruited athlete by the Naval Academy, and 0 otherwise.

(3) Nomination Source. The nomination sources are also used as independent variables because individual groups may benefit from the award of RAB points.

(i) *Nomination from Senator or Representative (Nomsenrp)*. This is a dichotomous variable where 1 represents candidate was nominated by a senator or a representative, and 0 otherwise.

(ii) *Nomination from President or Vice President (Nomprvp)*. This is a dichotomous variable where 1 represents candidate was nominated by the President or Vice President of the United States, and 0 otherwise.

(iii) *Nomination from Secretary of the Navy (Nomenlrnc)*. This is a dichotomous variable where 1 represents the candidate was nominated by the Secretary of the Navy from the enlisted ranks or an NROTC program, and 0 otherwise.

(iv) *Nomination from the Superintendent (Nomsupe)*. This is a dichotomous variable where 1 represents candidate was nominated by the Superintendent of the Naval Academy, and 0 otherwise.

(v) *Nominated as a Qualified Alternate (Nomqalt)*. This is a dichotomous variable where 1 represents candidate was nominated by USNA as a qualified alternate, and 0 otherwise.

c. Candidate Multiple (CM)

The candidate multiple (CM) is the number associated with the statistical based scoring model the Naval Academy uses in the admissions process. The CM represents the high school performance of the application based on observable data such as high school grade point average, standardized test scores, physical aptitude tests, etc.

These indicators are normalized, computed and weighted into the CM algorithm. We use the candidate multiple as an independent variable because it easily identifies a candidate's initial qualification. For ease of interpretation throughout the study, we have divided the raw candidate multiple by a factor of 1000. The raw candidate multiple score typically ranges from approximately 50,000 to 77,000.

(1) Candidate Multiple/1000 (Cmthous). This is a continuous variable representing the candidate multiple (in thousands).

(2) Candidate Multiple Squared (Cmthsqrd). This is a continuous variable representing the square of the candidate multiple (in thousands). This variable is used to specify non-linearities in the **Cmthous** variable. This variable enables the use of the quadratic formula in the regression analysis.

Because the candidate multiple immediately identifies the initial quality of a candidate, we have separated the CM variable into four quartiles. The variables also are used to compute interaction variables with RAB points.

(3) A candidate multiple of 57,999 and below (CMTHLO58). This is a dichotomous variable with 1 representing the candidate belonging to this quartile of candidate multiple, and 0 otherwise.

(4) A candidate multiple between 60,999 and 58,000 (CMTH5861). This is a dichotomous variable with 1 representing the candidate belonging to this quartile of candidate multiple, and 0 otherwise.

(5) A candidate multiple between 64,999 and 61,000 (CMTH6165). This is a dichotomous variable with 1 representing the candidate belonging to this quartile of candidate multiple, and 0 otherwise.

(6) A candidate multiple above 65,000 (CMTH65HI). This is a dichotomous variable with 1 representing the candidate belonging to this quartile of candidate multiple, and 0 otherwise.

d. Recommendation of the Admissions Board (RAB)

The RAB is the independent variable in which this study is focused. It is the subjective aspect of the admissions process where the Admissions Board awards points to the candidate. The sum of the candidate multiple and the RAB produces the Whole Person Multiple (WM). The Whole Person Multiple is the final criteria by which

a candidate is considered for appointment to the Naval Academy. For ease of interpretation, we have divided the RAB by 500 creating:

(1) $RAB/500$ (RAB500). This variable is continuous representing the numerical amount of points awarded by the Admissions Board (divided by 500).

We have also created a few interactive variables between the RAB and the Candidate Multiple to see if the interaction effect is linear or non-linear. The interaction variables are discussed in the remaining sections.

(2) $Rab500 * CMThous$ (RABCM). This is a continuous variable representing the interaction between the **RAB500** (continuous) and **CMThous** (continuous). The interaction variable represents the impact of the RAB for various levels of the CM. It is created to determine whether the impact of RAB differs at different levels of CM.

Before discussing the interaction variables we must explain how the ranges of the candidate multiple were derived. If we chart the interaction of the RAB (RAB500) and the candidate multiple (CMThous) in a scatter plot, see Figure 14, we can clearly see break points in the interaction of these two variables. What this figure displays that candidates with lower CM scores tend to receive larger RABs in order to be considered “qualified” by the Admission Board. As the center of mass line begins to change its slope, at approximately **CMThous** = 58, it reaches a point where the candidates are hypothesized to be receiving RABs more for unobservable traits rather than to boost the CM for qualification. This range in the interaction also experiences an increase in scatter plot mass and the slope begins to flatten. **CMThous** = 61, the slope has completed its most drastic changes and continuing from 61 to 65 the slope turns slightly positive and this is the greatest concentration of plots. In this range, we find the mean of the CM, so it is not surprising that this is where most of the candidates fall in terms of initial observed qualification as defined by the CM and do not require a RAB for an appointment but are still receiving RABs based on desirable traits. From 65 to the right end of the scale we see that the slope of the line of mass turns slightly negative and continues on that path, indicating that these candidates are fully qualified and may receive RABs based on desirable unobserved traits in their admission package.

It must also be noted that this figure clearly illustrates that the RAB is awarded throughout the entire range of CM and not just to a certain range of the CM. It does clearly indicate, however, that a candidate must receive a larger RAB to be considered for appointment when they have a lower candidate multiple. But just because they have a low candidate multiple does not mean they are not “qualified.” The Admissions Board determines if a candidate is “qualified” and if there are sufficient means to justify a large RAB to a candidate, they will award the RAB and take a calculated risk on lower student performance.

(3) Rab500 * CMTHLO58 (RABLO58). This is a continuous variable representing the interaction between the **RAB500** (continuous) and **CMTHLO58** (dichotomous). The interaction variable represents the impact of the RAB to candidates in the 57,999 and below CM range.

(4) Rab500 * CMTH5861 (RAB5861). This is a continuous variable representing the interaction between the **RAB500** (continuous) and **CMTH5861** (dichotomous). The interaction variable represents the impact of the RAB to the candidates with a CM between 60,999 and 58,000.

(5) Rab500 * CMTH6165 (RAB6165). This is a continuous variable representing the interaction between the **RAB500** (continuous) and **CMTH6165** (dichotomous). The interaction variable represents the impact of the RAB to the candidates with a CM between 64,999 and 61,000.

(6) Rab500 * CMTH65HI (RAB65HI). This is a continuous variable representing the interaction between the **RAB500** (continuous) and **CMTH65HI** (dichotomous). The interaction variable represents the impact of the RAB to the candidates with a CM of 65,000 and above.

Table 5 --included below--provides a summary of the names and definitions of the explanatory variables. Table 6--included below--provides a summary of the interaction variables names and definitions.

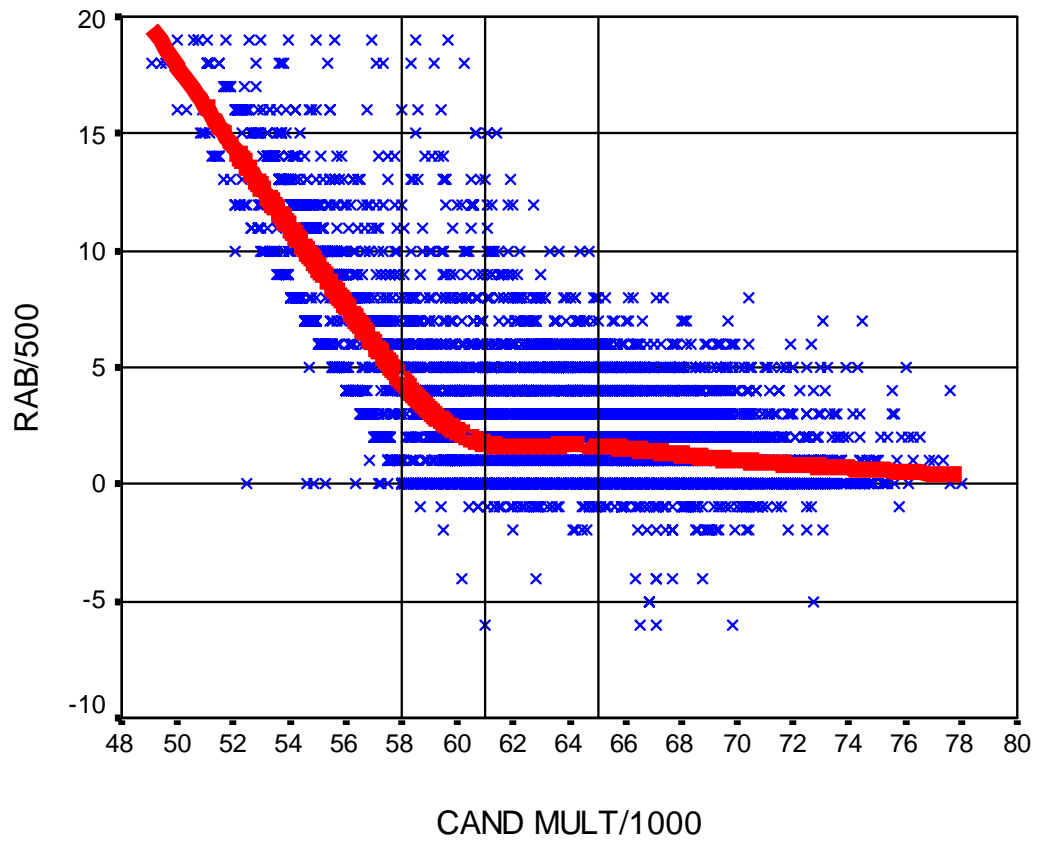


Figure 14. Chart of RAB and Candidate Multiple Interaction

Table 5. Explanatory Variables and Definitions Used in this Study

Explanatory Variables	Definitions
Female	Female = 1 if gender is female; =0 if male
Candidate's Ethnicity	Aframer = 1 if ethnicity is African American; =0 if otherwise Hispanic = 1 if ethnicity is Hispanic; =0 if otherwise Othrace = 1 if ethnicity is indicated as other minority; =0 if otherwise
Recruited Blue Chip Athlete	Recblchp = 1 if recruited as a "Blue Chip" athlete; =0 if otherwise
Nomination Source	Nomsenrp = 1 if nomination was awarded by State Senator or Representative; =0 if otherwise
	Nomprvp = 1 if nomination was awarded by President or Vice President of The United States; =0 if otherwise
	Nomenrtc = 1 if nomination was awarded by Secretary of the Navy; =0 if otherwise
	Nomsupe = 1 if nomination was awarded by Superintendent of USNA; =0 if otherwise
	Nomqalt = 1 if nomination was awarded by admission board as qualified alternate; =0 if otherwise
Candidate Multiple/1000	Cmthous = continuous variable if valid Cmthous = sysmiss if not valid
Candidate Multiple/1000 Ranges	CMLO58 = 1 if Cmthous is 57.999 or lower; =0 if otherwise CM5861 = 1 if Cmthous is between 58 and 60.999; =0 if otherwise CM6165 = 1 if Cmthous is between 61 and 64.999; =0 if otherwise CM65HI = 1 if Cmthous is 65 or higher; =0 if otherwise
Recommendations of the Admission Board (RAB)/500	RAB500 = continuous variable if valid RAB500 = sysmiss if not valid

Table 6. Interaction Variables and Definitions Used in this Study

Linearity and Interaction Variables	Definitions
Candidate Multiple/1000 (Squared)	Cmthsqrd = continuous variable if valid Cmthsqrd = sysmiss if not valid
RAB500 * CMLO58	RABLO58 = continuous variable if valid RABLO58 = 0 if not valid
RAB500 * CM5861	RAB5861 = continuous variable if valid RAB5861 = 0 if not valid
RAB500 * CM6165	RAB6165 = continuous variable if valid RAB6165 = 0 if not valid
RAB500 * CM65HI	RAB65HI = continuous variable if valid RAB65HI = 0 if not valid

C. HYPOTHESIZED EFFECTS

The hypothesized effects of the various demographic variables and the performance measures are a useful prelude to the methods of analyses section. Table 7 summarizes expected relationships between the explanatory variables and the dependent variables used in this study. For example, as the RAB500 increases, this study hypothesizes that a candidate is more likely to graduate from the Naval Academy, improve in order of merit standing, improve cumulative academic grade point average, improve cumulative military grade point average, and improve the likelihood of being selected for a leadership position as a striper.

Table 7. Explanatory Variables and Their Hypothesized Effects on Performance*

Explanatory Variables	Hypothesized Effect on:				
	GRAD	PctLOOM	CUMAQPR	CUMMQPR	STRIPER
	-	+	-	-	-
African American	-	+	-	-	-
Hispanic	-	+	-	-	-
Other Minority	-	+	-	-	-
Nomination SENRP	+	-	+	+	+
Nomination PRVP	+	-	+	+	+
Nomination ENRTC	-	+	-	-	-
Nomination SUPE	-	+	-	-	-
Nomination QALT	+	-	+	+	+
CMThous	+	-	+	+	+
RAB500	+	-	+	+	+
RABLO58	+	-	+	+	+
RAB5861	+	-	+	+	+
RAB6165	+	-	+	+	+
RAB65HI	+	-	+	+	+

* An expected positive relationship between an explanatory variable and a performance variable is denoted by a “+” sign, while a “-“ sign indicates a hypothesized negative relationship. For example, as RAB500 increases, this study hypothesizes that a candidate is more likely to graduate (+), more likely improve to a lower OOM percentile (-), more likely to improve CUMAQPR (+), more likely to improve CUMMQPR (+), and more likely to be selected for a striper position (+).

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IV. STATISTICAL ANALYSIS AND RESULTS

A. INTRODUCTION

The literature related to admissions policies of selective colleges identifies women, racial/ethnic minorities and athletes as being common challenges for Admissions Offices that strive to attract diverse student body who are likely to survive a rigorous academic program. At Annapolis, applicant packages are reviewed by the Admissions Board, where applicants are screened to be considered eligible for a nomination of those who meet minimum criteria for admissions. A sorting process begins with Senatorial and Congressional nominations being awarded by elected officials across the 50 states plus territories of Virgin Islands and Puerto Rico. The remaining candidates must then be ranked and further screened by the Admissions Office for consideration for one of the alternate nomination sources, which include Secretary of the Navy, Presidential and Vice Presidential and Qualified Alternates. The ultimate goal is still to select applicants with the desire, motivation, and ability to complete the rigorous four-year military and academic program at the Naval Academy.

B. SPECIFICATIONS FOR GRADUATION MODELS

To identify the separate impacts of the quantitative criteria contained in the Candidate Multiple score on student success from the impact of qualitative criteria resulting from subjective decisions of the Admissions Board, a series of non-linear regression models will be estimated. Step one estimates the impact on the likelihood of graduation of belonging to a special diversity group as well as the impact of receiving an alternative nomination (compared to those chosen for a regular Congressional Nomination.) Information on quantitative and qualitative scores are omitted from this initial step, which allows one to derive initial estimates of group membership on graduation.

In step two, the Candidate Multiple is added to the graduation model. This will allow the researcher to estimate if a membership in a diversity group or alternative nomination category still affects the graduation probability, independent of the CM score.

In step three, the qualitative RAB score assigned by the Admissions Board is added to the model. Again, the purpose is to estimate the effect of demographic background independent of the RAB score.

Two additional graduation models are specified to allow for interaction effects between the Candidate Multiple (quantitative) and RAB (qualitative) scores. In step four, the interaction is introduced by simply adding a multiplicative term (i.e., CM * RAB), whereas in step five, the RAB scores are added to the model across four ranges of the CM score. For example, if someone has a CM score of 57 (57,000 pts) and a RAB score of 4 (2,000 pts), their CM range would then be in the lowest of four possibilities, or “**RABLO58.**” Thus, if one “multiplies” the RAB score (4) times a value of “1” for being in the lowest CM range dummy variable, one includes this RAB score only in the first of four CM range interaction variables (i.e., RABLO58=4 and all other interaction RAB variables would be set to “0”). This process allows for greater flexibility when estimating RAB impacts on graduation across differing ranges of CM scores than using a simple multiplicative term as in Step four.

1. Findings of Empirical Models

a. Step One

Table 8 shows the “marginal effects” of the graduate logit model, the effect of a “change in” each independent variable on the probability of graduating. The first step in this logit model identifies the groups that are given special consideration by the Admissions Office. Table 4.1 shows that females are 8 percentage points less likely to graduate than males, while African American and Hispanic applicants are estimated to have graduation rates 8 points below that of whites. These results suggest a challenge to the Admissions Board when selecting minorities who are able to succeed at USNA. This also may suggest that the Naval Academy may need to look more closely at gender-racial diversity perspectives among the majority of white males and place continued emphasis on academic assistance, especially for racial minorities.

We also notice in Table 8 that Blue Chip athletes are 6 points less likely to graduate than those not recruited for a specific Division I NCAA sports program. This

also represents a challenge to the Admissions Office which emphasizes the competition at the Division I level and the indirect value added to Brigade of Midshipmen of offering Division I level sports.

Table 8. Logistic Regression Model of Graduation Marginal Effects

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	-0.086**	-0.087**	-0.088**	-0.087**	-0.091**
Race/Ethnicity					
African American (Aframer)	-0.084**	-0.062**	-0.061**	-0.054**	-0.056**
Hispanic (Hispanic)	-0.081**	-0.067**	-0.061**	-0.058**	-0.059**
Other Minority (Othrace)	-0.010	-0.006	-0.005	-0.004	-0.005
Athletic Status					
Blue Chip (Reclbchp)	-0.058**	-0.036**	-0.031*	-0.027*	-0.027*
Nomination Source					
President & VP (Nomprvp)	0.024	0.027	0.025	0.022	0.023
Qualified Alternate (Nomqalt)	0.028*	0.034**	0.033**	0.032**	0.033**
Enlisted & NROTC (Nomenrtc)	0.004	0.030*	0.031*	0.035*	0.040**
Superintendent USNA (Nomsupe)	-0.043	-0.040	-0.046	-0.035	-0.043
Graduation Year					
YR96	-0.045**	-0.045**	-0.043*	-0.042*	-0.044*
YR97	-0.005	-0.008	-0.004	-0.004	-0.005
YR98	-0.042*	-0.044**	-0.039*	-0.041*	-0.043*
YR99	-0.036*	-0.045**	-0.042*	-0.045**	-0.047**
YR00	-0.025	-0.034	-0.034	-0.037*	-0.038*
YR01	-0.019	-0.029	-0.031	-0.036*	-0.037*
CM & RAB					
CM/1,000 (Cmthous)		0.006**	0.008**	0.007**	0.007**
RAB/500 (RAB500)			0.004**	-0.040**	
Interactions					
CM/1000 *RAB/500 (RABCM)				0.001**	
Interactions Non-linear					
(RABLO58)					0.002
(RAB5861)					0.007*
(RAB6165)					0.014**
(RAB65HI)					0.009*
Model Chi-Square	141.509	171.226	180.515	189.717	192.705
-2 Log Likelihood	8548.64	8518.93	8452.3	8443.104	8440.116
Pseudo-R squared	0.017	0.020	0.022	.023	.023

* Significance Level > .05

** Significance Level > .01

The model in step one also compares four alternate sources to those admitted directly by Senator or Congressional Nominations (the omitted or reference group). Three of the nomination sources (Presidential & Vice Presidential, Secretary of the Navy, and Superintendent of the Naval Academy) have similar graduation rates as the Congressional direct applicants, since their estimated marginal effects do not differ from zero significantly. This is noteworthy because, as shown earlier, the average quantitative criteria contained in Candidate Multiple scores are generally lower for those nominated through these alternative sources. Appointments awarded through the Qualified Alternate nomination source, in spite of weaker quantitative criteria scores, are found to be 3 points more likely to graduate than those identified by regular Congressional nominations. This effect is statistically significant. One possible explanation for this unexpected finding may be that the RAB assessments of the Admissions Board along with the Admissions Office's assignment to the Qualified Alternate category are correlated with an applicant having a stronger desire and motivation to complete the four year program at Annapolis.

b. Step Two

The second step in the regression model adds the quantitative (CM) score from the applicant package to the graduation model. The CM score is based upon a formula of weighted numerical scores representing the applicant's high school performance (i.e., SAT, class rank, teacher recommendations, athletic and non-athletic extracurricular activities). The addition of the quantitative information to the model does not affect the impact of gender on graduation, suggesting the distribution of CM for females is similar to males. We see, however, nearly a 2 point reduction in the estimated impact of diversity group membership on graduation once we control for CM scores (e.g., African American CM mean is 58k compared to whites with a mean CM of 63k). In addition, the impact on graduation of being a blue chip athlete, given CM scores, falls by 2 points. Thus, once we control for CM score, the direct effect of minority status falls by about 25%.

Once we control for observed CM scores in the model we also find interesting changes in the estimated impact of applicants being sorted into one of the alternative nomination sources. For example, the impact on graduation of being chosen

as a Qualified Alternate nomination source increases from 2.8% to 3.4%. More importantly, we now find being assigned to an enlisted-NROTC nomination source raises the probability of graduating by 3 points compared to no difference in expected graduation in first model version. This finding supports the belief that having prior enlisted experience is significantly related to completion of the intense four-year program at USNA.

We also find the CM score is positive and significantly related to graduation. For example, an additional 4000 points (Mean CM =63,000) is estimated to increase the probability of graduation by 2.4 points. This supports the notion that information contained in the application package is positively and significantly related to the ability and personal drive to graduate from USNA.

c. Step Three

The third step includes the RAB score (i.e., qualitative criteria) assigned to applicant packages by the Admissions Board. The Admissions Board personally reviews each complete package knowing the initial quantitative score (CM) and adds “RAB” points (in blocks of 500 points to CM) within a committee voting process. Including qualitative information in the model does not have a large affect on the coefficient of gender but results in a slight decrease in the effect of racial/ethnic minority on graduation, suggesting the added value of qualitative information positively affects the probability of graduation. Once both quantitative and qualitative information are included in step three, it is estimated that females are 8.8 percentage points less likely to graduate, while African American applicants are 6.1 points less likely to graduate (compared to a 6.2 point difference with just quantitative CM scores in step two), and Hispanics are 6.1 points less likely to graduate (compared to 6.7 points less likely to graduate in step two). The estimated impact of additional nomination sources is the same as in Step two of the model.

In general, when the RAB is added to the model two things happen: first, the estimated impact of CM on graduation increases in size. For example, each +1000 points of CM increases the likelihood of graduation by 0.8%, an increase of 0.2% by including RAB in the model. Second, the RAB coefficient is positive and significant and indicates each 500 point RAB results in a 0.4% increased probability to graduate. For

example, 3 RABs equaling 1500 points increases the estimated likelihood of graduation by 1.2%. These findings suggest that there is value added from utilizing the qualitative information in the candidate packages and the existence of an interaction between qualitative scores (RAB) and quantitative scores (CM). This is evident because the estimated impact of CM rises significantly when RAB scores are added to the model.

Table 9 compares the accuracy of model predictions in terms of being able to classify applicants into graduates. Considering that four out of five accepted applicants graduate, the models of classification find it difficult to predict those more likely to attrite, and the change in the classification of attrite may be a better indicator of model accuracy than total prediction figures. With this in mind, we see below that the addition of quantitative and qualitative criteria improves the fit of the graduation model. Not only does the “model Chi-Square” increase, referring back to Table 8, from 141.5 to 192.7 (nearly 30%), but the percentage of cases that are correctly predicted to attrite increases from 46% to 54%.

Table 9. Accuracy of Model Predictions of Graduate Model (Attrition Cases)

# of Cases Correctly Classified	Step 1	Step 2	Step 3	Step 4	Step 5
Attrite	45.7	51.4	53.3	54.2	54.4
Graduate	68.2	63.9	63.0	62.3	62.4
Total	63.3	61.2	60.9	60.5	60.6

d. Step Four and Step Five

The final two steps in the logit model introduce the interactions of the qualitative and the quantitative information. We model two interactions. The first is the interaction of RAB and CM (Step 4). The second divides the CM score into four ranges and interacts each range with the RAB score (Step 5).

In step 4, the estimated coefficients on gender, minority, blue chip and nomination source are similar and not affected significantly compared to Step 3. The interaction effect on the resulting graduation probability estimated by step 4 is shown in Table 10 and Figure 15. We notice the non-linear interaction in the figure, as the

increment in graduation rates increases at a decreasing rate for any level of RAB along given CM ranges. In addition, the impact of increments in the quantitative RAB scores for a given CM level gradually becomes greater over higher levels of the CM score. For example, at a 57,000 CM score, four additional RAB points is estimated to raise the likelihood of graduation by 2.9% points (.756-.727), whereas the same increment of RABs at the 66,000 CM level is estimated to raise the projected graduation rate by 4.9% points (.865-.816). Clearly the impact of RABs on graduation differs across CM ranges.

Table 10. Percent Graduation Estimated by Step 4

RAB points awarded	Candidate Multiple (1000's)			
	57	60	63	66
0 pts	0.727	0.751	0.774	0.795
1000 pts	0.742	0.771	0.797	0.821
2000 pts	0.756	0.789	0.818	0.844
3000 pts	0.770	0.806	0.837	0.865

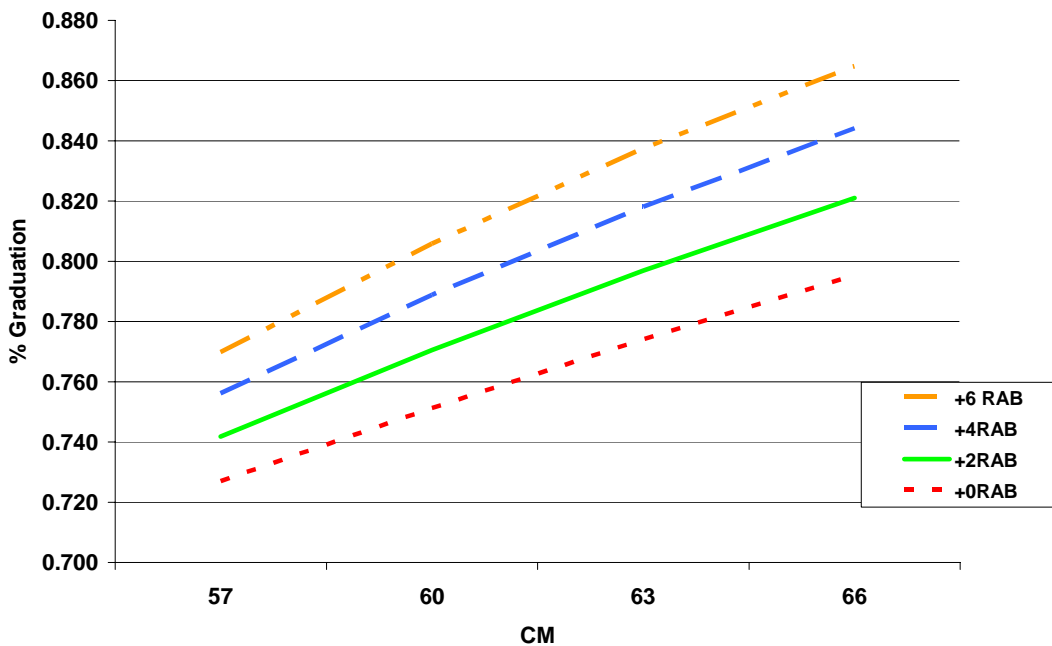


Figure 15. Percent Graduation Estimated by Step 4

Table 11 and Figure 16 represent the estimated probability results from Step 5 of our graduation model with given CM and RAB scores. Step five utilizes the RAB*CM interaction but breaks the CM into four ranges. This adds flexibility to the non-linear restrictions that are inherent in the logit model. The results suggest RAB points awarded to applicants with a CM<58k have no impact on desire, motivation or ability to graduate. The largest impact of RABs on graduation is found in the middle range of the CM, around the CM mean of 63k. For example, an additional 4,000 RAB points awarded to those having a 63,000 CM score is expected to increase the probability of graduating by 5.3% points (.822-.769), but only by 3.2% points for those with a CM score of 66,000. This finding affects 28.4% (2359 of the 8299 cases) of the accepted applicants who have a CM near the mean value of 63k. For the CM ranges either side of the mean CM value of 63k (which are: 58k to 61k and 65k+), the impact is small, but still positive.

Figure 16 also charts the resulting graduation probability given the same Candidate Multiple and number of RAB's. Notice the lines representing the increasing CM values are no longer restricted by linear properties. We now can visually detect the flexibility this model gives us as we interpret the estimated results. The most dramatic difference is the visible peak at the Candidate Multiple mean value (63k). This result suggests that an entrant who applies with a 63k Candidate Multiple whom the Admissions Board finds deserves RAB points for demonstrated character and performance traits will be more likely to graduate from the rigorous 4 year program.

Table 11. Percent Graduation Estimated by Step 5

RAB points awarded	Candidate Multiple (1000's)			
	57	60	63	66
(0 RAB) 0 pts	0.719	0.745	0.769	0.792
(2 RABs) 1000 pts	0.724	0.760	0.797	0.809
(4 RABs) 2000 pts	0.729	0.775	0.822	0.824
(6 RABs) 3000 pts	0.734	0.789	0.845	0.824

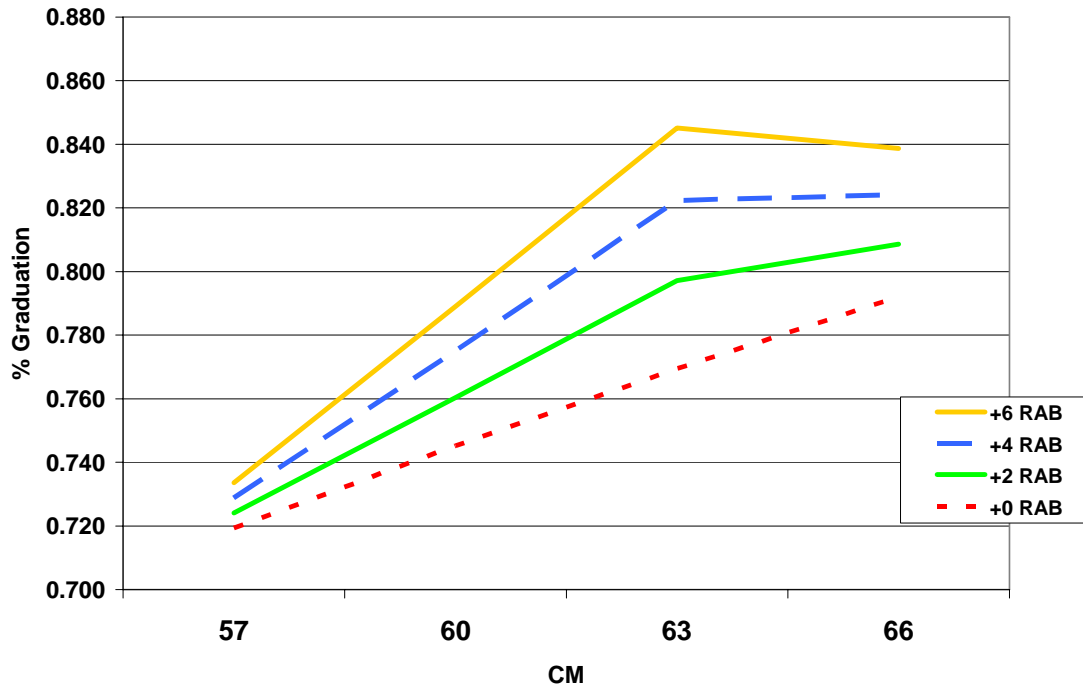


Figure 16. Percent Graduation Estimated by Step 5

C. SPECIFICATIONS FOR ORDER OF MERIT MODELS

Using the same five step process as in the graduation model, we estimate the impact of both the quantitative criteria (CM) and the qualitative criteria contained in the RAB on midshipmen order of merit (OOM). We converted the order of merit to percentile order of merit by stacking and ranking the graduate cases as we described in Chapter 3. Most of our discussion for this outcome measure is focused on step five, as we have determined that step five is the most comprehensive and flexible model identifying RAB interactions by Candidate Multiple ranges.

Table 12, which displays the “marginal effects” of the order of merit model, reveals that the coefficient on gender is insignificant. This finding supports the belief that gender plays no role in the overall summary measure of performance among graduates. Racial and ethnic minority groups and blue chip athletes, on the other hand,

are more likely to have a lower order of merit standings (the positive sign of the marginal effects in Table 12 indicate a higher percentile ranking) upon graduation.

Table 12. Marginal Effects of OOM Model

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	-0.914	-0.191	0.036	-0.025	-0.043
Race/Ethnicity					
African American (Aframer)	25.836**	16.645**	15.817**	16.267**	16.359**
Hispanic (Hispanic)	13.351**	7.430**	6.732**	6.922**	6.958**
Other Minority (Othrace)	9.370**	7.987**	7.635**	7.667**	7.669**
Athletic Status					
Blue Chip (Recblchp)	15.556**	6.019**	5.280**	5.501**	5.493**
Nomination Source					
President & VP (Nomprvp)	2.545	0.813	1.373	1.256	1.153
Qualified Alternate (Nomqalt)	2.081**	-0.954	-0.826	-0.863	-0.889
Enlisted & NROTC (Nomenrtc)	11.302**	0.088	-0.610	-0.262	-0.366
Superintendent USNA (Nomsupe)	-0.380	-1.142	-1.047	-1.170	-1.070
CM & RAB					
CM/1,000 (Cmthous)		5.568**	-2.985	5.979**	5.692**
CMThous Squared		-0.065**	-0.039**	-0.069**	-0.066**
RAB/500 (RAB500)			-0.692**	3.453**	
Interactions					
CM/1000 * RAB/500 (RABCM)				-0.066**	
Interactions Non-linear					
(RABLO58)					-0.103
(RAB5861)					-0.654**
(RAB6165)					-0.558**
(RAB65HI)					-1.055**
Adjusted R Squared	.129	.281	.283	.284	.284
F value	106.62	229.76	212.67	197.39	171.09
Sig	.000	.000	.000	.000	.000

* Significance Level > .05

** Significance Level > .01

The minority variables have relatively large positive coefficients, which fall somewhat when the quantitative and qualitative criteria scores are included in the order of merit performance model. In Step 5 we estimate that the OOM percentile ranking of

Hispanic and other minority groups to be roughly 7% points higher than for whites, while blacks are estimated to be over 16% points higher on average. With graduating classes averaging just under 1,000, these higher percentiles translate into minorities being ranked from 70 to 160 places lower than whites even after one accounts for their Candidate Multiple and RAB scores. These results project a continued challenge to the Admissions Office when they award nominations to ethnic minorities who are less likely to graduate and to perform below that of the majority white midshipmen. The findings for Blue Chip athletes are similar to those for minorities and the large positive coefficients fall from 15% points to 5% points when quantitative and qualitative criteria are introduced into the model. In Step 5 blue chip athletes are 5 points higher in percentile rank or 50 ranking slots lower than those that are not highly recruited by the athletic department.

As for the nomination sources in this model, Qualified Alternates and enlisted/ROTC nomination sources are estimated to only have a lower class (order of merit) standing (higher percentile number) in Step One. However, once the Candidate Multiple is accounted for in the model the nomination source coefficients become statistically insignificant. Suggesting, midshipmen who are awarded a Congressional Nomination and graduate perform, on average, no differently in overall Order of Merit rankings than graduates awarded alternative nomination sources.

Table 12 shows that the quantitative criteria embedded in the CM score are significantly related to summary performance ranking of accepted applicants who graduate. The non-linear impact of Candidate Multiple scores on OOM percentile ranking based on the coefficients in Table 12 are calculated and shown in Table 13.¹ As evident from these figures, higher Candidate Multiple scores are expected to improve a graduate's overall relative class standing by approximately 1.8 to 3.0 percentage points or by 18 to 30 positions for each 1,000 point higher CM score.

¹ The regression equation of the complete model of OOM can be written as: $OOM = X + 5.692 * CM - 0.066 * CM^2$. Thus the change in OOM for 1000 pt change in CM is simply the derivative of OOM with a respect to the CM, or; $\Delta OOM = 5.692 - 0.132 * CM$. This equation is used to derive the figures cited in the text above.

Table 13. Estimated Changes in OOM Performance Ranking

+1,000 Points From CM Score	Estimated Change in % OOM
57,000	-1.83
60,000	-2.23
63,000	-2.62
66,000	-3.02

The impact of the qualitative RAB scores on OOM of graduates is significant only for those with scores above 58,000 and the relative size of these impacts is slightly smaller compared to the CM scores. Table 14 shows the relative change in estimated OOM percentile for a given CM score while increasing the RAB awards by 1000 point increments. If we evaluate this impact for those with high Candidate Multiple scores of 65,000 and above (which has the largest estimated RAB impact on OOM ranking), we find that a 1,000 point higher RAB score (i.e., an increment of two RABs) would be estimated to lower OOM percentile by 2.1% points, or by 21 relative positions in a graduating class. Figure 17 charts the estimated impact of the qualitative value of the RAB for given Candidate Multiple ranges and provides a visual representation of the estimated increase in class (percentile) ranking.

Table 14. Estimated OOM Percentile by Step 5

	Estimated Change in OOM from CM (1,000s):			
Change in RAB from:	57	60	63	66
(0-2) 0 to 1000 pts	-0.206*	-1.308	-1.116	-2.11
(2-4) 1000 to 2000 pts	-0.206*	-1.308	-1.116	-2.41
(4-6) 2000 to 3000 pts	-0.206*	-1.308	-1.116	-2.11

* Not statistically significant to model

In summary, the information contained in the quantitative Candidate Multiple score appears to have a slightly greater impact on the overall performance of graduates than that contained in the qualitative RAB score. In addition, the assessment of the entire

admissions package by the Admissions Office used to sort applicants into one of the alternative nomination sources suggests that applicants with lower SAT scores and weaker high school ranking or grades but with higher qualitative RAB scores are not only more likely to graduate from the Academy, but are expected to perform equally well compared to those awarded a Congressional Nomination.

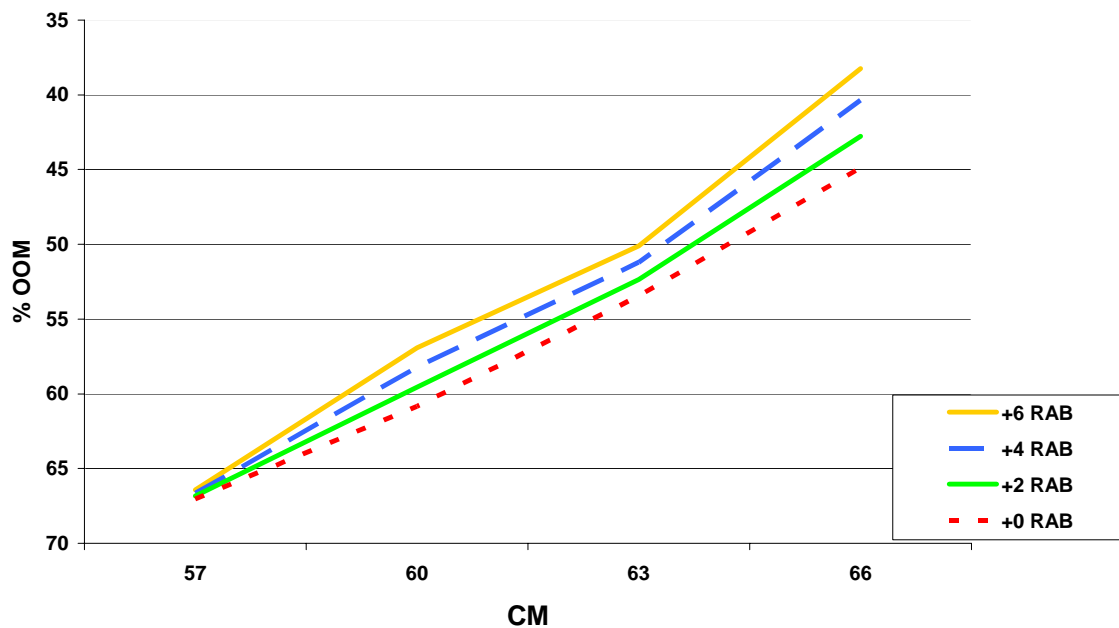


Figure 17. Effect of CM and RAB on OOM Estimated by Step 5

D. SPECIFICATIONS FOR CUMULATIVE ACADEMIC QPR MODELS

In this model we estimate the impact of both the quantitative and qualitative criteria on a student’s cumulative academic QPR. Once again, we report overall results but focus our discussion on Step 5 of the model.

To fully understand the impact of explanatory variables on cumulative academic QPR, it is helpful to emphasize the scale of the dependent variable. Academic QPR is calculated on a 0.0 to 4.0 scale with 2.0 being the minimum cutoff for graduation. Since we only have graduates in this model, the range of the AQPR data in the given cases is from 2.0 to 4.0. Figure 18 shows the cumulative distribution of AQPR around the median value of 2.85 with three 0.05 increments on either side illustrating how small

changes in the scale of AQPR will result in relatively large changes in the proportion of graduates. This is important to illustrate because the discussion of the impact of the Candidate Multiple and RAB on AQPR may appear at first to be relatively inconsequential because of the small estimated coefficients found in the model results.

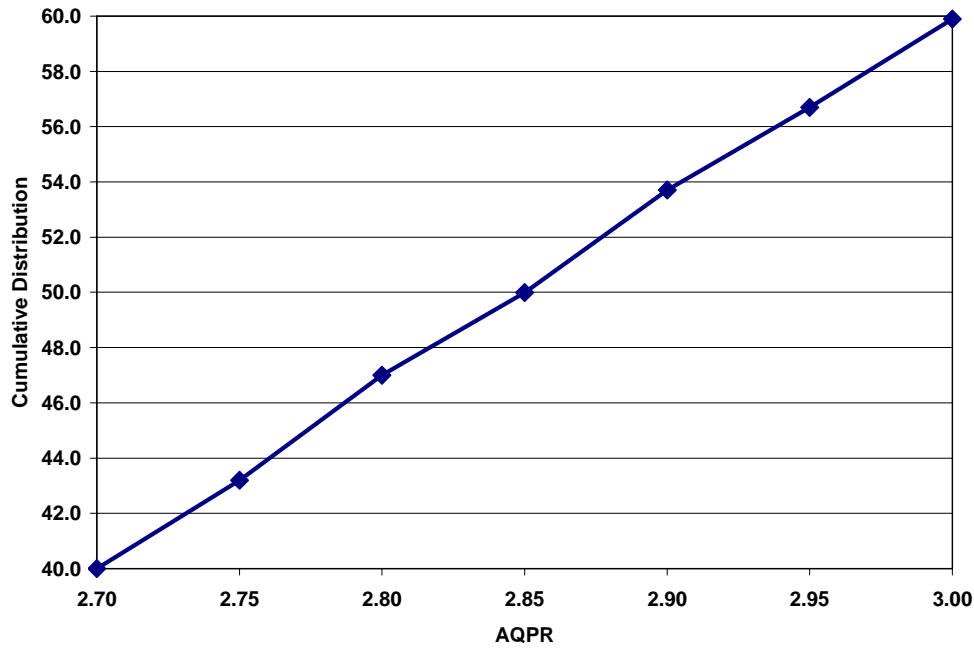


Figure 18. Cumulative AQPR Distributions of Graduates

Table 15, which shows the “marginal effects” of the cumulative academic QPR model, finds that gender is not statistically significant, supporting the notion that, all things being equal, gender plays no role in the academic performance of graduates. Racial and ethnic minority groups along with blue chip athletes have significant and negative coefficients in this model suggesting that these groups, holding both quantitative and qualitative scores constant, have a lower academic QPR upon graduation. The African American differential suggests that this group graduates on average, with a 0.29 point lower GPA than whites. In terms of the cumulative distribution, this means that, on average, African American graduates will be ranked roughly twenty percent lower than whites, or by 200 positions in a graduating class of 1000. Likewise, Hispanic graduates are found to graduate with an average 0.13 point lower GPA and Other Minority groups 0.11 point lower GPA than white graduates.

Table 15. Marginal Effects of AQPR Model

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	0.000	-0.012	-0.014	-0.014	-0.140
Race/Ethnicity					
African American (Aframer)	-0.484**	-0.300**	-0.294**	-0.292**	-0.294**
Hispanic (Hispanic)	-0.267**	-0.142**	-0.132**	-0.132**	-0.132**
Other Minority (Othrace)	-0.153**	-0.121**	-0.115**	-0.114**	-0.115**
Athletic Status					
Blue Chip (Recblchp)	-0.305**	-0.115**	-0.107**	-0.105**	-0.105**
Nomination Source					
President & VP (Nomprvp)	-0.068**	-0.033	-0.039	-0.040	-0.039
Qualified Alternate (Nomqalt)	-0.039**	0.020	0.018	0.018	0.019
Enlisted & NROTC (Nomenrtc)	-0.198**	0.022	0.027	0.030	0.032
Superintendent USNA (Nomsupe)	-0.112	0.029	0.027	0.030	0.030
Graduation Year					
YR96	-0.013	-0.024	-0.025	-0.024	-0.024
YR97	0.049	0.024	0.028	0.026	0.026
YR98	0.069	0.050	0.053**	0.049	0.049
YR99	0.051	-0.025	-0.025	-0.032	-0.031
YR00	0.053	-0.031	-0.036	-0.041	-0.041
YR01	0.130	0.038	0.029	0.023	0.023
CM & RAB					
CM/1,000 (Cmthous)		-0.106**	-0.040	-0.117**	-0.110**
CMThous Squared		0.001**	0.001**	0.001**	0.001**
RAB/500 (RAB500)			0.009**	-0.068**	
Interactions					
CM/1000 * RAB/500 (RABCM)				0.001	
Interactions Non-linear					
(RABLO58)					0.002
(RAB5861)					0.012**
(RAB6165)					0.011**
(RAB65HI)					0.019**
Adjusted R Squared	.139	.301	.303	.304	.304
F value	77.01	180.46	171.85	163.71	148.04
Sig	.000	.000	.000	.000	.000

* Significance Level > .05

** Significance Level > .01

Of the nomination sources in this model, three of the four show significance in the first step of the model but as soon as CM is accounted for in step two, nomination source becomes significant. Again, this finding is important in that these applicants who were not awarded a direct Congressional Nomination and having lower SAT scores and lower high school GPA nevertheless performed on par with those selected directly by Congressional Senators or Representatives.

The non-linear impact of Candidate Multiple scores on AQPR specified in the model (i.e. a quadratic term) from the coefficients in Table 15 and are calculated and shown in Table 16.² These figures show higher Candidate Multiple scores improving a graduate’s overall academic QPR to range from 0.004 to 0.022 points for each 1,000 point higher CM score increment.

Table 16. Estimated Change in AQPR Performance Based on CM

+1,000 Points from CM Score	Estimated Change in AQPR
57,000	0.004
60,000	0.010
63,000	0.016
66,000	0.022

Continuing with the results of step 5, we see the impact of the RAB on the selected Candidate Multiple ranges. The results show once again that RABs given to entrants categorized in the lowest Candidate Multiple range are not statistically significant. In the two middle ranges (**RAB5861** and **RAB6165**), however, we find a significant relationship between RAB scores and academic performance. For example, 1,000 point RAB (i.e. 2 RABs) awarded to an applicant with a 63,000 CM is estimated to graduate with an AQPR 0.023 points higher than an applicant that did not receive any RAB points. Table 17 shows applicants with RABs in the highest range of Candidate

² The regression equation of the complete model of AQPR can be written as: $AQPR = X - 0.11 * CM + 0.001 * CM^2$. Thus the change in AQPR for 1000 pt change in CM is simply the derivative of AQPR with a respect to the CM, or; $\Delta AQPR = -0.11 + 0.002 * CM$. This equation is used to derive the figures cited in the text above.

Multiples (**RAB65HI**) have the largest impact on academic performance, estimated with a 0.038 GPA points higher per 1,000 point RAB awarded. Figure 19 visually depicts the relationship of the RAB given Candidate Multiple for the estimated academic QPR values.

Table 17. Estimated Changes in AQPR from Step 5

Change in RAB from:	Estimated Change in AQPR from CM (1,000s):			
	57	60	63	66
(0-2) 0 to 1000 pts	.003	.024	.023	.036
(2-4) 1000 to 2000 pts	.004	.024	.023	.038
(4-6) 2000 to 3000 pts	.003	.024	.022	.038

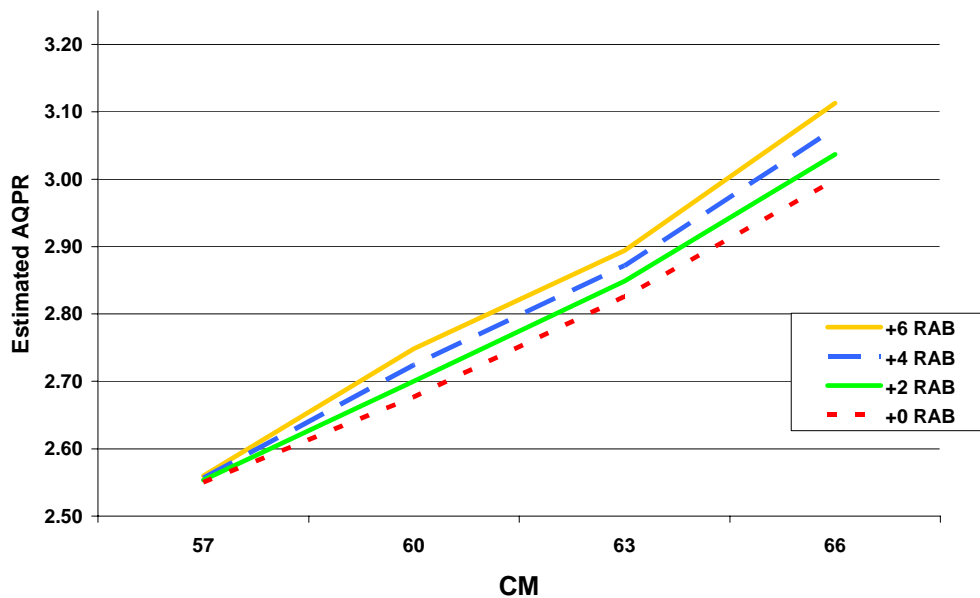


Figure 19. Estimated Effect of CM and RAB on AQPR by Step 5

In summary, both quantitative and qualitative admissions scores are related to academic performance of graduates. While the impact of higher Candidate Multiple scores on academic GPA increases non-linearly, it is interesting to note that the estimated impacts of higher RABs on GPA is relatively larger. For example, 1,000 points on the Candidate Multiple score in the 60,000 to 62,000 range is estimated to result in an

increase of their GPA by only +.010, whereas 1,000 more RAB points in this CM range is expected to raise GPA by 0.024. Similar differences between estimated impacts of CM and RAB on GPA are found at higher ranges of the Candidate Multiple scores.

Once CM and RAB scores are accounted for those receiving direct Congressional Nominations are no more likely to have higher GPA's than those awarded an alternative nomination. The academic performance differential of ethnic minorities and blue chip athletes observed in admissions applications appear to be perpetuated in college. Both groups, given their different Candidate Multiple and RAB scores, achieve GPA's significantly below that of white applicants not highly recruited to play Division I level sports at Annapolis.

E. SPECIFICATIONS FOR CUMULATIVE MILITARY QPR MODELS

In military performance model we estimate the impact of both quantitative and qualitative criteria on the cumulative military QPR. As with the academic QPR, we must realize the scale in which we are working with in this model. Military QPR is also calculated on a 0.0 to 4.0 scale, and once again only including graduates in the model. Figure 20 shows the cumulative distribution of MQPR from the median value of 3.17 with three 0.05 increments on either side illustrating how small changes in the scale of MQPR results in relatively large changes in the proportion of graduates. It is important to recognize this relationship when interpreting the estimated impacts of Candidate Multiple and RAB on MQPR, because the estimated coefficients revealed in the model are relatively small.

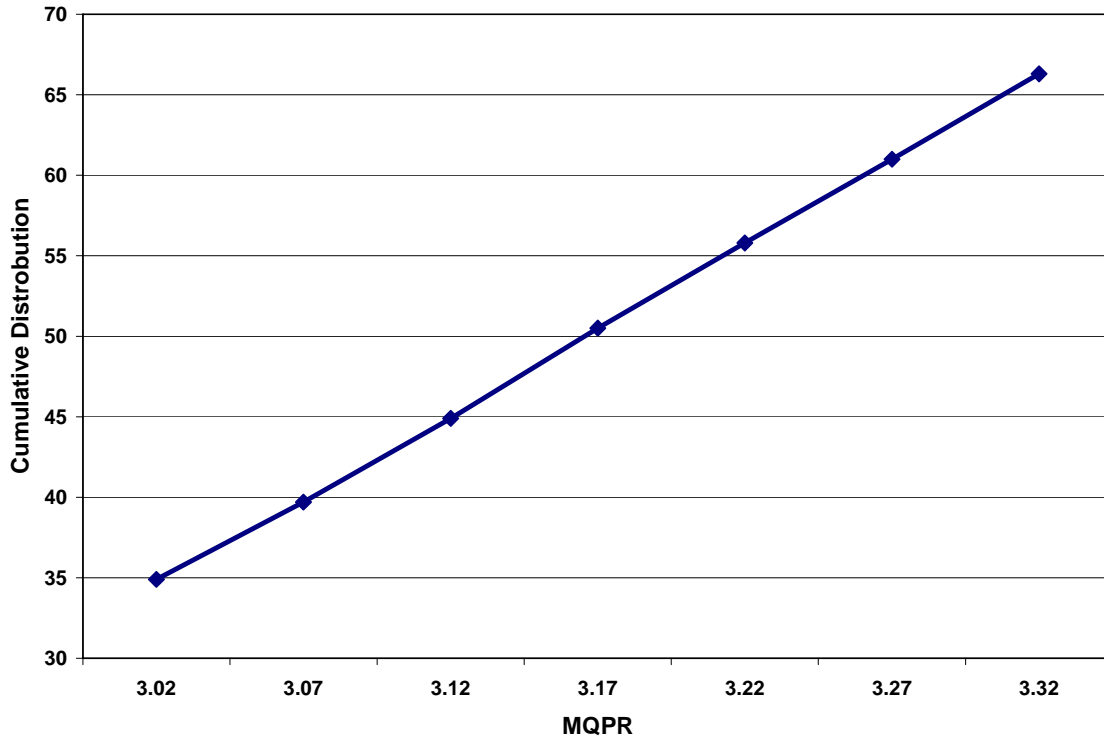


Figure 20. Cumulative MQPR Distributions of Graduates

Table 18 shows the “marginal effects” for the model of cumulative military QPR. The results reveal gender as not being statistically significant. Racial and ethnic minority groups have significant and negative coefficients in this model suggesting that these groups, holding both quantitative and qualitative scores constant, are estimated to have a lower military QPR upon graduation. African American graduates are estimated to have a 0.087 lower military GPA than white graduates. Referring back to the distributive figure above, this means that an African American graduate, on average, will be ranked approximately eight percentage points lower than whites or by 80 positions in a graduating class of 1000. Similarly, Hispanic graduates are found to graduate with an average 0.06 point lower and Other Minority groups 0.03 point lower than white graduates. Blue chip athletes are not found to have a statistically significant effect in this model.

A fascinating result found in the nomination categories reveals the Qualified Alternate is the only source having statistical significance in the model. This result is

curious as it estimates the Qualified Alternate has a 0.023 point higher military GPA upon graduation than that of a graduate who was awarded a direct Congressional Nomination. In addition, the Qualified Alternate is only slightly affected by the introduction of quantitative or qualitative criteria, as the coefficient is reduced by only 0.002 points by step five. This suggests that the Qualified Alternate possesses traits and characteristics that are desirable to increased military performance, that are unrelated to quantitative criteria (CM).

Included in the military performance model, is the cumulative academic QPR (**Cumaqpr**) as an independent variable, and the results show that accounting for the academic influence on military performance is highly significant throughout all steps of this model. The relatively large size of the coefficient (.491) as compared to the others in the model further suggests that the military QPR performance is highly correlated with academic QPR performance. More specifically stated, for every full academic GPA point, military GPA is estimated to increase by almost a half a point.

Table 18. Marginal Effects of MQPR Model

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	-0.007	-0.006	-0.007	-0.007	-0.007
Race/Ethnicity					
African American (Aframer)	-0.087**	-0.090**	-0.087**	-0.087**	-0.087**
Hispanic (Hispanic)	-0.596**	-0.062**	-0.057**	-0.057**	-0.060**
Other Minority (Othrace)	-0.374**	-0.037**	-0.035**	-0.035**	-0.035**
Athletic Status					
Blue Chip (Reclbchp)	-0.001	-0.006	-0.002	-0.001	-0.001
Nomination Source					
President & VP (Nomprvp)	0.018	0.017	0.014	0.013	0.014
Qualified Alternate (Nomqalt)	0.025**	0.024**	0.023**	0.023**	0.023**
Enlisted & NROTC (Nomenrtc)	-0.008	-0.014	-0.012	-0.011	-0.012
Superintendent USNA (Nomsupe)	0.006	0.005	0.004	0.005	0.005
Graduation Year					
YR96	-0.091**	-0.090**	-0.091**	-0.090**	-0.091**
YR97	-0.122**	-0.122**	-0.120**	-0.120**	-0.120**
YR98	-0.136**	-0.135**	-0.134**	-0.135**	-0.135**
YR99	-0.194**	-0.192**	-0.192**	-0.194**	-0.193**
YR00	-0.214**	-0.212**	-0.215**	-0.216**	-0.215**
YR01	-0.234**	-0.232**	-0.237**	-0.238**	-0.238**
CUMAQPR	0.486**	0.492**	0.491**	0.490**	0.491**
CM & RAB					
CM/1,000 (Cmthous)		0.002	0.036*	0.018	0.025
CMThous Squared		-.00003	-.0003*	-.0001	-.0002
RAB/500 (RAB500)			0.005**	-0.013	
Interactions					
CM/1000 * RAB/500 (RABCM)				0.0003	
Interactions Non-linear					
(RABLO58)					0.003**
(RAB5861)					0.004*
(RAB6165)					0.005**
(RAB65HI)					0.007**
Adjusted R Squared	.577	.577	.578	.578	.578
F value	605.21	538.46	512.19	486.80	442.32
Sig	.000	.000	.000	.000	.000

* Significance Level > .05

** Significance Level > .01

The non-linear impact of Candidate Multiple scores on MQPR specified in the model (i.e., quadratic term) from the coefficients in Table 18 are calculated and shown in Table 19.³ These figures are surprising as they do not support the expected overall improvement in military QPR as Candidate Multiple scores increase. Instead, the positive relationship between military performance and the CM peaks around 60,000 after which higher Candidate Multiple Scores are estimated to reduce military performance scores. This finding is powerful as we look at the estimated impact of RAB on military QPR.

Table 19. Estimated Change in MQPR Performance Based on CM

+1,000 Points from CM Score	Estimated Change in MQPR
57,000	0.0022*
60,000	0.001*
63,000	-0.0002*
66,000	-0.0014*

*CM is not statistically significant in this model

The results of step 5 emphasize the importance of the non-linear interaction of the Candidate Multiple with the RAB scores on military performance. Where the CM is estimated to negatively affect military performance as it increases, the RAB continues to impact the military QPR positively throughout all ranges of CM and remains statistically significant. For example, 1,000 point RAB (i.e., 2 RABs) awarded to an applicant with a 63,000 CM is estimated to raise MQPR by 0.011 points compared to an applicant who did not receive any RAB points. Applicants in the highest CM range (**RAB65HI**) who receive between 1,000 and 2,000 RAB points have the largest estimated impact on military performance, 0.024 GPA points higher per 1,000 point RAB awarded. These results in particular suggest that the Admissions Board is capturing and identifying traits in the applicant which relate positively to military performance and are aptly awarded RAB points. The negative relationship the Candidate Multiple has to military

³ As noted in the previous footnote, the regression equation of the complete model of MQPR can be written as: $MQPR = X + 0.025 * CM - 0.0002 * CM^2$. Thus the change in MQPR for 1000 pt change in CM is simply the derivative of MQPR with a respect to the CM, or; $\Delta MQPR = 0.025 - 0.0004 * CM$. This equation is used to derive the figures in the cited text above.

performance, on the other hand, suggests that the Candidate Multiple may not be a good predictor of military performance on a stand alone basis but when interacted with the RAB across the CM ranges, the impact increases with the increase in CM. This relationship is broken down in Table 20 by illustrating estimated changes in MQPR with 1,000 point increases in both CM and RAB. As evidenced by the relationships of the two criteria to the military performance measure, the qualitative criteria in the RAB is capturing strengths of the applicant that are most evident to military performance.

Figure 21 shows estimates from the model using the “marginal effects” for the RAB and CM values. It is an interesting visual representation of the impact of the RAB across the CM range. The RAB clearly has a positive impact across the range of Candidate Multiple scores as illustrated by this representation but also take notice of the impact the RAB has to the higher range of Candidate Multiple scores. Following the peak estimate of MQPR at 63,000 Candidate Multiple points, notice how the positive impact of the RAB is greater with each increasing RAB awarded.

Table 20. Estimated Changes in MQPR from Step 5

	Estimated Change in MQPR from CM (1,000s):			
Change in RAB from:	57	60	63	66
(0-2) 0 to 1000 pts	.007	.007	.010	.014
(2-4) 1000 to 2000 pts	.007	.008	.011	.024
(4-6) 2000 to 3000 pts	.006	.007	.010	.014

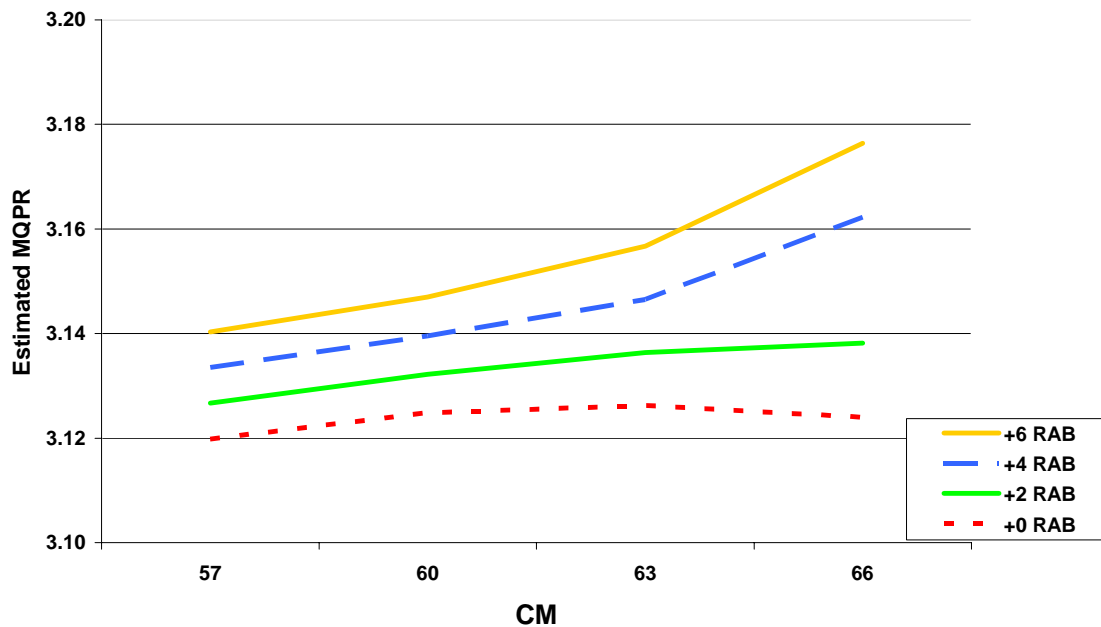


Figure 21. Estimated Effect of CM and RAB on MQPR by Step 5

In summary, the impact of qualitative admissions scores on military performance remain positive and significant, whereas the quantitative admissions scores became slightly negative as CM increases. For example, 1,000 points on the Candidate Multiple score in the 65,000 and higher range is estimated to have no significant impact on military performance (-.001 MQPR), whereas 1,000 more RAB points is expected to raise military QPR by 0.014. This relationship between the qualitative criteria and the qualitative criteria leads us to believe that the military performance measure is closely related to the awarding of a RAB from the Admissions Board. The Qualified Alternate is estimated to graduate with a military QPR 0.023 point higher than those who were awarded a direct nomination from a Congressional source, whereas all the other nomination sources are no more likely to have higher military QPR's. The academic performance differential of ethnic minorities observed in admissions applications remains evident in the military performance model as the minority groups are estimated to graduate, on average, with lower military GPA's compared to the white graduates. The blue chip athletes regain some performance ground in this model as they are likely to

graduate with similar military GPA's as non recruited applicants possibly suggesting leadership and physical courage demonstrated on the athletic field pays off for these graduates in military performance measure.

F. SPECIFICATIONS FOR STRIPER SELECTION MODELS

For the striper selection model we revert back to the logit model because the outcome performance measure is dichotomous. In this model, we estimate the impact of both quantitative and qualitative criteria on striper selections. We chose to include this model because it is an interesting change in performance perspectives. To be selected for a striper position at the Naval Academy, midshipmen must be selected by a panel of active duty military officers who evaluate their daily observed performance. In short, this model provides a performance measure that is highly subjective but takes into account quantitative performance of the midshipmen to select midshipmen for leadership billets in the Brigade of Midshipmen.

The results of Table 21 reveal that gender is not statistically significant in this model along with African American and Hispanic minorities once the Candidate Multiple is accounted for. "Other Minority" is the only group that is statistically significant and shows that this group is 4 percent less likely to be selected for a striper position. The results find that blue chip athletes are 11 percent less likely to be selected for leadership billets. This result is not surprising as most blue chip athletes spend the majority of their time outside of company area practicing or competing in their Division I level varsity sport, thus reducing face time and observed performance while in leadership roles within their company areas. The year groups in this model are all statistically significant and this result is expected because the comparison year group of 1995 had the largest number of striper billets available, thus rendering the largest selection percentage of all the year groups. The inclusion of these year group variables helps to account for the change in percentage of striper billets in each class based on the number of available positions and the number of midshipmen in the class. The reader is referred to Chapter 3 for further explanation of striper billet distribution among the year groups.

Table 21. Marginal Effects of Striper Model

	Step 1	Step 2	Step 3	Step 4	Step 5
Gender	0.025	0.023	0.022	0.022	0.022
Race/Ethnicity					
African American (Aframer)	-0.044	-0.011	-0.011	-0.007	-0.009
Hispanic (Hispanic)	-0.069**	-0.049*	-0.042	-0.041	-0.041
Other Minority (Othrace)	-0.051*	-0.045*	-0.042*	-0.042*	-0.041*
Athletic Status					
Blue Chip (Reclbchp)	-0.152**	-0.117**	-0.113**	-0.111**	-0.111**
Nomination Source					
President & VP (Nomprvp)	-0.010	-0.003	-0.006	-0.008	-0.007
Qualified Alternate (Nomqalt)	0.000	0.010	0.010	0.010	0.010
Enlisted & NROTC (Nomenrtc)	-0.007	0.031*	0.032*	0.036*	0.035*
Superintendent USNA (Nomsupe)	-0.016	-0.012	-0.017	-0.014	-0.016
Graduation Year					
YR96	-0.039*	-0.040*	-0.039*	-0.039*	-0.039*
YR97	0.074**	-0.075**	-0.073**	-0.075**	-0.074**
YR98	0.055**	-0.056**	-0.054**	-0.056**	-0.054**
YR99	-0.046**	-0.057**	-0.059**	-0.062**	-0.060**
YR00	0.056**	-0.067**	-0.071**	-0.074**	-0.072**
YR01	0.054**	-0.065**	-0.072**	-0.076**	-0.074**
CM & RAB					
CM/1,000 (Cmthous)		0.008**	0.011**	0.010**	0.011**
RAB/500 (RAB500)			0.007**	-0.020	
Interactions					
CM/1000 * RAB/500 (RABCM)				0.0004	
Interactions Non-linear					
(RABLO58)					0.005**
(RAB5861)					0.008**
(RAB6165)					0.008*
(RAB65HI)					0.008*
Model Chi-Square	134.38	183.4	199.38	202.3	202.5
-2 Log Likelihood	6025.94	5976.88	5960.93	5958.01	5959.82
Pseudo-R squared	.021	.029	.031	.032	.031

* Significance Level > .05

** Significance Level > .01

The Candidate Multiple is highly significant and has a significant impact on the striper selection in this model. For example, for every 1,000 point CM increase a

midshipman is 1 percent more likely to be selected for a striper position. The interesting results come when looking at the RAB interaction variables and how the estimated impact is nearly the same for all CM ranges above 58,000. This result suggests that it is very difficult to predict military leadership from application packages when they are evaluated by the Admissions Board.

Table 22. Accuracy of Model Predictions of Striper Model

# of Cases Correctly Classified	Step 1	Step 2	Step 3	Step 4	Step 5
Striper	72.5	67.3	65.0	64.7	65.1
Non-Striper	40.9	49.6	51.9	52.4	52.0
Total	47.0	53.0	54.4	54.7	54.5

Table 23 shows the estimates from the model using the “marginal effects” given RAB and CM values. For example, a 1,000 point RAB award for an applicant who has a 63,000 CM is expected to increase the probability of being selected for a leadership striper billet by 1.4 percent compared to an applicant who did not receive any RAB points. Figure 22 charts the estimated impact of the qualitative value of the RAB given Candidate Multiple ranges.

Table 23. Estimated Change in Striper Selection Percentage from Step 5

Change in RAB from:	Estimated Change in Probability of Striper Selection from CM (1,000s):			
	57	60	63	66
(0-2) 0 to 1000 pts	0.008	0.013	0.014	0.018
(2-4) 1000 to 2000 pts	0.007	0.015	0.016	0.020
(4-6) 2000 to 3000 pts	0.009	0.016	0.016	0.020

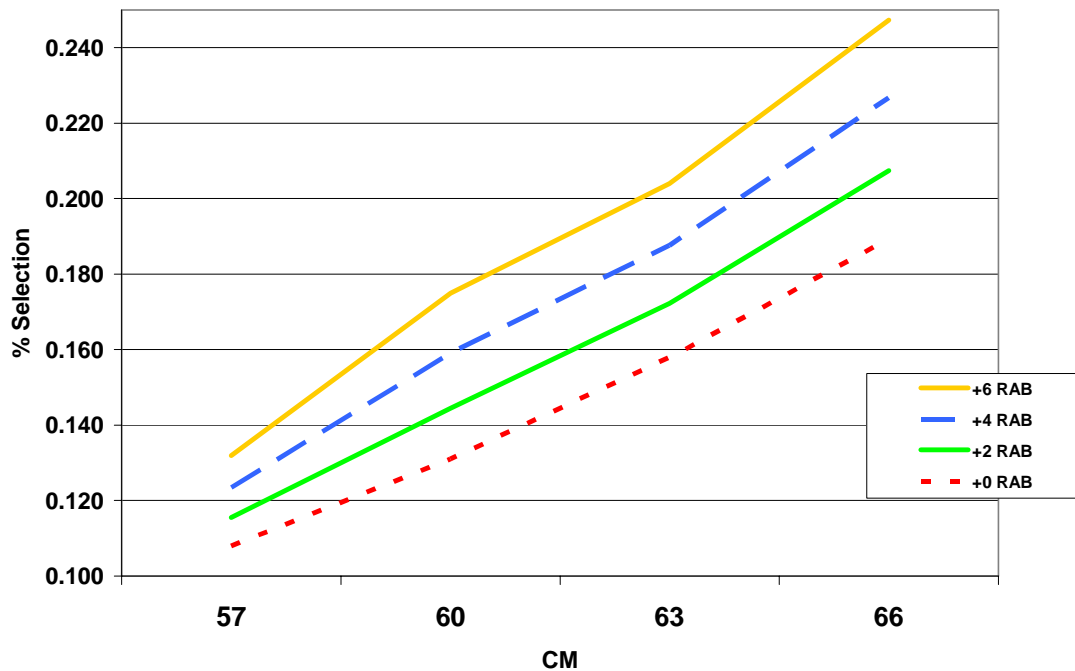


Figure 22. Effect of CM and RAB on Striper Selection by Step 5

In summary, the military leadership measure that is focal point of the striper performance measure is difficult to predict at the time of the Admissions Board as they review the application packages. However, both quantitative and qualitative admissions scores are positively related to the probability of selection to a striper billet. While the impact of higher Candidate Multiple scores on probability of selection to a striper position increases almost linearly, it is interesting to note that the estimated impact of higher RAB scores on probability of striper selection is significantly greater. For example, 1,000 points on the Candidate Multiple score at the mean value of 63,000 increases the likelihood of selection by 1 percentage point, where a 1,000 point increase in RAB score increases the likelihood by 1.4 percentage points. This is a significant increase given that only 18 to 20 percent of the class is selected for these striper positions.

G. CHAPTER SUMMARY

The chapter summary provides us with an opportunity to take an overall look at the results from the five performance models and summarize the overall findings and impacts each of the variables have to the models. Although gender was statistically significant in the graduation model it was statistically insignificant in the other four performance outcome models suggesting that the biggest challenge for the Admissions Board is identifying and admitting females with the drive and motivation to graduate from the rigorous four year program at USNA. Females who do graduate, all else equal, perform on par with the males in the other four performance outcome measures, which suggests that the Admissions Board is identifying and admitting females with the ability to succeed and perform well.

In general, minorities are faced with an education gap, as we discussed in the literature review, where even at USNA they are shown performing, on average, lower in all but the Striper Selection model. The performance models reveal minorities, on average, are less likely to graduate, more likely to be lower in Order of Merit, and more likely to have a lower academic and military grade point average. However, in the Striper Selection model, African American and Hispanic graduates are just as likely to be selected for military leadership positions their First Class year at the Naval Academy. The results further emphasizes the challenge the Admissions Board faces in identifying and admitting qualified minority candidates who have the drive and motivation to succeed in the rigorous four year program at the Academy. Minorities, however, may not perform at the same level as the comparison white group academically but the Striper Selection model shows that African American and Hispanic graduates are attaining leadership positions. This strengthens the argument for continued diversity within the Brigade of Midshipmen to prepare young officers of all races and ethnicities for combat leadership.

Blue Chip Athletes bring a different dimension of diversity to the Brigade of Midshipmen. These athletes embody the fighting spirit of the Brigade as they compete in the Division I level varsity sports programs for USNA. Appropriately, the military performance model supports this generalization because in the military performance model the Blue Chip Athlete is statistically insignificant suggesting that they perform

equally with the non-recruited graduates. This statistical insignificance is a revealing finding because the blue chip athletes perform, on average, lower in all the other performance models. The Blue Chip Athlete is less likely to graduate, more likely to rank lower in Order of Merit, more likely to have a lower academic grade point average and less likely to be selected for leadership positions within the Brigade of Midshipmen but will most likely perform equally in military grade point average as their non-recruited peers.

The nomination sources provided curious results as they varied in significance and relationship to the performance outcome measures. Qualified Alternate and Enlisted/ROTC nominations are statistically significant and positive in the graduation model suggesting that those applicants selected for these nominations are more likely to graduate than those selected by the primary Congressional nomination source. The Order of Merit and Academic models found all the nomination sources to be statistically insignificant. The Military QPR model, on the other hand, revealed that Qualified Alternates are more likely to earn a slightly higher military QPR than those selected for Congressional Nominations and the Striper Selection model revealed Enlisted/ROTC nominations more likely to be selected for leadership positions within the Brigade.

Table 24. Estimated Impacts of 1,000pt CM vs. 1,000pt RAB at Mean CM

Outcome Measure	Model Results
Graduation	RAB twice the impact
Order of Merit	CM twice the impact
Academic QPR	RAB twice the impact
Military QPR	RAB positive & statistically significant CM not statistically significant
Striper Selection	RAB 50% greater impact

Table 24 summarizes the findings of the estimated impact of the Candidate Multiple and the RAB. The findings vary in magnitude and relationship to the performance outcome measures across the range of Candidate Multiple but overall the RAB is shown providing the extra value added to the admissions process that is identifying applicants that are more likely to succeed at the Naval Academy. In

reviewing the performance models, we compare the impacts that a 1,000 point increase of CM has versus a 1,000 point increase in RAB has on each of the outcome measures at the mean CM value of 63,000 points.

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V. SUMMARY AND CONCLUSIONS

A. SUMMARY

The Naval Academy is challenged with selecting well rounded candidates, with diverse backgrounds and who bring diverse strengths to the student body and at the same time, have high probabilities of success. A quantitative system is maintained by the Naval Academy for evaluating applicants, called the Candidate Multiple that is anchored on proven high school performance measures, such as SAT and high school GPA. The Admissions Board then adds an additional input, called Recommendation of the Admissions Board (RAB), which is subjective in nature and is the primary qualitative input to the Naval Academy admissions process. The qualitative RAB input is added to the quantitative Candidate Multiple to calculate the Whole Person Multiple. This Whole Person Multiple is the score used for the final decision of candidate selection and acceptance.

1. Candidate Multiple

This study focuses primarily on validating the RAB as a predictor of student success; however, it is imperative to understand the impact of the Candidate Multiple on the performance outcomes in order to fully appreciate the impact of the RAB. Because of the non-linear properties of the Candidate Multiple, four examples are used with various CM values to show the impact of the Candidate Multiple in the performance models. Table 25 summarizes the impact of a 1,000 point increase in the Candidate Multiple for each of the performance measures evaluated at various CM values. The summary shows the non-linear properties of the performance models as well, where 3 out of the 4 models have increasing CM impacts that are statistically significant. The impacts of the 1,000 point increase in CM are greater as the Candidate Multiple increases, suggesting the greater the Candidate Multiple the better the performance outcome is likely to be. The only statistically significant model where the 1,000 point increase in CM actually decreases in impact is the Graduation model, which suggests a higher Candidate Multiple is more likely to graduate but the 1,000 point increase at the higher CM value has a smaller positive effect on the outcome.

Table 25. Summary of Impact of a 1,000 Point CM Change

+1,000 CM Points from CM Score	Estimated Change in GRAD	Estimated Change in % OOM	Estimated Change in AQPR	Estimated Change in MQPR	Estimated Change in Striper
57,000	0.009	-1.83	0.004	0.0022*	0.008
60,000	0.008	-2.23	0.010	0.001*	0.009
63,000	0.008	-2.62	0.016	-0.0002*	0.009
66,000	0.007	-3.02	0.022	-0.0014*	0.011

*CM not statistically significant in this model

More specifically, the summary table shows a candidate with a Candidate Multiple of 63,000 (mean value of CM for year groups 1995-2001) is estimated to have an 0.8% better probability of graduating, would have been 26 places higher in class rank, 0.016 points better academically (on a 4.0 scale), and 0.9% more likely to be selected to a striper position if they had earned 1,000 more points in their Candidate Multiple. The Candidate Multiple has a positive and significant impact on the probability of graduation but the impact of a 1,000 point increase becomes smaller as the CM increases. The higher the CM, the more likely the candidate is to graduate. Similarly, the higher the Candidate Multiple the lower the estimated Order of Merit percentile. For instance, increasing the mean CM value by 1,000 points to 64,000 points, the candidate is estimated to be 2.62 percentile points lower which equates to a higher class standing and out of a class of 1000 that would be 26 places higher in the standing. The same increase to the mean CM would result in an estimated 0.016 points greater cumulative Academic QPR (on a 4.0 scale) but interestingly, that same increase in CM would not impact the Military QPR. The statistical insignificance of Candidate Multiple in the MQPR model suggests that the CM, which is based on a statistical scoring model, is not a good predictor of Military performance at the Naval Academy. Finally, a 1,000 point increase from the mean CM, to 64,000 points, would increase a candidate's likelihood of being selected for a striper position within the Brigade by 0.9%.

2. RAB

Although, the Candidate Multiple is the backbone of the first few steps of the Admissions candidate selection process at the Naval Academy, it is the addition of the qualitative measures that takes the selection process to the next level, which involves creation of the whole person multiple. This study has shown that the Candidate Multiple has a statistically positive and larger impact on all of the success measures but MQPR. However, our goal in this study was to uncover the intrinsic value of the Recommendations of the Admissions Board. The value added of the RAB to the overall admissions process at the Naval Academy is measured by creating models that include RAB scores in addition to the Candidate Multiple scores for alternative performance outcome measures. These models do not use the RAB in lieu of CM scores but adds the RAB to the model to show the increased impact the RAB has on the student performance models given the CM score. As shown by our findings in Chapter 4, the RAB provides an important and valuable aspect to the Admissions Board as it is highly predictive of success as measured by the performance outcome measures used in this study. Table 26 summarizes the impact a 1,000 point RAB has on each outcome performance measure at successively higher Cm scores. Like CM, the impacts of RAB on student performance are non-linear in nature. That is, the estimated impact of RAB becomes larger at higher CM scores for all five performance models.

Table 26. Summary of Impact of a 1,000 Point RAB

+1,000 RAB Points from CM Score	Estimated Change in GRAD	Estimated Change in % OOM	Estimated Change in AQPR	Estimated Change in MQPR	Estimated Change in Striper
57,000	0.005	-0.206*	0.003	0.007	0.008
60,000	0.015	-1.308	0.024	0.007	0.013
63,000	0.016	-1.116	0.023	0.010	0.014
66,000	0.017	-2.110	0.036	0.014	0.018

* Not statistically significant in model.

It is also interesting to note that the impacts of additional RAB scores on student performance generally exceed estimates of CM scores. For example, a candidate with the mean Candidate Multiple of 63,000 points that received 2 RABs (or 1000 pts) is 1.6% more likely to graduate than a candidate with a Candidate Multiple of 63,000 points with no RABs awarded. This impact is twice that of a 1,000 point increase in Candidate Multiple, which increases the graduation probability by only 08%. Unlike the graduation model, the Order of Merit model does not tell a similar story for the RAB. A candidate with a CM of 63,000 points who receives 2 RABs (or 1,000 points) is predicted to read 1.16 percentage points higher in class rank percentile (equating to roughly 11 places in class standing) than a candidate with the same CM who did not receive a RAB. In this case the quantitative CM has twice the impact than the qualitative RAB (2.23 percentile to 1.116 percentile increase, respectively). Continuing with Academic QPR, a candidate with CM of 63,000 points who receives 2 RABs (or 1,000 points) is estimated to have a Academic QPR 0.023 points higher (on a 4.0 scale) than a candidate with the same CM who did not receive any RAB points. The 1,000 points from the RAB input results in an estimated improvement of 0.023 points to the AQPR, whereas a 1,000 point CM increase (with no RAB) would only increase AQPR by an estimated 0.016.

The Candidate Multiple was not found to be significant for the Military QPR model but the RAB was found to be positive and statistically significant. In particular, a candidate with a CM of 63,000 points and 2 RABs (or 1,000 points) is expected to have a MQPR 0.010 points higher (on a 4.0 scale) than a candidate with the same CM who did not receive a RAB. This finding suggests that the qualitative input to the admissions process is a much better predictor of military performance than the quantitative scoring model of the Candidate Multiple alone. Finally, the Striper model estimates that a candidate with a 63,000 point CM and 2 RABs (or 1,000 points) is 1.4% more likely to be selected than a candidate with the same CM and no RABs awarded. Once again comparing the impact of the 1,000 point increase from the quantitative and the qualitative side of things, the RAB has a 50% greater impact on striper selection. Looking at the relationships and the magnitude of significance of the RAB and the Candidate Multiple to each performance measure across the CM value range provides insight to the qualities and value added the RAB brings to the Naval Academy admissions process.

Overall, the RAB is providing a value added to the admissions process as evidenced in the areas highlighted by the outcome performance measures in this study. The award of a RAB to a candidate improved the outcome in every model, except OOM, emphasizing the value of having a qualitative input to the admissions process and the positive impact the RAB has to the overall process in selecting a well rounded, diversified and capable student body.

B. CONCLUSIONS & RECOMMENDATIONS

Based on our results, we conclude that the Recommendations of the Admissions Board (RAB) add value to the overall admissions process at the Naval Academy. The RAB is a strong predictor of student performance at USNA. The value added, however, does come with some cost to the Admissions Board in the form of the time, effort and resources devoted by the board members. The extensive review each and every record goes through requires a committed effort from all the Admissions Board members as they search for the next class of incoming candidates. The costs, however, are minimized in that the time spent on interviews and the time spent by civilians and officers on the Admissions Board are defined within the broad definitions of job responsibilities and do not incur additional faculty resource costs to the institution.

An immediate recommendation to the Admissions Office is to recognize the predictive quality of the RAB and to continue to employ the qualitative review of the admissions packages. A secondary recommendation is to invest time and resources to track and develop explicit criteria on which RABs are awarded to candidates. The process of documenting and developing the explicit criteria could prove to be valuable for further identifying candidate qualities that predict student performance. More specifically, it could also be used to identify attributes within various demographic groups that are predictive of student performance. With the above recommendations in mind, a follow-on recommendation would be to construct a database to record the specific quality or subjective measures for which a RAB is awarded.

Further study in this area could focus on other outcome performance measures using the same or similar methods to evaluate the impact of the RAB. Or, the same measures and method could be used to evaluate a larger data set covering more year groups from the Naval Academy.

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