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MONTEREY, CALIFORNIA

THESIS

**SELECTION OF NAVAL ACADEMY GRADUATES FOR
NUCLEAR TRAINING**

by

John M. Killila

June 2006

Thesis Advisor:

Armando X. Estrada

Associate Advisor:

Matthew A. Carr

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SELECTION OF NAVAL ACADEMY GRADUATES FOR NUCLEAR TRAINING

John M. Killila
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B.S., United States Naval Academy, 1999

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June 2006**

Author: John Murphy Killila

Approved by: Armando X. Estrada, Ph.D.
Thesis Advisor

CDR Matthew A. Carr, Ph.D.
Associate Advisor

Dr. Robert N. Beck
Dean, Graduate School of Business and Public
Policy

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ABSTRACT

This study examines some of the criteria used in selecting Naval Academy graduates for entry into the Navy's Nuclear Power Program. Data from 1,096 Naval Academy graduates who attended Nuclear Power School (NPS) between 1997 and 2003 is analyzed using hierarchical linear regressions. Two models are used in the study. In the first model the independent variables are major type, service community assigned, and Order of Merit (class rank). In the second model the independent variables are major type, service community assigned, Cumulative Academic Quality Point rating (CAQPR), Technical Quality Point Rating (TQPR), and Military Quality Point Rating (MQPR). The dependant variable in both models is Nuclear Power School grade point average. The study found that the more engineering based and officer's major was at the Academy the better they perform at NPS. It also finds that officers assigned to the Surface Warfare-Nuclear community perform slightly better than those assigned to the Submarine community. Lastly, the strongest predictor examined is the variable that measures general cognitive ability. Order of Merit and CAQPR are the strongest predictors of NPS GPA in their respective models. TQPR is a weak predictor of NPS GPA and MQPR is negatively related to performance at NPS.

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I. INTRODUCTION

A. BACKGROUND

For half a century the United States Navy has operated nuclear power plants at sea. USS Nautilus (SSN-751) signaled the Navy's nuclear era on January 17, 1955 with the historic message "Underway on nuclear power" (Johnson, 2002, p. 15). Since then one hundred ninety-three other nuclear powered submarines have entered the fleet (Naval Vessel Register, 2005). These submarines have operated in every ocean and even under the polar ice cap. Additionally, Nuclear power drives ten of the Navy's aircraft carriers.

The Navy is very proud of its nuclear safety record. In its fifty year history the American nuclear fleet has never had a major nuclear accident, a stark contrast to other areas of the nuclear power industry. The Russian nuclear fleet has experienced numerous nuclear accidents resulting in the loss of life (Weir and Boyne, 2003). Russians are also responsible for the worst nuclear disaster in history, Chernobyl. However, America is not immune to nuclear problems. The accident at Three Mile Island ended the American public's acceptance of nuclear power. No new nuclear power plants have been built in the United States since that accident.

One of the key's to the Navy's outstanding safety record is the high quality of its nuclear trained personnel. For years the Navy allowed only the best students to enter the Nuclear power program. The Navy has justified this selection process by pointing at its safety record. However, in recent years a shortage of applicants

has forced the Navy to become less selective. The nuclear power program is now taking candidates with lower academic performance. This trend is very apparent at the Naval Academy where the average order of merit (class rank) of graduates entering the nuclear community has steadily declined. There is a concern that the lowering "quality" of candidates could adversely affect the Navy's nuclear power program.

B. PURPOSE

This study examines the performance of Naval Academy graduates at Nuclear Power School to assess the impact of academic quality (as measured by USNA performance) on performance at nuclear power school.

Specifically, this study examines the importance of three indicator of academic performance, which include academic major, order of merit and surface warfare community on NPS performance.

C. BENEFITS OF THE STUDY

There are many potential benefits of this study for the US Navy. The results of this study can provide the Navy with information regarding the relative worth of different academic indicators on NPS performance. The results of this study can also provide guidance for the selection of submariner graduating from USNA. Further, because the Chief of Naval Operations directed the Naval Academy to increase the percentage of Midshipmen with technical majors as a way of increasing the potential pool of qualified applicants for various warfare communities including the submarine force, this study will examined

whether there are any benefit to having a technical major in the nuclear program. The results of the study can be used set the proper fraction of technical majors.

Lastly the study shows the difference in performance between nuclear Surface warfare officers and Submarine officers. Now the same standards apply for both types of officers. The study will show if the time surface officers spend at sea prior to nuclear power school is an advantage or deterrent.

D. SCOPE AND LIMITATIONS

1. Scope

This thesis examines data from graduates of the United States Naval Academy who entered the nuclear power pipeline between 1994 and 2003. The study is limited to the Naval Academy for a number of reasons. First, limiting the study to Naval Academy graduates allows for control of institutional differences. Midshipmen at the Naval Academy can choose one of nineteen majors. While some the majors are not technical (e.g., English, History), all Midshipmen must take a core curriculum which is filled with math, science, and engineering courses. Therefore, grouping English majors from the Naval Academy to English majors from other institutions is not valid. Majors are only one area you would have to account for if multiple institutions were used. Other variables have much different meaning at the civilian institutions than they do at the Naval Academy. Therefore the study was limited to Naval Academy graduates.

Secondly, as a Submarine officer attached to the Academy the author is involved in the training and recruitment of Midshipmen to attend Nuclear Power School.

Understanding the links between performance at the Academy and performance in Nuclear Power School will help him counsel Midshipmen interested in pursuing a career in Submarines. Results of the study can also be used to target Midshipmen who have a good chance of success in the nuclear power pipeline for recruitment into the nuclear community. Finally, the study will help officers prepare Midshipmen for Nuclear Power School. By knowing which Academy performance factors are important predictors, officers can help Midshipmen focus on specific areas to improve.

2. Limitations

This study is limited in two ways. First, only the records which were released by Nuclear Power School are analyzed. Therefore, available data sets the bounds of what records are included in the study.

Secondly, the dependant variable is limited in meaning. It only measures academic ability in nuclear power school. While it is desirable for all candidates to pass nuclear power school, passing is not the real goal. Safe operation of nuclear power plants is the mission of the program. Ideally a variable could be found which measures safe power plant operation. In reality it is difficult to link plant operation to an individual. Plants are run by teams. Additionally, plant operational data is classified and not easily available.

The study makes the assumption that good performance in power school yields safer operators. This assumption is held as truth in the nuclear power program. It is used in

personnel assignment. Scores from nuclear pipeline schools are used to decide if an officer is fit to serve as an Engineer.

E. ORGANIZATION OF STUDY

This thesis is divided into five chapters. The first chapter is the introduction. It states the purpose of the study and provides relevant background information. The second chapter is a literature review of the topic. The literature review looks at academic performance theories to derive empirical and theoretical support for the hypotheses examined. The third chapter presents the methodology of the study. Each variable used is explained as is the structure of the regression model. Chapter four presents the results of regression analyses examining the impact of academic variables on performance at Nuclear Power School. The last chapter presents the conclusions from the study and provides a series of recommendations.

F. CHAPTER SUMMARY

This chapter provides a basic overview of the thesis. The study looks at the performance of Naval Academy graduates in nuclear power school. Understanding what makes a good power school student is important in selecting the candidates who will succeed in the school, but more importantly, have the ability to safely operate power plants at sea.

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II. LITERATURE REVIEW

A. GENERAL COGNITIVE ABILITY (*g*)

General Cognitive Ability (*g*) "can be said to be the most powerful single predictor of overall job performance (Gottfredson, 1997, p. 83). But what is *g*? Often equated with intelligence quotient (IQ), *g* is a construct which measures an individual's general aptitude. Perhaps it is better to state what *g* is not. Verbal aptitude, spatial aptitude, and numerical aptitude are specific abilities; therefore they are narrower than *g* (Schmidt, 2002). General Cognitive Ability is a broad measure which contributes to one's ability in all aptitudes.

This description is very cumbersome. Different researchers define *g* in slightly different ways. Schmidt (2002) defines *g* as "essentially the ability to learn" (p. 188), while Gottfredson (1997) asserts *g* is "the ability to deal with cognitive complexity - in particular, with complex information processing" (pp. 92-93). These definitions help give *g* real meaning. Others do not try to describe the concept of *g*. Instead they define *g* in terms of its effect on cognitive measures. They see it as "the underlying trait that leads to the well documented positive intercorrelation observed between measures of cognitive behaviors" (Kuncel, Hezlett, and Ones, 2004, p. 148). While this definition may be the "most correct" (it is based on research), it is not nearly as useful in understanding what *g* is.

Describing the concept of *g* may be hard; but understanding its effects is fairly easy. Many studies have been performed to test the importance of *g*. Because *g*

is a concept, every researcher must determine their own way to measure it. There is no official “*g* test”. Luckily this is not a problem. Most tests designed to measure ability of any kind measure *g*. This is because most tests measure multiple specific abilities (Schmidt, 2002). Therefore researchers have many options available to them when measuring *g*. For example Linda Gottfredson (1997) used the national Adult Literacy Survey (NALS) and IQ tests to measure *g*. She found that a higher *g* was associated with positive life outcomes (such as employment, wage level, high school completion, and lasting marriage).

While a few still challenge the preeminence of *g* (Sternberg and Wagner, 1993), the debate between *g* and specific cognitive abilities as more important predictors of performance is virtually over (Ree and Earles, 1992; Olea and Ree, 1994). Repeatedly studies find that *g*, more than anything else, is the best predictor of future performance (Thorndike, 1985; Schmidt, 2002; Jensen 1993; Kuncel et al., 2004; Ree and Earles, 1992).

In 1991 Ree and Earles used the Armed Services Vocational Aptitude Battery (ASVAB) to study the roles of general ability (*g*) and specific ability on performance in military pipeline schools. Using linear regression models they found general ability to be predictive of performance, and little to no advantage in adding specific abilities to their model in addition to *g*. John Winkler (1999) also used the ASVAB to study *g*. He designed an experiment to examine performance of three hundred and twenty-four teams of Army communication specialists under simulated wartime conditions. Each team consisted of three Soldiers assigned at random. The teams were rated on how well they

established a communication network. Winkler found that teams with a higher overall g performed their jobs at a higher level. Devine and Philips agreed with Winkler in their 2001 meta-analysis which showed a positive correlation between cognitive ability within teams and team performance.

General cognitive ability is an excellent predictor of performance in the workplace. A meta-analysis of eighty-five years of data found that g combined with work samples, integrity tests, or structured interviews had high validities when compared to job performance (Schmidt and Hunter, 1998). Other studies have shown the international generalizability of g . A meta-analysis of European Community data sets showed g to be a very good predictor of training success and job performance on the other side of the Atlantic (Salgado, Anderson, Moscoso, Bertua, and DeFruyt, 2003). Even the most recent studies (Morgeson, Delaney-Klinger, and Hemingway, 2005) find g to be positively related to job performance.

While general cognitive ability is important, it does not explain the variance in all performance measures. A study of salespeople showed that cognitive ability predicted how supervisor ratings but not actual sales criteria (Vinchur, Schippmann, Switzer III, and Roth, 1998). This is not surprising to supporters of g 's importance. In 1992 Schmidt and Hunter stated that "the central determining variables in job performance may be general mental ability (g), job experience, and a broad trait of Conscientiousness" (p. 92). Later studies

supported Schmidt and Hunter's hypothesis (Kolz, McFarland, and Silverman, 1998; Lowery, Beadles II, and Krilowicz, 2004; Avis, Kudisch, and Fortunato, 2002).

Kolz et al. (1998) examined the relationship between *g*, job experience, and job performance. They studied one hundred seventy-six employees with the same job at a manufacturing company. The Bennett Mechanical Comprehension Test (BMCT) and the Number Ability subscale of the Employee Aptitude Survey (EAS) were used to measure *g* (both tests are significantly correlated with *g*). Experience was equated with time employed while performance was measure via supervisor evaluations on three dimensions. A regression analysis showed that at least one of the measures of *g*, either BMCT or EAS, predicted each dimension of job performance. Additionally, the combination of work experience and *g*, as measured by EAS, significantly predicted job performance.

Lowery et al. (2004) looked at *g* and the other leg of Schmidt and Hunter's 1992 hypothesis-personality. They looked at the performance of seventy-three small machine operators at a large apparel manufacturer. Intelligence and personality, specifically the construct need for achievement, were compared to performance as measured by productivity. Their regression showed that *g*, while very predictive of performance, could be even better if combined with personality. They also found that personality had a great impact on employees with high mental ability, but almost no effect on those with low mental ability.

A study by Avis et al. in 2002 looked at conscientiousness, *g*, and job performance of cashiers in a large North American retail organization. They developed

their own measures to assess the cognitive ability and conscientiousness of the cashiers. Job performance was determined by supervisor ratings. Multiple regressions were run to analyze the relationships. Avis et al. found that to conscientiousness explained variance in performance above and beyond cognitive ability. However, they do admit that the relatively low complexity of the job studied may have lowered the strength of *g* in predicting performance.

General Cognitive Ability is important. It is very predictive of everything from school grades, to job performance, to creativity (Kuncel et al., 2004). In fact *g* is "almost always the 'most important' factor" when looking at job or academic performance (Reeve and Hakel, 2002, p. 51).

B. ACADEMIC PERFORMANCE

Many different theories have been proposed to explain academic performance. Personality traits, expectancy and needs theory, goal setting, learning styles, and self-efficacy have all been used to model student performance (Nguyen, Allen, and Fraccastoro, 2005; Geiger and Cooper, 1995; Boyle, Duffy, and Dunleavy, 2003; VanderStoep, Pintrich, and Fagerlin, 1996; Sharon, 1998; Sideridis and Kaissidis-Rodafinos 2001). However, none of these are as predictive as past academic performance for undergraduate students (McKenzie and Schweitzer, 2001; Zeegers, 2004; Henson, 1976; Elmers and Pike, 1997; Power, Robertson, and Baker, 1987). In fact "the correlation between secondary school grades and Grade Point average (GPA) at university is generally about 0.5" (McKenzie and Schweitzer, 2001, p. 22).

In 2001 researchers McKenzie and Schweitzer of Australia studied freshmen to "examine the relationship between academic, psychosocial, cognitive, and demographic variables, and the academic performance (first semester GPA) of...university students" (p. 24). Of the fourteen variables entered in to their study only three were found to be significant: prior grades; self-efficacy; and integration. Like in the Henson study, McKenzie and Schweitzer found prior grades most important, accounting for 39 percent of the variance in GPA. The next strongest variable, self-efficacy, accounted for only 8 percent of the variance.

Another Australian researcher, Peter Zeegers, performed a similar study in 2004. He surveyed first and third year university students to examine their approaches to learning, self-regulation, and self-efficacy. Zeegers ran a different model for each year group. As in the previous studies, prior academic performance correlated strongest with academic achievement. The model for first year students compared secondary school grades to freshman GPA. These had a correlation of 0.34. For third year university students Zeegers used prior year GPA instead of secondary school grades. In this model prior academic performance had an even stronger correlation (0.71) with academic achievement.

Henson (1976) studied undergraduate male freshmen to see how expectancy, ability, and personality affected effort and performance. He used a survey to measure expectancy and personality. Ability was measured using college transcripts and admission records. These were correlated to performance as measured by student grade

point average at the end of the semester (about two months after they took the survey). While Henson found no correlation between expectancy and performance, he found every academic ability variable to be significant. Past undergraduate grade point average correlated strongest to academic performance. SAT scores had the next strongest correlation.

The predictive value of prior grades and standardized tests, such as the SAT and ACT, are common findings in educational research (Allen, 1992; Pike and Saupe, 2002). In 2002 Pike and Saupe compared three different college grade prediction models: a traditional regression; a high-school-effects model; and a hierarchical linear model. The traditional regression used ACT score, high school class rank and core course indicators. The high-school-effects added 123 dummy-coded variables which identified each of the 124 sending high-schools. Over eight thousand student records from a Midwestern university were used to analyze the models. The hierarchical model combined the variables in a more complex process. The high-school-effects model was the most predictive of actual student performance (it had the smallest average residual: 0.071). However, the traditional regression model, which only took into consideration student ability, was almost as good with a mean residual of 0.076. Pike and Saupe concluded that test scores and prior academic performance are significantly related to college GPA and account for around a third of the variance in freshman college grades.

The finding that high school GPA and test scores predict college performance holds true across different academic disciplines. For example, in 1998 Borde looked at

nearly four hundred marketing students at a public university in Florida. He designed an ordinary least squares model to predict the final grade in a marketing course. In addition to prior academic performance, Borde used variables to represent student demographics (i.e. age and gender), employment status, and source of entry (i.e. high school, community college, or college transfer). His model explained around 40 percent of a student's grade. He found that academic performance was strongly related to performance in a marketing course. Studies in other academic areas demonstrate similar results. In addition to marketing, performance in business (Pharr and Bailey, 1993), allied health (Platt, Turocy, and McGlumphy, 2001), and honors classes (Wade and Walker, 1994) is predicted by high school GPA, test scores, or their combination. Even when examining retention GPA remains significant (Cabrera, Nora, and Castaneda, 1993).

Past grades predicting future grades is not just common sense it is a result of General Cognitive Ability. Academic performance is not simply a measure of specific abilities. Getting a good grade in a class requires "engaging in many...complex and ill-defined tasks" such as labs, group projects, and presentations (Kuncel et al., 2004, p. 151). This means a grade in a math class measures more than just math ability, it also measures g . It follows that a grade point average, which incorporates classes from multiple subjects, would be an even better measure of g .

Officers attend Nuclear Power School (NPS) after they finish their undergraduate degrees, therefore NPS somewhat similar to graduate school. In multiple studies of

graduate school students, previous grade point average (GPA) is found to be very predictive of enrollment (Mullen, Goyette, and Soares, 2003) and performance (Kuncel, Hezlett, and Ones, 2001; Oldfield and Hutchinson, 1996; Yang and Lu, 2001; Carver and King, 1994; Hoefer and Gould, 2000; Feeley, Williams, and Wise, 2005; Kuncel et al., 2005; Powers, 2004; Dunlap, Henley Jr., and Fraser, 1998). For example, Feeley, Williams and Wise's (2005) analyzed graduate student success for one hundred and forty-two communication students at the University of Buffalo. They examined the effects of Graduate Record Exam (GRE) score and undergraduate GPA (UGPA) on graduate GPA (GGPA) and graduation. The resulting regression found only UGPA to be a significant predictor of GGPA. The predictive value of previous academic performance holds true for professional disciplines as well. Both medical school (Ferguson, James, and Madeley, 2002) and law school (Henderson, 2004) performance are predicted by undergraduate grades.

Similar to undergraduate performance, graduate performance is also predicted by standardized tests. The Graduate Record Exam (GRE) is known to be an effective predictor of graduate performance in psychology (Goldberg, and Alliger, 1992), social work (Dunlap et al., 1998), and veterinary medicine (Powers, 2004). Additionally, the Pharmacy College Admission Test (PCAT) predicts performance in pharmacy programs and on licensing examinations (Kuncel et al., 2005).

That being said not everyone is convinced of using standardized tests to select students for graduate programs. Some in the physics community feel that even a correlation of 0.48 between GRE score and graduate school

grades in physics is too weak to use for admissions (Glanz, 1996). Oldfield and Hutchinson (1996) challenged the effectiveness of the GRE in predicting grades in two specific classes in a Master's of Public Administration curriculum. They found evidence that GPA from early postgraduate courses is more predictive of academic performance. Likewise, Henderson (2004) found undergraduate GPA to be a much more stable predictor of law school performance than the Law School Admissions Test (LSAT). He hypothesized that the timed nature of the LSAT reduces its effectiveness by measuring test-taking speed as well as mental ability.

In 2000, Hoefer and Gould examined how to best model student performance in graduate business programs. They compared using a linear regression, a non-linear regression, and a neural network to examine data from business students. All three models found undergraduate GPA and Graduate Management Admissions Test (GMAT) scores to be important determinants of academic performance.

Exams, such as the Graduate Management Admissions Test (GMAT), designed to measure aptitude predict performance in graduate programs. However, they are not quite as effective as undergraduate grade point average. In their study, Yang and Lu (2001) sought to find how much of graduate academic performance could be explained by precedent factors. After maximizing their model they found three variables explained graduate GPA: undergraduate GPA; GMAT quantitative; and GMAT verbal. Undergraduate GPA was the most important with a standardized beta over twenty times the magnitude of the GMAT variables.

A notable exception is the study of non-traditional master of business administration (MPA) students by Carver and King (1994). They studied students enrolled in an off campus MPA program. The students all had full time jobs and attended class on the weekends. While both variables were significant, Carver and King found the GMAT to be more predictive than undergraduate grade point average. In a similar study of non-traditional students Arnold, Chakravarty, and Balakrishnan (1996) found GMAT to be the strongest predictor of performance in Executive Master of Business Administration (EMBA) programs. Their study showed that EMBA student performance is predicted by the same model as traditional MBA students but to a lesser extent.

This section discussed academic performance. Academic performance is a measure of *g*. The best predictor of future academic performance is past academic performance. Additionally, exams designed to test specific abilities, such as the GMAT, are predictive of academic performance.

C. THE RICKOVER HYPOTHESIS

Admiral Hyman G. Rickover, "Father of the Nuclear Navy," stated his strong views on Midshipmen studies to the House Armed Services Committee in 1976:

I think teaching management as a major subject for an undergraduate is ridiculous and I can see no way that it contributes to the ability of a junior officer to do his job... All Midshipman should take a common core of subjects taught at the same academic level. Electives should be offered if time in the program of core subjects can be found, but these electives should be rigidly limited to those which will prepare Midshipmen for their role as naval officers. The social sciences should be specifically excluded (found in Woelper, 1998).

This assertion has since been known as the Rickover hypothesis.

Bowman (1990) challenged the Rickover hypothesis. He found "little if any relationship between the academic world of Academy graduates and the real world of (a) junior officer serving in the surface or submarine warfare communities" (Bowman, 1990). However, he did not look at pipeline performance. His dependent variables were Lieutenant fitness report grades and retention beyond initial service obligation.

In 1998 Eric Woelper took a look at the Rickover hypothesis. In his study the relationship between major and undergraduate grades as they relate to submarine officer performance was analyzed. He did look at nuclear pipeline performance, but only at the pass/fail level. Unlike Bowman, Woelper found that good grades and engineering majors had significant positive effects on officer performance.

The most recent look at the Rickover hypothesis was performed by Chris Polk (2003). Like Woelper, Polk's study modeled the nuclear pipeline performance as pass/fail. He limited undergraduate grades to only technical classes (such as math, science, and engineering).

Polk found that engineering majors and a high Technical Quality Point Rating (TQPR) aid in pipeline completion, however, he also found that undergraduate performance was insignificant in predicting qualification as an Engineer Officer (qualification as an Engineer occurs about two year after an officer reports onboard his first submarine). In his detailed analysis Polk showed that at

high TQPR's major made little difference, but at low TQPR's engineers out performed others by around 25 percent. Interestingly Polk found no relationship between Military Quality Point Rating (MQPR) and nuclear pipeline performance. In 2003 Jeff Rodgers studied surface warfare officers and found MQPR to be the number one predictor of junior officer performance.

D. SUMMARY

This chapter began by presenting theory of General Cognitive Ability (g). It showed how g was a good predictor of job and academic performance. Next it explained that the best predictor of academic performance was prior performance in the classroom. The chapter concluded with a description of the Rickover hypothesis and a brief summary of the studies performed to test it.

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III. RESEARCH METHODOLOGY

A. DATA DESCRIPTION

1. Description of the Sample

Data for this study was obtained with the assistance of the Office of Institutional Research, Planning, and Assessment of the United States Naval Academy. Nuclear Power School performance data was provided to the Naval Academy. The data set contains Nuclear Power School (NPS) performance for 1,096 Naval Academy graduates who attended Nuclear Power School between 1997 and 2003.

The file contained data for several variables including academic major, Service Warfare Community, and performance data for USNA, and NPS performance. Figure one displays the relationship among the variables in the model. United States Naval Academy performance is broken down into four component variables which include Order of Merit, academic quality point rating, technical quality point rating, and military quality point rating.

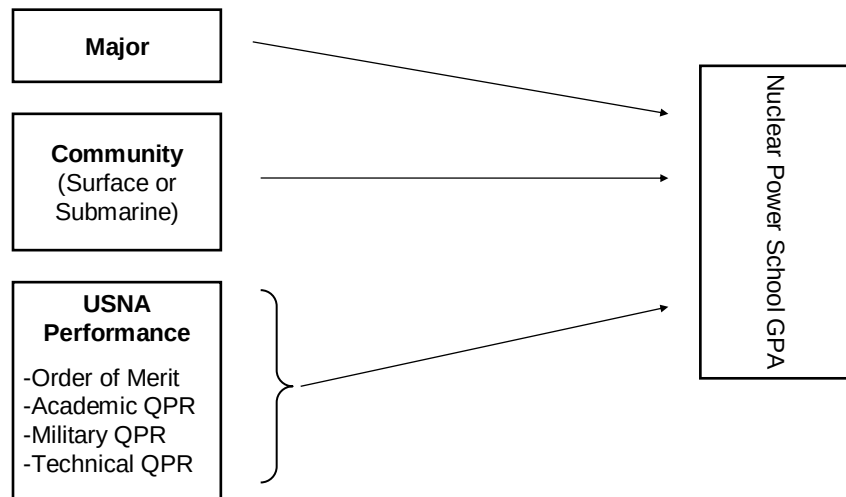


Figure 1. Variable Used in Study

2. Definition of the Dependent Variable

The dependent variable for this study is performance at Nuclear Power School as measured by grade point average. Nuclear Power School is a six month long intense study of nuclear reactor theory and construction. Students take courses in math, physics, and engineering. Grades are based on academic examinations given in each course as well as a comprehensive exam covering the entire six month school.

Grades are given on a score of zero through four, similar to a grade point average. A 2.5 average is required to pass. The course and comprehensive exam grades are weighed and averaged to form the Nuclear Power School grade point average.

3. Description of the Independent Variables

The study includes three indicators of performance at the Naval Academy: Technical Quality Point Rating (TQPR); Cumulative Academic Quality Point Rating (CAQPR); and Military Quality Point Rating (MQPR). These variables provide measures of Midshipmen academic performance and therefore should to some degree predict performance in the nuclear pipeline. Two non-performance variables are also in the model, type of major and service assignment. The dependent and independent variables are listed, described, and coded in Table 1.

Table 1. Variable Descriptions

VARIABLE	DESCRIPTION
Nuclear Power School GPA	Final GPA at Nuclear Power School (Range: 0-4)
Major Group	Major group is determined by recoding major_c into Group 1, 2 or 3.
GROUP 1	Engineering Majors
GROUP 2	Science and Math Majors
GROUP 3	Non-technical Majors
OOM_PCT	Order of merit at graduation divided by class size. (Range 0-1)
CAQPR	Quality Point Rating at graduation (Range 0-4)
TQPR	Quality Point Rating in technical classes at graduation (Range 0-4)
MQPR	Military Quality Point Rating (Range 0-4)
Community	Warfare community the Midshipman was assigned to
NUC SUB	Assigned as a Submarine officer
NUC SURF	Assigned as a Surface warfare officer (nuclear)

a. Major Group

The Naval Academy offers nineteen different majors. Midshipmen request a major during the second semester of their Fourth Class year. The Academy tries to accommodate all requests but may place Midshipmen as necessary to maintain the proper ratio of technical and

non-technical majors or to prevent over filling of a department (United States Naval Academy Catalog 2004-2005, 2004).

Naval Academy majors are divided into three groups. Group one is the engineering majors. Group two contains the math and science majors. Group three has the humanities and social sciences. Group one and two are considered technical. The majors contained in each group are listed in Table 2. The study uses the Naval Academy's major group designation in the analysis.

Table 2. Majors by Group at USNA

Group 1	Group 2	Group 3
Aerospace Engineering Electrical Engineering General Engineering Mechanical Engineering Naval Architecture Ocean Engineering Systems Engineering	Chemistry Computer Science General Science Information Technology Mathematics Oceanography Physics Quantitative Economics	Economics English History Political Science

b. Order of Merit Percent (OOM_PCT)

Order of Merit is a numerical ranking of all the graduating members of an Academy class. It is equivalent to class rank at other institutions. It ranges from "1" to the total number of Midshipmen in a class, usually between nine hundred and one thousand. Order of Merit is derived from a complex formula which has numerous inputs including grades, military performance, physical aptitude, and demerits accumulated (USNA INSTRUCTION 1531.51A, 1996). The top graduate is ranked number one.

In order to compare the Order of Merit of Midshipmen from different classes Order of Merit is divided by class size. The result is a percentile rank (OOM_PCT) which is used in the regression analysis.

c. Cumulative Academic Quality Point Rating (CAQPR)

The Cumulative Academic Quality Point Rating is a grade point average of all courses taken by a Midshipman. It is identical to a civilian college's grade point average. Grades are converted into a numerical score (A=4, B=3, C=2, D=1, F=0) and weighted by semester hour. The total is then averaged to yield the CAQPR. The CAQPR does not take military aspects of the institution into account and therefore is not the sole basis of Order of Merit.

d. Technical Quality Point Rating (TQPR)

The Technical Quality Point Rating is a grade point average of only the "technical" courses taken over a Midshipman's career. Technical courses include all math, science, and engineering courses. The total number of courses contained in the average depends on each Midshipman's major (engineering majors take more technical courses than English majors do). However, the Naval Academy's core curriculum ensures that every Midshipman, regardless of major, takes over forty-five semester hours of technical courses.

Grades in technical courses are converted into a numerical score (A=4, B=3, C=2, D=1, F=0) and weighted by semester hour. The total is then averaged to yield the TQPR, a number between zero and four.

e. Military Quality Point Rating (MQPR)

The Military Quality point rating is a grade point average which reflects a Midshipman's 'military

ability.' Basically it is a weighted average of five different military performance measures (USNA INSTRUCTION 1531.51A, 1996). The most heavily weighted aspect of MQPR is the Military Performance grade assigned by a Midshipman's company officer. The four remaining areas, in decreasing order of weight, are Conduct, Physical Education, Professional Courses, and Athletic Performance. The MQPR formula yields a grade point average like number between zero and four.

f. Community

Community is a nominal variable, which describes the service warfare community an officer is assigned to. Because this study looks at the nuclear pipeline Service Assignment is limited to Surface Warfare Officers (Nuclear) and Submarine Officers. Both communities attend the same Nuclear Power School. However, they take different paths to get to Nuclear Power School. Submarine officers go to NPS right after commissioning. Surface Warfare Officers attend Nuclear Power School after their first tour (about eighteen months) as a division officer. Therefore, Surface Warfare Officers are a little older and have more experience than their Submarine classmates.

B. STATISTICAL ANALYSIS

The study models the relationship between the Naval Academy and Nuclear Power School using linear regressions.

A linear regression is used to predict continuous dependent variables, in this case Nuclear Power School grade point average. The goal of the analysis is to predict the outcome value given any set of independent variables.

A linear regression models the relationship between the independent and dependant variables as a first order equation:

$$Y = A + B_1X_1 + B_2X_2 + \dots + B_iX_i$$

The dependent variable, Y, is the predicted outcome for a given set of independent variables, X₁ through X_i. The regression analysis provides the coefficients, B₁ through B_i, and the constant, A.

A hierarchical regression is used in this analysis. Hierarchical regression allows the user to specify the order independent variables are entered into the analysis. It is useful when prior research suggest that different factors may affect the independent variable. The last variable entered in a hierarchical regression is the variable of interest.

A hierarchical regression is used to analyze the model. This allows the unique contribution of each variable to be observed. The model is run twice. First, the model is run using Order of Merit as the only Academy performance variable. This model is shown in Figure 2.

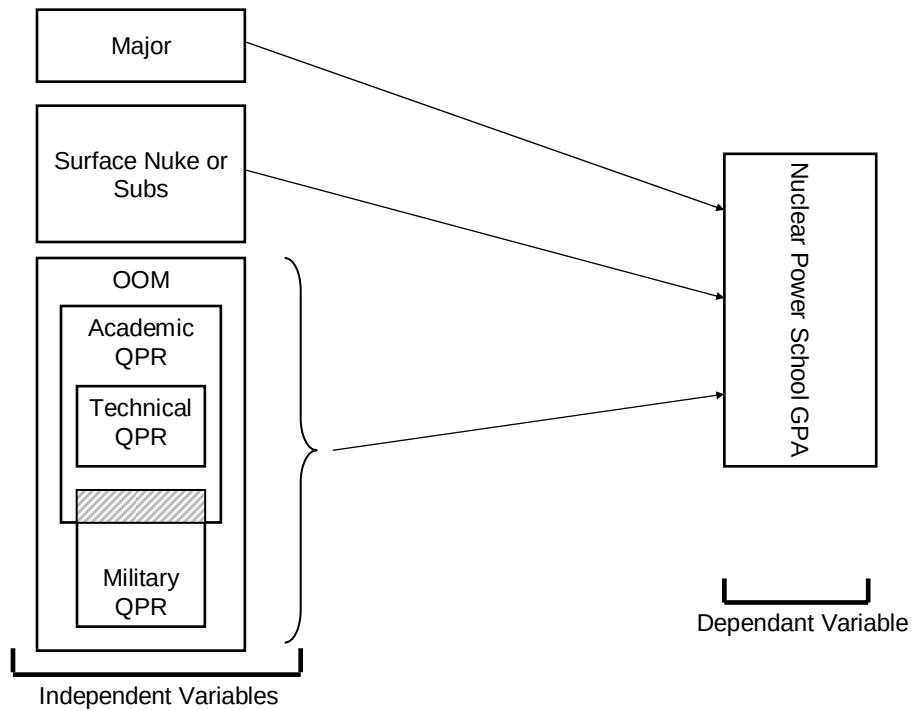


Figure 2. First Model

The hierarchical order variables are inserted into the first model is shown in Table 3. Each step adds an additional independent variable to the regression. Major Group is the first variable entered. In step two, warfare community is added. The third step enters Order of Merit.

Table 3. Order of Independent Variable Entry for Model 1

<u>STEP 1</u>	<u>STEP 2</u>	<u>STEP3</u>
Major Group	Major Group	Major Group
	Community	Community
		Order of Merit

In the second model, shown in Figure 3, Order of Merit is replaced with Cumulative Academic Quality Point Rating, Technical Quality Point Rating, and Military Quality Point

Rating. These three variables makeup a large part of Order of Merit, therefore Order of Merit is not included in this model.

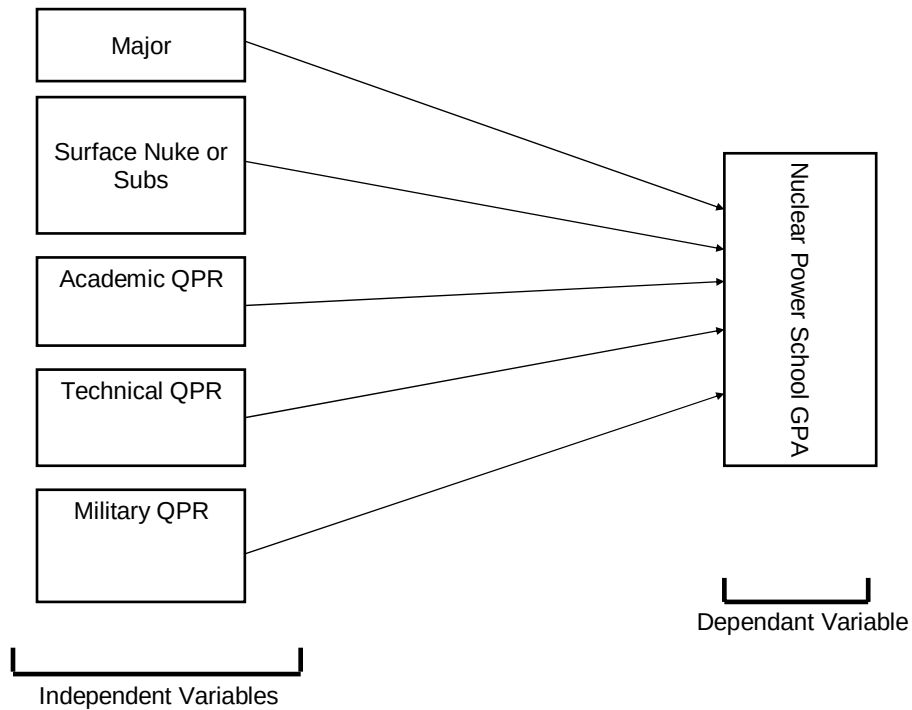


Figure 3. Second Model

The order of entry into the second model, shown in Table 4, is similar to the first. Step one is Major Group and step two is community. Instead of Order of Merit, Cumulative Academic Quality Point Rating and Military Quality Point Rating are entered in step three. The fourth step adds Technical Quality Point Rating to the regression.

Table 4. Order of Independent Variable Entry for Model 2

<u>STEP 1</u>	<u>STEP 2</u>	<u>STEP3</u>	<u>STEP4</u>
Major Group	Major Group	Major Group	Major Group
	Community	Community	Community
		CAQPR	CAQPR
		MQPR	MQPR
			TQPR

SPSS version 11.0.1 is used to analyze data and perform regressions. Specifically the linear regression function was used. This function is found under the analyze -> regression menu of the SPSS software package.

IV. DATA ANALYSIS

A. INTRODUCTION

This chapter presents the results of the hierarchical linear regression analysis used to test the proposed models. The chapter contains three sections. The first section presents descriptive statistics of the variables used in the study. The second section presents the results of the test of the Model 1 which examines how Major Group, Community, and Order of Merit predict Nuclear Power School Grade Point Average (NPS GPA). The last section presents the results of the test of Model 2. Model 2 examines how Major Group, Community, and three components of Order of Merit predict Nuclear Power School Grade Point Average (NPS GPA). Cumulative Academic Quality Point Rating (CAQPR), Technical Quality Point Rating (TQPR), and Military Quality Point Rating (MQPR) are the three components of Order of Merit examined by Model 2.

B. DESCRIPTIVE STATISTICS

Table 5 displays the mean and standard deviation for each of variable included in the study. Table 5 also shows the distributional properties of Major Group and Community.

Table 5. Variable Statistics

Variable	Mean/Proportion	Standard Deviation
Nuclear Power School GPA	3.12	0.375
Major Group		
Group 1	54.7%	-
Group 2	25.0%	-
Group 3	20.3%	-
Community		
Subs	76.5%	-
Surface Nuke	20.7%	-
Other	02.7%	-
OOM_PCT	37.6%	24.8%
CAQPR	3.18	0.404
MQPR	3.21	0.293
TQPR	3.09	0.510

Initial examination of the mean for Nuclear Power School GPA by Major Group indicates that engineering majors have the highest performance followed by science/math majors and then humanities majors (Figure 4).

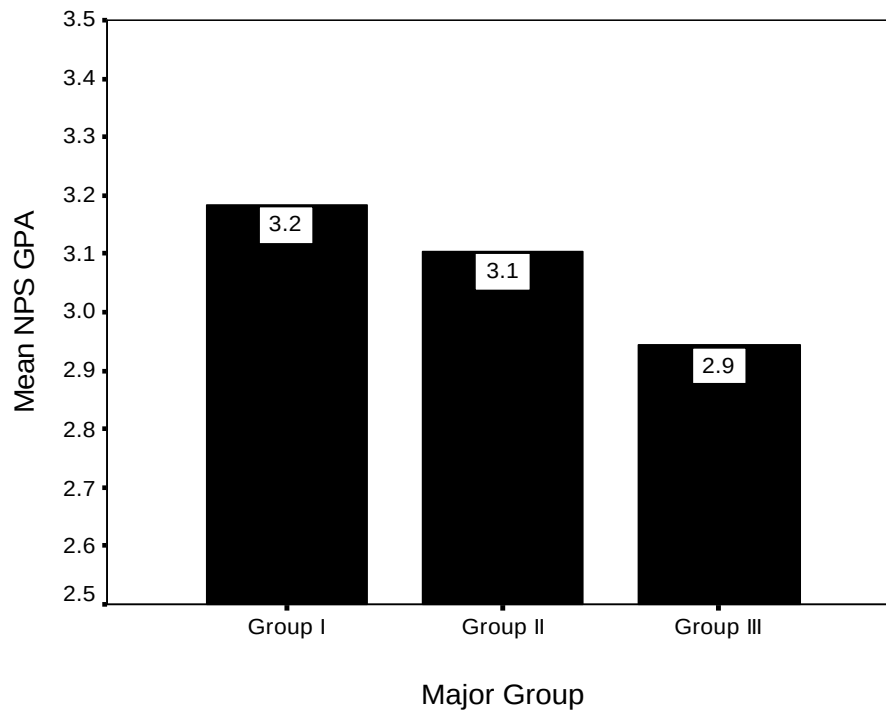


Figure 4. Mean NPS GPA by Major Group

Figure 5 presents the mean NPS GPA for each community. Surface Warfare officers have a slightly higher average NPS GPA (around one tenth of a point) than Submarine officers.

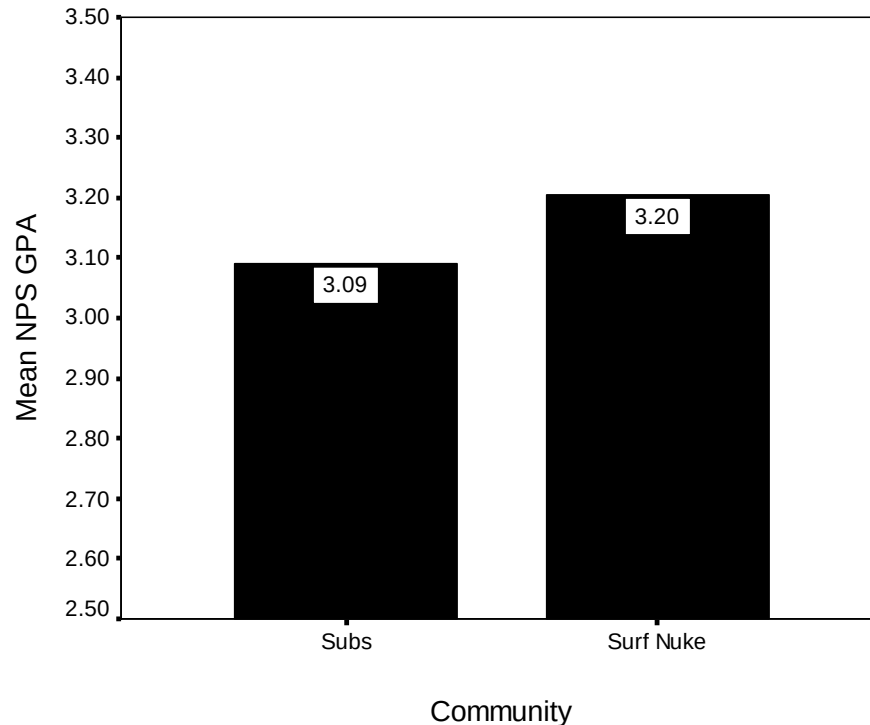


Figure 5. Mean NPS GPA by Community

C. HIERARCHICAL LOGISTIC REGRESSION ANALYSIS OF PREDICTORS OF NUCLEAR POWER SCHOOL GPA (MODEL 1)

The first model specifies that NPS GPA can be predicted by type of major, warfare community, and performance at the Academy as measured by Order of Merit. This model is shown in Figure 2. As shown in Table 3, the order of entry into the regression is Major Group, Community, OOM_PCT.

In this analysis Major Group is a nominal variable; therefore, it is recoded into dummy variables before running the regression. Group 1 is chosen as the standard to compare Group 2 and Group 3 majors against. Because

dummy variables are required, step one of the regression needs two coefficients even though the only variable being analyzed is Major Group. Table 6 shows the results of Model 1.

In the first step both Major Group variables are significant at the 99% level, and both negatively affect Nuclear Power School GPA. However, Group 3 majors suffer a much greater reduction in GPA, almost a quarter of a point. This result is not surprising. More experience in technical courses should aid performance in Nuclear Power School.

Table 6. Hierarchical Logistic Regression Analysis of Predictors of NPS GPA: Model 1 (N=1095)

Variable	B	Standard Error B	t	p	β
Step 1					
Constant	3.184	0.015	214.497	0.000	
Major: Group 2	-0.080	0.026	-3.005	0.003	-0.092*
Major: Group 3	-0.241	0.029	-8.426	0.000	-0.258**
Step 2					
Constant	3.159	0.016	202.839	0.000	
Major: Group 2	-0.090	0.026	-3.408	0.001	-0.104*
Major: Group 3	-0.250	0.028	-8.814	0.000	-0.268**
Community: Other	0.087	0.067	1.307	0.191	0.038
Community: SWO Nuke	0.132	0.027	4.872	0.000	0.142**
Step 3					
Constant	3.477	0.019	186.648	0.000	
Major: Group 2	-0.067	0.021	-3.126	0.002	-0.078*
Major: Group 3	-0.244	0.023	-10.554	0.000	-0.262**
Community: Other	0.061	0.055	1.120	0.263	0.027
Community: SWO Nuke	0.092	0.022	4.149	0.000	0.099**
OOM_PCT	-0.008	0.000	-23.393	0.000	-0.556**

Note. * $p < .01$; ** $p < .001$. $R^2 = .061$ for Step 1 ($p < .001$); $\Delta R^2 = .079$ for Step 2 ($p < .001$); $\Delta R^2 = .386$ for Step 3 ($p < .001$). Major Group 2 is dummy coded such that 1 = Math/Science major and 0 = engineering majors; Major Group 3 is dummy coded such that 1 = Humanities/Social Science major and 0 = engineering majors; Community: Other is dummy coded such that 1 = any service assignment except SWO Nuke and Subs and 0 = service assigned Subs; Community SWO Nuke is dummy coded such that 1 = service assigned SWO Nuke and 0 = service assigned Subs; OOM_PCT is a fractional variable where a smaller fraction represents a higher class standing and 1 is assigned to the individual at the bottom of the class.

The second step of the regression enters the dummy variables for service community. NUC SUB is chosen as the standard to compare the other communities against. The two dummy variables entered into the regression are NUC SURF and Other.

Adding variables to account for community increases the negative weight of the Major Group variables. The Community: Other variable is not significant. All other variables in the regression are significant at the 99% level. Nuclear surface officers perform better than submariners by about a tenth of a point.

The last step of the regression enters Order of Merit Percentile (OOM_PCT) which is a continuous variable. In this final step every variable is significant at the 99% level except Community: Other. OOM_PCT is inversely related to NPS GPA. OOM_PCT has a range of zero to one, and is derived by the equation:

$$\text{OOM_PCT} = \frac{\text{OOM}}{\text{No in class}}$$

The top person in each class has a very small OOM_PCT and the last person's OOM_PCT is one. Because "better" is smaller the negative coefficient is expected. Do not let the small value of OOM_PCT confuse you. It actually shows a strong effect. Because OOM_PCT is a percent the coefficient really shows that raising Order of Merit by one percent (about 10 places) is reflected in an increase of 0.008 in Nuclear Power School GPA.

The addition of OOM_PCT to the model lessens the impact of the other variables to a small degree. The greatest change is seen in SWO Nuke, which sees a 30

percent reduction in the value of its coefficient. The coefficient for Group 2 is reduced by 26 percent while the coefficient for Group 3 remains almost constant.

D. HIERARCHICAL LOGISTIC REGRESSION ANALYSIS OF PREDICTORS OF NUCLEAR POWER SCHOOL GPA (MODEL 2)

The second model specifies that NPS GPA can be predicted by type of major, warfare community, and performance at the Academy as measured by Cumulative Academic Quality Point Rating (CAQPR), Technical Quality Point Rating (TQPR), and Military Quality Point Rating (MQPR). This model is shown in Figure 3. As shown in Table 4, the order of entry into the regression is first Major Group, then Community, and last the performance variables CAQPR, TQPR, and MQPR.

In this analysis Major Group is a nominal variable; therefore, it is recoded into dummy variables before running the regression. Group 1 is chosen as the standard to compare Group 2 and Group 3 majors against. Because dummy variables are required, step one of the regression needs two coefficients even though the only variable being analyzed is Major Group. Table 7 shows the results of Model 2.

In the first step both Major Group variables are significant at the 99% level, and both negatively affect Nuclear Power School GPA. However, Group 3 majors suffer a much greater reduction in GPA, almost a quarter of a point. This result is not surprising. Less experience in technical courses should hurt performance in Nuclear Power School.

Table 7. Hierarchical Logistic Regression Analysis of Predictors of NPS GPA: Model 2 (N=1095)

Variable	B	Standard Error B	t	p	β
Step 1					
Constant	3.184	0.015	214.497	0.000	
Major: Group 2	-0.080	0.026	-3.005	0.003	-0.092**
Major: Group 3	-0.241	0.029	-8.426	0.000	-0.258***
Step 2					
Constant	3.159	0.016	202.839	0.000	
Major: Group 2	-0.090	0.026	-3.408	0.001	-0.104**
Major: Group 3	-0.250	0.028	-8.814	0.000	-0.268***
Community: Other	0.087	0.067	1.307	0.191	0.038
Community: SWO Nuke	0.132	0.027	4.872	0.000	0.142***
Step 3					
Constant	1.598	0.094	17.063	0.000	
Major: Group 2	-0.087	0.020	-4.272	0.000	-0.100***
Major: Group 3	-0.227	0.024	-9.637	0.000	-0.244***
Community: Other	0.064	0.051	1.256	0.209	0.028
Community: SWO Nuke	0.131	0.021	6.250	0.000	0.141***
CAQPR	0.546	0.057	9.641	0.000	0.589***
TQPR	0.075	0.041	1.828	0.068	0.102*
MQPR	-0.128	0.039	-3.275	0.001	-0.100**

Note. * $p < .1$, ** $p < .01$; *** $p < .001$. $R^2 = .061$ for Step 1 ($p < .001$); $\Delta R^2 = .079$ for Step 2 ($p < .001$); $\Delta R^2 = .463$ for Step 3 ($p < .001$). Major Group 2 is dummy coded such that 1 = Math/Science major and 0 = engineering majors; Major Group 3 is dummy coded such that 1 = Humanities/Social Science major and 0 = engineering majors; Community: Other is dummy coded such that 1 = any service assignment except SWO Nuke and Subs and 0 = service assigned Subs; Community SWO Nuke is dummy coded such that 1 = service assigned SWO Nuke and 0 = service assigned Subs; CAQPR, TQPR, and MQPR are grade point average like variables with a range of 0 - 4, where 4 is perfect.

The second step of the regression enters the dummy variables for service community. NUC SUB is chosen as the standard to compare the other communities against. The two dummy variables entered into the regression are NUC SURF and Other.

Adding variables to account for community increases the negative weight of the Major Group variables. The Community: Other variable is not significant. All other variables in the regression are significant at the 99 percent level. Nuclear surface officers perform better than submariners by about a tenth of a point.

The last step of the regression enters the Academy performance variables CAQPR, TQPR, and, MQPR. All three of these continuous variables are components of Order of Merit. About 65 percent of Order of Merit is based on academic performance (USNA INSTRUCTION 1531.51A, 1996). CAQPR measures overall academic performance and TQPR measures academic performance in technical classes (math, science, engineering). Military performance accounts for 17.7 percent of Order of Merit (USNA INSTRUCTION 1531.51A, 1996). MQPR measures a Midshipman's military performance. The rest of Order of Merit (about 18 percent) is based on physical ability and Midshipman conduct (USNA INSTRUCTION 1531.51A, 1996). These two areas are not represented in the model.

In this final step every variable is significant at the 99 percent level except Community: Other and TQPR. TQPR is significant at the 90 percent level while Community: Other remains insignificant. CAQPR and TQPR are both positively related to NPS GPA; however CAQPR is almost six times as powerful as TQPR. This is interesting.

General academic ability is more predictive in Nuclear Power School, a highly technical school, than academic ability in technical classes. Another interesting result is the negative relationship between MQPR and NPS GPA. Better military performance yields lower grades in Nuclear Power School. The magnitude of MQPR's B is minor; much less than CAQPR and about equal to that of TQPR.

The addition of the three Academy performance variables model lessens the impact of the other variables to a small degree. The greatest change is seen in Major: Group 3, which sees a nine percent reduction in the value of its coefficient. The changes in the coefficients of the remaining variables are very minor.

E. SUMMARY

This chapter shows how the data is analyzed. Two hierarchical regressions are examined. Both models find that Engineering majors perform best at Nuclear Power School and humanities majors the worst. Nuclear surface warfare officers perform better than Submarine officers. Finally, good performance at the Naval Academy has a strong positive effect on NPS GPA.

V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

1. Model 1 (Major; Community; and OOM)

The first model examines how Major, Community, and Order of Merit (OOM) affected Nuclear Power School grade point average (NPS GPA). The order of entry into the hierarchal regression is discussed in Chapter III and is shown in Table 3. The results of the regression are discussed in Chapter IV and summarized in Table 6.

a. How Major Affects NPS Performance

As expected, undergraduate major significantly affects performance at Nuclear Power School (NPS). Students with Group 2 (hard sciences and math) majors have a NPS GPA that is slightly lower than Group 1 (engineering) majors. It should be noted that the Group 2 variable has the weakest β of all the variables measured. The reason the Group 2 β is weak is probably because Group 1 and Group 2 majors both take highly technical courses and therefore have a similar knowledge base.

A Group 3 (humanities and social sciences) major's performance is affected to a greater extent. They earn NPS GPA's which are a quarter of a point lower than students with Group 1 majors. Therefore the more technical a person's undergraduate major the better they perform at NPS. This follows the Rickover Hypothesis that technical courses prepare Junior Officers for success in the fleet. The results are also expected because NPS is a highly technical school that primarily teaches and evaluates engineering knowledge.

The hierarchical regression showed that Major Group is unrelated to Community and OOM. The coefficients for the Major Groups remained fairly steady as additional variables were added to the regression in each step. Therefore, Major Group explains a different part of the variance of NPS GPA than Community or OOM.

b. How Community Affects NPS Performance

The study shows that Surface Warfare Officers (SWO Nuke) perform slightly better than Submarine Officers at NPS. Adding OOM to the regression reduces the affect of being a SWO Nuke by about thirty percent. Therefore, the Community variable is only slightly related the undergraduate performance variable OOM.

The only difference between Submarine Officers and SWO Nukes is the time in their life when they attend NPS. Submarine Officers attend NPS immediately after graduating from the Academy. The only exception is for a handful of students who are given the opportunity to earn a graduate degree between the Academy and NPS. On the other hand, SWO Nukes go to a ship and serve as a division officer after they graduate from the Academy. They have around eighteen months of sea duty under their belts when they arrive at NPS. This additional experience and time to mature makes SWO Nukes better students at NPS.

The Community: Other variable does not significantly affect NPS GPA. This variable describes NPS students who were not originally assigned to either the Submarine or SWO Nuke communities but ended up at NPS. Because Community: Other describes a small number of officers with varied and unknown histories the lack of significant affect on NPS GPA is expected.

c. How OOM Affects NPS Performance

The strongest predictor (as shown by the β value with the greatest magnitude) in the first model is OOM. A large part of what OOM measures is general cognitive ability (g). As the overall measure of a Midshipman at the Naval Academy, OOM takes into account academic performance in all classes. Therefore, it is an approximate measure of g . As expected, based on previous research, a measure of g (OOM) predicts academic performance (NPS GPA). For example, moving up in the class by twelve percent (around one hundred and twenty places) will raise NPS GPA by a tenth of a point. This also agrees with previous research done on the Nuclear power community which shows that performance in NPS is correlated with undergraduate grades.

As stated before, adding OOM to the regression lowers the strength of the Community: SWO Nuke variable by around thirty percent and only slightly affects the magnitude of the Major variables. Therefore, community and major are fairly independent of OOM. Surface warfare officers and engineering majors do better at NPS no matter what their OOM was.

2. Model 2 (Major; Community; CAQPR; TQPR; and MQPR)

The second model examines how Major, Community, and three undergraduate performance variables affect Nuclear Power School grade point average (NPS GPA). The undergraduate performance variables are: Cumulative Academic Quality Point Rating (CAQPR), Technical Quality Point Rating (TQPR), and Military Quality Point Rating (MQPR). The order of entry into the hierarchical regression

is discussed in Chapter III and is shown in Table 4. The results of the regression are discussed in Chapter IV and summarized in Table 7.

a. How Major Affects NPS Performance

As expected, undergraduate major significantly affects performance at Nuclear Power School (NPS). Students with Group 2 (hard sciences and math) majors have a NPS GPA that is slightly lower than Group 1 (engineering) majors. It should be noted that the Group 2 variable is tied for the weakest β of the variables measured (it tied with MQPR). The reason the Group 2 β is weak is probably because Group 1 and Group 2 majors both take highly technical courses and therefore have a similar knowledge base.

A Group 3 (humanities and social sciences) major's performance is affected to a greater extent. They earn NPS GPA's which are around a quarter of a point lower than students with Group 1 majors. Therefore the more technical a person's undergraduate major the better they perform at NPS. This follows the Rickover Hypothesis that technical courses prepare Junior Officers for success in the fleet. The results are also expected because NPS is a highly technical school that primarily teaches and evaluates engineering knowledge.

The hierarchal regression showed that Major Group is unrelated to Community and the three undergraduate performance variables. The coefficients for the Major Groups remained fairly steady as additional variables were added to the regression in each step. Therefore, Major Group explains a different part of the variance of NPS GPA than Community, CAQPR, TQPR, or MQPR.

b. How Community Affects NPS Performance

The study shows that Surface Warfare Officers (SWO Nuke) perform slightly better than Submarine Officers at NPS. Adding CAQPR, TQPR, and MQPR to the regression does not affect the SWO Nuke coefficient. Therefore, the Community is independent of the there undergraduate performance variables used.

The only difference between Submarine Officers and SWO Nukes is the time in their life when they attend NPS. Submarine Officers attend NPS immediately after graduating from the Academy. The only exception is for a handful of students who are given the opportunity to earn a graduate degree between the Academy and NPS. On the other hand, SWO Nukes go to a ship and serve as a division officer after they graduate from the Academy. They have around eighteen months of sea duty under their belts when they arrive at NPS. This additional experience and time to mature makes SWO Nukes better students at NPS.

The Community: Other variable does not significantly affect NPS GPA. This variable describes NPS students who were not originally assigned to either the Submarine or SWO Nuke communities but ended up at NPS. Because Community: Other describes a small number of officers with varied and unknown histories the lack of significant affect on NPS GPA is expected.

c. How CAQPR, TQPR, and MQPR Affect NPS Performance

The strongest predictor (as shown by the β value with the greatest magnitude) in the second model is CAQPR. As a measure of performance in academic classes in multiple varying fields, CAQPR is a measure of general cognitive

ability (g). OOM's measurement of g is clouded because military and physical variables are mixed in. Because CAQPR only looks at a Midshipman's academic performance it is a much more pure measure of g . As expected, based on previous research, a measure of g (CAQPR) predicts academic performance (NPS GPA) very well. In fact it is a better predictor than OOM is in Model 1. The predictive power of CAQPR also agrees with previous research done on the Nuclear power community which shows that performance in NPS is correlated with undergraduate grades.

Surprisingly, TQPR is one of the weaker predictors (as shown by β value) of NPS GPA. One would expect that because NPS is a technical engineering school that grades in technical classes would be very strong predictors. In fact, TQPR predicts less than twenty percent of the variance predicted by CAQPR. This may be because TQPR is not as good a measure of g as CAQPR. While the relationship is weak, it is positive. Better grades in technical classes yield a higher NPS GPA.

The most interesting result of the second model shows the relationship between MQPR and NPS GPS. The regression coefficient for MQPR is small and negative. Therefore, the better a Midshipman performs militarily at the Academy the worse they will perform at NPS. This result is contrary to the Polk (2003) study which found no relationship between MQPR and NPS performance and the Rodgers (2003) study which found a strong positive relationship between MQPR and junior officer performance. Further study should be done to determine why higher military performance is related to lower grades at NPS.

Adding the three undergraduate variables to the regression has a very minimal effect on the coefficients of the Major or Community variables. Therefore, community and major are fairly independent of CAQPR, TQPR, and MQPR. The three groups of variables, major, community, and undergraduate performance, predict different aspects of the variance in NPS GPA.

3. Summary of Conclusions

This study confirms two long held beliefs in nuclear officer recruiting. First, the more technical your major the better you should do at Nuclear Power School. Second, the higher your CAQPR the better you should do at NPS. The study also showed that officers assigned to the SWO Nuke community tend to do better at NPS. OOM and CAQPR are very predictive of NPS performance but surprisingly TQPR is a weak predictor. For unknown reasons MQPR is negatively related to performance at NPS. Finally, the hierarchical regression showed that major, community, and undergraduate performance all independently affect NPS performance.

B. POLICY IMPLICATIONS

The results of this study do not create an argument for major policy changes with respect to selection of Midshipmen for nuclear power training. The current practice is to focus on recruiting Midshipmen in technical majors and Midshipmen with high OOM's or CAQPR's. Group 3 majors should not be written off. According to this model 0.5 CAQPR will negate the negative effect of having a Group 3 major. Therefore the model supports the current practice of recruiting Group 3 majors with slightly higher CAQPR's.

1. Assign Borderline Candidates SWO Nuke

One item that might be considered is changing the screening requirements for SWO Nukes. Officers who have

served a tour on a ship perform better at NPS than those officers who are directly out of the Academy. Naval Reactors could consider allowing borderline nuclear candidates to be assigned to the SWO Nuke community. If they finish the nuclear pipeline they could be allowed to transfer to the Submarine community. They would have fallen a little behind their year group but not more than an officer who attended graduate school. While this change would be a huge culture shift for the community it could help the Academy make up its falling Submarine numbers.

2. Expand Technical Majors

The last policy issue that should be considered is the assignment of Midshipmen to majors. There are many valid reasons for expanding the Group 3 majors at the Academy. The war on terror needs officers who understand the politics and culture of the Middle East. Additionally, language skills are becoming more and more important to the war fighter. At the same time the Navy is becoming more and more "high-tech." Officers who understand the complex equipment in use are vital to maintaining the fleet. When making decisions about majors Academy officials must keep in mind all the communities and weigh the costs and benefits to each. In the end expanding Group 3 majors may be the right thing to do in spite of the negative consequences to nuclear officer recruiting.

C. RECOMMENDATIONS FOR FUTURE RESEARCH

After performing this study many other questions came up. I will present three that I believe would be worth examining.

1. Officer Performance at Prototype and Engineer School

This study only looked at performance at NPS. NPS is a very academic environment. The follow-on school, Nuclear Power Training Unit (Prototype), is less academic and more hands on. The students study and take exams, but they also are evaluated on actually physically operating a nuclear power plant. Therefore the school is a much better measure of how an officer might perform in the fleet. Comparing Academy performance to performance at Prototype would give a better idea of what type of Midshipman is best for the Nuclear power program.

2. How MQPR Affects Submarine Officer Performance

The negative relationship between MQPR and NPS GPA is surprising. Examining how MPQR predicts officer performance in the fleet would be interesting. Rodgers (2003) thesis could be used as a model to see if MPQR is as predictive of Submarine Officer Fitness Report scores as it is of Surface Warfare Officer Scores.

3. Officer Performance in the Engine Room

Probably the most useful study to the Submarine force would look at what predicts officer performance in an operational engine room. This is a difficult study to perform for many reasons. One is the lack of a simple dependant variable. I recommend two different options. First, Operational Reactor Safeguards Examination (ORSE) results could be used. The ORSE is a periodic exam which every nuclear powered ship undergoes. It is an extremely thorough, multi-day inspection that checks every aspect of reactor plant operations. The second option for a dependant variable is a collection of incident reports. Incident reports are records of problems which occurred on

navy nuclear power plants. They describe the event, what caused it, and how it was fixed. Both, ORSE results and incident reports provide a picture of how officers are performing at sea. The difficulty is both ORSE results and incident reports are classified. Therefore, obtaining the data would be very difficult.

D. SUMMARY

This chapter discusses the results and implications of the study. Two long held beliefs of nuclear officer recruiting are confirmed. First, the more technical your major the better you should do at Nuclear Power School. Second, the higher your CAQPR the better you should do at NPS. Additionally, two policy implications are discussed. First, borderline candidates should be accepted, but first serve a tour as a Surface Warfare Officer. Second, technical majors at the Naval Academy should be expanded. This would create more qualified candidates for Nuclear Training. Finally, three areas are suggested for further research: Officer performance at Prototype and Engineer School; how MQPR affects Submarine officer performance in the fleet; and examining how Academy graduates perform in actual Submarine engine rooms.

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