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THESIS

IMPROVING USMC RETENTION QUALITY THROUGH REENLISTMENT PRE-APPROVAL
by
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March 2021
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Improving the quality of Marines retained has long been an objective of the Marine Corps' mission. This study assesses the effectiveness of utilizing a recently proposed binary logistic regression to select the most qualified Marines, based on their performance data, for pre-approved retention. Currently, all Marines desiring retention must submit a Reenlistment, Extension, and Lateral Move (RELM) request and await the Marine Corps' approval or rejection decision. Implementing a targeted reenlistment pre-approval process could improve the quality of retention in the Marine Corps.

To target the highest quality Marines, this study looks at the quality of Marines selected for pre-approved retention in relation to the overall First-term Alignment Plan (FTAP) retention goal and examines the effectiveness of pre-approval selection at identifying improved subsequent term performance for those Marines who have already been retained. This study also analyzes the potential impact of pre-approved retention on the availability of boat-spaces and the number of reenlistment requests submitted.

The results suggest that by targeting the highest quality (Tier-I) Marines, improved quality retention can be obtained without exceeding FTAP retention goals. Additionally, the results indicate the proposed pre-approval model effectively predicts quality performance in a Marine's subsequent term as indicated by tier calculation performance variables.

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IMPROVING USMC RETENTION QUALITY THROUGH REENLISTMENT PRE-APPROVAL

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requirements for the degree of

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LIST OF ACRONYMS AND ABBREVIATIONS

CFT	combat fitness test
CM	courts-martial
CNA	Center for Naval Analysis
Con	conduct score
DOD	Department of Defense
EAS	end of active service
ECC	expiration of current contract
ECF	enlisted career force controls
EDIPI	electronic data interchange personal identifier
FTAP	first-term alignment plan
FY	fiscal year
JEPES	junior enlisted performance evaluation system
M&RA	Manpower and Reserve Affairs
MARADMIN	Marine administrative message
MCMAP	Marine Corps Martial Arts Program
MCTFS	Marine Corps Total Force System
MMEA	Manpower Management Enlisted Assignments
MOL	Marine on-line
MOS	military occupational specialty
MPP	Manpower Plans and Policy
NDAA	National Defense Authorization Act
NJP	non-judicial punishment
OAD	Operations Analysis Directorate
ODSE	Operational Data Store Enterprise
PFT	physical fitness test
P-O	person-organization
Pro	proficiency score
PTS	perform to serve
RELM	reenlistment lateral move request
STAP	subsequent term alignment plan

TFDW	Total Force Data Warehouse
TFRS	Total Force Retention System
USMC	United States Marine Corps
UUID	unique user identifier

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I. INTRODUCTION

This study examines the use of reenlistment pre-approval as a targeted incentive to retain the highest quality Marines. In this study, I conduct a statistical analysis of the performance metrics the Marine Corps currently uses to assess the quality of potential reenlistees. The findings show that pre-approving the highest quality Marines could account for approximately 43% of the Marine Corps' First-term Alignment Plan (FTAP) objective each year. In turn, such pre-approvals would eliminate the requirement to review thousands of high-quality reenlistment requests, freeing up manpower time and fiscal resources for more thorough reviews of the lesser qualified applicants.

A. BACKGROUND

Over the last decade, the Marine Corps has implemented changes to its reenlistment processes to better focus on quality. The most significant change was implementing a tiered evaluation system to identify Marines who have excelled in relation to their peers (USMC, 2011). Despite this focus on quality, the Marine Corps has continued to struggle to retain the most talented Marines, particularly in technical occupational specialties that compete with strong civilian markets (Military Personnel, 2019). In response, the Marine Corps has utilized reenlistment incentives (e.g., monetary bonuses and duty station preferences) to entice those talented Marines to choose the Marine Corps over the civilian job market, but more needs to be done.

The National Defense Authorization Act for Fiscal Year (FY) 2020 established the minimum active-duty manning level the Marine Corps must achieve by 30 September 2020 as 186,200 personnel (National Defense Authorization Act [NDAA], 2019). To achieve and maintain this manning level, the Marine Corps utilizes two complementary methods, new accessions, and retention. In FYs 2016, 2017, and 2018, the Marine Corps recruited, on average, just over 31,000 new enlistees each year (Office of the Under Secretary of Defense, Personnel and Readiness, 2020). Once these new Marines reach the end of their enlistment term, they must decide which direction they would like their future to take. They can either choose to reenlist or end their service in pursuit of other endeavors. However, for those Marines desiring to stay in the Marine Corps, the decision is not entirely theirs.

In May 2019, Lieutenant General Michael Rocco, Deputy Commandant for Manpower and Reserve Affairs (M&RA), testified before the House Armed Services Subcommittee on Military Personnel that the Marine Corps has the highest turnover in the Department of Defense (DOD) and only retains roughly 30% of first-term enlistees, the lowest percentage when compared to the other services (Military Personnel, 2019). During each of the last five FYs, FY16-FY20, the Marine Corps sought to retain approximately 4,000 to 6,000 Marines per year (United States Marine Corps [USMC], 2015; USMC, 2016a; USMC, 2017; USMC, 2018; USMC, 2019). Restricting retention to these levels allows Marine Corps leadership discretion with regard to shaping the force (Congressional Budget Office, 2006). This discretion reinforces the 35th Commandant of the Marine Corps' guidance, which stated, "The goal of retention is to retain the most qualified instead of the 'first to volunteer,' while meeting manpower requirements and goals" (Amos, 2010, p. 14). General David Berger, the current Commandant of the Marine Corps, echo's General James Amos' opinion and recognizes that "[The Marine Corps'] manpower system was designed in the industrial era to produce mass, not quality" (2019, p. 7), and needs to be updated.

B. OBJECTIVES

This study's primary objective is to assess the accuracy and feasibility of implementing a reenlistment pre-approval process utilizing the current reenlistment tier system elements to improve retention quality. Currently, all Marines desiring retention must submit a Reenlistment, Extension, and Lateral Move (RELM) request and wait for the Marine Corps' approval or rejection decision. Implementing a reenlistment pre-approval process would accomplish multiple goals for the Marine Corps. First, pre-approving RELM requests for the most qualified Marines could increase the number of high-quality Marines retained. Second, pre-approving reenlistments would reduce the number of RELM packages M&RA personnel would have to review, facilitating more detailed reviews of the lesser qualified applicants while also saving time and resources.

Third, by pre-approving Marines for reenlistment, the Marine Corps communicates the value they see in a Marine. It tells a highly qualified Marine competitive in a civilian market that the Marine Corps desires them.

C. RESEARCH QUESTIONS

This study assesses the effectiveness of utilizing a recently proposed reenlistment pre-approval model to select the most qualified Marines, based on their performance data, for pre-approved retention. To what extent does the proposed model accurately identify the highest quality Marines without exceeding First-term Alignment Plan (FTAP) goals or pre-approving Marines disqualified for retention? How can the proposed model be refined to improve retention quality? My findings indicate that by limiting reenlistment pre-approvals to Tier-I Marines, the Marine Corps can effectively target high quality Marines without exceeding FTAP allocated retention limits.

In addition to the primary research questions, I also examine whether advertised Military Occupational Specialty (MOS) availability, as indicated by boat-spaces, impacts the rate of reenlistment submission? In this regard, my findings do not identify a correlation. Finally, I look at how selection for retention pre-approval affects performance in a Marine's subsequent term. My results show that retained Marines who would have been selected for pre-approval by the model perform better on average than retained Marines not selected for pre-approval.

D. SCOPE, LIMITATIONS, AND ASSUMPTIONS

1. Scope

This study focuses on the population of first-term enlisted Marines whose first enlistments expired in FY 2016-FY 2020. Utilizing the FY retention goals published by M&RA's Manpower Management Enlisted Assignments (MMEA) Branch as a baseline, I compare the quality of those Marines who applied for and accepted reenlistment to those who did not submit a request or whose reenlistment request was denied by the Marine Corps.

2. Limitations

a. Command input to Tier Recommendation

An important aspect of the reenlistment tier assignment process is the command recommendation that can move a Marine, up or down, to a tier level other than their numerically calculated tier. As command recommendations are not available for Marines who did not submit a reenlistment request, this study only uses numerically calculated tiers.

b. Changes to Performance Evaluation

On 1 February 2021, the Marine Corps transitioned to a new method of assessing junior enlisted performance. The Junior Enlisted Performance Evaluations System (JEPES replaced the legacy proficiency and conduct markings (USMC, 2020). This study's population all received proficiency and conduct marks as an aspect of their performance to calculate their reenlistment tier category. As such, no data exist for this population about the Junior Enlisted Performance Evaluations System (JEPES) and how it would alter their calculated quality.

3. Assumptions

The Marine Corps JEPES will assess performance with the same or improved accuracy as the proficiency and conduct marks did previously. Therefore, I assume calculated tiers based on new JEPES scores will more accurately assess performance. Any model developed utilizing proficiency and conduct marks should be enhanced when replaced by JEPES scores.

E. LITERATURE REVIEW

This topic's literature review focuses on previous works involving military retention, both endogenous and exogenous, to the Marine Corps. While most of the literature focuses on how military services can utilize incentives such as monetary bonuses and preferred duty station locations as tools to meet quantitative retention goals, there is an emerging interest in retaining quality over quantity. In 2007, the Center for Naval Analysis (CNA) conducted a study for the Navy to identify more responsive and cost-effective methods of retaining the most qualified sailors (Koopman, 2007). In 2014, Alexandra Cole conducted a study of the Marine Corps' computed tier system's impacts on the retention of quality first-term personnel. In 2015, Lucas Crider evaluated the Marine Corps' tiered evaluation system's effectiveness in predicting Marines' future success. More recently, in January 2021, the Marine Corps' Operations Analysis Directorate (OAD) proposed a model for pre-approving first-term Marines for retention (Terry et al.) by evaluating submitted reenlistment requests.

The first two studies find that appropriate incentives are necessary within the reenlistment process, but current incentives do not address the quality component (Koopman, 2007) (Cole, 2014). The third study finds that although the tier system is the foundation for identifying quality Marines for retention, it could be improved to enhance overall organizational effectiveness and quality (Crider, 2015). The OAD study identified a binary logistic regression model that accurately predicted reenlistment approval while minimizing false selections (Terry et al., 2021); however, the OAD study looks only at Marines who sought retention. This study builds upon the OAD research by expanding the reenlistment approval predictive model to all first-term Marines with expiring enlistments.

When the CNA conducted its review to determine better methods for retaining quality, the Navy had recently implemented a Perform to Serve (PTS) policy "intended to improve the quality of reenlistments and level manning" (Koopman, 2007, p. 2). The PTS used an algorithm to measure sailor quality, similar to the Marine Corps' tier system, which should have improved reenlistment quality. However, the CNA report noted that "the PTS system led to few people being denied reenlistment" (Koopman, 2007, p. 3). The CNA report concluded that PTS was ineffective at improving retention quality at that time, and since monetary bonuses did not bridge the gap from military pay to available civilian pay, the Navy should consider other incentives and policies directed at retaining quality should (Koopman, 2007).

In reviewing the tier system's impact on quality retention, Cole (2014) analyzes Marines' quality based on the relationship between their expiration of active service (EAS) date and when they submitted for reenlistment. Her research indicates higher quality levels are associated with earlier reenlistment submissions, and preference may exist to approve higher quality Marines early in the FY reenlistment window, which runs for 15 months from July through September of the following year. Like the CNA's PTS findings, Cole notes that the overall quality of retention appears to remain the same as before the tier system implementation. Furthermore, she notes that after implementation of the tier system, "70% of tier 4 Marines, [the lowest quality], were still being offered reenlistment" (p. 57). Cole also notes that for the Marine Corps to improve overall retention quality, an increase must occur in the number of highest tier Marines who apply for reenlistment, which could come through a targeted pre-approval process.

Crider (2015) expands on Cole's research to look at the future successes of Marines retained from each tier category, as measured by performance evaluation averages, career longevity, promotion speed, and physical fitness levels. His study indicated that as a retained Marine drops from tier one to tiers two, three, or four (i.e., the assessed quality of the retained Marine goes down), their likelihood of success in these measured categories decreased from one tier to the next lower tier. Crider also tests the effects of subdividing tiers two and three to provide a broader range tier system. The results of subdividing the tiers led him to conclude that although the tiered evaluation system currently identifies individual quality to an extent, there is room for improvement. He also recommends that "the Marine Corps should develop incentives to target individuals identified as high-quality" (p. 62).

The most recent study in this arena focuses on evaluating current tier quality algorithms and developing purpose-built algorithms to assist the retention process (Terry et al., 2021). Their research finds the current tier quality algorithm's accuracy to be around 65%, with a false positivity rate of nearly 25%. After analyzing multiple purpose-built models, the OAD study reduces the false positivity rate to nearly 0% by utilizing a binary logistic regression. The team notes that a limitation of their research was only analyzing Marines who submitted a reenlistment request rather than looking at the entire FTAP population, which this study aims to do.

F. MOTIVATION FOR THIS STUDY

When General David Berger took the Marine Corps' helm as its 38th Commandant, he brought a bold strategy and vision of how the Marine Corps of the future would fight.

He assessed that the current Marine Corps force structure needed to change so that as an organization, it is better organized, trained, and equipped to meet future requirements (Berger, 2019). Increasing retention of the most qualified and most talented Marines is a crucial element in adequately staffing the Marine Corps of 2030. For the Marine Corps to be successful in retaining the most qualified, it must identify the Marines it needs to retain and subsequently communicate to them the Marine Corps' desire to keep them on board. Understanding the Marines' motivation facing a reenlistment decision helps the Marine Corps communicate its desire to retain them.

The FY 2016 EAS Enlisted Survey Results indicate that having pride in the Marine Corps is one of the most influential factors in Marines' decisions to reenlist, followed closely by their desire to lead and train fellow Marines (USMC, 2016b). Examining these results through an organizational behavior lens indicates that establishing a good person-organization (P-O) fit motivates Marines to reenlist. In an article in *Personnel Psychology*, Dr. Amy Kristof defines P-O fit is as "the compatibility between people and organizations that occurs when: (a) at least one entity provides what the other needs, or (b) they share similar fundamental characteristics, or (c) both" (1996, pp. 4-5). Wanting to lead and train Marines satisfies the first element of this definition. Having pride in the Marine Corps demonstrates the unity of personal and organizational values, the second element of the definition. Dr. Kristof also proposes that the perceived P-O fit may be more impactful on an individual than the actual P-O fit. I believe that pre-approving the most qualified Marines for retention communicates to those the Marine Corps needs to retain that their performance is valued. It also reinforces that the Marine Corps wants them to stay, a message that may bolster the Marine's perceived P-O fit and increase their desire to reenlist.

G. CHAPTER SUMMARY

This chapter details the purpose and context necessitating this study. Previous research and the motivation for this topic supply the foundation upon which this study begins. Increasing the overall quality of persons serving in the Marine Corps will always be a top priority. This study proposes one method of doing so by targeting high-quality

Marines through reenlistment pre-approvals. The following chapters will provide greater fidelity and detail into the current reenlistment processes and the methodologies I utilize to conduct this research.

II. BACKGROUND

A. WHAT IS FORCE DESIGN?

Force design refers to how the future Marine Corps, as an organization, is structured, manned, trained, and equipped to fulfill its statutory obligations to the United States of America. The design of the force directly affects manpower policies and desired retention goals. As the senior military officer in the Marine Corps, it is the Commandant's responsibility to ensure the Marine Corps is prepared to meet future operating environments' demands. As the assessment of future threats changes, so too must the Marine Corps' design. Therefore, General Berger (2020) has directed the Marine Corps to examine all facets of its force design to ensure proper alignment of the future force with the National Defense Strategy. In his *Force Design 2030* report, General Berger noted that "while the Future Force we are developing is different in terms of structure and capabilities, it is consistent with our historical roots as Fleet Marine Forces and directly supports our Title 10 responsibility to seize and defend advanced naval bases and perform all such duties as directed by the President" (p. 13). The Marine Corps now, and in its future design, will continue operating as the premier crisis response force for the nation (Berger D. H., 2020); retaining the most talented and most qualified Marines is instrumental in ensuring this.

B. MARINE CORPS ENLISTED RETENTION PROGRAM

As outlined in Marine Corps Order 1040.31 (USMC, 2010), the objective of the Marine Corps' enlisted retention and career development program is twofold: 1) "To provide the Marine Corps with the most qualified force by grade and MOS to support staffing all authorized career force billets" and 2) "To standardize promotion tempo across all MOSs to match time-in-service targets" (p. 1-1). The Marine Corps utilizes Enlisted Career Force Controls (ECFCs), published annually by the Commandant of the Marine Corps via Manpower Plans and Policy (MPP) branch of M&RA, to ensure these objectives are achieved (USMC, 2010). According to the M&RA website, ECFCs were implemented in 1985 to manage better the personnel levels of enlisted Marines (Enlisted Plans [MPP-20], 2020). One of the two main ECFCs utilized to achieve retention of both quantity and quality Marines is the First-term Alignment Plan (FTAP) and the Subsequent Term Alignment Plan (STAP).

1. First-Term Alignment Plan

The Enlisted Retention Manual (2010) defines First-term Marines as those active-duty Marines still fulfilling their service obligations on an initial contract or an extension to that initial contract. The Marine Corps FTAP is a "retention program used to reenlist First-term Marines, by MOS, to meet career force requirements, while preventing promotion stagnation and ensuring opportunities for advancement" (USMC, 2010, p. A-3). Additionally, the FTAP established which MOSs are open to reenlistments and accept lateral moves and which MOSs are closed (USMC, 2010).

MMEA publishes the FTAP annually to provide guidance on the retention goals for each FY. The scope of each FY FTAP covers all first-term Marines who have an Expiration of Current Contract (ECC) date during that FY, which runs from 1 October to 30 September. For example, an active duty Marine whose initial contract expires on 1 December 2019 would be covered under the scope of the FY 2020 FTAP. A first-term Marine whose ECC is 1 September 2020, or a Marine whose original ECC was 1 August 2019 but received a 6-month extension to 1 February 2020 would also be within the FY 2020 FTAP scope.

An integral component of FTAP is a quality breakdown of each Marine's performance within their MOS. On 5 July before each FTAP (e.g., 5 July 2019 for FTAP 2020), the Total Force Retention System (TFRS), an electronic processing system utilized for retention, captures performance data from the Marine Corps Total Force System (MCTFS) for each FTAP Marine. From the performance data, TFRS computes a tiered breakdown with Tier-I being the top 10% within their MOS, Tier-II the next 30% of their MOS, Tier-III the next 50% of their MOS, and Tier-IV being the last 10% of their MOS.

2. Subsequent Term Alignment Plan

The Marine Corps defines any "Marine serving on their second or subsequent [contract], including any extensions to that contract" as a career Marine (USMC, 2010, p. A-1). Career Marines are managed by the STAP, which is "the retention program used to proactively target and reenlist career Marines while improving retention and promotion tempos across all MOSs (USMC, 2010, p. A-6). The success or failure of previous FTAPs influences the STAP, which is also published annually by MMEA to establish retention goals for all career Marines. Although retention of STAP Marines is not the target of this research, subsequent term Marines' performance qualities are analyzed to identify the accuracy of pre-reenlistment quality predictions. Furthermore, if reenlistment pre-approval correlates with higher quality in subsequent term performance, there may be an impact on future STAP goals.

C. REENLISTMENT, EXTENSION, AND LATERAL MOVE, REQUEST PROCESS AND ROUTING

The Marine Corps currently utilizes an iterative process to facilitate reenlistments for first-term Marines. The process begins between 26 and 24 months before a Marine's ECC with an initial interview between the Marine and their Career Planner (USMC, 2010). The Career Planner is an enlisted career Marine in each unit responsible for advising commanders and Marines on all aspects of retention (USMC, 2010). This initial interview allows the Career Planner to familiarize the Marine with the FTAP process, ensure the Marine the available reenlistment benefits and incentives, and ensure the Marine meets all reenlistment or lateral move prerequisites (USMC, 2010). A year later, 14-12 months before their ECC, the Marine, and Career Planner execute an FTAP Interview to review the FTAP process, reiterate the benefits of a Marine Corps career, and reinforce the need for a complete and competitive performance record (USMC, 2010).

If a Marine decides to pursue reenlistment after completing the first-term interviews, they must then work with the Career Planner to generate a RELM package that follows the process flow outlined by Cole (2014) in Figure 1. Although not all twenty-five to thirty thousand FTAP Marines submit a RELM each year, MMEA must still review thousands of RELM packages each year, consuming a significant amount of time and resources.

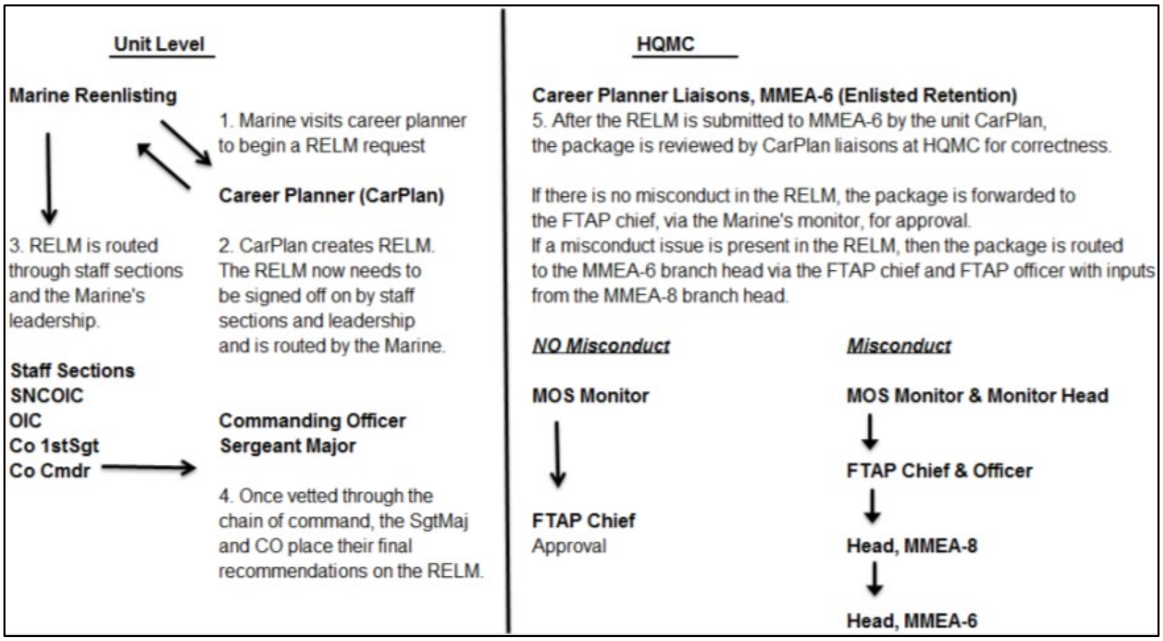


Figure 1. RELM request Process Flow. Source: Cole (2014).

D. CHAPTER SUMMARY

This chapter provides the necessary background associated with the Marine Corps' reenlistment process. As this study focuses on targeting high-quality Marines within the FTAP category, it is important to understand the current retention framework. The following chapters address the potential improvements to this process through a reenlistment pre-approval approach targeting the highest quality Marines.

III. DATA AND METHODOLOGY

This study quantitatively analyzes USMC retention eligibility requirements and performance measurements to assess the applicability of a reenlistment pre-approval process by combining multiple data sources. This chapter describes the sources of data, the formulation of the sample population of FTAP Marines, and the data cleaning and merging process facilitating the statistical analysis conducted using the STATA software program. As this study involves multiple phases, data cleaning resulted in numerous datasets. The first phase of data cleaning results in a dataset comprising only Marines who submitted a reenlistment request for FY 2013 through FY 2019. The second compiled dataset contains all Marines with expiring first-terms from FY 2016 to FY 2020. The final phase of data cleaning results in a third dataset comprised of only those Marines who the Marine Corps retained in FYs 2016 through 2019. The chapter concludes with a description of the methodology utilized in each phase of this study.

A. DATA SOURCES

1. Total Force Retention System

The Total Force Retention System (TFRS) is an electronic processing system that facilitates the processing of all Reenlistment, Extension, and Lateral Move (RELM) requests (USMC, 2010). The data stored in TFRS is derived directly from the Marine Corps Total Force System (MCTFS) and may not be current due to delayed unit diary reporting (USMC, 2010). This study utilizes the TFRS data associated with all RELM requests submitted for FY 2013 through FY 2019 to reproduce and confirm the results reported by Terry et al. (2021). Later in this chapter, I provide a detailed breakdown of the variables and data cleaning process.

2. Total Force Data Warehouse

The Total Force Data Warehouse (TFDW) houses historical manpower data from numerous USMC and DoD systems and is the Marine Corps' official system of record for end strength reporting (USMC, 2021b). The data of interest for this study provided by

TFDW comes primarily from the monthly uploading of data from MCTFS and Operational Data Store Enterprise (ODSE). The accessed TFDW datasets contain performance and demographic variables for all active-duty enlisted Marines within this study's scope. The collected TFDW data was utilized to identify reenlistment eligibility and calculate reenlistment tier quality per the Enlisted Retention Manual, Marine Corps Order 1040.31.

B. PHASE ONE DATA CLEANING

This section identifies the procedures I use to clean and merge the data files sourced from TFRS and TFDW to re-create and confirm the results of Terry et al. (2021). To ensure accuracy and maintain the data files' integrity, I clean the TFRS and TFDW datasets independently before merging them.

1. TFRS Data

The TFRS data includes panel and pooled cross-sectional datasets for those Marines who submitted a RELM request from FY 2003 to FY 2019 and aggregated MOS averages and availability for each FTAP. The TFRS datasets contained individual Marine performance variables, legal action history, boat-space availability for each MOS in each FY, and reenlistment request variables.

a. Marine Performance dataset

The Marines' performance data from TFRS arrived as cross-sectional datasets containing observations for Marines who submitted a reenlistment package between FY 2003 and FY 2019. The data includes 164,333 observations, each uniquely identified by an electronic data interchange personal identifier (EDIPI). To protect all Marines' identities whose information was utilized for this study and to ensure compatibility with all data sourced from TFDW, I replaced all EDIPIs with a unique user identifier (UUID) number supplied by TFDW and removed the EDIPIs from the dataset. I transform each performance variable from character to numeric to facilitate statistical analysis. Using the date of rank variable, I create a Meritorious Promotion indicator variable equal to one if the date of rank was the second of the month and the grade change was positive (i.e., not a reduction in rank). I remove all observations before FY 2013 to limit the scope of observations to the years utilized in the study by Terry et al. (2021).

b. Legal Action Dataset

The legal action dataset sourced from TFRS contains 22,691 observations grouped by EDIPI. As with the performance dataset, I replace the EDIPIs with corresponding UUIDs. The pooled cross-sectional dataset contains a legal action date variable and a legal action type variable for each observation. I convert the legal action type variable to indicator variables for civilian convictions, courts-martial type (e.g., general, special, or summary), and non-judicial punishments (NJP). To identify the number of legal actions incurred by each Marine, I calculate the sum of each legal type by UUID, resulting in a cross-sectional dataset of 19,412 unique observations containing the number of NJPs and courts-martial for each UUID.

c. Boat-Space Availability dataset

The boat-space availability dataset arrived as time-series data with a boat-space availability value for each MOS in each FY. To facilitate this dataset's merging with the individual Marine observations, I transform the data from long to wide using MOS as the identifier variable and FY as the sub-observation identifier variable. The resulting dataset contains one observation per MOS with a variable of available boat-spaces for each FY. Once merged with the other datasets, each Marine's observation includes the number of boat-spaces available for their MOS in their respective FTAP year.

d. RELM Requests Dataset

The TFRS pooled cross-sectional dataset of RELM requests contains 164,332 observations of submitted RELMS from FY 2003 to FY 2019 with multiple requests per EDIPI. The dataset includes RELM type, RELM status, RELM approval/disapproval dates, and reenlistment tier category variables. I convert the RELM type variable to indicator variables for reenlistment requests, extension requests, and lateral move requests. As with the other TFRS datasets, I remove all observations before FY 2013, replace the EDIPIs with UUIDs, and remove the EDIPI variable. I convert the RELM status variable to indicator variables for RELM Approved, RELM Disapproved, RELM Revoked, and RELM Declined (i.e., Marine elected not to reenlist despite having their RELM approved). I convert the reenlistment tier category variables to numerals equivalent to their tier (e.g., Tier I = 1, Tier II = 2, etc.). To filter out the multiple requests per Marine, I sort the data by the RELM completion date per UUID and keep the last request submitted (i.e., most recent) per UUID. To facilitate analysis in later phases, I generate a RELM submitted variable equal to one for all observations in this dataset.

2. TFDW Data

TFDW provided panel and pooled cross-sectional datasets comprised of observations for all enlisted Marines regardless of whether a RELM was submitted. The following categories were panel datasets: PFT, CFT, Proficiency and Conduct Marks, MCMAP Belts, Rifle Qualification, and Legal Action. TFDW provided cross-sectional datasets for ASVAB Scores and Demographics.

a. PFT and CFT Datasets

The PFT and CFT datasets contain observations grouped by UUID for each semi-annual PFT and CFT during a Marine's enlistment. The PFT dataset contains 2,399,577 observations, and the CFT dataset 1,991,485 observations. Each dataset contains a variable for each fitness test element, an overall event score variable, and an event date variable. I convert all non-time/date variables to numeric and each time variable (e.g., run times) to minutes and seconds format to facilitate statistical analysis. To filter out multiple PFT and CFT scores per Marine for the initial phase, I sort the observations by event completion date within each UUID. I then remove all observations occurring after the RELM completion date. I retained only the PFT and CFT observations occurring closest to the RELM completion date resulting in 218,964 PFT observations and 217,789 CFT observations.

b. Proficiency and Conduct Marks Dataset

The proficiency and conduct marks dataset contains 3,141,951 observations grouped by UUID. Each observation includes the average proficiency and conduct marks for their current grade, current enlistment, and in service as calculated on the date TFDW uploaded the data from MCTFS. The dataset stores all six variables as numeric values without decimals (e.g., 4.4 average proficiency in enlistment stored as 44). Using the snapshot date variable, I sort the observations within each UUID, remove all occurrences after the RELM complete date, and retain the nearest snapshot of proficiency and conduct marks to that date, resulting in 230,036 observations.

c. MCMAP Belts Dataset

The MCMAP Belt dataset is also grouped by UUID with 817,701 observations containing each belt level attained and each belt's associated award date. For the tier level calculations, I convert each MCMAP Belt to its corresponding numerical value. Tan belts have a numerical value of five, Gray Belts are ten, Green Belts 15, Brown Belts 20, 1st Degree Black Belts 25, 2nd Degree 30, 3rd Degree 35, 4th Degree 40, 5th Degree 45, 6th Degree 50, Green Belt Instructor 60, Brown Belt Instructor 70, 1st Degree Black Belt Instructor 80, 1st Degree Black Belt Instructor 1st Degree 90, 1st Degree Black Belt Instructor 2nd Degree 95, and Chief Instructor 100. I convert all text MCMAP belt entries into their corresponding value to facilitate tier calculations and statistical analysis. Using the date belt earned variable, I sort the observations within each UUID, remove all occurrences after the RELM completion date, and retain the nearest MCMAP Belt score to that date, resulting in 145,652 observations.

d. Rifle Qualification Dataset

The Rifle Qualification dataset contains 1,451,214 observations grouped by UUID with rifle score and qualification date variables. I convert the rifle scores from character to numeric to facilitate statistical analysis. I sort the data by rifle qualification date, remove all observations occurring after the FTAP performance calculation date, and retain the nearest rifle score to that date, resulting in 219,438 observations.

e. Demographics

The cross-sectional Demographics dataset from TFDW contains 506,995 uniquely identified by UUID with a continuous variable for age, categorical variables for grade, gender, race/ethnicity, education, and MOS, and date variables for EAS date and pay entry base date (PEBD). I convert the pay grade variable from a categorical variable to a continuous rank variable representing the pay grade. For example, Private (E1) is equal to one, Private First Class (E2) is equal to 2, and so on. I convert gender to an indicator variable equaling one if gender is Male and zero if gender is Female. I convert the education variable to binary using the same logic as the education information in the TFRS dataset. I transform the race/ethnicity variable from categorical to seven indicator variables representing the following categories: American Indian/Alaskan, Asian, African American, Hawaiian/Pacific Islander, Hispanic, White, and Other/Unknown.

3. Phase One Data Merging and Statistics

To create the phase one dataset, I merge the cleaned TFRS datasets with the cleaned TFDW datasets using the UUID variable. As this study focuses only on pre-approving Marines for reenlistment within their current MOS, I retain only observations where reenlistment requests are equal to one. As both TFRS and TFDW pull data from MCTFS, multiple variables existed for the same event (e.g., TFRS CFT Score, and TFDW CFT Score, etc.). Due to TFRS data being pulled in July each year, diary entries ran in MCTFS after the TFRS pull date for events completed before the pull date are not up to date in TFRS. However, TFDW pulls data monthly, so post-dated events missed by TFRS are captured by TFDW, resulting in minor inconsistencies between TFRS and TFDW reported values. In instances where duplicate variables existed with different values, I retain the max score for that observation. After merging the datasets, I drop all observations with missing values. This merge process creates a dataset of 37,591 reenlistment request observations from FY2013 to FY2019. Table 1 shows the summary statistic of the variables I retain and use in the phase one dataset.

Table 1. Dataset One Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
uuid	37,591	N/A	N/A	N/A	N/A
tier	37,591	2.18	0.80	1	4
fy	37,591	2016	1.96	2013	2019
pft	37,591	258.14	30.26	0	300
cft	37,591	285.51	22.39	0	300
pro	37,591	44.17	1.07	0	48
con	37,591	44.11	1.11	0	48
rifle	37,591	309.14	19.73	0	350
mcmap	37,591	19.18	14.59	0	95
njp_count	37,591	0.08	0.28	0	3
cm_count	37,591	0.00	0.01	0	1
merit	37,591	0.09	0.28	0	1
relmapproved	37,591	0.99	0.10	0	1
relmdeclined	37,591	0.09	0.29	0	1
relmrevoked	37,591	0.00	0.01	0	1
relmcompledate	37,591	N/A	N/A	2 Aug 2012	19 Sep 2019
numofbtspaces	37,591	121.63	123.99	0	515
availboatspace	37,591	1.00	0.01	0	1
mos	37,591	N/A	N/A	0111	8011
rank	37,591	4.11	0.52	1	5
dateofrank	37,591	N/A	N/A	1 Dec 2008	16 Aug 2019
ecc	37,591	N/A	N/A	1 Sep 2012	6 Oct 2021
age	37,591	26.50	3.04	20	47
gender	37,591	0.90	0.30	0	1
submittedrelm	37,591	1	0	1	1

Note: Means and Standard Deviations were omitted for date and categorical variables.

C. PHASE TWO DATA CLEANING

This section identifies the procedures I use to clean and merge the data files to create a dataset comprising all Marines with expiring first-terms from FY 2016 to FY 2020. As with phase one, I clean the TFRS and TFDW datasets independently before merging them for phase two.

1. TFRS Data

From the TFRS datasets, I only need the RELM approval, RELM submitted, and boat-space availability variables for phase two. I clean these variables in the same manner as described in phase one.

2. TFDW Data

In addition to utilizing the raw TFDW datasets from phase one, phase two includes a pooled cross-sectional Legal Action dataset from TFDW containing legal action date and legal action type variables for each observation. I clean this Legal Action dataset in the same manner as the TFRS Legal Action dataset in phase one. For this phase, I also clean the reused datasets in the same manner as in phase one, except for the method utilized to filter out multiple event occurrences. Since only 20% of the sample population contains RELM complete dates, I use the 5 July FTAP tier calculation date as the cutoff for all performance, rank, and legal action variable filtering instead of the RELM complete date. This cleaning method reduces the PFT and CFT datasets from 2,399,577 observations, and 1,991,485 observations respectively to 218,964 PFT observations, and 217,789 CFT observations. The cleaning reduces the Proficiency and Conduct dataset from 3,141,951 to 230,036 observations, the MCMAP dataset from 817,701 to 145,652 observations, the rifle qualifications dataset from 1,451,214 to 219,438, and the legal action dataset from 134,516 to 56,970 observations.

The Dates of Rank dataset contains 2,030,158 observations grouped by UUID with a pay grade variable and a date rank achieved variable. I convert the pay grade variable from a categorical variable to a continuous rank variable representing the pay grade. For example, Private (E1) is equal to one, Private First Class (E2) is equal to 2, and so on. Using the date of rank variable, I create a Meritorious Promotion indicator variable equaling one if the Marine's date of rank was the second of the month and the grade change was positive. I sort the dataset by date of rank, remove all observations occurring after the FTAP performance calculation date, and retain the nearest rifle score to that date, resulting in 219,438 observations in the Dates of Rank dataset.

3. Phase Two Data Merging and Summary Statistics

I create the second dataset by merging the RELM approval, RELM submitted, and boat-space availability variables from the TFRS dataset with the TFDW datasets using the UUID variable. Once combined, numerous missing values exist across multiple performance variables for observations without a RELM submission before FY 2016. After removing all missing observations, I find a significant difference in the sample sizes between pre- and post-FY 2016, as indicated in Table 2.

Table 2. Distribution of Observations by FY

FTAP	Freq.	Percent	Cum.
2013	5,573	3.89	3.89
2014	4,670	3.26	7.15
2015	5,455	3.81	10.96
2016	23,330	16.28	27.24
2017	28,152	19.65	46.89
2018	25,347	17.69	64.58
2019	27,874	19.45	84.03
2020	22,880	15.97	100
Total	**143,281**	**100**	

Note: Missing performance values prevalent in pre-FY2016 data

I retain only observations from FY 2016 to FY 2020 to maintain statistical accuracy and calculate reenlistment tier levels, resulting in a dataset with 127,583 observations across five FYs. Table 3 displays the summary statistics for the phase two dataset.

Table 3. Dataset Two Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
uuid	127,583	N/A	N/A	N/A	N/A
tier	127,583	2.60	0.79	1	4
ftap	127,583	2017	1.37	2016	2020
pft	127,583	235.13	60.31	0	300
cft	127,583	276.60	36.49	0	300
pro	127,583	43.37	1.36	14	49
con	127,583	43.26	1.52	11	49
rifle	127,583	306.35	25.09	0	350
mcmap	127,583	13.78	9.35	0	90
njp_count	127,583	0.20	0.51	0	6
cm_count	127,583	0.01	0.10	0	3
merit	127,583	0.05	0.21	0	1
numofbtspaces	127,583	133.11	150.34	0	515
availboatspace	127,583	0.76	0.43	0	1
mos	127,583	2,600.63	2,388.52	100	8,972
rank	127,583	3.83	0.75	1	5
dor	127,583	N/A	N/A	1 Oct 2008	5 Jul 2019
ecc	127,583	N/A	N/A	1 Oct 2015	30 Sep 2020
age	127,583	23.75	2.38	17	40
gender	127,583	0.91	0.28	0	1
pebd	127,583	N/A	N/A	10 Oct 2000	13 Jul 2019
submittedrelm	127,583	0.20	0.40	0	1
relmapproved	25,585	0.99	0.11	0	1

Note: Means and Standard Deviations were omitted for date and categorical variables.

D. PHASE THREE DATA CLEANING

This section identifies the procedures I use to clean and merge the datasets to analyze all first-term Marines retained by the Marine Corps from FY 2016 through FY 2019.

1. TFRS Data

I only need the RELM approval, RELM submitted, RELM Declined, and boat-space availability variables from the TFRS datasets for phase three. These variables are cleaned in the same manner as described in phase two.

2. TFDW Data

In addition to utilizing the original TFDW performance datasets from phases one and two, phase three includes an Awards pooled cross-sectional dataset grouped by UUIDs with variables for award remark code, award device code, award date, and award description. Each of the original TFDW datasets is cleaned in the same initial manner as discussed in phase one. However, for the legal action dataset and each performance dataset, rather than keeping the nearest occurrence before the RELM complete date, in this phase, I remove observations for all values occurring before, and more than four years beyond, the RELM completion date. The data cleaning results in pooled cross-sectional datasets grouped by UUID for the PFT, CFT, Proficiency and Conduct Marks, MCMAP Belts, and Rifle Qualification datasets, and a cross-sectional dataset for Legal Action. I collapse each of these datasets to create a mean, a minimum, and a maximum variable in each dataset. The resulting PFT dataset contains 103,368 observations, the CFT dataset 96,527 observations, the Proficiency and Conduct Marks dataset 100,417 observations, the MCMAP Belt dataset 38,944 observations, and the Rifle Qualification dataset contains 86,156 observations.

The Awards dataset contains 4,808,327 observations grouped by UUID with variables for award code, device code, award name, and date awarded. I generate indicator variables for personal awards, valor devices, and combat condition devices. I then remove all observations for service, and unit awards, as they are not part of this study. As with the other performance data, I remove all awards received before, and more than four years beyond, the RELM completion date. Utilizing the created indicator variables, I collapse the dataset by UUID resulting in a cross-sectional data set with 106,698 observations and variables for the total number of personal awards, the total number of valor devices, and the total number of combat conditions devices earned by each Marine after being retained.

3. Phase Three Data Merging and Summary Statistics

I merge the cleaned phase three TFDW datasets with the phase two-post analysis dataset resulting in a cross-sectional dataset of 30,838 observations of Marines retained between FY 2016 and FY 2019.

Table 4. Dataset Three Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Variable	Obs	Mean	Std. Dev.	Min	Max
uuid	30,838	N/A	N/A	N/A	N/A	enl_term	30,831	1.81	0.58	1	3
tier	30,838	2.31	0.78	1	4	pft_mean	27,929	238.16	51.09	0	300
ftap	30,838	2017.53	1.11	2016	2019	pft_min	27,929	216.22	79.22	0	300
pft	30,838	254.38	39.63	0	300	pft_max	27,929	255.15	41.74	0	300
cft	30,838	285.46	25.58	0	300	cft_mean	27,180	263.80	43.58	0	300
pro	30,838	43.97	1.08	21	48	cft_min	27,180	243.14	74.22	0	300
con	30,838	43.91	1.14	21	49	cft_max	27,180	279.91	33.91	0	300
rifle	30,838	308.95	21.00	0	348	pro_mean	27,558	21.16	17.75	0	49
mcmap	30,838	17.33	12.41	0	90	pro_min	27,558	9.13	17.76	0	49
pre_njps	30,838	0.11	0.35	0	4	pro_max	27,558	28.06	21.63	0	50
pre_cms	30,838	0.00	0.05	0	2	con_mean	27,558	21.10	17.70	0	49
merit	30,838	0.07	0.26	0	1	con_min	27,558	9.10	17.71	0	49
btspace_num	30,838	107.79	126.13	0	515	con_max	27,558	28.01	21.60	0	50
availboatspace	30,838	0.90	0.30	0	1	rifle_mean	19,563	312.23	19.93	122	350
mos	30,838	N/A	N/A	100	8972	rifle_min	19,563	306.20	28.99	1	350
rank	30,838	4.89	0.68	1	7	rifle_max	19,563	317.69	16.72	127	350
age	30,838	25.55	2.55	19	40	mcmap_mean	11,150	25.95	15.49	5	95
gender	30,838	0.90	0.31	0	1	mcmap_min	11,150	21.78	12.40	5	95
pebd	30,838	N/A	N/A	10 Oct 2000	6 Mar 2018	mcmap_max	11,150	29.94	21.19	5	95
submittedrelm	30,838	1.00	0.00	1	1	award_count	25,509	0.59	0.75	0	5
relmapproved	30,838	1.00	0.00	1	1	valor_count	25,509	0.00	0.02	0	1
relmdeclined	30,838	0.00	0.00	0	0	cmbtcnd_count	25,509	0.01	0.09	0	2
relmcompledate	30,767	N/A	N/A	5 Jul 2015	15 Apr 2020	post_njps	30,838	0.07	0.28	0	4
pmos	30,838	N/A	N/A	100	8972	post_cms	30,838	0.01	0.08	0	2

Note: Means and Standard Deviations were omitted for date and categorical variables.

E. METHODOLOGY

For this study, I use the statistical analysis software STATA version 16.0 to clean and analyze the data. To answer each of the research questions, I separate the analysis process into three phases. The first phase aims to recreate, as closely as possible, the results reported by Terry et al. (2021). In the second phase, I expand the sample from only Marines who submitted reenlistment requests to all FTAP Marines. I use the third phase to examine the statistical performance of retained Marines to identify the predictive model's ability to predict subsequent term success.

1. Phase One

I begin this phase by recreating, as closely as possible, the binary logistic regression results reported by Terry et al. (2021). As noted, their study indicates that the binary logistic regression model utilizing the Marine Corps' tier calculation variables predicted the probability of RELM approval with a false positive selection rate between 0% and 1%. Using the same tier calculation variables, I check for a correlation between variables amongst my phase one dataset. I find proficiency and conduct marks highly correlated (see Table 5), as did Terry et al. (2021). After accounting for the collinearity, I split the 37,591 observations into an 80% training set and 20% validation set to confirm the binary logistic regression proposed by Terry et al. (2021).

Table 5. Tier Calculation Variable Correlation Matrix

	pft	cft	pro	con	rifle	mcmap	njp_count	cm_count	merit
pft	1.000								
cft	0.353	1.000							
pro	0.241	0.170	1.000						
con	0.216	0.151	0.856	1.000					
rifle	0.044	0.032	0.096	0.076	1.000				
mcmap	0.178	0.120	0.218	0.212	0.052	1.000			
njp_count	0.002	-0.008	-0.147	-0.270	0.003	-0.019	1.000		
cm_count	0.000	0.003	-0.009	-0.021	0.001	0.000	0.003	1.000	
merit	0.125	0.098	0.240	0.238	0.011	0.114	-0.031	0.002	1.000

Utilizing the following binary logistic regression, as proposed by Terry et al. (2021):

$$\begin{aligned}\Pr(\text{Reenlistment Approval}) = \beta_0 + \beta_1\text{PFT} + \beta_2\text{CFT} + \beta_3\text{Conduct} + \beta_4\text{Rifle} + \beta_5\text{MCMAP} + \\ \beta_6\text{Meritoriously Promoted} + \beta_7\text{NJP} + \beta_8\text{Courts-Martial} + \varepsilon\end{aligned}$$

I generate a pre-approval indicator variable equal to one if the probability of reenlistment approval is greater than 0.5 and equal to zero otherwise. Using this variable compared with whether the RELM was approved, I calculate the rate of false positives generated by this model.

2. Phase Two

After validating the model's accuracy using the RELM submitted dataset, I refit the binary logistic regression model to on larger dataset of all FTAP Marines. Before running the regression on the entire FTAP sample population, I calculate each Marine's tier score by multiplying the Proficiency and Conduct scores by ten, the Meritorious Promotion variable by 100, then summing those values with the PFT, CFT, Rifle, and MCMAP scores. I then create the average scores within each MOS by FTAP for each performance variable. I create Tier level cutoff values within each MOS by FTAP at the 90th, 60th, and 10th percentiles to facilitate individual tier assignment. If a Marine's calculated tier score is above the 90th percentile for their MOS and FTAP, I assign them to Tier-I. If the tier score is between the 60th and 90th percentiles, I assign them to Tier-II. If the tier score is between the 10th and 60th percentiles, I assign them to Tier-III, and if their tier score is below the 10th percentile, I assign them to Tier-IV. After calculating tiers, I adjust the tier assignments based on legal actions. If a Marine has only one NJP, they are limited to no higher than Tier II, regardless of the calculated tier score. Two or more NJPs restrict Marines to placement no higher than Tier-III, and any Courts-Martial convictions prohibit placement higher than Tier-IV. Table 6 shows the breakdown of tiers by FTAP upon completion of the tier score calculation and tier level assignment process. Figure 2 (Cole, 2014) is an example of a tier calculation worksheet that assigns Marines to tiers in the manner described above.

Table 6. Tier Assignment by FTAP

FTAP	Tier I	Tier II	Tier III	Tier IV	Total
2016	2,278	7,053	11,781	2,218	**23,330**
	9.76%	30.23%	50.50%	9.51%	**100.00%**
2017	2,706	8,545	14,208	2,693	**28,152**
	9.61%	30.35%	50.47%	9.57%	**100.00%**
2018	2,442	7,656	12,812	2,437	**25,347**
	9.63%	30.20%	50.55%	9.61%	**100.00%**
2019	2,671	8,410	14,112	2,681	**27,874**
	9.58%	30.17%	50.63%	9.62%	**100.00%**
2020	2,137	6,884	11,656	2,203	**22,880**
	9.34%	30.09%	50.94%	9.63%	**100.00%**
Total	**12,234**	**38,548**	**64,569**	**12,232**	**127,583**
	9.59%	**30.21%**	**50.61%**	**9.59%**	**100.00%**

CPL I. M. MARINE		
PMOS 0621		
Event	MOS Avg (as of 02-08-2012)	SNM's Scores
PFT	246	274
CFT	282	284
Proficiency	430	430
Conduct	430	430
Rifle	293	303
MCMAP	MMB - Tan Belt	MMD - Green Belt
Meritorious Promotion	N/A	0
	1691	1751
Legal History	Type	Date
0 NJP(s)	N/A	N/A
Tier Chart		
Tier I (10%) 91%-100%		
Tier II (30%) 61%-90%		
Tier III (50%) 11%-60%	X	
Tier IV (10%) 1%-10%		

Figure 2. Tier Calculation Sheet. Source: Cole (2014).

After calculating the tiers, using the Marines who submitted a RELM package as the training group, I refit the binary logistic regression, and generate the pre-approval indicator variable for all observations in the dataset. Using the pre-approval indicator variable, I analyze the performance trends associated with each tier level's observations in association with their pre-approval selection results. I also examine the effect of boat-space availability on RELM submission rates and pre-approval selection.

3. Phase Three

In phase three, I focus on examining the performance trends during a Marine's second term. Utilizing the phase three dataset, I compare the performance values of observations selected for pre-approval with those not chosen for pre-approval. I also analyze the average time to promotion to the next rank for pre-approved observations versus not pre-approved observations. These analyses intend to identify the effectiveness of pre-approval prediction at identifying sustained quality performance after reenlisting.

F. CHAPTER SUMMARY

This chapter outlines the data I utilize in this study and the analysis methodology. I describe the data sources and the data cleaning and merging process conducted in each phase to generate datasets formatted for analyses. I provided descriptions of each dataset along with summary statistics of each phase's cleaned dataset. Lastly, I explain the methodology for each type of analysis conducted within each phase of the study.

IV. RESULTS AND ANALYSIS

This chapter discusses this study's findings related to the primary and secondary research questions after reconfirming the proposed model's accuracy. Does the proposed model accurately identify the highest quality Marines without exceeding FTAP goals or pre-approving Marines disqualified from retention? How can the proposed model be refined to improve retention quality? Does advertised MOS availability, as indicated by boat-spaces, impact the rate of reenlistment submission or pre-approval? Lastly, is a selection for retention pre-approval an indicator of improved performance in a Marine's subsequent term?

I begin by analyzing the phase one elements to confirm the predictive model's accuracy, as proposed by Terry et al. (2021). I then analyze the results of applying the binary logistic regression model to all FTAP Marines to answer the primary research question and assess the impact of MOS availability. Finally, using the phase two results, I examine the model's ability to identify continued quality performance during a Marine's second term.

A. PHASE ONE: PROPOSED MODEL ACCURACY

Using the coefficients from the binary logistic regression run on the training sample, I predict pre-approval for all phase one dataset observations. Table 7 displays the pre-approval prediction results compared with the RELM packages' historical results and the results broken down by tier. I calculate the overall model accuracy by adding the number of disapproved RELMs not predicted for pre-approval with the number of approved RELMs and dividing the sum by the total number of observations. The model correctly matches predicted pre-approved/not pre-approved to the historical RELM approval outcome for 37,210 of the 37,591, indicating an overall model accuracy rate of 98.98%, as depicted in Figure 3. I calculate the false-negative rates by dividing the number of approved RELMs not predicted for pre-approval by the total number of observations, resulting in a 0.03% false-negative rate. Terry et al. (2021) explain that limiting false positives, which results in the pre-approval of a Marine whom the Marine Corps elects not to retain, is a primary objective of their model. I calculate the rate of false positivity within my sample by dividing the number of disapproved RELMs predicted for pre-approval by the total number of observations. The identified false positive rate within this sample is 0.98%, consistent with the false-positivity rate of 0%-1% reported by Terry et al. (2021). It is worth noting that the preponderance of false positives within my sample occurs in the observations calculated as lower quality, in tiers three and four.

Table 7. Predicted Pre-approval versus Historical Reenlistment Request Results of FY 2013-FY2019 Overall and by Tier

	Not Preapproved	Preapproved	Total
Disapproved	4	368	**372**
Approved	13	37,206	**37,219**
Total	**17**	**37,574**	**37,591**

	RELM Disapproved		RELM Approved		
	Not Preapproved (True Negative)	Preapproved (False Positive)	Not Preapproved (False Negative)	Preapproved (True Positive)	Total
Tier I	0	2	0	8,492	**8,494**
Tier II	0	68	0	14,494	**14,562**
Tier III	1	241	7	13,428	**13,677**
Tier IV	3	57	6	792	**858**
Total	**4**	**368**	**13**	**37,206**	**37,591**

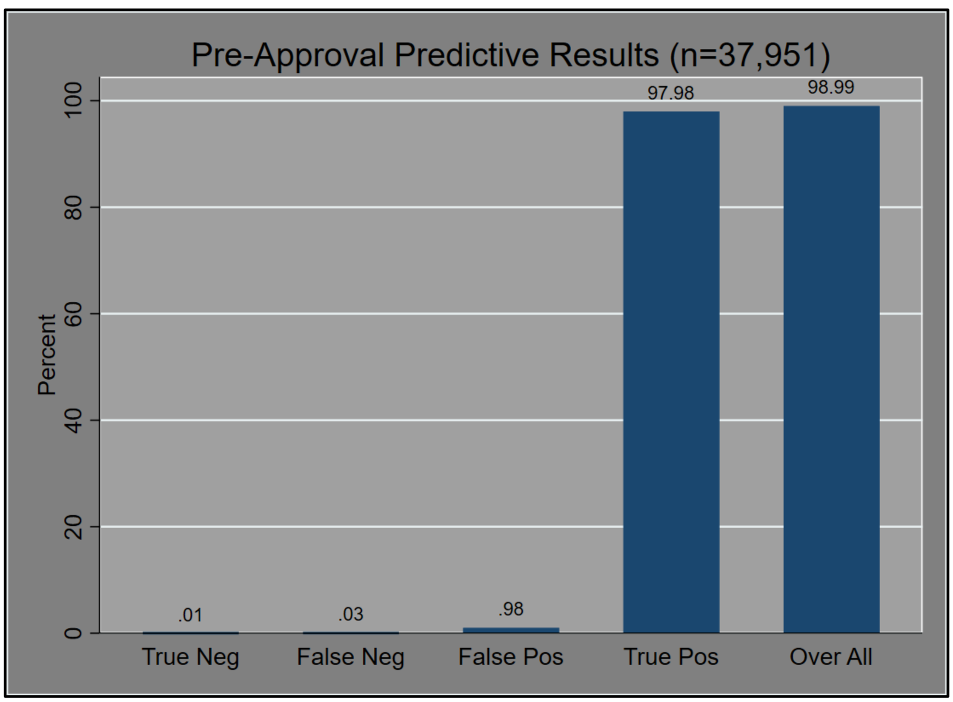


Figure 3. Pre-approval Model Accuracy (Phase One)

B. PHASE TWO: FULL FTAP ANALYSIS

1. Model Results

To expand the confirmed logistic binary regression model to the phase two dataset, I refit the regression model to the portion of the phase two dataset whose RELM submitted variable was equal to one (approximately 20% of the dataset). I find all variables except CFT and courts-martial count statistically significant at the 95% confidence level. I find the most impactful variables regarding reenlistment approval to be NJP counts and Meritorious promotions. As shown in Figure 4, each NJP occurrence results in a Marine being 72.73% less likely to be selected for reenlistment approval. Conversely, a Marine promoted meritoriously is 166.86% more likely to be approved for reenlistment. Using the coefficients from the RELM Submitted portion of the phase two dataset, I generate pre-approval predictions for all 127,583 observations of the FTAP sample population to identify the likelihood of retention for those Marines who did not submit for reenlistment.

Variable	RELM Approved Odds Ratio
PFT Score	1.008^{***}
	(0.001)
CFT Score	0.997
	(0.003)
Avg Conduct Marks	1.647^{***}
	(0.082)
Rifle Score	1.009^{***}
	(0.002)
MCMAP Belt Score	1.027^{**}
	(0.009)
Meritoriously Promoted 1=Yes, 0=No	2.669^{*}
	(1.237)
Total # of NJPs	0.273^{***}
	(0.025)
Total # of Courts Martial	0.847
	(0.618)
Observations	25,585

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

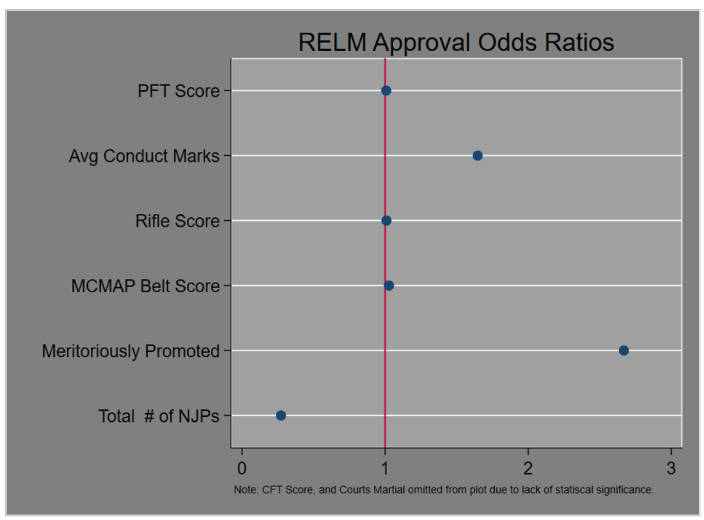


Figure 4. RELM Approval Odds Ratios

As this data utilizes the TFDW data only, rather than the combined TFRS and TFDW data used in phase one, I recalculate the model's accuracy at predicting pre-approval compared with the historical results of FY 2016 – FY 2019 reenlistment requests. The model's overall accuracy drops slightly to 98.62%, while the true-positive accuracy increases to 98.61%. The false positives also increase somewhat, to 1.3%. However, the false positivity rate amongst tiers one and two remain less than 1%, indicating most of the false positivity is attributed to tiers three and four. Table 8 shows the model's accuracy breakdown when applied to the RELM Submitted portion of the phase two dataset, and Figure 5 displays the accuracy percentages.

Table 8. Predicted Pre-approval versus Historical Reenlistment Request Results of FY 2016-FY2020 Overall and by Tier

	Not Preapproved	Preapproved	Total
Disapproved	4	335	**339**
Approved	17	25,229	**25,246**
Total	**21**	**25,564**	**25,585**

	RELM Disapproved		RELM Approved		
	Not Preapproved (True Negative)	Preapproved (False Positive)	Not Preapproved (False Negative)	Preapproved (True Positive)	Total
Tier I	0	3	0	4,354	**4,357**
Tier II	0	64	0	10,708	**10,772**
Tier III	3	233	13	9,672	**9,921**
Tier IV	1	35	4	495	**535**
Total	**4**	**335**	**17**	**25,229**	**25,585**

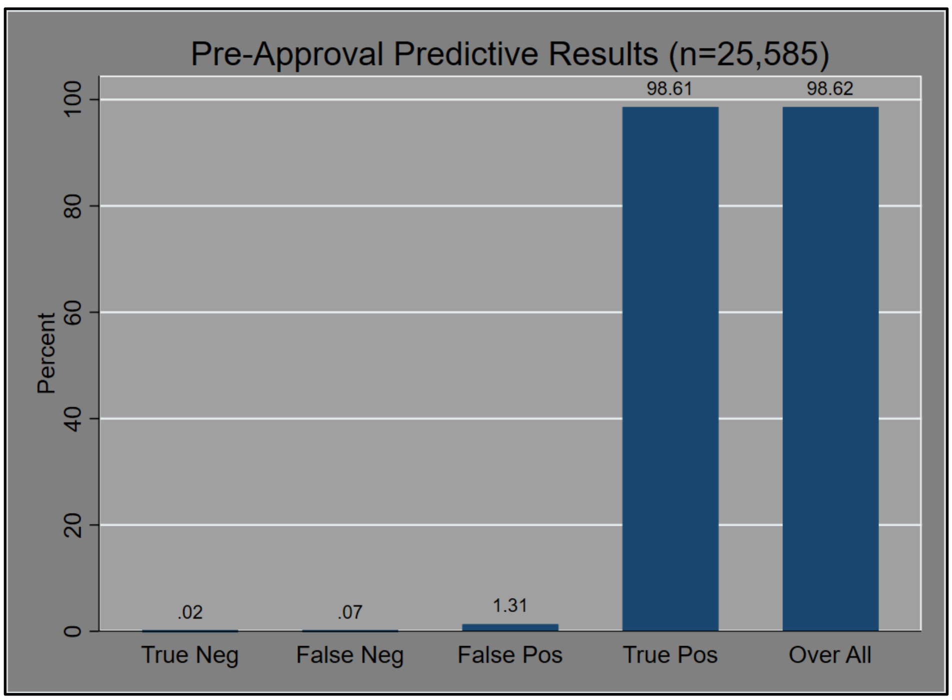


Figure 5. Pre-approval Model Accuracy (Phase Two)

After generating the predicted pre-approval values for all 127,583 observations, I find the model predicts pre-approval for over 98% of the population. When I examine pre-approval prediction by tier, I find the pre-approval rate for high-quality Marines (i.e., Tier-I and II) to be 99.97% and low-quality Marines (i.e., Tier-III and IV) to be 97.11%. Overall, these results indicate a very permissive pre-approval model. Table 9 shows the pre-approval prediction breakdown by tier and overall.

Table 9. FY 2016-2020 Predicted Pre-Approvals by Tier

	Tier I	**Tier II**	**Tier III**	**Tier IV**	**Total**
Not Preapproved	0	13	955	1,266	2,234
% of Tier	0%	0.03%	1.48%	10.35%	1.75%
Preapproved	12,234	38,535	63,614	10,966	125,349
% of Tier	100%	99.97%	98.52%	89.65%	98.25%
Total	**12,234**	**38,548**	**64,569**	**12,232**	**127,583**

2. Effects on Reenlistment Pool

An essential element of expanding the pre-approval model to all FTAP Marines is assessing how the model increases the pool of high-quality reenlistees. Figure 6 shows the density of pre-approved observations at the top end of PFT and CFT scores is greater than the number of observations without RELM submissions, with the same performance level. Likewise, Figure 7 reflects the greater density of pre-approved observations over observations without submitted RELM for Proficiency and Conduct Scores greater than 44 and 42 (actual marks of 4.4 and 4.2), respectively.

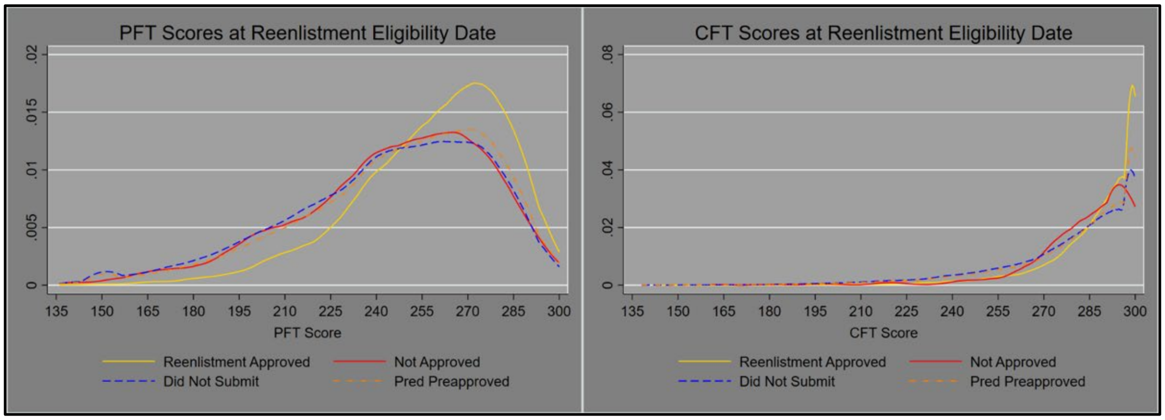


Figure 6. PFT and CFT Scores Kernel Density Plots

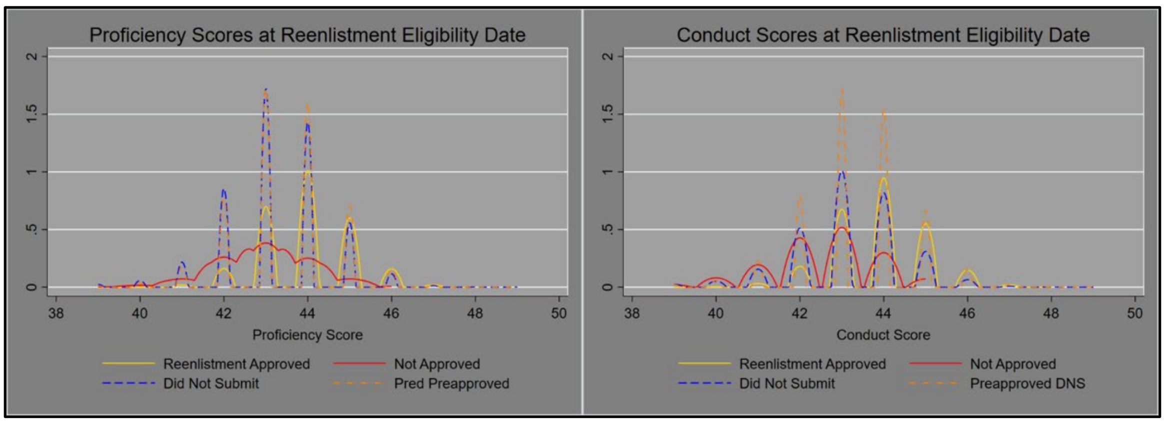


Figure 7. Proficiency and Conduct Scores Kernel Density Plots

Among the MCMAP scores, a distinct divide exists between those observations with standard MCMAP belts and an instructor-level MCMAP belt. To best show the densities, I split the two groups for graphing purposes. As seen in Figure 8, standard MCMAP belt pre-approved density is greater for green belts (i.e., Score of 15) and beyond, while for MCMAP Instructors, the pre-approved density is greater for Brown belts (i.e., Score of 70) and beyond.

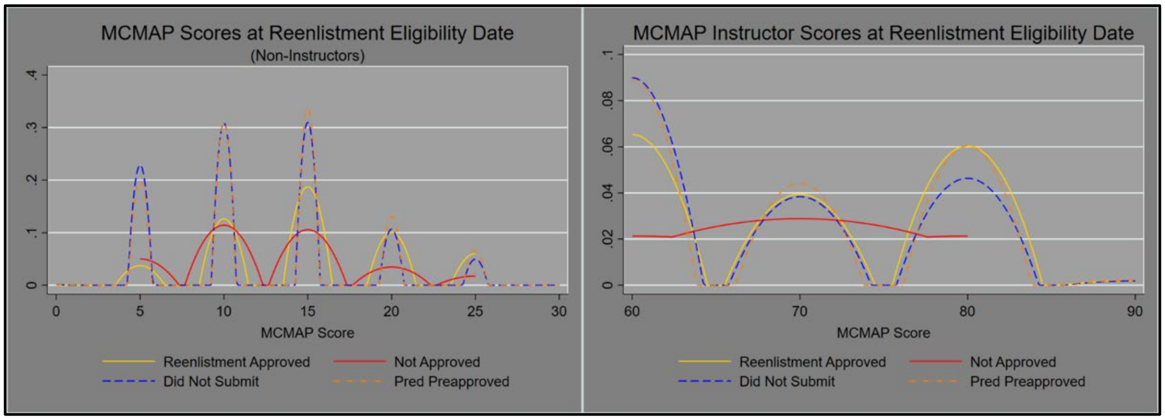


Figure 8. MCMAP Scores Kernel Density Plots

Although the gap is less distinct than in the other performance variables, Figure 9 shows that within the Rifle Qualification score variable, scores greater than 300 reflect pre-approval density is greater than the density for observations without a submitted RELM.

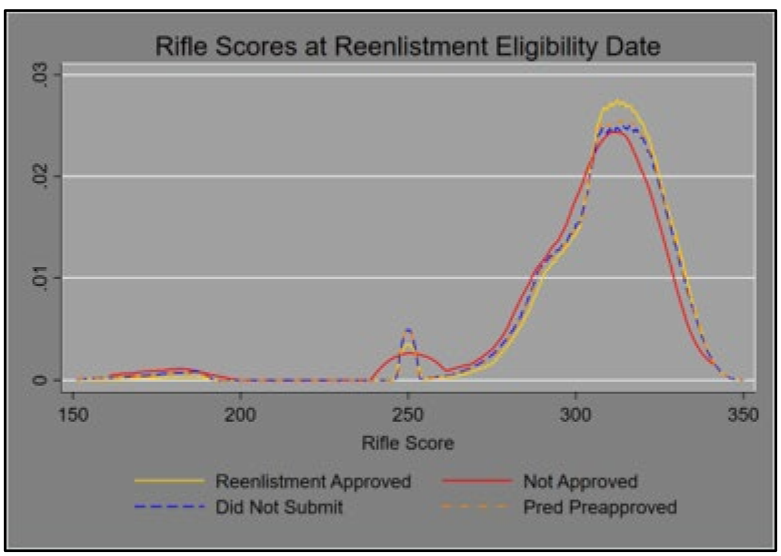


Figure 9. Rifle Scores Kernel Density Plot

Overall, the greater density of pre-approval observations compared to not-submitted observations at the higher end of each performance variable confirms that unrecognized quality exists within the unsubmitted packages. By offering pre-approved reenlistments to these top performers, the Marine Corps can target those Marines possessing the quality level worthy of retention who did not submit a package.

3. Pre-approval Effects on FTAP Goals

Since FY 2019, the Marine Corps has published annual FTAP goals via official Marine Administrative Messages (MARADMIN); before this, the FTAP goals came out via TFRS messages that require a TFRS account to access. Table 10 depicts the published FTAP goals for FY 2016 – FY 2020 and their relative percentage to that year's FTAP population.

Table 10. Published FTAP Goals

	Target	% of FTAP
FTAP 2016	5,962	23%
2017	6,185	23%
2018	4,805	22%
2019	5,934	24%
2020	6,052	24%

Adapted from Z. Basich, email to author, February 23, 2021.

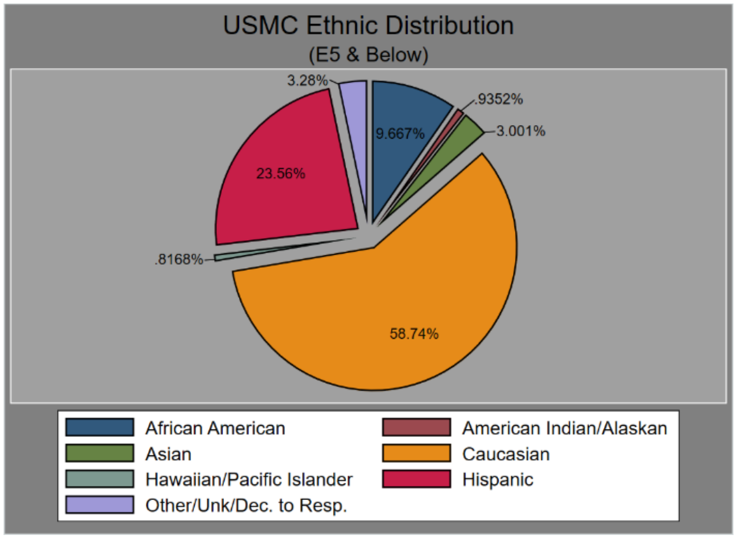
In comparison, Table 11 shows the number of Marines pre-approved by high-quality (i.e., Tiers I and II) and low quality (i.e., Tiers III and IV) and the percentage of high-quality Marines pre-approved in comparison to that year's FTAP goal. In all five years analyzed, the number of pre-approved high-quality Marines exceeds the desired FTAP retention goals, indicating an overly permissive model.

Table 11. Breakdown of FTAP Pre-Approvals by Tier

	Tier I	Tier II	High Quality	% of FTAP Goal	Tier III	Tier IV	Low Quality	Pre-approved Total
FTAP 2016	2,278	7,053	9,331		11,693	2,094	13,787	**23,118**
	9.85%	30.51%	40.36%	156.51%	50.58%	9.06%	59.64%	**100.00%**
2017	2,706	8,545	11,251		14,068	2,479	16,547	**27,798**
	9.73%	30.74%	40.47%	181.91%	50.61%	8.92%	59.53%	**100.00%**
2018	2,442	7,655	10,097		12,644	2,139	14,783	**24,880**
	9.82%	30.77%	40.58%	210.14%	50.82%	8.60%	59.42%	**100.00%**
2019	2,671	8,406	11,077		13,866	2,364	16,230	**27,307**
	9.78%	30.78%	40.56%	186.67%	50.78%	8.66%	59.44%	**100.00%**
2020	2,137	6,876	9,013		11,343	1,890	13,233	**22,246**
	9.61%	30.91%	40.52%	148.93%	50.99%	8.50%	59.48%	**100.00%**
Total	**12,234**	**38,535**	**50,769**		**63,614**	**10,966**	**74,580**	**127,349**
	9.76%	**30.74%**	**40.50%**		**50.75%**	**8.75%**	**59.50%**	**100.00%**

4. Impact of Model on Demographics

After identifying the pre-approval rate among tiers, I examine demographics to ensure there is no racial or ethnic bias amongst the selection rates. Utilizing the reported ethnic distribution of active duty Sergeants and below from the Marine Corps' Manpower Performance Indicators website as the baseline, I compare selection and retention rates amongst the racial/ethnic categories. Figure 10 shows that as of 23 February 2021, the population of Sergeants and below in the Marine Corps is 9.67% African American, 0.9352% American Indian or Alaskan, 3.001% Asian, 58.74% Caucasian, 0.8168% Hawaiian or Pacific Islander, 23.56% Hispanic, and 3.28% other unknown or declined to respond (USMC, 2021a). Comparatively, the racial distribution within my sample population is 9.7% African American, 1.189% American Indian or Alaskan, 2.634% Asian, 64.36% Caucasian, 0.6858% Hawaiian or Pacific Islander, 18.13% Hispanic, and 3.305% other, unknown, or declined to respond. As shown in Figure 11, although the sample distribution of Caucasians and Hispanics is slightly different than the overall USMC distribution, Marines are selected for pre-approval at the same proportion as they exist overall in the sample. This demographically proportional pre-approval rate suggests the model is not injecting any unintentional racial bias.



Adapted from USMC Manpower Performance Indicators (2021a).

Figure 10. Sergeant and Below Racial/Ethnic Diversity as of 23 February 2021

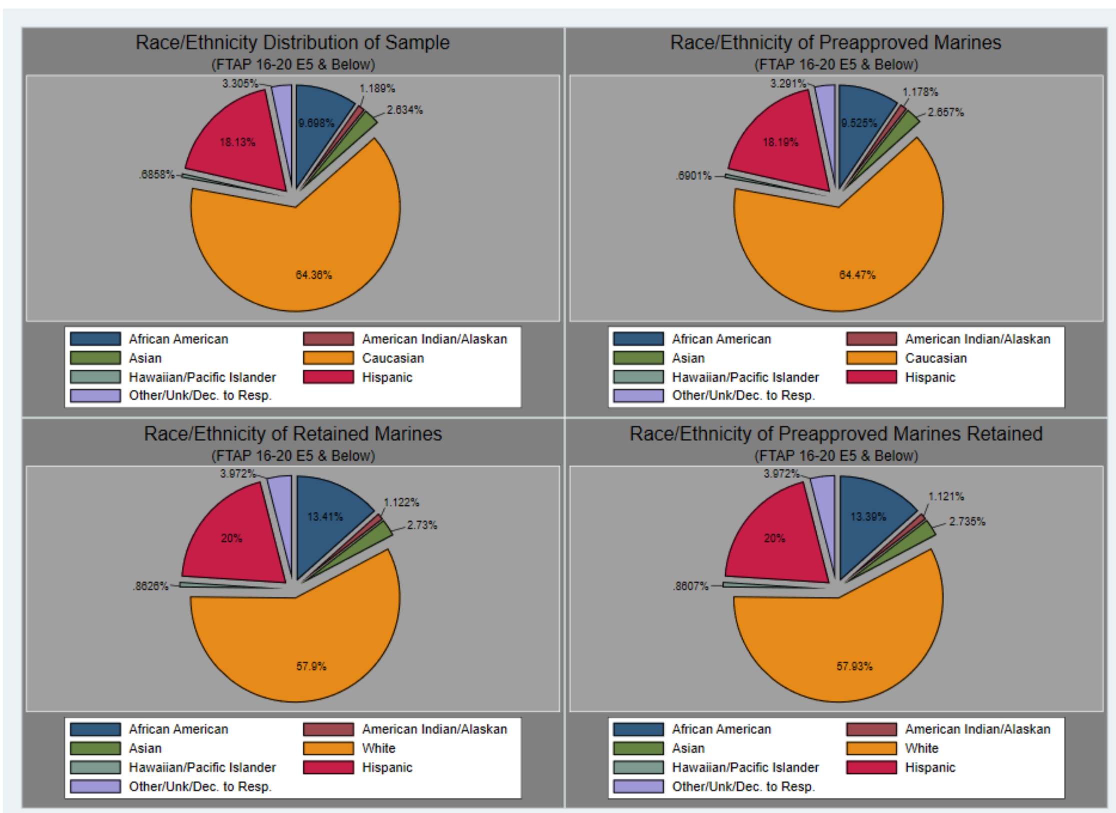


Figure 11. Racial/Ethnic Distributions of Pre-approved and Retained Marines within Sample

5. Boat-Space Availability Analysis

To determine how MOS availability, as indicated by boat-spaces, impacts the rate of reenlistment submission and pre-approval selection, I regress the pre-approval and RELM submission variables against the number of boat-spaces variable. As Figure 12 depicts, there does not appear to be a correlation between either the rate of RELM submission or pre-approval. The coefficient on the pre-approval variable is nearly zero and not statistically significant. Although the coefficient on the RELM submitted variable is statistically significant at the 95% confidence level, at -0.0003, there is practically no effect on the rate of RELM submission as the number of boat-spaces increases by one.

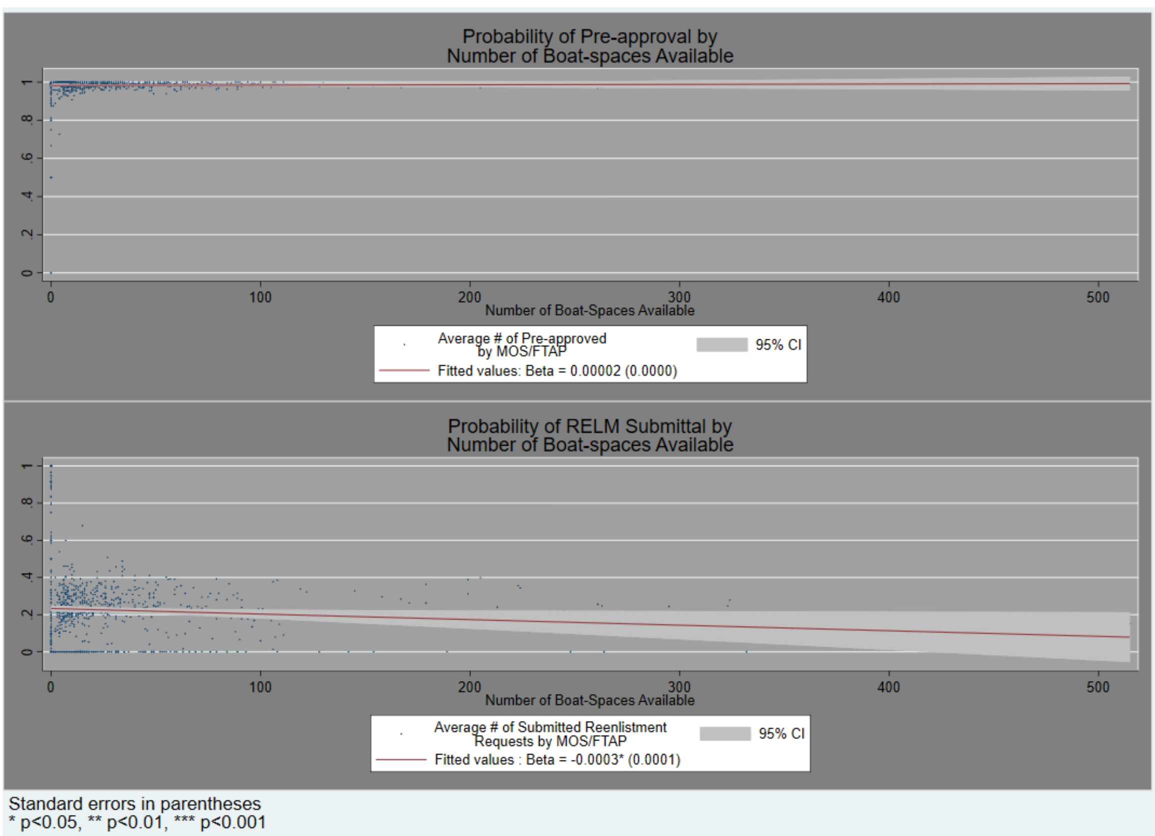


Figure 12. Effects of MOS Availability (boat-spaces) on Pre-approval and RELM Submissions

C. PHASE THREE: EVALUATION OF FOLLOW-ON PERFORMANCE

To assess the perceived effect of the reenlistment pre-approval selection on follow-on performance, I regress each of the tier calculation variables and the count of personal awards and associated devices received against the pre-approval indicator variable. For the tier calculation variables, I find the difference in performance between scores at the time of FTAP tier calculation and the average scores over the subsequent four years to be statistically significant at the 99.9% confidence level for all variables except CFT, MCMAP, and Courts-Martial. Amongst the award variables, only the average number of personal awards was significant at the 99.9% confidence level. Differences in all other variables were not statistically significant at the 95% confidence level. Table 12 reports the effects pre-approval selection has on each tier calculation variable, while Table 13 reports the effects of pre-approval selection on the award variables.

Table 12. Effects of Pre-approval on Tier Calculation Variables during 2nd Term

	PFT Average	CFT Average	Max Proficiency	Max Conduct	Rifle Average	MCMAP Average	NJP Average	CM Average
preapproved	50.111***	6.643	2.507***	3.577***	15.869***	7.207	-0.639***	0.001
	(8.400)	(7.961)	(0.244)	(0.267)	(4.456)	(5.477)	(0.090)	(0.054)
Constant	188.110***	257.160***	42.171***	41.024***	296.375***	18.750***	1.692***	0.077
	(8.395)	(7.957)	(0.244)	(0.267)	(4.454)	(5.475)	(0.090)	(0.054)
Observations	27,929	27,180	17,310	17,310	19,563	11,150	2,167	2,167

Notes: * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses.

Table 13. Effects of Preapproval on Awards during 2nd Term

	Personal Award Average	Award w/ Valor Device	Award w/ Combat Conditions Device
preapproved	0.552***	0	0.008
	(0.149)	(0.004)	(0.018)
Constant	0.04	0	0
	(0.149)	(0.004)	(0.018)
Observations	25,509	11,699	11,699

Notes: * p<0.05, ** p<0.01, *** p<0.001; Standard errors in parentheses.

On average, for retained Marines selected for pre-approval, their average PFT score over their next four years of service is roughly 50 points higher than retained Marines not pre-approved. After controlling for Marines who did not receive proficiency or conduct marks due to their rank, the findings indicate pre-approved retained Marines earn 0.25 and 0.35 marks higher in proficiency and conduct, respectively. The rifle qualifications scores indicate that, on average, pre-approved retained Marines score almost 16 points higher during their subsequent term than retained Marines not selected for pre-approval. In addition to performing better on average, pre-approved retained Marines are less likely to encounter legal actions in their following term, as the negative coefficient on the NJP variable indicates. Furthermore, on average, pre-approved retained Marines earn 0.55 more personal awards than retained Marines not predicted for pre-approval.

D. CHAPTER SUMMARY

This chapter summarizes the findings of my statistical analysis. Although I find the model proposed by the OAD study limits false positives to less than 1%, when applied to the entire FTAP sample, the model selects over 98% of the sample population for pre-approval. The model does indicate that pre-approving Marines targets excess quality residing in Marines who elect not to submit a RELM request. The data also shows an apparent lack of correlation between the number of available boat-spaces and the rate of RELM submission or reenlistment pre-approval. Furthermore, no racial bias appears to exist within the pre-approval model. Lastly, the results indicate Marines selected for pre-approval continue to perform better in their second term, on average, than Marines not selected for pre-approval.

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V. CONCLUSION

This study's primary objective is to assess the accuracy and feasibility of implementing a reenlistment pre-approval process utilizing the current reenlistment tier system to increase retention of high-quality first-term Marines. My findings indicate reenlistment pre-approval does effectively target the highest quality Marines for retention, and if adequately constrained, does so without exceeding FTAP goals. Furthermore, the results do not indicate a correlation between reported MOS availability and reenlistment request submissions. Lastly, selection for retention pre-approval does indicate higher quality performance, on average, during the subsequent term.

A. RECOMMENDATIONS

1. Restrict Reenlistment Pre-approval to Tier-I Marines

I find the binary logistic regression model proposed by Terry et al. (2021) to be statistically accurate in identifying Marines eligible for pre-approval. However, my analysis indicates the initial definition of high-quality as Marines in reenlistment tier categories one and two is too permissive. I recommend restricting the definition of high-quality for reenlistment pre-approval to Marines identified as tier one. Doing so would allow the Marine Corps to pre-approve approximately 43% of its annual retention goal at the beginning of each FTAP.

2. Incorporate Reenlistment Pre-approval into FTAP Phase One

Marines selected for pre-approval could be notified of their selection via Marine On-Line (MOL) at the beginning of each FTAP campaign. The reenlistment pre-approval notification should be accompanied by a reasonable window of time (e.g., 30 days) to allow Marines to discuss their options with their family, Career Planner, and Command before choosing to accept or deny the reenlistment with associated reenlistment incentives. Furthermore, choosing not to accept the pre-approved reenlistment should be non-punitive, meaning a pre-approved Marine could still submit a legacy reenlistment request within their FTAP after deciding not to accept the pre-approval selection. By providing a time-constrained option at the outset of each FTAP campaign, MMEA can quickly gauge reenlistment interest, make early adjustments, and refine the FTAP goals and guidance.

B. SUGGESTIONS FOR ADDITIONAL RESEARCH

This study focused solely on First-term Marines seeking to reenlist and does not examine lateral moves or extensions, leaving multiple avenues for continued research. Expanding the research to assess the impact on Subsequent-Term Marines or First-term Marines submitting Lateral Move or Extension requests may provide valuable insights into the best ways to incorporate pre-approval models into the Marine Corps' broader retention policies. Additionally, as the Junior Enlisted Performance Evaluation System has replaced Proficiency and Conduct Marks, it would be prudent to reexamine reenlistment pre-approval selection rates amongst the tier levels to ensure continued accuracy under the new evaluation method once that data becomes available.

A cost evaluation of the overall impact of reducing the number of reenlistment packages required to be reviewed by MMEA annually could identify potential fiscal and manpower savings. If even 50% of the Marines offered pre-approved reenlistment accept the offer, MMEA and subordinate reenlistment authorities would be able to review roughly a thousand fewer reenlistment requests per FTAP. However, it is impractical to estimate how many Marines pre-approved for reenlistment would accept the offer at this time and based purely on the statistical analysis of historical performance data. A well-designed human research study that surveys all first-term Marines could provide insight into what percentage of Marines would accept a reenlistment pre-approval offer.

C. CLOSING REMARKS

For over 245 years, the Marine Corps has proven itself a formidable military force time and again, and I believe this is a direct result of the quality of the brave men and women comprising its ranks. I do not think the current retention system is broken, but I believe we can improve it. My desire is the results of this study will provide leaders and policymakers within the Marine Corps' Enlisted Retention branch the statistical evidence necessary to make informed decisions on reenlistment pre-approval policies.

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