NPS-AM-26-307

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Show Me the Money: A Machine Learning Analysis of Army and Marine Corps Continuation Pay for Optimizing Incentive Timing

March 2026

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The research presented in this report was supported by the Acquisition Research Program of the Department of Acquisition, Finance and Manpower Naval Postgraduate School.

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ABSTRACT

Continuation Pay (CP), introduced in 2018 under the Blended Retirement System (BRS), is a mid-career retention incentive that may be offered between 8 and 12 years of service (YOS), yet most services offer it only at 12 YOS. Despite this flexibility, little empirical research evaluates the optimal timing of CP, and no studies use observed CP take-up behavior to assess alternative timing policies. This thesis addresses that gap by applying machine learning (ML) methods to historical Army and United States Marine Corps (USMC) CP data to estimate the effects of expanding CP eligibility from a single 12 YOS offer to a discretionary 8–12 YOS window. Using Army CP decision data to train an ML model, projections are generated for USMC personnel under both 8–12 YOS and current 12 YOS policies. Assuming comparable decision behavior across services, the 8–12 model increases projected end strength by 5,709 Marines within a fully BRS population between 8 and 16 YOS. Annual take-up is projected at 4,247 Marines, with costs of $58 million at a 2.5 multiplier and $121.9 million at a 5.0 multiplier. Retention gains exceed CP costs on a per-dollar basis at both multiplier levels. If retention shortfalls exist within the 8–12 YOS window, adoption of an 8–12 YOS CP policy is recommended, particularly before fully auto-enrolled BRS cohorts dominate the mid-career population. The 8–12 model mitigates mid-career retention drop-offs by aligning incentives with individual career decision points.

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ACKNOWLEDGMENTS

Thank you to my beautiful wife Lima and my cats for listening to my constant ramblings about this thesis for over a year. Thank you to Mr. James Landry from the Army G1 for supporting me in getting the Army CP data. Thank you to my advisors, Manpower & Reserve Affairs, the Person-Event Data Environment team, the Research Facilitation Laboratory team, and Mr. Jason Manley for consistently supporting my data requests and questions. Finally, thank you to my long-time study partner, who I can bounce questions and code off of at any time day or night, Clarence G. P. Thomas.

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LIST OF ACRONYMS AND ABBREVIATIONS

ADVANA	Advancing Analytics
AUC	area under the curve
BRS	Blended Retirement System
CP	Continuation Pay
DoD	Department of Defense
EDIPI	Electronic Data Interchange Personal Identifier
ML	machine learning
MOS	Military Occupational Specialty
NPS	Naval Postgraduate School
RMC	regular military compensation
TM2030	Talent Management Campaign Plan 2030
TSP	Thrift Savings Plan
USMC	United States Marine Corps
XGBoost	Extreme Gradient Boosting
YOS	years of service

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I. INTRODUCTION

A. BACKGROUND

The Secretary of Defense (2017) implemented the Blended Retirement System (BRS) across the Department of Defense (DoD) on January 1, 2018, to modernize military retirement and provide transferable benefits to the 80% of military members who do not serve the 20 years required for a traditional pension. Like the Legacy system, the BRS includes a 20-year cliff-vested pension, but it also features a defined contribution plan with government matching contributions of up to 5%. This defined contribution component of the BRS, similar to a 401(k) plan, is called the Thrift Savings Plan (TSP). Marines who enter the service on or after January 1, 2018, are automatically enrolled in the BRS, whereas Marines who were serving on or before December 31, 2017, are grandfathered into the Legacy Retirement System. If those Marines had fewer than 12 years of service (YOS), they could choose to remain in the Legacy Retirement System or opt into the BRS. These Marines had until December 31, 2018, to decide whether they were going to opt into the BRS. Those with 12 YOS or more as of December 31, 2017, were not eligible to switch from the Legacy Retirement System to the BRS (Secretary of Defense, 2017).

The National Defense Authorization Act (2024) requires that a mid-career incentive be offered to all BRS personnel who meet YOS requirements and are eligible to incur a four-year additional service obligation. This incentive is known as Continuation Pay (CP) and is determined by the individual services to be offered anytime from 7–12 YOS. For active-duty personnel, CP is a one-time monetary incentive paid upon acceptance that ranges from a multiplier of 2.5 to 13 times monthly basic pay. While the statutory minimum requires that a service member serve at least three additional years upon accepting CP, service policy requires a four-year contractual obligation (National Defense Authorization Act, 2024).

The BRS represents the current and future retirement system for the Uniformed Services, and seven years into its implementation, an increasing portion of the force is both covered by the BRS and approaching CP eligibility windows. Increasing service members' understanding of the incentive and the timing of its offering is therefore crucial for improving mid-career retention rates. U.S. Marine Corps (2023) explains that one of the USMC priorities in Talent Management Campaign Plan 2023–2025 (TM2030) is a concentrated, informed approach to force maturation to build the structure needed to be successful and thrive on the future battlefield (U.S. Marine Corps, 2023).

Since the beginning of the BRS on January 1, 2018, the Marine Corps has offered CP only when a Marine reaches 12 YOS, establishing a single, fixed incentive point. The other services, with the exception of the Army, follow the same CP model, reflecting a near-uniform approach to CP timing across the DoD. The Army, by contrast, allows service members to decide when to take the CP incentive at any point between their 8th and 12th YOS. U.S. Marine Corps (2022) explains that the USMC is the only service that has changed the active-duty multiplier: from 2.5 times monthly basic pay to 5 times monthly basic pay since the beginning of 2023 (U.S. Marine Corps, 2022).

The Assistant Secretary of the Army (ASA) released a 2025 memorandum outlining future CP policy for Army personnel, reflecting ongoing adjustments and experimentation with CP timing in current and planned policy. It states that the Army continues to offer CP to BRS participants during 8 to 12 YOS, consistent with policy in place since 2018. The memo further explains plans for the offering window to shift to 7 to 12 YOS in calendar year 2026 and to 7 to 10 YOS in calendar year 2027 (Department of the Army, 2025).

B. RESEARCH PURPOSE

The purpose of this research is to analyze whether the USMC would retain more personnel at a lower cost by utilizing an 8–12 YOS CP model instead of the current 12 YOS model, thereby optimizing CP timing. This analysis is conducted by training a machine learning (ML) model using Army data under the 8–12 YOS CP timing structure. Under the assumption that Marines and Soldiers have similar predictive characteristics in taking up CP, the ML model is then applied to eligible Marine Corps personnel to generate predicted CP outcomes under the 8–12 model. The findings provide insight into how the timing of the incentive influences take-up behavior, informing decision-makers on how to optimize CP timing to achieve desired mid-career retention in the Marine Corps. The null hypothesis is that there is no difference between the two models in retention and cost efficiency. The two models are (1) CP offered at 12 YOS and (2) CP offered at the service members' discretion at any point between 8 and 12 YOS. The alternative hypothesis is that there is a difference between the two models in retention and cost efficiency.

C. RESEARCH QUESTIONS

- When should the Marine Corps offer Continuation Pay (CP) to maximize retention and return on investment?
- Should the Marine Corps continue offering CP only at 12 YOS, or expand to an 8–12 YOS window similar to the Army?
- What is the career return on investment for Army and USMC personnel who take up CP?
- What are significant predictors of CP non-take-up among Marine Corps personnel?

D. IMPORTANCE OF RESEARCH

The increasing number of personnel who will become eligible for the CP incentive in the coming years underscores why determining the correct timing of the incentive is strategically important. Analyzing Army CP take-up rates provides Marine Corps decision makers with insight into the expected take-up rate if the Marine Corps were to adopt the Army's 8–12 YOS CP model or a different model from the current 12 YOS approach. Answering these research questions offers the Marine Corps a greater understanding of how to adjust between the left and right lateral limits of the incentive to achieve desired mid-career retention, force shaping, and end strength.

E. BENEFITS AND LIMITATIONS

The benefit of this study lies in the insight it provides to decision-makers on potential take-up and retention rates of mid-career personnel if CP is offered at a time other than the current 12 YOS mark. A key limitation of this study is that the historical personnel analyzed in this thesis faced a slightly different decision matrix than future personnel. The historical group had to choose whether to opt into the BRS and then whether to take up CP, whereas future personnel will all fall under the BRS by default and will only need to decide whether to take up CP.

CP must be offered at different times historically to enable ML models to be trained on variation in incentive timing. Without developing a full structural econometric decision model, which would take years to complete, this research models CP at an alternative timing structure used by another service by applying the Army CP model to the USMC to assess whether it represents the optimal approach. As a result, the ML model is trained on Army CP take-up data and reflects underlying differences between Army Soldiers and Marines. Despite these limitations, the model is used to predict future Marine CP take-up behavior if the USMC adopts the Army CP model.

F. ORGANIZATION OF REPORT

The thesis is organized into five chapters. Chapter I provides the introduction, including the background, purpose, and motivation for the research. Chapter II presents the literature review, summarizing prior studies, methodologies, and analyses in this field. Chapter III outlines the data, data-cleaning process, and methodology used in the analysis. Chapter IV presents the data analysis, results, and findings. Chapter V concludes the thesis and offers recommendations for immediate action and for future research.

II. LITERATURE REVIEW

A. OVERVIEW

Since this thesis analyzes the financial decisions of Marines to take up CP, this chapter begins by summarizing the financial management studies and recommendations in prior research, as well as the training and knowledge that Marines receive while serving in the Fleet Marine Force. This chapter also examines the quantitative research on the CP incentive; in particular, it summarizes the data and methodologies used across the limited studies on BRS and CP.

B. FINANCIAL MANAGEMENT TRAINING AND KNOWLEDGE

Throughout the literature, many studies recommend expanding the financial literacy of Marines and other service members to improve their understanding of military compensation, particularly relative to the civilian sector. This assessment aligns with common observations in the Fleet Marine Force, where Marines do not receive targeted training on how their basic pay and incentives compare to those in the civilian sector, nor do they receive instruction on the full range of financial incentives available to them. Improved financial literacy may have cascading effects, including increased retention rates. The following articles examine military compensation and the effectiveness of financial education programs on financial outcomes.

The Department of Defense (2025) reports in its recent DoD compensation review that military pay remains highly competitive with the civilian labor market. The DoD completed the Fourteenth Quadrennial Review of Military Compensation in 2025. The review examines the principles and structure of the military compensation system and compares them to civilian-sector wages and benefits, consistent with its four-year review cycle. Specifically, the report finds that military compensation is strongly competitive with the civilian labor market, with overall pay exceeding the 70th percentile benchmark. Enlisted members through 20 YOS are at the 83rd percentile of civilian pay, while officers are at the 76th percentile (Department of Defense, 2025).

Department of Defense (2025) finds that enlisted members with fewer than 10 YOS earned more than the 90th percentile of pay compared to civilians with high school diplomas. Those with 10 to 20 YOS earned above the 80th percentile compared to civilians with some college or an associate's degree. Officers with fewer than 10 YOS were above the 80th percentile compared to civilians with bachelor's degrees, while officers with 10 to 20 YOS fell slightly below the 70th percentile compared to civilians with master's degrees. One of the core recommendations from this review is to improve communication with service members, ensuring they understand the monetary benefits of military service and how total compensation compares to the civilian sector. Overall, these findings underscore the need for enhanced financial education across the DoD and the Marine Corps (Department of Defense, 2025).

Several studies show that financial education improves individual financial decision-making. While Kaiser et al. (2022) is not directly related to the military, it is widely considered the gold standard for randomized controlled trials and provides a credible evaluation of financial literacy programs. Kaiser et al. (2022) analyzes the growing literature on the causal effects of financial education programs through a meta-analysis of 76 randomized experiments. The analysis of the evidence therein concludes that financial education programs are found, on average, to produce positive causal effects on both financial knowledge and behavior (Kaiser et al., 2022). In an older study, Kaiser and Menkhoff (2020) conduct a quantitative meta-analysis of financial education programs for youth using 37 experiments. They find that, on average, financial education programs have sizeable impacts (+0.33 standard deviation) on financial knowledge that are comparable to educational interventions in other areas. In subgroup analyses, they find beneficial effects from more intensive financial education treatments (Kaiser and Menkhoff, 2020).

While the Kaiser articles support financial education for improving financial outcomes broadly, McKenzie (2022) focuses on its effectiveness in the context of major financial decisions. McKenzie expresses skepticism toward most financial education interventions, arguing that many programs lead only to incremental gains in knowledge and limited behavioral changes. He contends that financial education is most effective when delivered immediately before individuals face large financial decisions they do not fully understand. McKenzie analyzes the Kaiser studies and acknowledges their efforts to address issues such as publication bias. He concurs that positive financial effects can occur when interventions are low cost and targeted toward timely, high-stakes financial decisions in which individuals can act immediately on the information provided (McKenzie, 2022).

The Ahn et al. (2023) study highlights the importance of financial education for military service members, particularly for decisions they make themselves and observe their peers making. The study analyzes how workplace peers influence retirement plan decisions made by mid-career Navy personnel. Personnel must choose between a larger future pension benefit or an immediate bonus accompanied by a reduced pension. The study examines the decision between the “High-3” Legacy Retirement System, which provides higher long-term pension benefits, and the “Redux” plan, which offers a $30,000 immediate bonus in exchange for reduced pension benefits. Approximately 25% of eligible personnel choose Redux, and evidence indicates that 36% of Redux participants report regretting their decision compared with only 5% of those who selected High-3. The choice between these plans can result in lifetime payout differences of several hundred thousand dollars (Ahn et al., 2023).

In their design, Ahn et al. (2023) show personnel are already in conditionally random peer groups because personnel are assigned to different units with substantial randomness based on experience and mission needs. The authors estimate peer effects on lower-tenured personnel’s decisions using a linear-in-means model, where the outcome variable is the decision to choose Redux and the treatment variable is the fraction of peers within the unit who selected Redux. The authors find that observing costly financial decisions made by peers in the past, such as selecting Redux, is associated with subsequent decision-makers making more prudent financial choices. Specifically, a 10% increase in the share of peers selecting the Redux plan decreases the probability that lower-tenured personnel will choose Redux by 12.5%. (Ahn et al., 2023).

Cavanaugh (2018) highlights gaps in service members’ financial knowledge that persist even among highly educated military populations. Cavanaugh (2018) analyzes service members’ general and TSP-specific financial knowledge. The study surveys 1,305 active-duty officers and service members at the Naval Postgraduate School (NPS) to assess financial literacy. The study finds that 24.2% of surveyed Marines score below a 70% passing grade on general financial knowledge questions. Additionally, 42.6% of participants score below a 70% passing grade on TSP-specific general financial knowledge questions, and 65.6% fail TSP-specific, scenario-based questions. The study recommends expanding both TSP and general financial training for service members. While the TSP failure rates may be partly explained by the relative newness of the TSP in 2018, the general knowledge failures indicate a broader need for increased financial education. Because the sample consists primarily of highly performing officers at NPS, general financial knowledge is likely even lower among younger enlisted members and officers across the services. However, the study's low response rate of 12.9% limits the strength of its conclusions (Cavanaugh, 2018).

Clelan et al. (2022) reinforce the need to educate Marines on differences between military and civilian compensation and career structures. The authors analyze the monetary and non-monetary incentives offered in the Marine Corps and find that, at the end of a Marine's first term, Marines' military compensation is comparable to that of typical civilian counterparts on an annual pre-tax basis. After the first term, military compensation surpasses civilian compensation. The study recommends increased long-term career and financial messaging for Marines nearing the end of their first term to improve understanding and potentially enhance retention (Clelan et al., 2022).

The recommendations in Clelan et al. (2022) are based on multiple figures in the study that plot the estimated median earnings profile for civilian personnel with an associate's degree against average regular military compensation (RMC) for enlisted Military Occupational Specialties (MOS). RMC consists of basic pay, basic allowance for subsistence, and basic allowance for housing. At most ages, average RMC exceeds the median civilian compensation comparison and shows an expanding positive earnings gap later in the age profile, particularly after age 40. These large differences in lifetime earnings between Marines and civilian counterparts suggest that the Marine Corps should ensure Marines are fully aware of the monetary and non-monetary benefits of career service. Despite this compensation differential, most Marines choose to leave the service, with a substantial share exiting after a single term. This pattern suggests a lack of financial career knowledge within the Marine Corps (Clelan et al., 2022).

These studies use experiments, surveys, and quantitative analyses to evaluate the effectiveness of financial education programs both broadly and within the military context. The first three articles, which are not military-specific, conclude that financial education improves financial outcomes, particularly when targeted toward an upcoming financial decision. Ahn et al. (2023) further demonstrate the influence of peers' financial decisions, showing that past decisions made by service members affect the financial choices of junior personnel. The remaining studies recommend expanding financial education within the military, with an emphasis on communicating the monetary value of military compensation relative to civilian counterparts with similar education and skill levels. Collectively, these studies emphasize the importance of targeted financial education focused on compensation benefits, career milestones, retirement decisions, and comparisons between military and civilian pay and benefits, which may ultimately influence long-term retention decisions.

C. CONTINUATION PAY RESEARCH

Next, I review existing DoD studies on CP. Research on the effects of CP on retention and cost typically employs structural econometric models, in contrast to this study's use of ML methods. These studies demonstrate how the timing of CP offerings affects both mid-career retention and the overall cost of the incentive. The CP literature primarily relies on structural economic models that predict CP take-up by modeling individual utility functions or using historical retention patterns. Together, these studies summarize the current empirical evidence on the effectiveness of CP as a retention incentive.

Asch et al. (2017) at the RAND Corporation investigate the retention effects and estimated costs of CP under the BRS. Using a Dynamic Retention Model, the authors model individual decision-making over a service member's life cycle. The model estimates behavioral parameters using individual-level data for 25,000 enlisted personnel and 25,000 officers who begin service in 1990 or 1991 and are followed through 2010. It accounts for retention decisions as a function of individual choices and random shocks in each period (Asch et al., 2017).

In simulations within Asch et al. (2017), the RAND Corporation's Dynamic Retention Model finds that a CP multiplier at or near 2.5 for enlisted personnel and roughly 10 to 12 for officers sustains baseline force size and retention. The baseline retention profiles are derived from 2009 active-component enlisted and officer data, representing the long-run steady state under the legacy retirement system. RAND uses the Dynamic Retention Model to identify an optimized CP multiplier for each service, which minimizes the difference between BRS-simulated retention and the 2009 baseline retention pattern. The optimized CP multiplier for active enlisted Marines is 3.4 times monthly basic pay and 9.71 times monthly basic pay for active-duty Marine officers (Asch et al., 2017).

While Asch et al. (2017) estimates CP offered at 12 YOS, it does not examine the effects of offering CP earlier in a career, such as between 8 and 12 YOS, nor does it identify the optimal timing for CP across the services. The model does not account for variability in CP timing, including offering CP at 8 or 10 YOS instead of at 12 years. It also does not use historical CP take-up data because such data did not exist at the time of the study, as the BRS had not yet been implemented. Additionally, the Dynamic Retention Model does not treat CP take-up as a separate behavioral decision. Instead, CP acceptance is implicit for personnel who remain in service through the CP decision point at approximately 11–12 YOS, such that all eligible personnel who are retained at that point receive CP (Asch et al., 2017).

The BRS reduces the lifetime value of the traditional pension for members who remain in service until 20 YOS. CP is intended to offset this reduction through a mid-career incentive. Since the implementation of the BRS in 2018, CP multipliers have been set at 2.5 and 5 across the services. The Dynamic Retention Model in Asch et al. (2017) calculates the CP multiplier required to maintain baseline force size and retention patterns under the BRS. As a result, the model-implied multipliers are driven by the assumption that retention patterns and force structure should remain consistent with pre-BRS levels (Asch et al., 2017).

In a related study, Clelan et al. (2022) at the Center for Naval Analyses identify monetary and non-monetary incentives to increase retention among enlisted Marines using a Dynamic Decision Model based on annual snapshots from 2010 to 2019. The Dynamic Decision Model estimates the probability of reenlistment based on each Marine's expected wage if they remain in service versus separating, as well as expectations for how their military career and personal life evolve over time. The study uses Marine Corps demographic and contract data from end-of-fiscal-year snapshots for 2010–2019 and follows Marines across these years, identifying reenlistment decisions through observed changes in enlistment status from one September to the next (Clelan et al., 2022).

The Dynamic Decision Model within Clelan et al. (2022) assumes that Marines choose to remain in or leave the service based on the option that maximizes their utility. To measure utility, the model estimates how Marines value military compensation and benefits, career expectations, and civilian compensation and benefits. This structural model simulates the impact of counterfactual, or "what-if," scenarios related to Marine retention decisions. One objective of the Dynamic Decision Model is to estimate a Marine's utility function that best fits observed decisions in the data and then predict behavior under various counterfactual scenarios (Clelan et al., 2022).

Clelan et al. (2022) predicts CP take-up rates for the Marine Corps under alternative CP timing scenarios. These scenarios are based on critical MOSs (02XX, 05XX, 06XX, 08XX, 17XX, 26XX, 59XX, 62XX, 68XX, 72XX) rather than the full force, using a sample of 5,338 Marines and assuming a 100% take-up rate. Using the Dynamic Decision Model on this MOS-specific sample, the authors find that offering CP at 10 YOS with a multiplier of five times monthly basic pay produces the greatest retention gain relative to cost. They also find that changes in predicted retention are relatively small compared to total CP costs when CP timing varies (Clelan et al., 2022).

One recommendation from Clelan et al. (2022) is to adjust the timing of monetary incentives for Marines, as changes in timing may be more cost-effective than increasing the monetary value of the incentive itself. The Dynamic Decision Model, like the Dynamic Retention Model, does not use historical CP take-up data. The study notes that models relying solely on historical data are ill-suited for predicting outcomes in new or previously unobserved scenarios because no historical reference exists (Clelan et al., 2022). This limitation motivates the use of alternative data sources, such as cross-service historical Army CP data, to inform projections of CP policies for the Marine Corps.

Spratt et al. (2024), in collaboration with the Center for Naval Analyses, conduct a study evaluating the effects of the BRS on naval personnel, with a focus on the CP incentive. One of the four research questions therein asks which CP policy maximizes Navy enlisted inventory at the lowest cost. To answer this question, the study employs an inventory simulation model alongside a Dynamic Decision Model. The Dynamic Decision Model relies on annual snapshots of sailor reenlistment decisions, career characteristics, and demographic data from 2000 to 2023. Most model parameters are estimated using more recent data from 2017 to 2023 (Spratt et al., 2024).

Spratt et al. (2024), first runs a simulation using steady-state inventory counts under the assumption that 37,700 sailors enter the Navy each year, which matches the Fiscal Year 2023 recruiting goal. The study then estimates the model assuming a 100% CP take-up rate at a multiplier of 2.5. The analysis finds that offering CP at 9 YOS is the inventory-maximizing scenario. It also finds that sailors at 8 or 9 YOS are more likely to leave at the earliest decision point and are marginal decision-makers with greater sensitivity to retention bonuses than those at 12 YOS. These results suggest that offering CP at 9 YOS yields higher retention at lower cost than increasing the CP multiplier from 2.5 to 3 at 12 YOS (Spratt et al., 2024).

Next, Spratt et al. (2024), estimates the implementation costs of this CP policy change and develops a simulation model using the 2023 Enlisted Master Record snapshot to identify decision points and model sailors' career characteristics. The models assume, for simplicity, that any sailor eligible for CP takes it, with alternative scenarios using fixed CP take-up percentages. The study limits the sample to sailors enrolled in the BRS and simulates their careers through 2030, applying average loss rates by YOS from 2018 to 2022. This process produces simulated BRS population sizes by YOS. To estimate costs, the study uses the historical pay grade distribution and the 2024 basic pay tables. Costs are calculated as the product of population size, average CP cost, and the CP take-up rate (Spratt et al., 2024).

Spratt et al. (2024) estimates the costs of shifting CP eligibility from 12 YOS to 9 YOS under different CP take-up rates of 60%, 70%, 80%, 90%, and 100%. The authors also include a "historical" column that is not derived from observed CP take-up data, but instead from the probability of a sailor serving four additional years beyond their current YOS. For example, a sailor who reaches 9 YOS has a 75% probability of remaining for four more years. As a result, the historical column represents the most likely CP take-up rate based on observed retention patterns rather than actual CP take-up behavior. In contrast, the 100% take-up scenario serves as an upper-bound confidence interval estimate. The table shows that implementing an 11 YOS CP policy in 2030 has higher upfront costs than implementing a 9 YOS CP policy in 2026 (Spratt et al., 2024).

Spratt et al. (2024) concludes that if the Navy intends to use CP as a retention tool, offering it at 9 YOS is more cost-effective than later alternatives. It further recommends implementing this change as early as possible to reduce upfront costs. This recommendation is driven by projections showing a substantial increase in the CP-eligible population over the next 1 to 5 years as the force fully transitions to the BRS. Like other studies, this analysis does not use historical CP take-up data; instead, the models rely on historical retention rates and fixed CP take-up assumptions, such as 60% or 70% (Spratt et al., 2024).

Meanwhile, Cullen (2024) conducts a policy evaluation by analyzing CP take-up rates following the Marine Corps' decision to increase the multiplier from 2.5 to 5 times monthly basic pay in 2023. This approach estimates the causal impact of the multiplier increase on CP take-up rates. Using Marine Corps data from 2018 to 2023 and a linear probability model, the study finds that the higher multiplier increases the likelihood of eligible Marines taking CP by 5.9 percentage points relative to those offered the 2.5 multiplier. The baseline take-up rate is 67% for eligible enlisted Marines and 50% for eligible officers. Cullen also incorporates performance evaluations (Fitness Reports) and finds that above-average performers are more likely to take CP. Unlike prior studies, Cullen's model is the first to use observed historical CP take-up data rather than fixed assumed take-up rates to evaluate changes in CP policy, such as the USMC's multiplier increase (Cullen, 2024).

Finally, Thorton (2025) estimates the effect of the BRS on retention. Its findings suggest that the BRS improves retention. The study analyzes 10 years of Marine Corps data using a regression discontinuity design and finds that Marines under the BRS separate at rates 5.2 to 7.6 percentage points lower than those under the Legacy Retirement System. Unlike prior studies, this analysis uses a regression discontinuity design to control for omitted variables and isolate the causal effect of the BRS on retention. The approach exploits a time-based policy cutoff on January 1, 2018, when the Legacy Retirement System transitions to the BRS (Thorton, 2025).

Overall, the CP literature identifies several consistent findings and recommendations. Across studies, researchers emphasize the need for further evaluation of CP policy design, particularly how adjustments to incentive timing and multiplier size can improve mid-career retention and CP take-up. The study by Asch et al. (2017), conducted prior to BRS implementation, emphasizes the higher multiplier required to offset the reduction in pension value under the BRS relative to the Legacy Retirement System. More recent studies by Clelan et al. (2022) and Spratt et al. (2024) use economic decision models to project that offering CP earlier, at 10 or 9 YOS, respectively, produces greater retention gains relative to cost. Cullen (2024) and Thorton (2025) use historical data and causal methods, including a linear probability model and a regression discontinuity design, to estimate the effects of increasing the CP multiplier and the impact of the BRS on retention.

These models and studies evolve over time as assumptions and data improve, particularly with several years of BRS and CP data now available. Differences across structural model studies include the use of alternative decision frameworks, data sources, and fixed assumptions regarding CP take-up rates. Collectively, these studies are pivotal in shaping current understanding of the BRS and the CP incentive and how they affect overall force retention, size, and structure.

D. SUMMARY

The financial literature highlights multiple studies on the effects of financial education programs on financial knowledge and decision-making. These studies recommend improved financial education and training for service members, including greater awareness of how military compensation and incentives compare to those in the civilian sector. More targeted financial training may lead to improved outcomes for both Marines and the service, such as higher retention rates, through better understanding of the long-term benefits of a military career and its compensation relative to civilian alternatives. Additional research is needed to establish a causal relationship between low financial education and negative financial decisions. This thesis' second research question contributes to this gap by examining predictors and trends in non-take-up of CP, which may help link CP non-take-up behavior to gaps in financial education.

The literature also reviews existing DoD studies on CP. These studies demonstrate how the timing of CP offerings affects both mid-career retention and the overall cost of the incentive. CP literature primarily uses structural economic models that predict CP take-up by modeling individual utility or relying on historical retention rates. Only Cullen (2024) relies on observed historical CP take-up data, focusing on changes in the CP multiplier. Thorton's (2025) thesis further motivates the present study by providing evidence on the retention effects of the BRS and supporting the evaluation of expanded CP policies. Collectively, these studies summarize the current empirical evidence on CP as a retention incentive.

To date, no studies use observed historical CP take-up rates to model alternative CP timing policies. As a result, it remains unclear whether offering CP earlier in a career, such as at 9 or 10 YOS, improves retention more cost-effectively than current approaches. While the Dynamic Retention Model developed by Asch et al. (2017) is appropriate for pre-implementation analysis of the BRS, this thesis applies ML methods using recent CP take-up data to identify significant predictors of CP participation and to forecast future CP take-up behavior. Although Clelan et al. (2022) argue that historical data alone cannot project outcomes under untested policies, this study extends that framework by leveraging observed CP behavior from the Army, which has implemented an 8–12 YOS CP window. Using this cross-service evidence allows for informed projections of CP take-up under alternative timing scenarios for the Marine Corps.

This thesis contributes to the literature by comparing observed CP take-up across different offering windows to evaluate when the incentive is most effective. It uses historical CP take-up data from the Army's implementation of CP between 8 and 12 YOS since the incentive's introduction in 2018. The ML model draws on this cross-service evidence to simulate future CP take-up behavior among Marines under alternative timing scenarios. This approach differs from prior studies by incorporating observed CP participation rather than assumed take-up rates and provides a predictive baseline for Marine take-up if the service adopts an 8–12 YOS CP window. Using historically observed data also helps bridge the gap between internal validity and the external validity required for evaluating changes to CP policy in the Marine Corps. Overall, this thesis addresses the question of optimal CP timing by applying new data, observed take-up behavior, and ML methods to CP policy analysis.

III. DATA AND METHODOLOGY

A. DESCRIPTION OF DATA

The datasets used in this study are unpublished Department of Defense personnel records accessed through approved channels and are not publicly available due to privacy and security restrictions. The USMC data is obtained from the DoD Advancing Analytics (ADVANA) system and the Army data is obtained from the DoD Person-Event Data Environment (PDE). Both datasets include social-demographic, BRS, and CP variables. The USMC dataset consists of active-duty Marine observations from December 31, 2017, through June 30, 2025. The Army demographic dataset includes active-duty Soldier observations from December 31, 2017, through February 28, 2025, with a separate Army CP dataset capturing CP takers through May 4, 2025.

Final cleaned datasets include a study-specific unique person identifier, snapshot dates, contract start and end dates, rank, YOS, MOS, reporting unit codes, grade, age, marital status, race, sex, ethnicity, religion, BRS variables, and CP variables. The Army dependents-count variable is unreliable; therefore, the dependents covariate is excluded from both the USMC and Army datasets. This study merged all source files using stable unique identifiers, including the Electronic Data Interchange Personal Identifier (EDIPI), and then created study-specific unique person identifiers.

The study separated the Army and the Marine Corps datasets into three analysis datasets per service. All data frames support summary statistics; data frame 2 is used to train the ML models, and data frame 3 provides the current active-duty population for future projections. All tables and figures in this thesis are generated using the final cleaned data frames.

- Data frame 1 (BRS Opt-In): Includes all personnel eligible to choose between the Legacy retirement system and BRS. The outcome variable equals 1 for BRS opt-in and 0 for opt-out.
- Data frame 2 (CP Decision): Includes all CP-eligible personnel who made a CP decision. In the USMC data, Marines who do not make a CP election

by 12 YOS are recorded as system decliners ("S"), while a "D" code indicates an active decline before 12 YOS. In the Army data, CP acceptors are observed directly; CP decliners are defined as BRS Soldiers who reached 12 YOS without accepting CP.

- Data frame 3 (Separation/Survival): Includes all personnel across the full observation window and captures their final dataset appearance. Individuals exiting the dataset are treated as separations, while those remaining on active duty at the end of the period are right-censored.

Figure 1 illustrates the construction of the three datasets. The analyses were conducted in R (version 4.3.2) within PDE, and each dataset is used to generate summary statistics for both services.

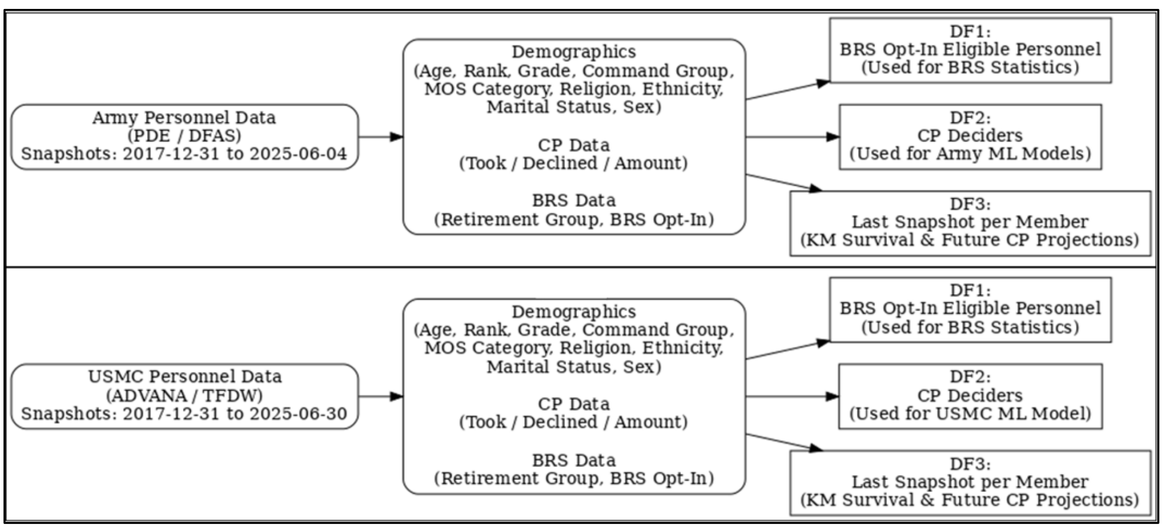

Figure 1. Data Flow Chart

B. ARMY SUMMARY STATISTICS

Table 1 reports year-by-year and total Army CP take-up rates among Soldiers who made a CP decision, with 2024 showing the highest full-year take-up rate at 76%. The table also reports CP costs under the Army's 2.5 base-pay multiplier, which has been in effect since the program's introduction in 2018. CP take-up is observed across multiple timing windows: 8–9, 9–10, 10–11, 11–12, and at 12 YOS. While early program years show relatively low Army take-up, rates in 2024 and 2025 closely resemble USMC take-up in those years (82% and 81%, respectively). CP take year is defined using the interval between Pay Entry Base Date and CP issue date, while CP decliners are defined as BRS Soldiers who reached 12 YOS without accepting CP. Eligible personnel include all individuals who made a CP accept or decline decision, with CP issue or decline dates assigned to the demographic snapshot closest to the decision date to allocate personnel across service-year bins. The 2025 values reflect partial-year CP data through May 4, 2025.

Table 1. Army Continuation Pay Take-Up

Table 1. Army Continuation Pay (CP) Take-Up

	2018	2019	2020	2021	2022	2023	2024	2025	Total
CP Elig.	763	1006	1383	2003	2783	4909	7394	2042	**22283**
CP Take	53	221	320	527	1360	2704	5627	1664	**12476**
CP Take Y8	3	8	15	9	33	408	1132	689	**2297**
CP Take Y9	6	10	6	7	56	438	1272	301	**2096**
CP Take Y10	5	11	39	54	392	769	1520	267	**3057**
CP Take Y11	27	136	202	371	690	865	1388	323	**4002**
CP Take Y12	12	56	58	86	189	224	315	84	**1024**
CP Deny	710	785	1063	1476	1423	2205	1767	378	**9807**
Accept %	7%	22%	23%	26%	49%	55%	76%	81%	**56%**
CP Cost (Mil)	0.69	2.84	3.97	7.08	19.10	36.65	81.40	23.27	**175.00**

Figure 2 plots CP take-up percentages since the incentive's inception and shows that officers consistently take up CP at higher rates than enlisted personnel, with 2024 take-up rates of 83% for officers and 71% for enlisted.

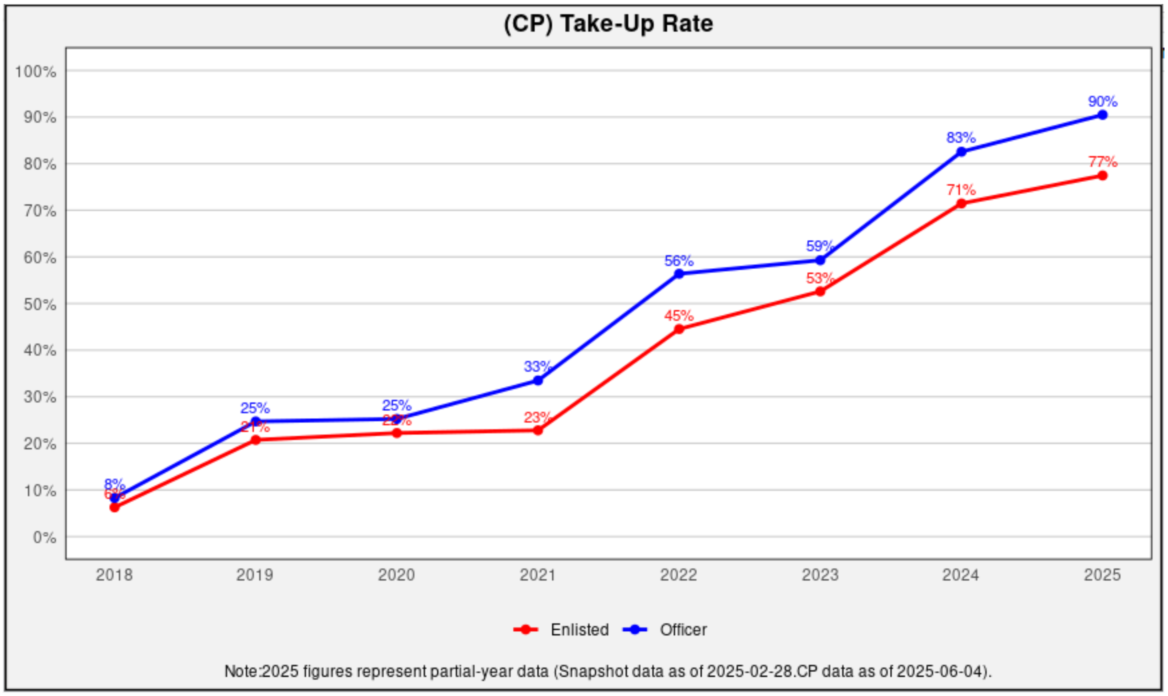

Figure 2. Army Percentage of Eligible Soldiers Who Accepted the Continuation Pay Bonus

Figure 3 plots overall CP take-up percentages since the incentive's inception and the distribution of CP take-up timing by YOS. From 2018–2022, most personnel accepted CP at later career points (11 or 12 YOS), while in 2023 and 2024 take-up is more evenly distributed across 8–11 YOS, with fewer acceptances at 12 YOS.

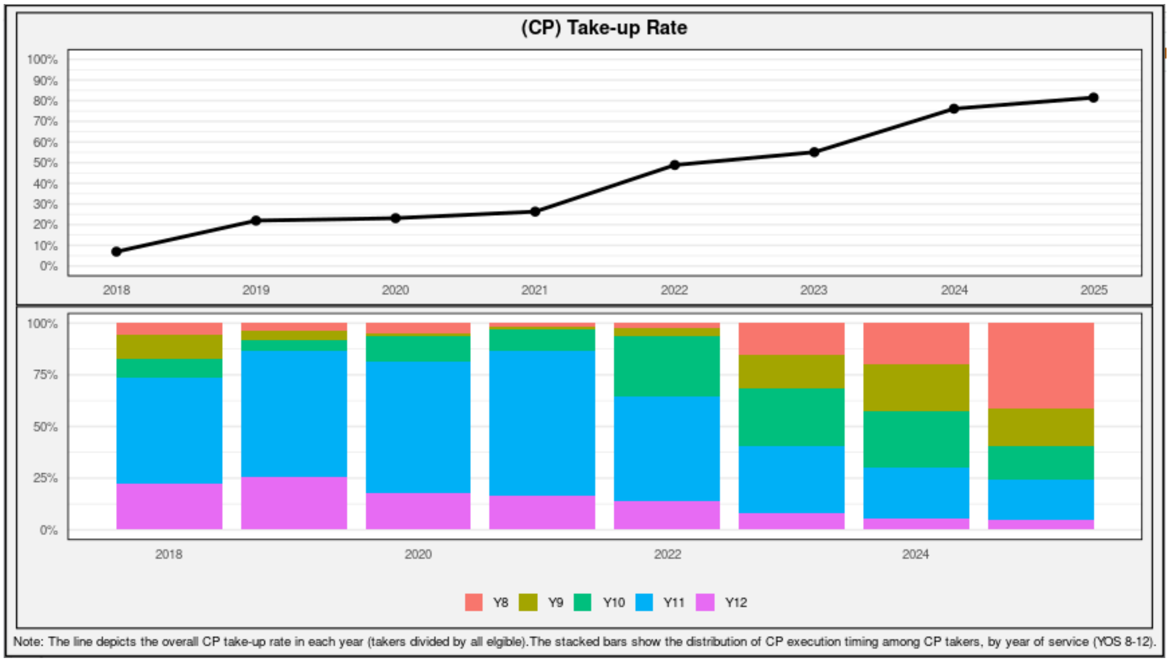

Figure 3. Army Continuation Pay Take-Up Overall and Share of Take-Up by Year (8–12)

Table 2 presents demographic characteristics of CP takers and CP decliners. Across most grade, marital status, and MOS categories, CP take-up rates range from approximately 50% to 64%, reflecting lower take-up during the Army's early CP years and substantially higher rates in more recent years. The Army dependents variable captures only dependents co-located with Soldiers stationed overseas, which likely understates true dependent counts; as a result, dependent-specific take-up rates should be interpreted with caution. Notably, subgroup totals may not equal overall totals due to missing or unknown demographic values or observations falling outside the categories shown in Table 2 (e.g., divorced marital status).

Table 2. Army Continuation Pay Demographics

Table 2. Army Continuation Pay (CP) Demographics			
Category	CP Take	CP Deny	Accept %
Officers	5,435	3,127	63
Enlisted	7,037	6,618	52
Married	9,401	7,413	56
Single	3,052	2,365	56
Combat MOS	2,191	2,159	50
Combat Support	9,388	7,059	57
Aviation Support	440	250	64
Pilot MOS	457	339	57
No Dependents	11	19	37
1 Dep	105	180	37
2 Dep	68	156	30
3 Dep	64	139	32
4 Dep	36	121	23

Table 3 presents the balance table for Army CP deciders, reporting subgroup counts, percentages, and p-values. The p-values assess statistically significant differences between CP takers and decliners within each category (e.g., by sex or MOS category).

Table 3. Descriptive Characteristics of Army Continuation Pay Deciders

Category	Variables	DECLINER	TAKER	P-Value
n		9807	12476	
SEX	F	1585 (16.2%)	2177 (17.4%)	<0.001***
	M	8222 (83.8%)	10299 (82.6%)	
MOS_CATEGORY4	Aviation Support	250 (2.5%)	440 (3.5%)	<0.001***
	Combat MOS	2159 (22.0%)	2191 (17.6%)	
	Combat Support	7059 (72.0%)	9388 (75.2%)	
	Pilot MOS	339 (3.5%)	457 (3.7%)	
MARITAL_5	Legally Separated	10 (0.1%)	16 (0.1%)	<0.001***
	Married	7413 (75.6%)	9401 (75.4%)	
	Single	2365 (24.1%)	3052 (24.5%)	
	Unknown/Blank	2 (0.0%)	1 (0.0%)	
	Widowed	17 (0.2%)	6 (0.0%)	
ETHNIC_7	American Indian/Alaska Native	73 (0.7%)	87 (0.7%)	<0.001***
	Asian	833 (8.5%)	989 (7.9%)	
	Black/African American	1930 (19.7%)	2532 (20.3%)	
	Declined/Unknown	248 (2.5%)	336 (2.7%)	
	Hispanic (non-Mexican)	842 (8.6%)	1039 (8.3%)	
	Mexican	528 (5.4%)	714 (5.7%)	
	White	5353 (54.6%)	6779 (54.3%)	
RELIGION_4	Christian	6530 (66.6%)	8499 (68.1%)	<0.001***
	Non-Christian	490 (5.0%)	738 (5.9%)	
	None	636 (6.5%)	463 (3.7%)	
	Unknown/Blank	2151 (21.9%)	2776 (22.3%)	
AGE_INT (Mean & SD)		34.6 (4.8)	32.6 (4.1)	<0.001***
COMMAND_GROUP	Operational	5173 (52.7%)	3197 (25.6%)	<0.001***
	Reserve	2 (0.0%)	0 (0.0%)	
	Support	2744 (28.0%)	2864 (23.0%)	
	Other	1888 (19.3%)	6415 (51.4%)	
GRADE_GROUP	Enlisted	6618 (67.9%)	7037 (56.4%)	<0.001***
	Officer	3127 (32.1%)	5435 (43.6%)	
Note: P-Value tests differences between CP Takers and Decliners (t-test for continuous; chi-squared for categorical). *p<0.10 **p<0.05 ***p<0.01				

Table 4 shows the distribution of Army-monitored command codes (Asg_unt_mjr_cmd_cd) using DoD Activity Address Directory major command definitions and collapses them into broad force-structure categories: operational units, support/generating force units, reserve component units, and a joint/other category.

Table 4. Army Continuation Pay Take-up by Command Group

Table 3. Army Continuation Pay (CP) Take-Up by Command Group

	CP Take	CP Deny	Accept %
Operational	3,197	5,173	38%
Support	2,864	2,744	51%
Reserve	0	2	0%
Other	6,415	1,888	77%

Figure 4 presents a Kaplan-Meier survival curve showing the probability that Army CP deciders remain on active duty after accepting or declining CP. CP takers enter the curve at their CP take year (8–12 YOS), while CP decliners enter at 12 YOS. Although CP decliners exhibit lower overall survival than takers, their survival probability does not drop sharply following the CP decision point. Sample sizes in Figure 4 are smaller than total CP taker and decliner counts because survival-analysis requires valid CP decision start dates, valid separation or censoring dates, and stop dates occurring after start dates; the analysis excludes observations that fail to meet these criteria. Personnel still on active duty at the final snapshot are treated as right-censored and contribute to the curve through their last observed YOS.

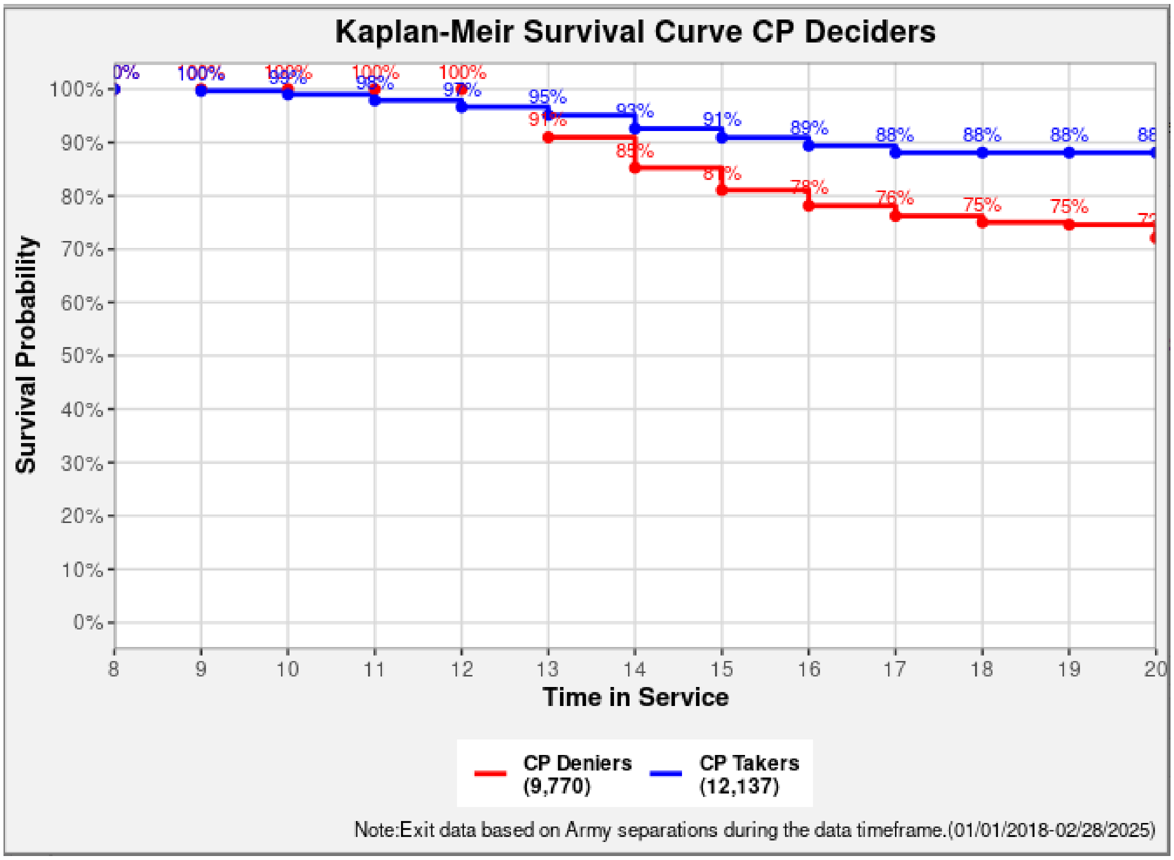

Figure 4. Army Continuation Pay Deciders Kaplan-Meier Survival Curve

Figure 5 presents Kaplan-Meier survival curves for CP takers by year of CP acceptance, along with a curve for CP decliners. Survival patterns are similar regardless of the year in which CP is taken, with most taker cohorts reaching approximately 90–95% survival after completing the four-year CP obligation. The exception is CP acceptance at 9 YOS, which declines to just under 80% survival following completion of the four-year service obligation at 13 YOS. Overall, the year the Soldier took CP appears to have limited influence on post-obligation retention, with observed survival bounded between approximately 80% and 95%. Only personnel with positive post-decision observation periods are included, and curves extending to 20 years reflect the maximum observed career lengths rather than a required service threshold.

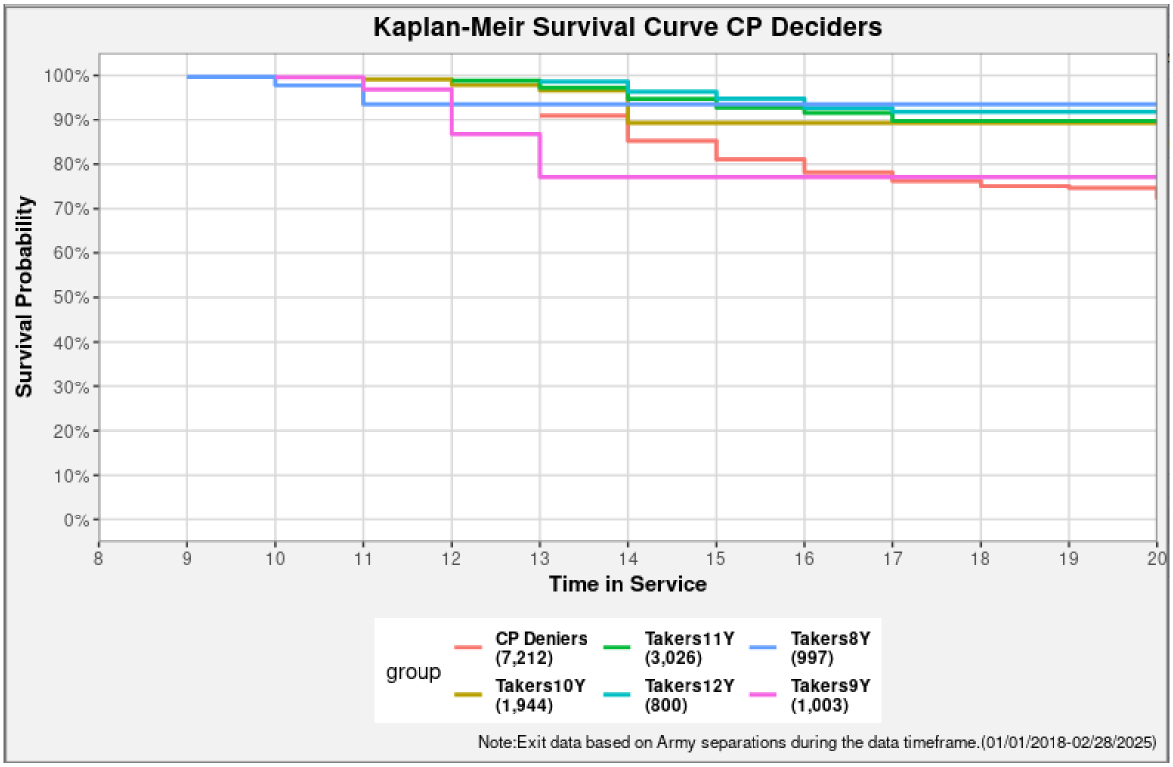

Figure 5. Army Continuation Pay Deciders Kaplan-Meier Survival Curve by Take-Up Year (8–12)

Table 5 summarizes the survival logic in tabular form and reports key post-CP decision outcomes. Most CP takers and decliners remain within their initial four-year post-decision window and are therefore right-censored in the survival analysis. A small share of CP takers fail to complete the four-year obligation, while 21.4% of CP decliners separate within four years of declining CP at 12 YOS. Across all CP take years, fewer than 0.5% of takers exit following completion of their four-year obligation.

Post-obligation survival estimates for CP acceptance at 8–10 YOS are based on limited observations, as only 91 total deciders from those cohorts have reached the post-obligation period; however, 99% of these personnel remain on active duty. More reliable estimates are available for CP takers at 11 and 12 YOS, where 674 individuals have completed their four-year obligation and 97% remain on active duty, indicating high post-obligation retention.

Table 5. Army Continuation Pay Deciders Survival Curve Chart

Outcome bucket	Decliners	Takers 10Y	Takers 11Y	Takers 12Y	Takers 8Y	Takers 9Y
Invalid/insufficient follow-up	33 (0.3%)	49 (1.6%)	60 (1.5%)	37 (3.6%)	120 (5.2%)	57 (2.7%)
Still active within 4-year period (right-censored)	5,579 (56.9%)	2,901 (95.0%)	3,351 (83.8%)	760 (74.5%)	2,146 (93.6%)	2,011 (96.1%)
Did not complete 4-year period	2,100 (21.4%)	39 (1.3%)	97 (2.4%)	39 (3.8%)	10 (0.4%)	16 (0.8%)
Completed 4 years and still active	1,887 (19.2%)	61 (2.0%)	477 (11.9%)	177 (17.4%)	16 (0.7%)	8 (0.4%)
Completed 4 years then separated (<20 YOS)	115 (1.2%)	5 (0.2%)	15 (0.4%)	5 (0.5%)		1 (0.0%)
Reached 20 YOS then separated	14 (0.1%)					
Reached 20 YOS and still active	75 (0.8%)			2 (0.2%)		

C. MARINE CORPS SUMMARY STATISTICS

Table 6 reports year-by-year and total CP take-up rates for Marines, with 2024 showing the highest take-up rate at 82%. The table also reports CP costs and reflects the Marine Corps' increase in the CP multiplier from 2.5 to 5.0 base pay for active-duty Marines beginning in early 2023. The CP-eligible population includes all Marines who made a CP accept or decline decision. CP take year is assigned using the CP payment or decline date placed in the demographic snapshot closest to that date. The 2025 values represent partial-year data through June 30, 2025.

Table 6. USMC Continuation Pay Take-Up

	2018	2019	2020	2021	2022	2023	2024	2025	Total
CP Eligible	236	288	414	552	719	1,027	1,315	1,099	**5,650**
CP Take	160	194	224	354	478	748	1,074	886	**4,118**
CP Deny	76	94	190	198	241	279	241	213	**1,532**
Accept Percent.	68%	67%	54%	64%	66%	73%	82%	81%	**73%**
CP Cost (Mil)	1.77	2.28	2.80	4.84	6.59	21.42	30.83	27.79	**98.32**

Table 7 provides a more detailed breakdown of CP decliners, showing that the majority of declines occur through system-decline when Marines pass 12 YOS without making an election, rather than through an active decision to decline CP. System decliners account for 1,398 of 1,532 total decliners, or 91.26%. The 2025 values represent partial-year data through June 30, 2025.

Table 7. USMC Continuation Pay Non-Take-Up

	2018	2019	2020	2021	2022	2023	2024	2025	Total
CP Eligible	236	288	414	552	719	1,027	1,315	1,099	**5,650**
CP Deny	76	94	190	198	241	279	241	213	**1,532**
Member Decline	0	1	6	10	24	36	34	23	**134**
No Elect, Decline	76	93	184	188	217	243	207	190	**1,398**
Decline Percent.	32%	33%	46%	36%	34%	27%	18%	19%	**27%**

Figure 6 plots CP take-up percentages since the incentive's inception and shows that enlisted Marines take up CP at higher rates than officers, with 2024 take-up rates of 85% for enlisted personnel and 75% for officers. Take-up rates for both groups increase after 2020, with a marked rise following the increase in the CP multiplier from 2.5 to 5.0 base pay beginning in 2023.

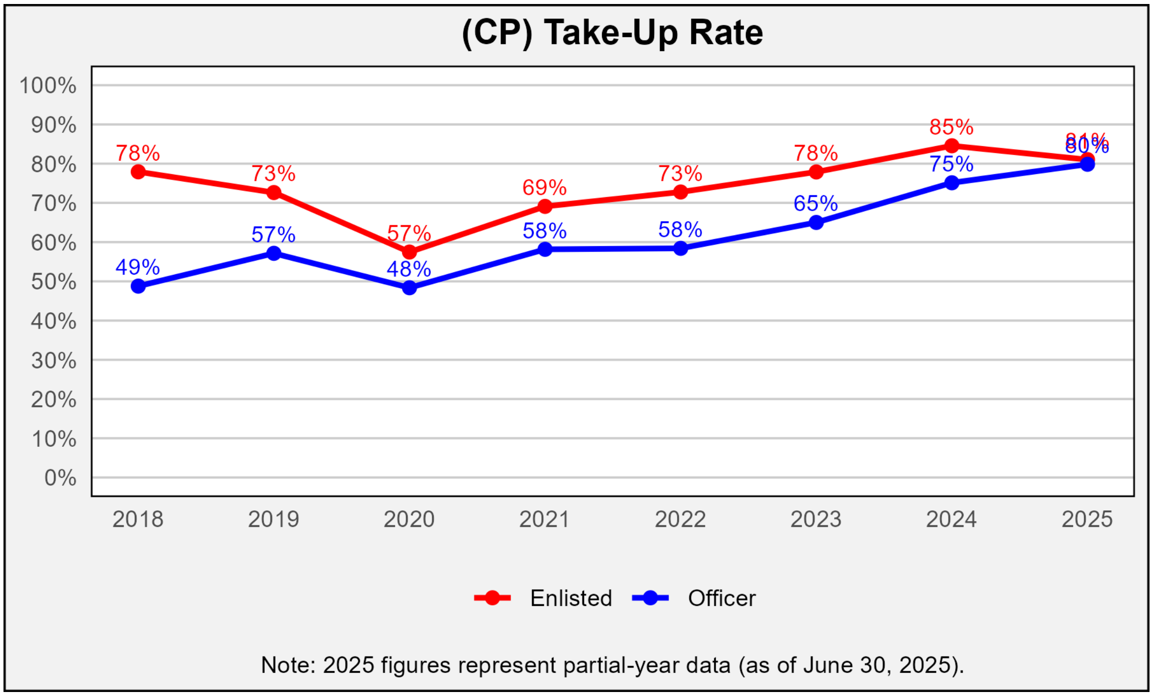

Figure 6. USMC Percentage of Eligible Marines Who Accepted the Continuation Pay Bonus

Table 8 presents demographic characteristics of CP takers and CP decliners. CP take-up rates range from 65% to 79% across most demographic groups, with the exception of pilots, who exhibit the lowest take-up rate at 45%. Subgroup totals may not equal overall totals due to missing or unknown demographic values or observations falling outside the categories shown in Table 8 (e.g., divorced marital status).

Table 8. USMC Continuation Pay Demographics

	CP Take	CP Deny	Accept %
Officers	1,365	716	66%
Enlisted	2,753	816	77%
Married	3,226	1,126	74%
Single	516	272	65%
Combat MOS	549	207	73%
Combat Support	2,523	685	79%
Aviation MOSs	687	195	78%
Pilot MOS	359	445	45%
No Dependents	931	430	68%
1 Dep	823	392	68%
2 Dep	767	252	75%
3 Dep	986	291	77%
4+ Dep	611	167	79%

Table 9 presents the balance table for USMC CP deciders, reporting subgroup counts, percentages, and p-values. The p-values assess statistically significant differences between CP takers and decliners within each category (e.g., sex or MOS category).

Table 9. Descriptive Characteristics of USMC Continuation Pay Deciders

Category	Variables	DECLINER	TAKER	P-Value
n		1532	4118	
SEX	f	144 (9.4%)	356 (8.6%)	0.4040
	m	1388 (90.6%)	3762 (91.4%)	
MOS_CATEGORY4	aviation mos	195 (12.7%)	687 (16.7%)	0.0010***
	combat mos	207 (13.5%)	549 (13.3%)	
	combat support	685 (44.7%)	2523 (61.3%)	
	pilot mos	445 (29.0%)	359 (8.7%)	
MARITAL_5	legally separated	4 (0.3%)	11 (0.3%)	0.0010***
	married	1126 (73.5%)	3226 (78.3%)	
	single	272 (17.7%)	516 (12.5%)	
	unknown/blank	130 (8.5%)	360 (8.7%)	
	widowed	0 (0.0%)	5 (0.1%)	
ETHNIC_7	american indian/alaska native	19 (1.2%)	44 (1.1%)	0.0010***
	asian	86 (5.6%)	221 (5.4%)	
	black/african american	140 (9.1%)	459 (11.1%)	
	declined/unknown	157 (10.2%)	340 (8.3%)	
	hispanic (non-mexican)	134 (8.7%)	412 (10.0%)	
	mexican	88 (5.7%)	390 (9.5%)	
	white	908 (59.3%)	2252 (54.7%)	
RELIGION_4	christian	994 (64.9%)	2727 (66.2%)	0.0460**
	non-christian	27 (1.8%)	56 (1.4%)	
	none	405 (26.4%)	984 (23.9%)	
	unknown/blank	106 (6.9%)	351 (8.5%)	
DEP_INT (Mean & SD)		1.63 (1.46)	1.93 (1.49)	
AGE_INT (Mean & SD)		32.16 (2.19)	32.03 (2.43)	
COMMAND_GROUP	operational	316 (20.6%)	816 (19.8%)	0.0540*
	other	508 (33.2%)	1254 (30.5%)	
	support	708 (46.2%)	2048 (49.7%)	
GRADE_GROUP	officer	716 (46.7%)	1365 (33.1%)	0.0010***
	enlisted	816 (53.3%)	2753 (66.9%)	

P-Value tests differences between CP Takers and Decliners (t-test for continuous; chi-squared for categorical). *p<0.10 **p<0.05 ***p<0.01

Figure 7 provides a more detailed view of CP take-up among pilots who made a CP decision from 2018 to 2025 and shows a modest increase in take-up following the 2023 CP multiplier increase.

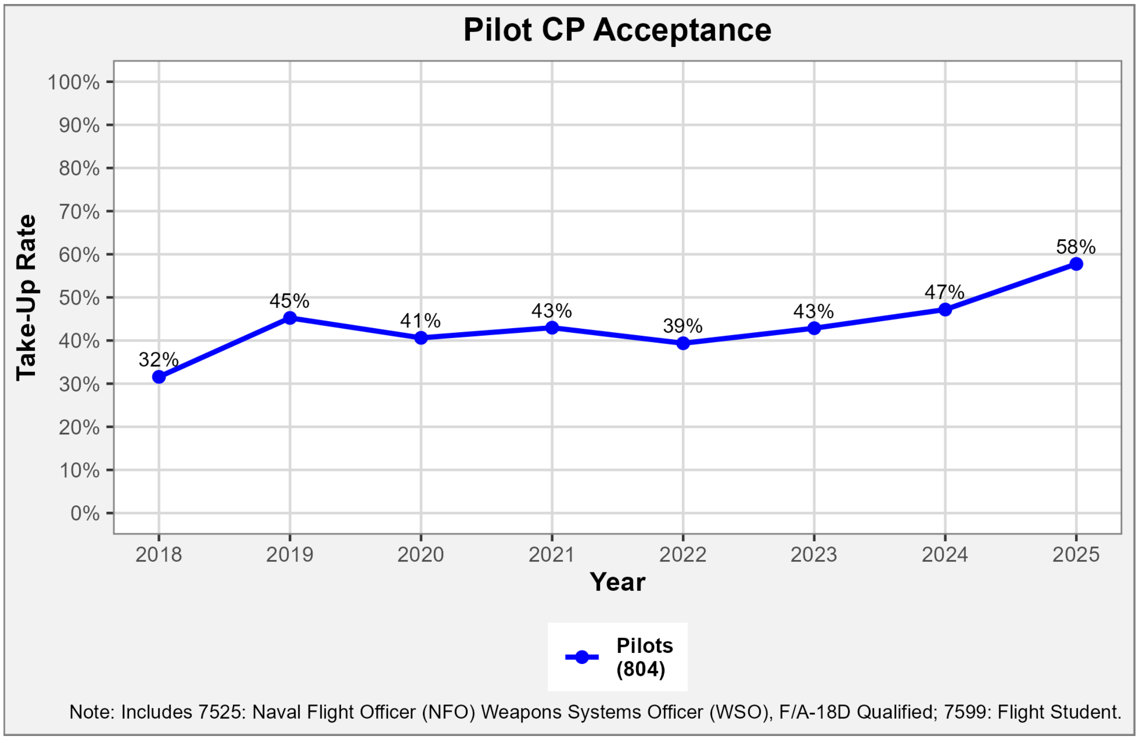

Figure 7. USMC Pilot Continuation Pay Acceptance

Figure 8 displays all pilot MOSs with CP acceptance rates below 68% and reports the number of personnel in each MOS who made a CP decision. The eight pilot MOSs shown from left to right in Figure 8 are defined by the following MOS titles:

- 7509 – VMA AV-8B Harrier II Pilot
- 7523 – VMFA F/A-18 Hornet Tactical Jet Pilot
- 7556 – VMGR KC-130 Hercules Co-Pilot
- 7557 – VMGR KC-130 Hercules Aircraft Commander
- 7532 – VMM V-22 Osprey Pilot
- 7565 – HMLA AH-1 Cobra Pilot
- 7563 – HMLA UH-1Y AH-1Z Venom Pilot
- 7525 – Naval Flight Officer (F/A-18D Weapons Safety Officer)
- 7518 – VMFA FRS F-35B Pilot

- 7543 – VMAQ EA-6B Prowler Pilot
- 7566 – CH-53K King Stallion Pilot
- 7547 – Night Systems Instructor

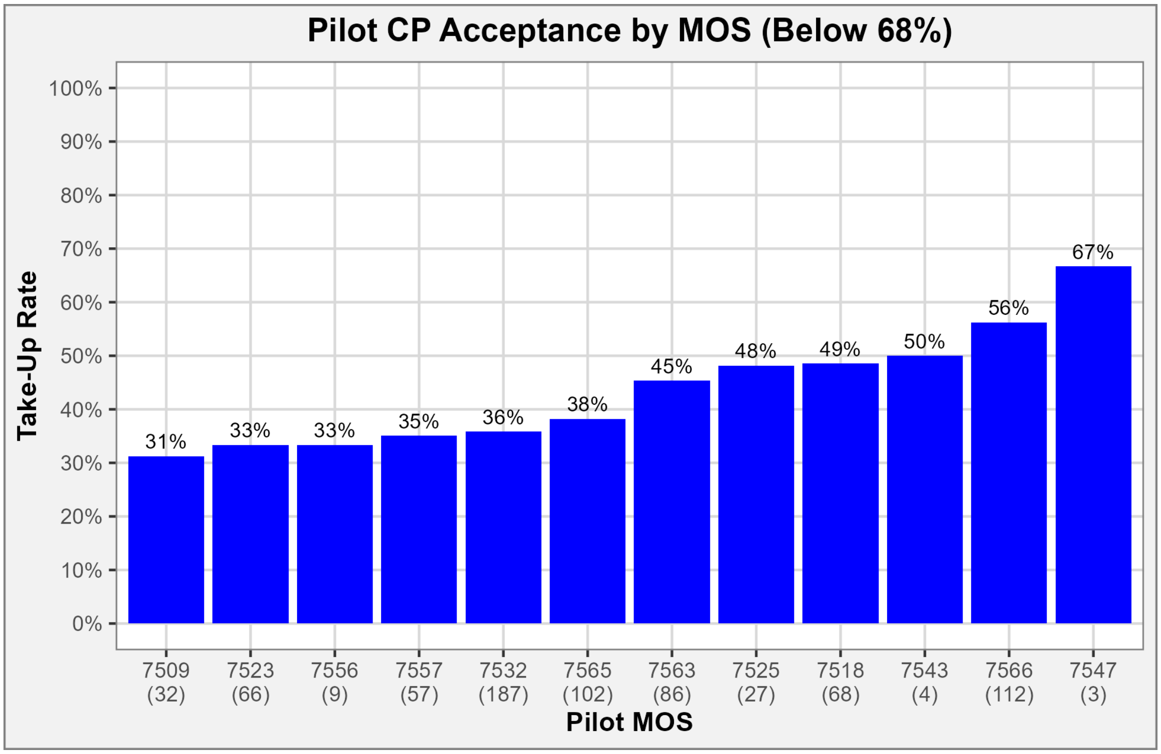

Figure 8. USMC Pilot Continuation Pay Acceptance by MOS (Below 68%)

Table 10 maps USMC-monitored command codes using major command definitions and collapses them into broad force-structure categories: operational units, support units, reserve component units, and joint/other units.

Table 10. USMC Continuation Pay Take-Up by Command Group

USMC Continuation Pay (CP) Take-Up by Command Group	CP Take	CP Deny	Accept %
Operational	816	316	72%
Support	2,048	708	74%
Other	1,254	508	71%

Figure 9 presents a Kaplan-Meier survival curve showing the probability that Marines remain on active duty after accepting or declining CP, with entry at 12 YOS when the CP decision is observed. The figure shows a steeper post-decision decline in survival for CP decliners compared to Army decliners.

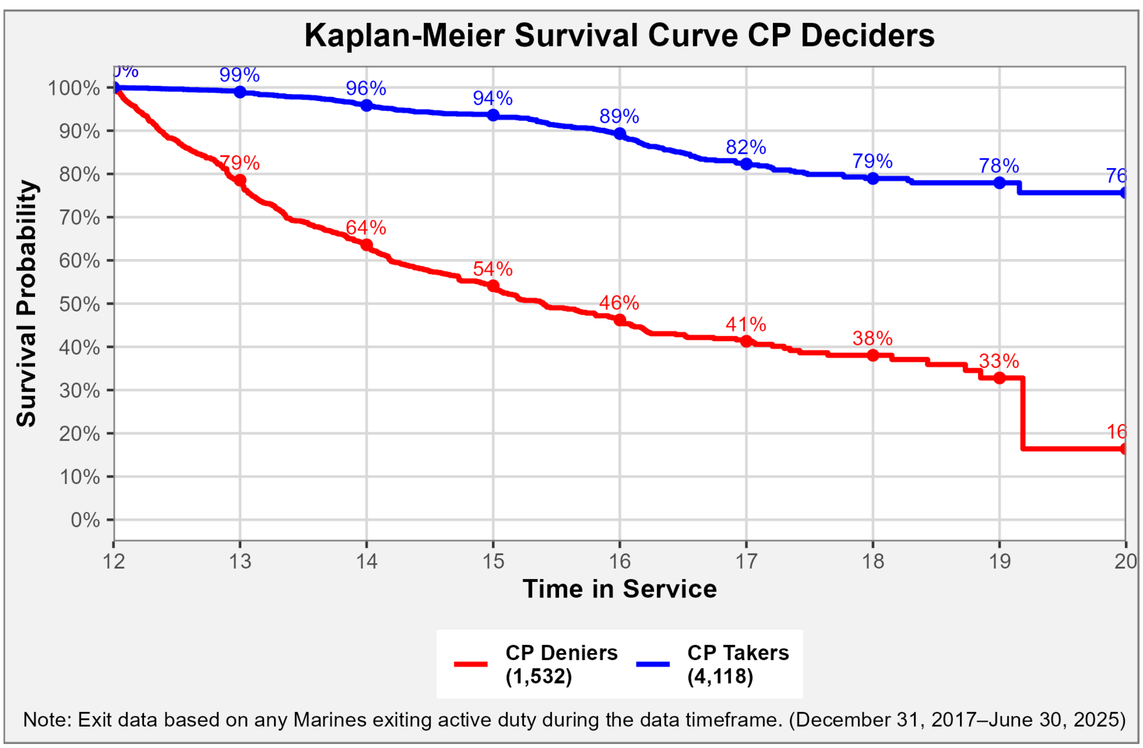

Figure 9. USMC Continuation Pay Deciders Kaplan-Meier Survival Curve

Table 11 summarizes the survival logic in tabular form and highlights key post-CP decision outcomes. Most CP takers remain within their initial four-year obligation period and are therefore right-censored in the survival analysis. A small share of CP takers fail to complete the four-year obligation, while 38.8% of CP decliners separate within four years of declining CP at 12 YOS; fewer than 1.5% of CP takers separate after completing the obligation.

The table also provides sufficient post-obligation data for CP takers, with 717 individuals observed beyond the four-year obligation and 92% remaining on active duty. This post-obligation survival rate is used in later USMC projections under the 8–12 YOS CP model.

Table 11. USMC Continuation Pay Deciders Survival Curve Table

Outcome bucket	Decliners	Takers
Invalid/insufficient follow-up	57 (3.7%)	131 (3.2%)
Still active within 4-year period (right-censored)	598 (39.0%)	3,095 (75.2%)
Did not complete 4-year period	595 (38.8%)	175 (4.2%)
Completed 4 years and still active	245 (16.0%)	661 (16.1%)
Completed 4 years then separated (<20 YOS)	37 (2.4%)	56 (1.4%)

D. COMBINED SUMMARY STATISTICS

Table 12 reports personnel counts and percentages of BRS opt-in by service. The majority of opt-in decisions occur between January 1 and December 31, 2018, consistent with policy timelines, with a smaller number of opt-ins appearing after January 1, 2019 in the panel data. These later opt-ins likely reflect personnel with prior active or reserve service who reentered active duty after 2018. Although Pay Entry Base Date verifies eligibility timing, the service-specific opt-in indicator serves as the authoritative source for BRS status in both the summary statistics and analysis datasets.

Table 12 shows the stark percentage difference in BRS opt-in between the Army and USMC. The opt-in counts in Table 12 are slightly higher than those reported by the DoD in 2020, which documented 88,897 Army active-duty opt-ins and 70,712 Marine Corps active-duty opt-ins (U.S. Department of Defense, 2020).

Table 12. Combined Blended Retirement System Decision Makers (Opt-In or Opt-Out)

BRS Decision Makers (Opt-In or Opt-Out)	Army	USMC
Full Sample (N)	328,158	175,071
BRS Opt-In (N)	94,146	91,443
BRS Opt-Out (N)	234,012	83,628
BRS Opt-In (%)	28.7%	52.2%

Table 13 reports overall CP take-up percentages by service. The Army's overall take-up rate is lower due to relatively low participation in the early years of the program. By 2024, take-up rates converge across services, at 76% for the Army and 82% for the USMC. Using partial-year data for 2025, through May 4 for the Army and June 30 for the USMC, take-up rates remain similar at 81% for both services.

Table 13. Combined Continuation Pay Take-Up Rate (Overall)

Continuation Pay (CP) Take-Up Rate (Overall)	Army	USMC
CP Eligible (N)	22,283	5,650
CP Take (N)	12,476	4,118
CP Deny (N)	9,807	1,532
CP Take (%)	56.0%	72.9%

Table 14 summarizes the three analysis data frames constructed for each service, reporting the number of observations in each and the number of personnel remaining on active duty at the final snapshot. These data frames are derived from panel datasets containing demographic, BRS, and CP information from 2018 through mid-2025. The Army panel contains 14 million observations due to quarterly snapshots, while the USMC panel contains 16 million observations due to monthly snapshots.

Table 14. Combined Sample Across Analysis Datasets

Sample Balance Across Analysis Datasets	Army	USMC
DF1: BRS Decision Sample (N)	328,158	175,071
DF2: CP Decision (N)	22,283	5,650
DF3: Survival Analysis Sample (N)	887,781	410,216
DF3: Active at Last Snapshot(N)	445,110	171,219

Table 15 presents a balance comparison between historic Army CP deciders at 8–11 YOS and future Marine Corps CP deciders/BRS personnel at 8–11 YOS. The table assesses similarity using subgroup percentages and standardized mean differences (SMDs), which measure differences between groups in standardized units and are independent of sample size. Because of large sample sizes, p-values in traditional t-tests are uniformly statistically significant and are therefore not informative for balance assessment. Accordingly, the SMDs and observed subgroup percentages provide the more meaningful evidence of comparability across services.

Balance is evaluated using SMD thresholds. Values between -0.10 and 0.10 indicate very similar samples; values between ±0.10 and ±0.20 indicate small differences; values exceeding ±0.20 indicate moderate differences; and values exceeding ±0.30 indicate large differences. Most covariates fall within the -0.20 to 0.20 range, indicating broadly comparable observable characteristics between the Army and projected USMC populations. Some variables show expected imbalances, such as AGE_INT, where Soldiers are older on average at the CP decision stage. Overall, 15 of 29 covariates fall within the ±0.20 SMD threshold, and 22 of 29 fall within ±0.30. These magnitudes indicate small-to-moderate differences across most observable characteristics, supporting the comparability of the Army and Marine Corps decision-stage populations for ML purposes.

Table 15. Comparison of Army Continuation Pay Decision Population and Projected USMC Decision Population, YOS 8–11

Category	Variables	Army	USMC	SMD	P-Value
n		21263	9559		<0.001
SEX	F	3601 (16.9%)	1087 (11.4%)	0.16	
	M	17662 (83.1%)	8472 (88.6%)	-0.16	
MOS_CATEGORY4	Aviation Support	664 (3.1%)	925 (11.1%)	-0.31	<0.001
	Combat MOS	4147 (19.5%)	1656 (19.8%)	-0.01	
	Combat Support	15686 (73.8%)	5170 (61.9%)	0.256	
	Pilot MOS	766 (3.6%)	601 (7.2%)	-0.16	
MARITAL_5	Legally Separated	24 (0.1%)	32 (0.3%)	-0.05	<0.001
	Married	16006 (75.3%)	6566 (68.7%)	0.15	
	Single	5208 (24.5%)	2183 (22.8%)	0.04	
	Unknown/Blank	3 (0.0%)	773 (8.1%)	-0.42	
	Widowed	22 (0.1%)	5 (0.1%)	0.02	
ETHNIC_7	American Indian/Alaska Native	152 (0.7%)	125 (1.3%)	-0.06	<0.001
	Asian	1760 (8.3%)	545 (5.7%)	0.10	
	Black/African American	4248 (20.0%)	1022 (10.7%)	0.26	
	Declined/Unknown	561 (2.6%)	241 (2.5%)	0.01	
	Hispanic (non-Mexican)	1792 (8.4%)	945 (9.9%)	-0.05	
	Mexican	1188 (5.6%)	1350 (14.1%)	-0.29	
	White	11562 (54.4%)	5331 (55.8%)	-0.03	
RELIGION_4	Christian	14355 (67.5%)	5487 (57.4%)	0.21	<0.001
	Non-Christian	1164 (5.5%)	157 (1.6%)	0.21	
	None	1036 (4.9%)	3143 (32.9%)	-0.77	
	Unknown/Blank	4708 (22.1%)	772 (8.1%)	0.40	
COMMAND_GROUP	Operational	7988 (37.6%)	1947 (20.4%)	0.39	<0.001
	Other	7964 (37.5%)	2972 (31.1%)	0.13	
	Reserve	2 (0.0%)	0 (0.0%)	0.01	
	Support	5309 (25.0%)	4640 (48.5%)	-0.50	
GRADE_GROUP	Enlisted	13077 (61.7%)	6870 (71.9%)	-0.22	<0.001
	Officer	8121 (38.3%)	2689 (28.1%)	0.22	
AGE_INT (Mean & SD)		33.4 (4.5)	29.6 (2.6)	1.04	<0.001

Note: P-Value tests Army vs USMC differences (t-test for continuous; chi-squared for categorical). *p<0.10 **p<0.05 ***p<0.01

Table 16 presents a comparison of the most recent active-duty snapshot of Army and USMC BRS-eligible personnel at 8–11 YOS. Standardized mean differences indicate that 16 of 25 covariates fall within ±0.20 and 21 of 25 fall within ±0.30. These magnitudes suggest predominantly small to moderate differences across observable characteristics, indicating broadly comparable CP-eligible populations across services and further supporting the application of the Army-trained model to the Marine Corps population.

Table 16. Comparison of Currently Active BRS Army and USMC Personnel, YOS 8–11

Category	Variables	Army	USMC	SMD	P-Value
n		18684	9559		
SEX	F	3277 (17.5%)	1087 (11.4%)	0.18	<0.001***
	M	15407 (82.5%)	8472 (88.6%)	-0.18	
MOS_CATEGORY4	Aviation Support	650 (3.5%)	925 (11.1%)	-0.30	<0.001***
	Combat MOS	3737 (20.0%)	1656 (19.8%)	0.00	
	Combat Support	13588 (72.7%)	5170 (61.9%)	0.23	
	Pilot MOS	709 (3.8%)	601 (7.2%)	0.15	
MARITAL_5	Legally Separated	16 (0.1%)	32 (0.3%)	-0.05	<0.001***
	Married	12764 (68.3%)	6566 (68.7%)	-0.01	
	Single	5893 (31.5%)	2183 (22.8%)	0.20	
	Unknown/Blank	6 (0.0%)	773 (8.1%)	-0.42	
	Widowed	5 (0.0%)	5 (0.1%)	-0.01	
ETHNIC_7	American Indian/Alaska Native	145 (0.8%)	125 (1.3%)	-0.05	<0.001***
	Asian	1590 (8.5%)	545 (5.7%)	0.11	
	Black/African American	3568 (19.1%)	1022 (10.7%)	0.24	
	Declined/Unknown	594 (3.2%)	241 (2.5%)	0.04	
	Hispanic (non-Mexican)	1656 (8.9%)	945 (9.9%)	-0.04	
	Mexican	1193 (6.4%)	1350 (14.1%)	-0.26	
	White	9938 (53.2%)	5331 (55.8%)	-0.05	
RELIGION_4	Christian	12098 (64.8%)	5487 (57.4%)	0.15	<0.001***
	Non-Christian	1215 (6.5%)	157 (1.6%)	0.25	
	None	482 (2.6%)	3143 (32.9%)	-0.86	
	Unknown/Blank	4889 (26.2%)	772 (8.1%)	0.49	
GRADE_GROUP	Enlisted	11664 (63.9%)	6870 (71.9%)	-0.17	<0.001***
	Officer	6593 (36.1%)	2689 (28.1%)	0.17	
AGE_INT (Mean & SD)		31.8 (4.0)	29.6 (2.6)	0.67	<0.001***

Note: P-Value tests Army vs USMC (t-test for continuous; chi-squared for categorical). *p<0.10 **p<0.05 ***p<0.01

E. METHODOLOGY

Most machine learning applications in military personnel research train and generate projections within a single service under its existing policy environment. As a result, forecasts are typically limited to outcomes under the policy already in place, since the available data reflect only those conditions. Consequently, most studies use machine learning models to predict future outcomes under the status quo policy framework.

This thesis adopts a different approach by using cross-service data to estimate how a service would respond to a policy it has not previously implemented. By aligning Army and Marine Corps personnel data from 2018–2025, this study trains a model on Army Continuation Pay (CP) decisions observed under the Army's 8–12 years of service (YOS) policy window and applies the model to Marine Corps personnel data. This calibrated model leverages observed Army decision patterns to simulate how Marines may respond under the same policy framework and projects expected CP take-up, cost, and end strength outcomes under an 8–12 YOS option.

This framework allows the Marine Corps to estimate the potential effects of a policy before it is implemented. More broadly, the framework demonstrates how machine learning can be used to evaluate personnel policies across services when one service has already implemented a policy that another is considering. In such cases, cross-service personnel data can inform projections of policy outcomes in advance of institutional commitment. This approach extends existing military retention forecasting by introducing a cross-service machine learning framework that enables policy evaluation using observed behavioral responses from another service.

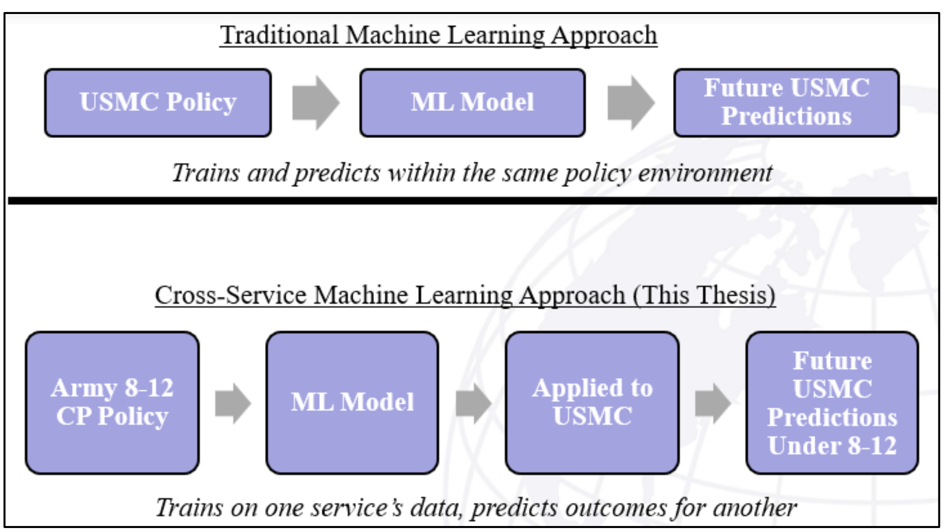

Figure 10. Cross-Service Machine Learning Framework

Having established balance or comparability in predictors, the analysis trains and tests a ML model with Army CP data using an 80/20 train-test split to address Research Question 1: When should the Marine Corps offer CP to maximize retention and return on investment? The trained model is then applied to eligible Marine Corps personnel to generate predicted CP outcomes under an 8–12 YOS CP framework. The Army is currently the only service that varies CP timing, allowing Soldiers to accept CP between 8 and 12 YOS; these observed decisions provide the behavioral basis for model training. The ML model projects outcomes under a counterfactual policy in which the USMC adopts an 8–12 YOS CP framework. This approach allows the USMC to evaluate the expected effects of an 8–12 YOS model without implementing the policy. Due to substantial differences in BRS opt-in rates across services, the analysis does not model the BRS opt-in decision and instead focuses exclusively on CP decision-making among BRS-eligible USMC personnel.

Summary statistics show that both Army and USMC CP frameworks retain takers at rates of 92% or higher following completion of the four-year CP obligation. As a result, this analysis does not require a separate ML model to predict post-obligation survival among CP takers.

This thesis uses Extreme Gradient Boosting (XGBoost) implemented in RStudio within PDE to train, test, and apply the ML models. XGBoost is an ensemble ML algorithm that builds predictions by sequentially combining many shallow decision trees, where each new tree is trained to correct prediction errors from prior trees. The algorithm learns complex decision behavior from observed data and can be applied to comparable populations to project outcome probabilities under alternative policy scenarios. Model training minimizes a logistic loss function for binary outcomes and a multinomial logistic loss for multinomial outcomes, fitting trees to the gradients of these loss functions to improve predictive performance.

The final prediction for a binary outcome is generated as a weighted sum of individual decision trees passed through a logistic link function, while multinomial models produce a probability distribution across multiple outcome categories. XGBoost automatically captures nonlinear relationships and interaction effects without requiring them to be specified in advance, improving out-of-sample performance and limiting overfitting.

To execute the ML models, this thesis aligned the Army 8–12 YOS CP decision dataset with the projected USMC dataset to ensure identical variable definitions, particularly for categorical covariates such as command group and MOS category. The analysis encoded all model inputs into numeric or binary formats through dummy variable creation, as required for XGBoost implementation in RStudio.

The final Army-trained model includes the following covariates, all transformed into numeric or binary form: age, rank, officer/enlisted status, command group indicators (operational, support, reserve, other), MOS category indicators (aviation support, combat MOS, combat support, pilot), religion categories (Christian, non-Christian, none, unknown), ethnicity categories (American Indian/Alaska Native, Asian, African American, Hispanic [Mexican and non-Mexican], White, declined/unknown), marital status categories (legally separated, married, single, widowed, unknown/blank), and sex (male, female).

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IV. RESULTS AND ANALYSIS

A. OVERVIEW

This chapter presents the ML analysis, including the results of the Army-trained ML models and the results of the predictions generated when those models are applied to USMC data. The chapter concludes with USMC future predictions under various CP scenarios to determine which CP model retains the most personnel and is the most cost-efficient.

Figure 11 provides an overview of the three ML models trained and tested in this thesis, the outcome variables used in each model, and the resulting areas under the curve (AUCs). An AUC of 1.0 indicates perfect classification and prediction. An AUC between 0.75 and 0.80 indicates good discrimination and quite strong predictive performance.

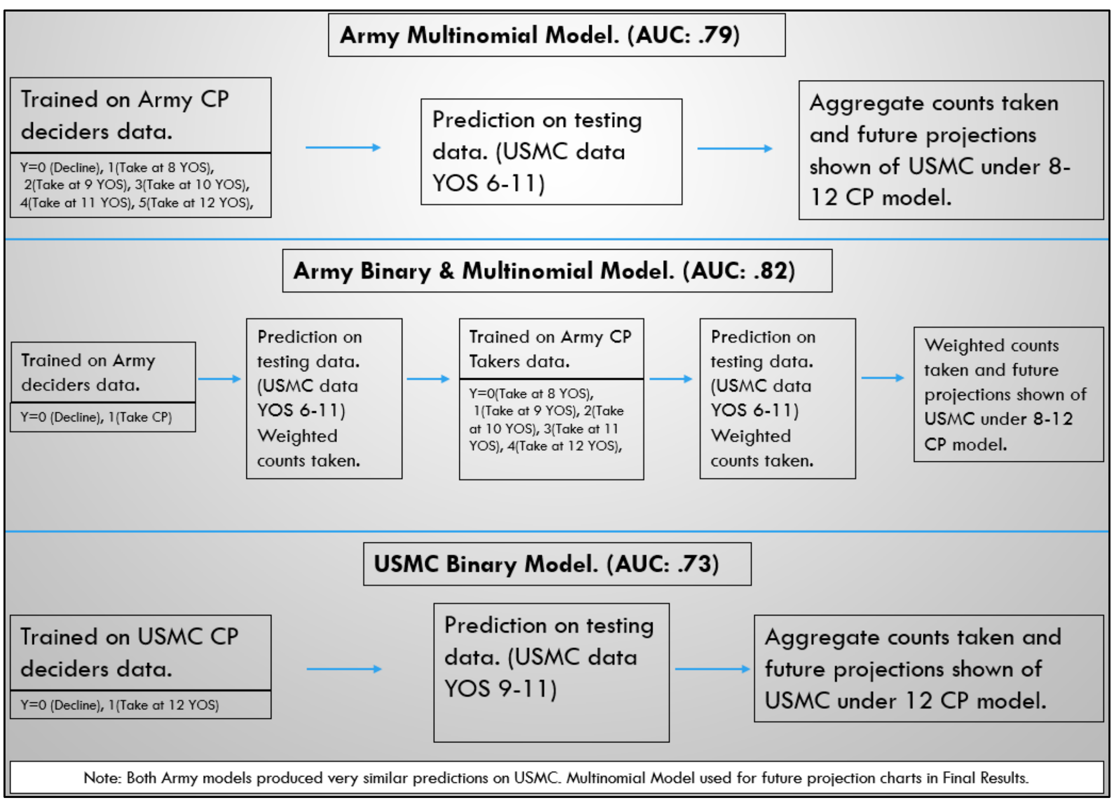


Figure 11. Machine Learning Model Flow Chart

B. ARMY 8–12 MULTINOMIAL MODEL

1. Training Army 8–12 Multinomial Model

The analysis constructs the outcome variable for Army personnel with a CP decision as a multinomial variable. The following metrics define the outcomes:

- 0 = decline CP
- 1 = take CP at YOS 8
- 2 = take CP at YOS 9
- 3 = take CP at YOS 10
- 4 = take CP at YOS 11
- 5 = take CP at YOS 12.

Out of Army CP takers, almost all accepted CP at YOS 8, 9, 10, 11, or 12. A small share of personnel had YOS greater than 12 at the time of a CP decision, representing 0.82% of acceptors and 2.80% of decliners. Administrative lag or retroactive CP decisions recorded after 12 YOS explain the YOS values greater than 12.

The analysis splits the Army CP dataset into training and testing samples using a random 80/20 split, without stratification on the outcome variable because all outcome categories contained sufficient observations. The model trains on the 80% training sample to learn relationships between covariates and outcomes. During training, the data pass through 150 boosting rounds, where each new tree corrects prediction errors from previous iterations, and each tree is fit using a random 80% subsample of observations and 80% of features to improve generalization and reduce overfitting.

2. Army 8–12 Multinomial Model Results

The model achieves an AUC of 0.79. The analysis evaluated the trained model on the remaining 20% holdout sample, with predictions compared to observed outcomes. The analysis rejoined predicted outcomes to the held-out data and evaluated them against actual CP decisions, producing the confusion matrix shown in Table 17.

In Table 17, rows represent predicted outcomes and columns represent observed outcomes in the held-out sample. The largest source of misclassification occurs when the model predicts CP decline while the individual ultimately accepts CP at YOS 8–12. The diagonal elements (shown in green) indicate correct predictions, and the model correctly classifies a substantial share of CP takers, even when the predicted take year does not exactly match the observed take year. This model produces an overall classification accuracy of 52%, defined as the percentage of exact matches between predicted and observed outcomes.

Table 17. Army Trained Multinomial Model Confusion Matrix

		Actual					
		0	1	2	3	4	5
Predicted	0	1771	151	169	300	538	174
	1	37	137	53	26	17	3
	2	20	80	84	45	20	1
	3	41	57	77	162	77	8
	4	94	31	34	79	145	21
	5	2	0	0	1	1	0

An AUC of 0.79 means that in 79% of randomly selected pairs consisting of one CP taker and one CP decliner, the model correctly ranked the taker above the decliner. In other words, when comparing one taker and one decliner, the model assigns a higher predicted probability of CP acceptance to the taker. Overall, the model is effective at distinguishing individuals who are more likely to accept CP but tends to be conservative, occasionally predicting "decline" for individuals who ultimately accept the incentive.

A sensitivity analysis shows the model is strong at predicting CP decliners, with a 90% recall rate for Class 0. The model correctly predicts CP takers at an overall rate of 47%, with 1,332 actual takers misclassified as decliners (Class 0). Recall is lower across the taker classes, indicating that the model tends to mislabel the specific year of CP acceptance. Class 1 achieves a 30% recall, Class 2 a 20% recall, Class 3 a 26% recall, Class 4 an 18% recall, and Class 5 a 0% recall.

Additional sensitivity analysis indicates that increasing the prediction confidence threshold improves accuracy and precision but applies to fewer observations as predictions become more restrictive. Recall rates remain relatively stable across confidence thresholds, suggesting that most uncertainty arises from borderline cases rather than clear outcomes. At higher confidence levels, the model identifies CP decliners with high reliability, while accurate prediction of the specific CP acceptance year for takers occurs primarily at lower confidence thresholds.

The characteristics that matter most to the model's predictive performance are shown in Table 18. Gain reflects the contribution of a variable to improving model predictions, while cover reflects how broadly a variable applies across observations when it is used, and frequency reflects how often a variable is used across all trees. Feature importance results indicate that age and pay grade are the most influential predictors, with command group also playing an important role.

Table 18. Army Trained Multinomial Model Variables of Importance

Variables Importance for Model			
Feature	Gain	Cover	Frequency
AGE	0.37	0.31	0.23
GRADE	0.20	0.24	0.18
COMMAND_GROUP_Other/Joint	0.15	0.05	0.04
COMMAND_GROUP_Operational	0.03	0.02	0.04
COMMAND_GROUP_Support	0.02	0.02	0.03
SEX	0.02	0.03	0.04
ETHNIC_7_White	0.02	0.02	0.04
MARITAL_STATUS_Married	0.02	0.02	0.04
MOS_CATEGORY_Combat_MOS	0.02	0.02	0.03
ETHNICITY_Black/African American	0.01	0.02	0.03
RELIGION_Christian	0.01	0.02	0.04
MOS_CATEGORY_Combat_Support	0.01	0.02	0.03
RELIGION__Unknown/Blank	0.01	0.02	0.03
ETHNICITY_Asian	0.01	0.02	0.03
OFFICER	0.01	0.01	0.01

The Army model is re-estimated using 100% of the data by adding back the 20% holdout sample.

3. Predicting USMC Outcomes Using the Army 8–12 Multinomial Model

With the calibrated model complete, predictions are made for USMC personnel to generate future projections under a counterfactual policy in which the USMC implements the Army 8–12 YOS model beginning in 2026. Because future personnel have already made their BRS or Legacy retirement choice, projections begin with the calibrated Army ML model predicting outcomes for USMC personnel who are BRS, CP eligible, and have not yet made a CP decision at the time of the data pull. For future projections, the eligible population includes BRS USMC personnel at YOS 11, 10, 9, 8, 7, and 6.

The analysis aligns USMC column names, formats, and variable classes exactly with the numeric and integer inputs used in the Army model. YOS is temporarily removed so it does not influence the model directly and lead to overfitting. The predict function in XGBoost is applied to the Army-trained ML model to generate predicted outcome probabilities for each USMC individual, and the outcome with the highest predicted probability is assigned as the individual's projected CP decision. YOS is then reintroduced into the USMC prediction dataset to identify which individuals at each YOS are projected to decline or accept CP and the year in which they are projected to accept. Aggregate counts are then computed by summing these individual classifications. Survival percentages are applied to YOS 7 and YOS 6 personnel to project which individuals are expected to reach YOS 8 in one and two years, respectively. These survival percentages are drawn from overall average counts and survival rates calculated from USMC snapshots spanning 2017–2024, as shown in Table 19.

Table 19 reports survival rates of 82% for Marines transitioning from YOS 7 to 8 and 69% for Marines transitioning from YOS 6 to 8. For example, after the ML model generates predictions for USMC personnel at YOS 6, survival rates are applied as proportional scaling factors, such that 69% of both predicted accepters and predicted decliners are carried forward as the cohort expected to reach YOS 8 in the third year of the 8–12 YOS model and face a CP decision. These survival estimates were validated using additional snapshots spanning December 31, 2017, through July 31, 2025, with differences of approximately 0.01 in some categories relative to Table 19.

Table 19. 2018–2025 Average Years of Service Counts and Survival Percentages

Average Using 12/31/2017-12/31/2024 Snapshots		
YOS	Count	Surv %
6	6405.25	0.84
7	5408.75	0.82
8	4409.25	0.85
9	3740.5	0.89
10	3333.25	0.92
11	3059.875	0.92
12	2825.25	0.95
13	2680.75	0.97
14	2594.25	0.98
15	2550.75	0.97
16	2481	0.00
6	6405.25	0.69
8	4409.25	

Table 19 enables accurate projections of personnel counts up to three years in the future, when the YOS 6 cohort reaches YOS 8. Notably, the YOS 6 cohort in the future projections represents the first fully auto-enrolled BRS population, such that BRS participation will approach 95–100% at that YOS. In contrast, the current overall YOS 8 population is 72% BRS, and the overall YOS 7 population is 76% BRS.

In the final active-duty snapshot in the dataset (June 30, 2025), the BRS population includes 7,749 Marines at YOS 6 and 4,713 Marines at YOS 7. Applying the survival rates shown in Table 19 yields the projected BRS counts used in the future analysis. The projected USMC BRS population used in the ML model and future projections is summarized by YOS in the following bullet points:

- YOS 12: 13
- YOS 11: 1,301
- YOS 10: 2,109
- YOS 9: 2,580
- YOS 8: 3,553
- YOS 7: 3,865 (4,713 × 0.82)
- YOS 6: 5,347 (7,749 × 0.69)

The projections for USMC personnel produce the distribution of projected CP takers, decliners, and take-year timing shown in Table 20. Future projections later in the thesis use Table 20 and assume that individuals projected to accept CP at later YOS survive to that YOS, while those projected to accept CP at a YOS earlier than their current YOS are assumed to accept CP at their current YOS. Overall, the model projects 3,337 CP decliners and 15,429 CP accepters, corresponding to an 82% overall CP acceptance rate.

The overall predicted CP acceptance rate closely aligns with the observed USMC 12 YOS CP take-up rates in 2024 and 2025 reported in the summary statistics, indicating that the model does not over-predict CP decline. Acceptance rates by YOS are 86% at YOS 6, 86% at YOS 7, 85% at YOS 8, 81% at YOS 9, 73% at YOS 10, and 63% at YOS 11. Notably, YOS 12 represents a very small sample of 13 Marines, as nearly all BRS personnel at YOS 12 already have a recorded CP decision in the data. Among projected CP accepters, 38% (5,927 of 15,429) are predicted to accept CP at a later YOS than their current YOS, while 17.8% of the projected population are decliners.

Table 20. USMC 8–12 Multinomial Model Future Predictions

USMC 8-12 Model Future Predictions

CURRENT_YOS	Decline	8	9	10	11	12
YOS 6	722	2,876	820	515	380	34
YOS 7	526	2,102	536	376	288	37
YOS 8	552	1,465	712	460	306	58
YOS 9	492	620	577	525	308	58
YOS 10	557	251	310	529	398	62
YOS 11	482	95	107	235	328	54
YOS 12	6	1	1	2	2	1

Notes: Survival shaping: YOS 6 scaled by 0.69 (6->8) and YOS 7 scaled by 0.82 (7->8). YOS 6 would be the first Auto-Enrolled 100% BRS Cohort when they reach YOS8.

C. ARMY 8–12 BINARY AND MULTINOMIAL MODEL

1. Training Army 8–12 Binary Model

The analysis constructs a second model by first training the Army 8–12 YOS CP data using a binary classification framework to distinguish CP decliners from CP takers, followed by a multinomial model applied only to CP takers. The following metrics define the outcomes of the binary model:

- 0 = take CP
- 1 = decline CP

The analysis then splits the Army CP dataset into training and testing samples using a random 80/20 split, without stratification on the outcome variable because all outcome categories contained sufficient observations. The first-stage model is trained via XGBoost with 150 boosting rounds using the binary outcome variable.

2. Army 8–12 Binary Model Results

The first-stage model achieves an AUC of 0.82. Table 21 shows the confusion matrix where the Army binary model correctly predicts 74% of CP decliners and 67% of CP takers.

Table 21. Army Trained Binary Model Confusion Matrix

		Actual	
		0	1
Predicted	0	1842	639
	1	654	1323

Next, Table 22 shows the variables that most strongly influence the model, with age, command group, and grade exerting the largest effects, similar to the multinomial model.

Table 22. Army Trained Binary Model Variables of Importance

Variables Importance for Model			
Feature	Gain	Cover	Frequency
AGE	0.31	0.30	0.24
COMMAND_GROUP_Other/Joint	0.21	0.04	0.03
GRADE	0.21	0.24	0.19
COMMAND_GROUP_Operational	0.05	0.03	0.04
COMMAND_GROUP_Support	0.03	0.02	0.03
OFFICER	0.02	0.01	0.01
MOS_CATEGORY_Combat_MOS	0.02	0.02	0.03
SEX_BIN	0.02	0.02	0.04
MARITAL_STATUS_Married	0.01	0.02	0.04
ETHNICITY__White	0.01	0.02	0.04
RELIGION_Unknown/Blank	0.01	0.02	0.03
RELIGION_Christian	0.01	0.02	0.04
MOS_CATEGORY_Combat_Support	0.01	0.02	0.03
ETHNICITY_Black/African American	0.01	0.02	0.02

The full Army binary model is re-estimated using the combined 80% training and 20% testing samples.

3. Predicting USMC Outcomes Using the Army 8–12 Binary Model

Marine Corps BRS future personnel are then projected through the full model, generating predicted probabilities of CP acceptance and decline for each individual, which sum to 100%. After applying the survival percentages for YOS 6 and 7, the model produces an expected 3,252 decliners and 15,516 takers.

4. Training the Post-Binary Army 8–12 Multinomial Model

Next, the Army CP taker data are used to train a multinomial model, where only Army CP accepters are included. The following metrics define the outcomes:

- 0 = take CP at YOS 8
- 1 = take CP at YOS 9
- 2 = take CP at YOS 10
- 3 = take CP at YOS 11
- 4 = take CP at YOS 12

The analysis then split the Army CP taker-only dataset into training and testing samples using a random 80/20 split, without stratification on the outcome variable because all outcome categories contained sufficient observations. The second-stage model is trained via XGBoost with 150 boosting rounds using the multinomial outcome variable.

5. Army 8–12 Post-Binary Multinomial Model Results

The model achieves an AUC of 0.80. After training the model, the resulting confusion matrix is shown in Table 23. Correct prediction rates by class are 41% for YOS 8, 27% for YOS 9, 32% for YOS 10, 72% for YOS 11, and 4% for YOS 12.

Table 23. Army Trained Post-Binary Multinomial Model Confusion Matrix

		Actual				
		0	1	2	3	4
Predicted	0	186	93	39	46	10
	1	100	115	77	49	13
	2	90	98	198	111	27
	3	77	112	286	573	146
	4	7	2	12	22	9

Next, Table 24 shows the variables that strongly influence the model, with age, grade, and command group exerting the largest effects, similar to the binary model.

Table 24. Army Trained Post-Binary Multinomial Model Variables of Importance

Variables Importance for Model			
Feature	Gain	Cover	Frequency
AGE	0.36	0.31	0.25
GRADE	0.19	0.19	0.17
COMMAND_GROUP_Other/Joint	0.07	0.04	0.04
SEX	0.03	0.03	0.04
COMMAND_GROUP_Operational	0.03	0.02	0.04
MARITAL_STATUS_Married	0.03	0.02	0.04
ETHNICITY__White	0.02	0.02	0.03
RELIGION_Christian	0.02	0.02	0.04
COMMAND_GROUP_Support	0.02	0.02	0.03
RELIGION_Unknown/Blank	0.02	0.02	0.03
ETHNICITY_Black/African American	0.02	0.02	0.03
MOS_CATEGORY_Combat_MOS	0.02	0.02	0.03
MOS_CATEGORY_Combat_Support	0.02	0.02	0.03
ETHNIC_Asian	0.02	0.03	0.03

The 20% test sample is recombined with the 80% training sample to produce a full multinomial taker model.

6. Predicting USMC Outcomes Using the Army 8–12 Post-Binary Multinomial Model

All USMC personnel were run through the multinomial model, with the weighted probability of decline remaining unchanged and the weighted probability of take distributed across the five CP take-year outcomes to generate full CP timing predictions under the 8–12 model. Probability-weighted counts of these predictions are reported in Table 25.

Table 25. USMC 8–12 Binary & Multinomial Model Future Predictions

USMC 8-12 Model Future Predictions						
CURRENT_YOS	**Decline**	**8**	**9**	**10**	**11**	**12**
YOS 6	673	2,957	792	483	374	67
YOS 7	511	2,101	523	379	292	58
YOS 8	541	1,457	685	470	321	80
YOS 9	486	614	561	526	319	73
YOS 10	553	255	307	518	404	73
YOS 11	482	102	107	230	322	59
YOS 12	6	1	1	2	2	1

Notes: Survival shaping: YOS 6 scaled by 0.69 (6->8) and YOS 7 scaled by 0.82 (7->8). YOS 6 would be the first Auto-Enrolled 100% BRS cohort when they reach YOS8.

Although the combined binary-multinomial approach exhibits slightly higher AUC and sensitivity metrics than the single multinomial model, the resulting predictions are nearly identical across approaches. Relative to the binary-multinomial model, the single multinomial model predicts 87 additional decliners, 77 fewer personnel accepting CP at YOS 8, 87 more at YOS 9, 34 more at YOS 10, 24 fewer at YOS 11, and 107 fewer at YOS 12. Given the close alignment of predicted outcomes, all charts in the ML model projections section are generated using the single multinomial model.

D. USMC 12 MODEL

1. Training USMC 12 Binary Model

The future projections also include a counterfactual scenario in which the USMC retains the 12 YOS CP model, offering CP exclusively at 12 YOS. This scenario uses a binary classification model trained on all USMC personnel who made a CP decision. The following metrics define the outcomes:

- 0 = decline CP
- 1 = take CP at YOS 12

The analysis then split the USMC CP dataset into training and testing samples using a random 80/20 split, without stratification on the outcome variable because all outcome categories contained sufficient observations. The binary model is trained via XGBoost with 150 boosting rounds using the binary outcome variable.

2. USMC 12 Binary Model Results

The model achieves an AUC of 0.73. Table 26 shows the resulting confusion matrix for the USMC binary model. The model correctly predicts 81% of CP takers and 57% of CP decliners.

Table 26. USMC-Trained Binary Model Confusion Matrix

		Actual	
		0	1
Predicted	0	183	156
	1	140	656

Table 27 displays variable importance by gain percentage and includes the count-of-dependents variable in the USMC ML model.

Table 27. USMC Trained Binary Model Variables of Importance

Variables Importance for Model			
Feature	Gain	Cover	Frequency
GRADE	0.29	0.28	0.15
MOS_CATEGORY_Pilot_Mos	0.19	0.07	0.02
AGE	0.12	0.15	0.19
DEPENDENTS	0.08	0.1	0.12
RELIGION_None	0.03	0.03	0.05
COMMAND_GROUP_Operational	0.02	0.01	0.04
ETHNICITY_White	0.02	0.02	0.04
MOS_CATEGORY_Combat_Support	0.02	0.02	0.03
ETHNICITY_Declined/Unknown	0.02	0.02	0.03
ETHNICITY_Mexican	0.02	0.04	0.02
COMMAND_GROUP_Support	0.02	0.02	0.03
MOS_CATEGORY_Combat_Mos	0.02	0.02	0.02
RELIGION_Christian	0.02	0.01	0.03
MOS_CATEGORY_Aviation_Support	0.02	0.02	0.03
SEX	0.02	0.03	0.02

The 20% test sample is recombined with the 80% training sample to produce a full binary model.

3. Predicting USMC Outcomes Using the USMC 12 Binary Model

Next, the USMC ML model is used to project CP take-up under the 12 YOS CP model over the next three years. The same BRS personnel used in the 8–12 projections are applied at YOS 11, 10, and 9 for the three-year projection window under the CP at 12 YOS policy. The projected BRS counts are defined by the following YOS:

- YOS 11: 1,301
- YOS 10: 2,109
- YOS 9: 2,580

The analysis generates predictions, reintroduces the YOS column to identify each individual's service year, and applies survival percentages to both takers and decliners to project progression from YOS 10 to 12 and from YOS 9 to 12. The survival rates shown in Table 28, 85% and 76%, are applied for these transitions, while a 92% survival rate is applied to YOS 11 personnel to project progression to YOS 12.

Table 28. USMC Survival Percentages Years of Service 10 to 12 and 9 to 12

10	3333.25	0.85
12	2825.25	

9	3740.5	0.76
12	2825.25	

The USMC model predictions produce three years of projected USMC takers in Table 29 under the 12 YOS CP model.

Table 29. USMC at 12 Years of Service Binary Model Future Predictions

USMC Future CP Takers YOS-12 Model by Policy Year (5 Multiplier)

Year	Take	Decline
Year 1	920	278
Year 2	1,332	460
Year 3	1,396	564

E. MACHINE LEARNING MODEL PROJECTIONS

Under the assumption that Marines make decisions similar to Soldiers, the analysis projects ML model predictions for future Marine Corps CP-eligible personnel to estimate CP take-up rates at 8–12 YOS. The analysis evaluates sensitivity, specificity, and model AUCs to assess predictive performance. These models then estimate Marine Corps CP take-up rates under a counterfactual policy in which the USMC aligns its CP offering window with the Army's 8–12 model. This approach generates counterfactual projections of how many Marines would accept CP at different YOS.

As noted previously, the single multinomial model produces USMC predictions nearly identical to those generated by the sequential binary-multinomial approach. Therefore, the following projection graphs are based on the single multinomial model, which predicts both CP acceptance or decline and the timing of CP acceptance among takers. Due to MOS coding inconsistencies, some Marine aviators were grouped under broader occupational categories in the projection dataset such as combat support. Although pilots exhibit lower CP take-up rates, their relatively small share of the total population means this limitation is not expected to materially affect aggregate projection results or retention estimates.

CP cost projections were made using an average 2.5 cost of $13,678, based on the Army's average CP payout at a 2.5 multiplier under the 8–12 model, and the average 5.0 cost of $28,697, based on the USMC's average CP payout at a 5.0 multiplier under the 12 YOS model. Because CP scales linearly with the multiplier, an alternative costing approach would scale the Army 8–12 average payout by 2 to approximate a 5.0 multiplier and scale the USMC 12 YOS average payout by 0.5 to approximate a 2.5 multiplier. Under this alternative, the 8–12 model would be less expensive at 5.0 than shown in the projections presented in this thesis, and the 12 YOS model would be slightly more expensive at 2.5 than shown. For example, scaling linearly would adjust the 12 YOS 2.5 multiplier cost from $13,678 to approximately $14,349 and the 8–12 YOS 5.0 multiplier cost from $28,697 to approximately $27,356, without altering the relative conclusions. These adjustments strengthen the conclusion that earlier CP timing is more cost-effective. These adjustments do not alter the relative cost-effectiveness or retention conclusions.

1. Three Years of Projected USMC Continuation Pay Takers 8–12 Model vs. 12 Model

Figure 12 presents projected CP take-up over the next three years, comparing the 8–12 model (stacked bars) with the 12 YOS model (single bars). The 8–12 model produces the highest number of takers in the implementation year, as personnel at YOS 8–12 are offered the incentive for the first time simultaneously. Projected takers decline in subsequent years, with Year 3 representing the first cohort in which 100% of Marines entering YOS 8 are BRS participants.

Model costs are calculated using a 2.5 multiplier for the 8–12 model, with an average cost of $13,678 per taker derived from Army CP averages, and a 5.0 multiplier for the 12 YOS model, with an average cost of $28,697 per taker derived from USMC 2024 CP costs. All projections are based on predicted outcomes from the Army-trained multinomial ML model applied to future USMC personnel, as reported in Table 20. The projections assume that personnel predicted to accept CP at later YOS survive to those years and that all takers are approved and have available boat spaces for a four-year reenlistment. Individuals projected to accept CP at a YOS earlier than their current YOS are counted as takers at their current YOS.

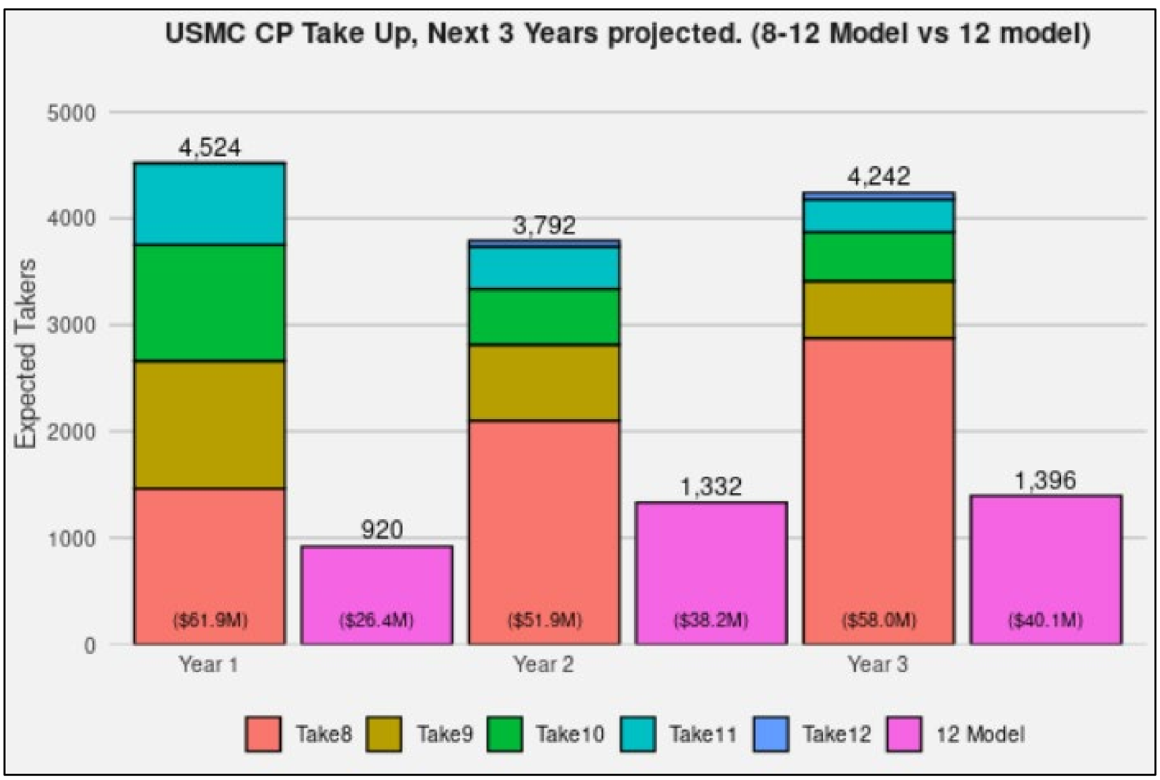


Figure 12. USMC Next 3 Years Projected, 8–12 Model at 2.5 Multiplier vs. 12 Model at 5.0 Multiplier

2. Future Years of Service Projections 12 Model vs. 8–12 Model

Figure 13 presents Year 1 projections for the USMC under the 8–12 YOS model and the current 12 YOS CP model. The figure shows projected CP takers and associated costs for both models, along with a no-CP baseline representing retention absent the incentive. Detailed calculations are presented in Appendix Table 30.

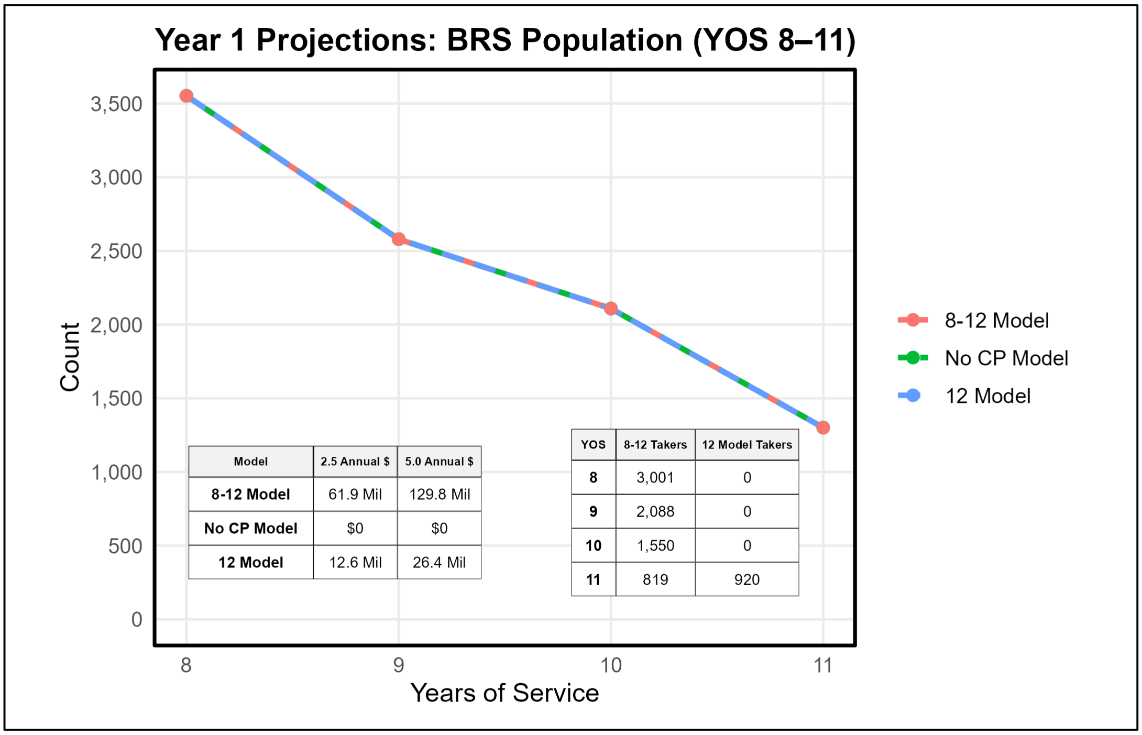


Figure 13. Year 1 Projections of Continuation Pay Models 12 vs. 8–12

Figure 14 presents Year 3 projections comparing the 8–12 YOS CP model with the 12 YOS CP model. CP decliners attrite at model-specific decliner attrition rates for year one after declining, where the Army 8–12 model shows 21.4% attrition following CP decline, which closely aligns with the 0.79 one-year survival rate observed in the USMC 12 YOS model. Accordingly, decliners experience a 0.79 survival rate in the first year after declining CP and continue to attrite thereafter using USMC 12 YOS decliner survival rates derived from the Kaplan-Meier survival curve shown in Figure 9.

The analysis applies USMC 12 YOS CP model decliner survival rates because the Army decliner survival curve shows minimal additional attrition in subsequent years, which contradicts expected non-take behavior. This pattern likely reflects data distortion from personnel who remained in service after declining CP, potentially due to lack of awareness of the incentive. Baseline year-to-year survival rates prior to the CP decision are applied to account for regular attrition, independent of CP outcomes. These annual survival estimates are validated using snapshots from December 31, 2017, through July 31, 2025, and are based on survival percentages reported in Appendix Table 30 in the "Survive %" column.

The model reports annual costs in Year 3 for each CP policy, including costs under the 2.5 and 5.0 multipliers, associated end-strength changes by CP policy, and cost per retained service member, calculated as annual CP cost divided by end-strength gains. Results show that the current 12 YOS CP model retains fewer personnel than the no-CP baseline, which follows standard year-to-year survival rates without an incentive. Detailed calculations are presented in Appendix Table 31.

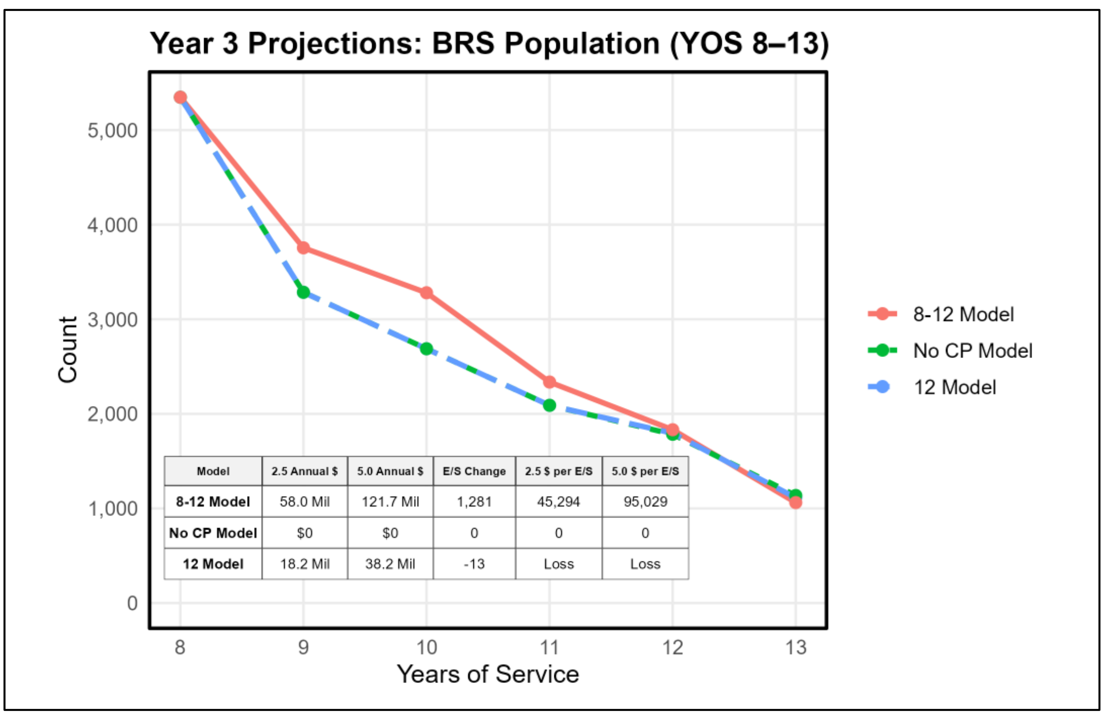


Figure 14. Year 3 Projections of Continuation Pay Models 12 vs. 8–12

Figure 15 presents projections of the 8–12 YOS CP model, the no CP model, and the 12 YOS CP model under a counterfactual scenario with a constant 100% BRS population between YOS 8 and 16, corresponding to a 2036 steady-state projection. Because the YOS 6 cohort in Table 20, corresponding to YOS 8 in Year 3 of the projections, is fully BRS, it provides a steady-state inflow of personnel into YOS 8–16, allowing the model to assume a constant annual entry of 5,347 Marines and a constant projected CP take-up of 4,625 Marines per year; this projection represents an upper-bound estimate, as it assumes all individuals survive to their predicted CP take year. The 12 YOS CP model applies a fixed overall take-up rate of 82%, based on the 2024 USMC CP take-up rate and consistent with the overall take-up rate projected by the 8–12 multinomial model in Table 20.

CP decliners attrite according to the Kaplan-Meier survival rates from the USMC summary statistics shown in Figure 9, while personnel prior to the CP decision attrite according to regular YOS survival rates reported in Appendix Tables in the “Survive %” column. CP takers attrite following completion of the four-year obligation using a 92% first-year post-obligation survival rate, after which regular YOS survival rates are applied. The 92% post-obligation survival rate is drawn from the USMC CP decider survival results shown in Table 11, where 92% of takers beyond their four-year obligation remain on active duty. USMC survival rates are applied rather than Army rates, as the Army post-obligation survival estimate of 97% is based almost entirely on personnel who accepted CP at YOS 11 and 12, with insufficient post-obligation data for Army CP takers at YOS 8–10. Detailed calculations for these three CP models are presented in Appendix Table 32.

Figure 15 demonstrates that the 8–12 YOS CP model is the most cost-effective and retention-maximizing policy, with cost per retained service member below the average CP payout at both the 2.5 and 5.0 multipliers. Annual costs and the projected end-strength gain of 8,517 Marines under the 8–12 model are shown in Figure 15, illustrating that retention gains substantially exceed incentive costs.

In contrast, the 12 YOS CP model produces net losses relative to the no-CP baseline, driven by high survival rates, a smaller eligible population, and limited marginal retention effects at YOS 12 and beyond. These dynamics suggest that the incentive is often paid to personnel who would have remained in service absent CP. Under the no-CP model, personnel experience minimal losses due to high baseline survival rates. In contrast, the 12 YOS CP model applies an 82% take-up rate at YOS 12, followed by a 79% first-year survival rate among decliners and USMC Kaplan-Meier decliner survival rates thereafter. This structure produces a small temporary retention increase at YOS 12 but results in an eventual end-strength deficit at YOS 14 and beyond, relative to the no-CP baseline.

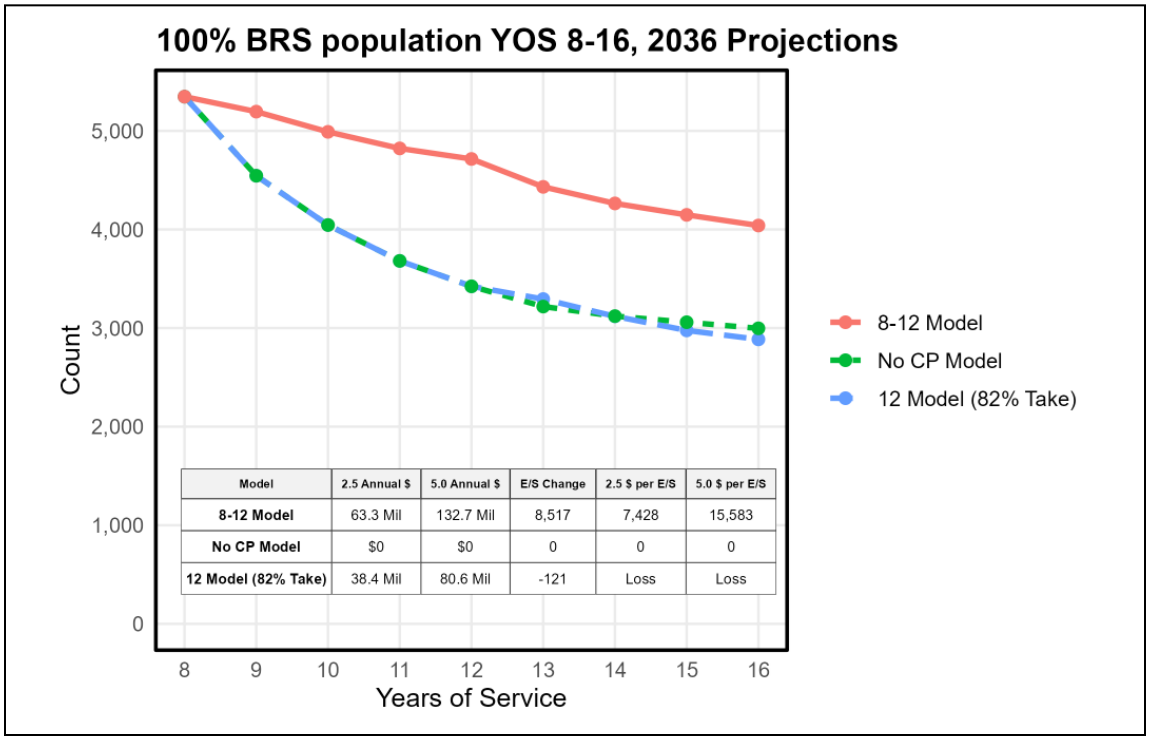
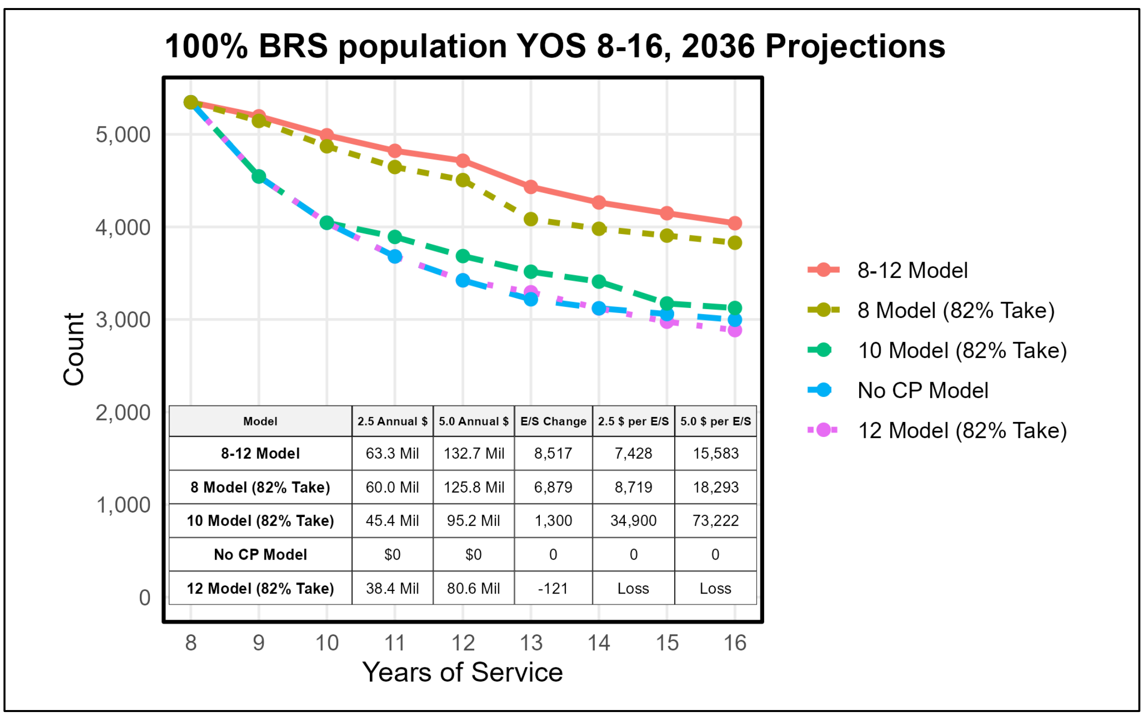


Figure 15. Year 2036 Projections, Years of Service 8–16, 8–12 Model vs. 12 Model with Costs, End Strength Increases, Cost per End Strength

Figure 16 extends the analysis in Figure 15 by applying the same calculations and assumptions while adding one-time CP offerings at 8 YOS and 10 YOS. These models use a fixed overall take-up rate of 82%, based on the 2024 USMC CP take-up rate and consistent with the overall take-up projected by the 8–12 multinomial model in Table 20.

Under the 10-year CP model, the results show that, at the 2.5 multiplier, the Marine Corps pays approximately $34,900 per additional unit of end strength retained relative to the no-CP baseline, which is substantially higher than the average CP cost of $13,678 at the 2.5 multiplier. In contrast, both the 8–12 model and the one-time 8-year model retain additional end strength at a cost below the average incentive payout under both the 2.5 and 5.0 multipliers, indicating that the incentive more than pays for itself when evaluated on a cost-per-retained-member basis. End-strength gains are calculated as the cumulative difference in personnel at each YOS relative to the no-CP baseline model.

If CP take-up rates were lower than assumed, projected end strength and total costs would decline, while cost per retained service member would increase; however, the 8–12 and 8-year models remain the most cost-effective options, consistently delivering higher end strength across YOS relative to alternative policies. The one-time 8-year model relies on a stronger behavioral assumption of similar take-up patterns, whereas the 8–12 model is more robust, as it is grounded in observed Army CP behavior captured through the ML framework. A breakdown of the calculations can be found in Appendix Table 32.

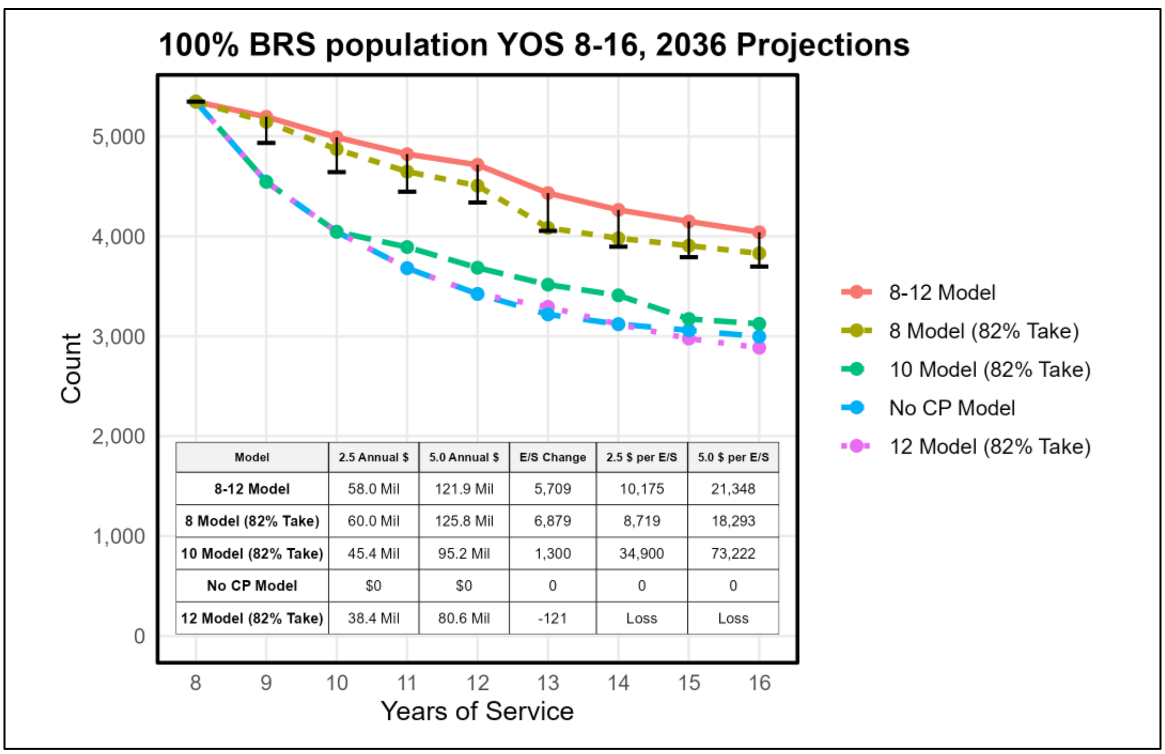


Model	2.5 Annual $	5.0 Annual $	E/S Change	2.5 $ per E/S	5.0 $ per E/S
8-12 Model	63.3 Mil	132.7 Mil	8,517	7,428	15,583
8 Model (82% Take)	60.0 Mil	125.8 Mil	6,879	8,719	18,293
10 Model (82% Take)	45.4 Mil	95.2 Mil	1,300	34,900	73,222
No CP Model	$0	$0	0	0	0
12 Model (82% Take)	38.4 Mil	80.6 Mil	-121	Loss	Loss

Figure 16. Year 2036 Projections, Years of Service 8–16, 8–12 Model, 12 Model, and Single Point Continuation Pay Offering 8 Model and 10 Model Using 82% Fixed Take-Up

Figure 17 presents an estimate for the 8–12 YOS CP model, reflecting a more precise projection in which individuals predicted to accept CP at later YOS are subjected to year-to-year survival rates before reaching their projected take year. Under this specification, the model projects annual CP take-up of 4,247 Marines, with annual costs of $58 million at the 2.5 multiplier and $121.9 million at the 5.0 multiplier, and an associated end-strength increase of 5,709 Marines. Cost per retained service member remains below the average CP payout at both multiplier levels. These results from Figure 17 are also reported in the abstract, as the lower projection represents the most precise estimate of the 8–12 model.

Although the one-time 8-year CP model slightly outperforms the 8–12 model, the 8–12 model projections are more reliable, as they are derived from ML methods grounded in observed Army CP behavior. The 8–12 model remains the most cost-effective and retention-maximizing policy option. Calculations are provided in Appendix Table 33.



Model	2.5 Annual $	5.0 Annual $	E/S Change	2.5 $ per E/S	5.0 $ per E/S
8-12 Model	58.0 Mil	121.9 Mil	5,709	10,175	21,348
8 Model (82% Take)	60.0 Mil	125.8 Mil	6,879	8,719	18,293
10 Model (82% Take)	45.4 Mil	95.2 Mil	1,300	34,900	73,222
No CP Model	$0	$0	0	0	0
12 Model (82% Take)	38.4 Mil	80.6 Mil	-121	Loss	Loss

Figure 17. Final Survival-Adjusted Projections for the 8–12 Years of Service Continuation Pay Model

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V. CONCLUSIONS AND RECOMMENDATIONS

A. OVERVIEW

This chapter presents the conclusions of the thesis by directly addressing the research questions based on the empirical results. The chapter also provides recommendations grounded in the analysis and concludes with suggestions for further research.

B. CONCLUSIONS

(1) When should the Marine Corps offer Continuation Pay to maximize retention and return on investment?

Regarding the primary research question concerning the optimal timing for the USMC to offer CP, the projections consistently show that offering CP between 8 and 12 YOS is the optimal policy for the USMC, maximizing end strength while retaining personnel at a cost lower than the incentive paid per Marine. Relative to the current 12 YOS CP model, the 8–12 model both increases retention and reduces cost per unit of end strength. While the one-time 8 and 10-year models rely on the strong assumption that take-up remains fixed at 82 percent, the ML framework leverages observed Army CP behavior to generate more credible projections without relying on fixed take-up assumptions. The analysis projects that the current 12 YOS CP model is retention-negative relative to a no-CP baseline, producing fewer Marines at later YOS than if the incentive were not offered.

Across all analyses, earlier CP timing increases the eligible population, leading to higher acceptance and reduced attrition during critical mid-career decision points. Survival analysis shows that 92 percent of USMC CP takers remain in service after completing their four-year obligation, and year-to-year survival rates increase sharply beyond 12 YOS. As a result, expanding CP eligibility to the 8–12 YOS window yields higher personnel counts both before and after completion of the CP obligation. The 8–12 model therefore functions as a retention-maximizing policy by offering the incentive at the point in the career when Marines are most likely to exit absent intervention.

From a force management perspective, CP should be viewed as a targeted retention tool rather than a default incentive. Expanding the offering window to 8–12 YOS allows the service to target Marines at the point of reenlistment during these key mid-career years, aligning the incentive with TM2030 objectives. If the USMC can meet manpower requirements at 8–12 YOS without CP, expanding retention through natural survival may be sufficient. If, however, retention shortfalls exist and force structure can absorb additional personnel at those YOS, the 8–12 YOS CP model provides a cost-effective mechanism to increase end strength. Any implementation should be compared against the cost of replacing experienced Marines through accession and training pipelines and evaluated alongside downstream force-shaping costs, including pay, promotion flow, and training capacity. Available Army and USMC data show that personnel retained to 12 YOS exhibit very high continuation rates thereafter, indicating that successful retention at earlier YOS yields durable manpower gains.

(2) What is the career return on investment for Army and USMC personnel who take up CP?

This section addresses the research question concerning the career return on investment for Army and USMC personnel who take up CP. The career return on investment for CP is high for both the Army and the USMC, as personnel who accept CP overwhelmingly remain in service beyond their four-year obligation. Among Army CP takers who completed the obligation period, 97% continued service, with the majority of observed post-obligation data drawn from takers at YOS 11 and 12. While additional data is needed to fully evaluate long-run outcomes for Army CP takers at YOS 8–10, early evidence indicates strong continuation behavior once personnel pass the obligation threshold. Similarly, 92% of USMC CP takers who completed their four-year obligation remained on active duty. These results indicate that CP effectively converts short-term retention into sustained career continuation, increasing personnel strength at higher YOS and generating substantial long-term retention returns relative to the initial incentive cost.

(3) What are significant predictors of Continuation Pay non-take-up among Marine Corps personnel?

This section addresses the research question concerning significant predictors of CP non-take-up among USMC personnel. Both summary statistics and ML results indicate that pilot MOS is a significant predictor of CP non-take-up among Marine Corps personnel. Descriptive analysis shows that pilots consistently exhibit lower CP acceptance rates relative to other demographic groups. This finding is reinforced by the USMC ML model, in which pilot MOS emerges as a meaningful contributor to the CP take-or-decline decision, indicating that pilots are more likely to decline CP than all other personnel. Together, these results identify pilot MOS as the primary observable characteristic associated with elevated CP non-take-up in the Marine Corps.

C. RECOMMENDATIONS

The Marine Corps should treat CP as a flexible, timing-based retention tool rather than a fixed one-time incentive. The findings of this thesis support adjusting CP timing in response to current retention gaps, end-strength requirements, and force-shaping constraints, particularly within the 8–12 YOS window. Analysts and decision-makers can use the framework developed in this research, combined with manpower needs, to determine when CP is most effective as a retention lever.

If the Marine Corps faces retention shortfalls between 8 and 12 YOS and has capacity to absorb additional personnel at those grades, implementing an 8–12 YOS CP timing model is preferable. This model functions as a targeted incentive by aligning CP eligibility with individual career decision points, recognizing that Marines reach career continuation decisions at different times within the 8–12 YOS window. By expanding eligibility across this range, the incentive engages Marines at the moment it is most likely to affect their decision to remain in service, resulting in higher acceptance and greater downstream retention beyond 12 YOS.

Even if the Marine Corps cannot accommodate the full end-strength increases projected under the 8–12 model, the policy remains superior to the current 12 YOS CP model. Earlier timing increases the likelihood that CP is offered to Marines whose retention is still uncertain, producing larger cohorts reaching 12 YOS and higher continuation thereafter. In contrast, the 12 YOS CP model frequently pays personnel who would have remained on active duty without the incentive, reducing its effectiveness and return on investment.

The Marine Corps should align multiplier selection with retention needs and force-structure capacity. Under an 8–12 YOS CP model, a 2.5 multiplier is likely sufficient to generate meaningful retention gains, as the projections are grounded in observed Army behavior at that multiplier level. A higher 5.0 multiplier should be considered only if retention shortfalls persist after implementing 2.5 multiplier under the 8–12 timing expansion, or if the objective is to target specific critical billets with greater incentive intensity. Because eligibility expands significantly under an 8–12 window, multiplier increases should be evaluated cautiously due to their nonlinear budget impact. In either case, the return on investment increases substantially as retained Marines continue service beyond their four-year CP obligation.

If retention requirements at 8–12 YOS are already being met through baseline survival, the Marine Corps should not expand CP, as doing so would subsidize retention that would have occurred naturally. The Marine Corps should apply CP selectively and conditionally, based on demonstrated retention need and available force-structure capacity. Over time, implementation of an 8–12 YOS CP timing model also provides a foundation for future refinement toward skill or MOS-specific targeting, further aligning CP with modern talent management practices.

Finally, if the Marine Corps elects to adopt an 8–12 YOS CP model, implementation should occur before the 8–12 YOS population becomes entirely composed of fully auto-enrolled BRS cohorts. Earlier adoption reduces front-loaded costs and allows the service to shape retention behavior as these cohorts enter their key mid-career decision points.

Because the literature review highlights persistent knowledge gaps among service members regarding incentives and career outcomes, prior research recommends expanding structured training on CP and the long-term benefits of a military career. This thesis recommends targeted annual training for first and second-term Marines, delivered through MarineNet, should provide a clear, data-driven overview of current incentives, Marine Administrative Messages, career decision points, and the monetary and non-monetary benefits of continued service relative to civilian alternatives. Presenting this information in a concise, accessible format would better equip junior Marines to make informed career decisions and improve the effectiveness of existing retention tools.

D. FURTHER RESEARCH

This thesis recommends further research into optimization-based models that integrate CP with other retention incentives. Such models could jointly optimize CP timing and multiplier levels to align incentive delivery with contract structures, Marine Corps manpower requirements, and the retention of specialized skills and MOSs.

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APPENDIX. CALCULATIONS OF PROJECTION FIGURES

Table 30. Calculations for Figure 13

100% BRS population YOS 8-16 so 2026 Projections				
Survive %	**YOS**	**12 Model (Current) 82% Tal**	**No CP Model**	**8-12 Model**
0.85	8	3,553	3,553	(1465@8, 712@9, 460@10, 306@11, 58@12, 552 decline) 3553
0.89	9	2580	2,580	(1197@9, 525@10, 308@11, 58@12, 492 decline)2580
0.91	10	2109	2,109	(1090@10, 398@11, 62@12, 557 decline)2107
0.93	11	(920 take) 1301	1,301	(765@11, 54@12, 482 decline) 1301
0.94	12			7 takers@12
0.97	13			
0.98	14			
0.98	15			
	16			
2.5 Annual Cost ($13,678)		(920*13,678) 12,583,760	$0	(4524*13,678) 61,879,272
5.0 Annual Cost($28,697)		(920*28,697) 26,401,240	$0	(4625*28,697) 129,825,228

Table 31. Calculations for Figure 14

100% BRS population YOS 8-16 so 2028 Projections				
Survive %	**YOS**	**12 Model (Current) 82% Take**	**No CP Model**	**8-12 Model**
0.85	8	5,347	5,347	(2876@8, 820@9, 515@10, 380@11, 34@12, 722 decline) 5347
0.89	9	(3865*.85) 3285	3,285	(2102@8, 536@9, 376@10, 288@11, 37@12+ 526 decline*.79) 3755
0.91	10	(3,553*.85*.89) 2688	2,688	(1465@8, 712@9, 460@10, 306@11, 58@12+552*.79*.64) 3280
0.93	11	1,396 takers(2580*.89*.91) 2090	2,090	(1197@9, 525@10, 308@11, 58@12+492*.79*.64) 2336
0.94	12	(1332 takers+(1,919-1332=587*.79) 1795	1784	(1090@10, 398@11, 62@12+557*.79*.64)1832
0.97	13	(920 take+381*.79*.64) 1113	(1,301*.93*.94)1137	(765@11, 54@12+482*.79*.64) 1062
0.98	14			
0.98	15			
	16			
2.5 Annual Cost ($13,678)		(1332*13,678) 18,219,096	$0	(4242*13,678) 58,022,076
5.0 Annual Cost($28,697)		(1332*28,697) 38,224,404	$0	(4242*28,697) 121,732,674
E/S Changes		-13	16,331	1,281
2.5 Cost/E/S Changes		Operating at a Loss	N/A	45294.36
5.0 Cost/E/S Changes		Operating at a Loss	N/A	95029.41
(USMC Decliners attrite by .79,.64,.54,.46,.41,.38,.33,.16)				
People before decision go by YOS survival curve				
People after 4 year take obligation go down .92 then survival curve				

Table 32. In-Depth Calculations Breakdown for Comparison of Models for Figure 16 and Continuation Pay Models for Figure 15

100% BRS population YOS 8-16 so 2036 Projections(USMC Decliners attrite by .79,.64,.54,.46,.41,.38,.33,.16)						
Survive %	YOS	12 Model (Current) 82% Take	No CP Model	8-12 Model	10 Model (82% Take)	8 Model
0.85	8	5,347	5,347	5,347	5,347	5347
0.89	9	(5347*.85) 4,545	4,545	(2,876@8, 820@9, 515@10, 380@11, 34@12)(4625 Takers+722*.79) 5,195	4,545	(4385 Takers+962*.79) 5,145
0.91	10	(4545*.89) 4,045	4,045	(4625 Takers+570*.64) 4,990	(4545*.89) 4,045	(4385 Takers+760*.64) 4,871
0.93	11	(4045*.91) 3,681	3,681	(4625 Takers + 365*.54) 4,822	(3317 Takers+728*.79) 3,892	(4385 Takers+486*.54) 4,647
0.94	12	(3681*.93) 3,423	(3681*.93) 3,423	(4625 Takers +197*.46) 4,715	(3317 Takers+575*.64) 3,685	(4385 Takers+262*.46) 4,506
0.97	13	(2808 Takers+615*.79) 3,294	(3423*.94) 3,218	(2,876*.92+1,749 Takers +90*.41) 4,432	(3317 Takers+368*.54) 3,516	(4385*.92+121*.41) 4,084
0.98	14	(2808 Takers+486*.64) 3,119	(3218*.97) 3,121	(2,646*.97+820*.92+929 Takers+37*.38) 4,264	(3317 Takers+199*.46) 3,409	(4084*.97+50*.38) 3,980
0.98	15	(2808 Takers+311*.54) 2,976	(3121*.98) 3,059	(2,567*.98+754*.98+515*.92+414 Takers + 14*.33) 4,148	(3409*.92+92*.41) 3,173	(3980*.98+19*.33) 3,906
	16	(2808 Takers+168*.46) 2,885	(3059*.98) 2,997	(2516*.98+739*.98+474*.98+380*.92+34 Takers +5*.16) 4,040	(3173*.98+38*.38) 3,124	(3,906*.98+6*.16) 3,829
2.5 Annual Cost ($13,678)		(2808*13,678) 38,407,824	$0	(4625*13,678) 63,260,750	(3317*13,678) 45,369,926	(4385*13,678) 59,978,030
5.0 Annual Cost($28,697)		(2808*28,697) 80,581,176	$0	(4625*28,697) 132,723,625	(3317* 28,697) 95,187,949	(4385*28,697) 125,836,345
Note: 82% fixed rate comes from 2024 Take-up rate and 8-12 model predicted take up overall was 82%. 5347 came from 7749 BRS personnel at YOS6 on 2025-07-31 multiplied by 69% making it to 8 YOS. These personnel made up 95% of the service personnel at YOS 6 showing its the first fully BRS Auto Enrolled cohort/YOS.						
Note: This is still upper bound projections for everyone as we are attriting the decliners at the correct rate, but expecting all takers to be elgible for reenlistment and have a boat space avaiable.						
Note: 92% of USMC Takers after obligation period stay in. Army was 97% but will apply the 92% to all USMC personnel after obligation period ends on the first year after obligation ends and then regular survival curve.						

Table 33. In-Depth Calculations Breakdown for Comparison of Models for Figure 17

100% BRS population YOS 8-16 so 2036 Projections(USMC Decliners attrite by .79,.64,.54,.46,.41,.38,.33,.16)						
Survive %	YOS	12 Model (Current) 82% Take	No CP Model	8-12 Model	10 Model (82% Take)	8 Model
0.85	8	5,347	5,347	5,347	5,347	5347
0.89	9	(5347*.85) 4,545	4,545	(2,876@8, 697@9, 437@10, 325@11, 29@12)(4364 Takers+722*.79) 4,934	4,545	(4385 Takers+962*.79) 5,145
0.91	10	(4545*.89) 4,045	4,045	(2,876@8, 697@9, 389@10, 289@11, 26@12+570*.64) 4,642	(4545*.89) 4,045	(4385 Takers+760*.64) 4,871
0.93	11	(4045*.91) 3,681	3,681	(2,876@8, 697@9, 389@10, 263@11, 24@12 + 365*.54) 4,446	(3317 Takers+728*.79) 3,892	(4385 Takers+486*.54) 4,647
0.94	12	(3681*.93) 3,423	(3681*.93) 3,423	(2,876@8, 697@9, 389@10, 263@11, 22@12 +197*.46) 4,338	(3317 Takers+575*.64) 3,685	(4385 Takers+262*.46) 4,506
0.97	13	(2808 Takers+615*.79) 3,294	(3423*.94) 3,218	(2,876*.92+1,371 Takers + 90*.41) 4,054	(3317 Takers+368*.54) 3,516	(4385*.92+121*.41) 4,084
0.98	14	(2808 Takers+486*.64) 3,119	(3218*.97) 3,121	(2,646*.97+697*.92+674 Takers+37*.38) 3,896	(3317 Takers+199*.46) 3,409	(4084*.97+50*.38) 3,980
0.98	15	(2808 Takers+311*.54) 2,976	(3121*.98) 3,059	(2,567*.98+641*.98+389*.92+285 Takers + 14*.33) 3,791	(3409*.92+92*.41) 3,173	(3980*.98+19*.33) 3,906
	16	(2808 Takers+168*.46) 2,885	(3059*.98) 2,997	(2516*.98+628*.98+358*.98+263*.92+ 22 Takers +5*.16) 3,697	(3173*.98+38*.38) 3,124	(3,906*.98+6*.16) 3,829
2.5 Annual Cost ($13,678)		(2808*13,678) 38,407,824	$0	(4247*13,678) 58,090,466	(3317*13,678) 45,369,926	(4385*13,678) 59,978,030
5.0 Annual Cost($28,697)		(2808*28,697) 80,581,176	$0	(4247*28,697) 121,876,159	(3317* 28,697) 95,187,949	(4385*28,697) 125,836,345
Note: 82% fixed rate comes from 2024 Take-up rate and 8-12 model predicted take up overall was 82%. 5347 came from 7749 BRS personnel at YOS 6 on 2025-07-31 multiplied by 69% making it to 8 YOS. These personnel made up 95% of the service personnel at YOS 6 showing its the first fully BRS Auto Enrolled cohort/YOS.						
Note: 92% of USMC Takers after obligation period stay in. Army was 97% but will apply the 92% to all USMC personnel after obligation period ends on the first year after obligation ends and then regular survival curve.						

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