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THESIS

BLENDED RETIREMENT SYSTEM: AN ANALYSIS OF MARINE CORPS OFFICER OPT-IN RATES BY MILITARY OCCUPATIONAL SPECIALTY

by

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BLENDED RETIREMENT SYSTEM: AN ANALYSIS OF MARINE CORPS OFFICER OPT-IN RATES BY MILITARY OCCUPATIONAL SPECIALTY

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ABSTRACT

In 2018, the National Defense Authorization Act created the Blended Retirement System (BRS), effectively removing the defined benefit plan and 20-year cliff-vesting requirement under the High-Three military retirement system. By removing the defined benefit plan and replacing it with a defined contribution plan, the BRS enables military members to separate prior to serving 20 years while having some form of retirement benefit that is easily transferable to other employers. As such, many constituents voiced concern that the BRS may cause long-term negative effects to both retention and accession missions. To determine whether military members chose to opt into the BRS due to their intent to separate from the service earlier, I use a military-to-civilian crosswalk for Marine Corps officer military occupational specialties (MOSs) to civilian standard occupational codes (SOCs). I then use Bureau of Labor Statistics wage data to match MOS-SOC wages to analyze whether higher or lower opt-in rates are observed in MOSs where civilian wages are higher or lower while also analyzing opt-in rates among critical-fill MOSs. By using a logistic regression model, I find that civilian wages and critical-fill MOSs have no statistically significant effects on BRS opt-in rates. Further study on the effects of BRS on retention is suggested, which may provide more insight to a member's decision to opt in and the potential associated effects on future retention.

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LIST OF ACRONYMS AND ABBREVIATIONS

BLS	Bureau of Labor Statistics
BRS	Blended Retirement System
CD	career designation
CMC	Commandant of the Marine Corps
DOD	Department of Defense
DRM	Dynamic Retention Model
GCT	General Classification Test
MarAdmin	Marine Administrative Message
MCRMC	Military Compensation and Retirement Modernization
MOS	military occupational specialty
MRS	Modernized Retirement System
NDAA	National Defense Authorization Act
O*NET	Occupational Information Network
OccFlds	occupational fields
PEBD	pay entry base date
PMOS	Primary Military Occupational Specialty
QRMC	Quadrennial Review of Military Compensation
SOC	standard occupational code
TFDW	Total Force Structure Division
TIS	time in service
TSP	Thrift Savings Plan
YOS	years of service

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I. INTRODUCTION

Since the introduction of the military's 20-year cliff-vesting retirement plan in the 1940s, military members who served at least 20 years have been receiving a military pension (Christian, 2006). While a military retirement means that service members receive a pension for the rest of their lives, many service members never serve long enough to receive such benefit. Over the past several years, though, Congress, through reviews and studies of military retirement reform, looked at methods to create a more equitable military retirement system. The cliff-vesting retirement plan, the High-Three, was considered inequitable, in part, because approximately 83 percent of enlisted service members and 51 percent of officers separate from the service prior to becoming eligible to receive a pension (Department of Defense [DOD], 2015). While creating an equitable retirement system was a priority, rising costs to the government also highlighted the need for reform, and military retirement was an area where substantial cost-savings could be made (Kamarck, 2019).

As a result of several reviews and reports of military retirement reform, the 2016 National Defense Authorization Act (NDAA) created the Blended Retirement System (BRS), a modernized retirement system that aligns more closely with 401(k) plans. With the creation of the BRS, policy makers forecasted that approximately 85 percent of service members will qualify for some sort of retirement benefit as compared to only 20 percent under the High-Three retirement system (Jeszeck & Todisco, 2019). By removing the cliff-vesting requirement—the most notable change from the High-Three system—the BRS allows service members to separate from the service before serving 20 years and still receive some sort of retirement benefits, provided they serve at least two years to begin receiving government contributions.

While praised as a means to make military retirement more equitable, the long-term effects of the BRS on retention have raised concerns throughout the Department of Defense (DOD). Some argue that service members may be more inclined to separate earlier from the service under the BRS as compared to the High-Three system, due to removing the High-Three cliff-vesting requirement (Jowers, 2018, para. 4; Military Officers Association of America, 2018; Reiley, 2017). If this is true, then military members who opted in to the

BRS may have elected to opt in with the intent to separate from the service prior to serving 20 years. Additionally, future military applicants under the BRS will have the opportunity to separate earlier than 20 years as well and still walk away with some retirement benefits. It is understandable then for policy makers to be concerned—implementing the BRS could adversely affect future retention or accession missions.

The BRS affects all DOD service members; however, my thesis explores the effects of the BRS on retention while narrowing the scope specifically to the Marine Corps. While recent research on military retirement reform is useful in understanding the broad impacts of the BRS and its associated effects on retention, no research exists on the effects of optin rates across the full range of military occupational specialties (MOSs). Therefore, my research examines how MOS differ in BRS opt-in rates while also examining how alternative civilian employment opportunities and associated wages may have influenced a member's decision to opt in or opt out. I further examine how opt-in rates differ between critical MOSs. As such, my research answers the following two research questions:

- To what extent are higher BRS opt-in rates observed in MOSs where comparable civilian standard occupational code (SOC) jobs receive higher compensation compared to those who do not?
- How do the BRS opt-in rates differ among Marine Corps officer population categories such as occupation fields (OccFlds), individual MOSs, or critical MOSs?

My initial hypotheses are that the BRS opt-in rates are observed in MOSs that have higher comparable civilian wages and that critical MOSs also have higher opt-in rates compared to non-critical MOSs. To test my hypotheses, I first use a military-to-civilian crosswalk, as used by Zunic (2018), to determine comparable civilian wage data for officer MOSs and examine the associated effects on the opt-in rate across the full range of MOSs. Second, I examine how officer opt-in rates differ by MOS OccFlds and individual occupations to understand how these fields and communities may affect opt-in rates. This research may provide a better understanding of the BRS opt-in behavior in efforts to inform the Marine Corps on the broad impacts that the BRS may have on future retention or accession missions for Marine Corps officer MOSs.

My findings reveal that there is variation of opt-in rates between MOSs, being that the aviation community opts in at higher rates compared to the combat arms and combat service support communities. With respect to civilian wages or critical MOSs, both are statistically significant but are not consistently significant throughout several models that I examine. This is attributed to the pilot MOS having higher comparable equivalent civilian wages using a military-to-civilian crosswalk, as well as having a higher proportion of critical MOSs within the aviation community. The results are, therefore, biased due to the pilot MOS causing statistically significant results, which causes inconsistent and biased results, leading me to conclude that neither civilian wages nor critical MOSs affected the BRS decision and are thus insignificant.

The remainder of my thesis is constructed in five chapters. Chapter II provides an overview on the past and current military retirement systems and the push for retirement reform. In Chapter III, I describe related academic literature on the effects of retirement compensation on turnover as well as previous military retirement reform studies. In Chapter IV, I describe my data and the methodology I use to obtain a military-to-civilian occupational wage crosswalk and its employment throughout the conduct of my research. Chapter V includes my estimated regression results and compilation of the data. Finally, in Chapter VI, I present my findings, limitations, and recommendations based on the outcomes of my research.

II. BACKGROUND

A. U.S. MILITARY RETIREMENT SYSTEMS

The U.S. military has three retirement systems: one for active component members, one for reservists, and one for members who are entitled to disability retirement. My thesis covers the active component retirement system only. For this population, there are four different methods for calculating service member retirement benefits, which are the Final Basic Pay System, High-Three, Redux, and the BRS. Depending on when members entered the service and the retirement choices they made during their career, each retirement plan will differ in total compensation. For the purpose of my thesis, I discuss only the High-Three and Blended Retirement System retirement plans for active component members. This is solely due to the population group this thesis includes, which are only those individuals who were a part of the active component and had the opportunity to choose either the High-Three or Blended Retirement System plans during the BRS election period that went into effect on 1 January 2018 until 31 December 2018.

B. HIGH-THREE RETIREMENT SYSTEM

Military members who entered the service on or after 8 September 1980 and before 1 January 2018 are eligible for the High-Three retirement plan. Under this retirement plan, service members who complete at least 20 years of military service are eligible to retire from the military and receive a pension. Their retired pay is calculated by using the average of the highest three years (36 months) of basic pay multiplied by 2.5 percent for each year of service (DOD, n.d.). At 20 years of service, a member would receive 50 percent of their average highest three years of basic pay (20 years of service times 2.5 percent), and the amount increases by 2.5 percent for every additional year served thereafter (DOD, n.d.). The High-Three plan is protected from inflation by annual cost of living adjustments according to Consumer Price Index but does not include any pay readjustments or bonuses either during service or upon retiring (DOD, n.d.).

C. THE PUSH FOR MILITARY RETIREMENT REFORM

Every four years, Congress requires the president to review the military compensation system, a review known as the Quadrennial Review of Military Compensation, or QRMC (Kamarck, 2019). The Tenth QRMC report published in 2008 by the DOD describes the High-Three retirement plan as "inequitable, inflexible, and inefficient" (DOD, 2008, p. 12). It is regarded as inequitable to service members because members receive no retirement compensation until they serve 20 years and because it does not align with private sector retirement benefits. Under federal law, private sector requires employers who provide retirement benefits to vest at least 80 percent of their employees within five years and 100 percent at seven years, depending on the type of vesting (DOD, 2008). Unlike the private sector, military retirement vesting does not occur until after the member reaches 20 years of service.

The second issue the QRMC discusses is flexibility of the system itself as a force management tool. The High-Three system, the report suggests, creates a "one-size-fits-all" structure that encourages the force to follow the same linear path, regardless of MOS, the current mission, or other environmental factors that affect force structure such as recruiting or retention goals. While the QRMC suggests current retention strategies have been effective, it contends that the High-Three system is not structured around the needs of the force but rather around the 20-year cliff-vesting requirement (DOD, 2008).

Lastly, the QRMC explains that it is an inefficient system due to its high cost. The high cost is attributed to the notion that service members' have a personal discount rate, which lowers the perceived value of the system to the member. Because of this lower perceived value, the government is paying a higher cost than it is perceived to be valued by the service member. As such, the perceived value of a 20-year retirement to the individual service member is valued less than the cost incurred by the government. Inefficiencies are thus created because the government is paying more than it needs in order to satisfy the member's perceived value of the retirement package itself (DOD, 2008).

As explained by the QRMC, the High-Three military retirement system lacks the ability for service members who serve less than 20 years to receive some sort of retirement

benefit (DOD, 2008). Due to these unattractive characteristics, in addition to the rising costs of the defined benefit plan, policy makers wanted reform. This reform, in their eyes, would be more equitable to the service member while also reducing costs to the government.

D. BLENDED RETIREMENT SYSTEM

1. Background

Since 2000, several studies and reviews, including previous QRMC reports, have recommended that the military retirement system be replaced with a retirement system that decreases costs, allows for early vesting and includes DOD contributions, and leads to higher overall compensation and value to the service member. The 2013 NDAA established the 11th QRMC, called the Military Compensation and Retirement Modernization Commission (MCRMC), which was an independent commission whose objective was to review and recommend changes to the military retirement system (Asch et al., 2015). MCRMC's proposal for retirement reform was to establish a blended approach to military retirement that included both defined benefit and defined contribution retirement plan characteristics. These recommendations were soon adopted and implemented by the 2016 NDAA (Asch et al., 2015).

2. The Blended Approach

On 1 January 2018 the BRS was fully implemented. Service members having less than 12 years of active component service as of 31 December 2017, according to their pay entry base date (PEBD), were given the option to make a one-time irrevocable decision to either opt into the BRS or opt out and remain with the legacy, or High-Three retirement plan (Commandant of the Marine Corps [CMC], 2016). Service members who had greater than 12 years of service as of 31 December 2017 had no choice and were grandfathered into the High-Three system. Any members who joined the service after 31 December 2017 were automatically enrolled in the BRS (CMC, 2016). Unlike the High-Three, under the BRS, members with 20 years of service receive 40 percent (2 percent times years served) of the average of the member's highest 36 months of basic pay, and an increase of 2 percent every year thereafter. The BRS attempts to compensate the difference of the High-Three

(40 percent pension versus 50 percent pension at 20 years) by applying a blended approach, using the Thrift Savings Plan (TSP) where member, government contributions, and continuation pay add to the value of the BRS that makes it more comparable in compensation with the High-Three system (DOD, 2017).

Service members have been able to contribute to the TSP, a defined contribution plan, since 2000. The TSP enables members to contribute percentages of their pay to either a traditional or Roth TSP, traditional being taxable and Roth TSP being tax-free investment vehicles. Under the BRS, the government automatically contributes 1 percent of basic pay into the TSP (DOD, 2017). Additionally, the government matches member contributions up to 5 percent but will only contribute up to a maximum of 5 percent (1 percent automatic and 4 percent matching) once a member serves two years (DOD, 2017). Members will only receive matching contributions above 1 percent as long as they make contributions themselves above 1 percent of their basic pay. Members are immediately vested in their contributions as well as government matching contributions; however, the 1 percent automatic government contribution and 4 percent government-matching contributions vest only after the member serves at least two years to be considered fully vested, which enables them to then transfer their TSP to other employers after they separate from the service (DOD, 2017).

The BRS also incorporates continuation pay multipliers and a lump-sum option that differs from the High-Three retirement system. Part of the BRS retirement package includes continuation pay, a one-time mid-career payment to the service member that is calculated from the current pay multiplier set by the services (2.5 percent in 2020) multiplied by the member's regular monthly basic pay. Continuation pay is a cash incentive designed to encourage retention that can either be paid directly to the member or rolled into their TSP (DOD, 2017). The lump-sum option gives servicemembers the choice to take a 25- or 50-percent lump-sum of their pension that will reduce their monthly pension payout until they reach 67 years old, at which point the pension is fully restored (Brockert, 2018).

3. Opt-in Eligibility

On 9 December 2016, the Marine Corps released a service-wide Marine Administrative Message (MarAdmin) notifying service members who were eligible to opt in or opt out of the BRS that the opt-in or opt-out period would begin on 1 January 2018 and end on 31 December 2018 (CMC, 2016). This was a one-time irrevocable decision that applied to certain members depending on time in service eligibility criteria. To be eligible to either opt in or opt out of the BRS, members must have had 12 years or less of total active component service, according to their PEBD, on or before 31 December 2017. Any member who had greater than 12 years of active component service according to their PEBD as of 31 December 2017 was automatically grandfathered into the High-Three system. Further, any member who joins the service on or after 1 January 2018 is automatically enrolled in the BRS (CMC, 2016).

E. SUMMARY

While military retirement reform had long been a topic of discussion of Congress, it was not fully implemented until 1 January 2018. Because the BRS is still in its infancy, the long-term effects of the BRS on future retention and accessions have yet to be fully understood, and trying to determine or forecast such effects is an effort worth exploring. Conducting further research into the BRS and understanding how opt-in rates vary by MOS may provide the Marine Corps with a better understanding of potential reasons for opting in versus opting out and how it affects retention rates across the full spectrum of military occupational specialties.

Initial assumptions lead me to believe that differences in opt-in rates will vary among all MOSs, especially considering that MOSs vary by community, technical ability, job demand, and transferability to the private sector. I estimate that the BRS opt-in rates are higher in critical MOSs as well as in MOSs that align to civilian sector jobs that have higher compensation. These assumptions align with the concerns brought up by policy makers that the BRS may adversely affect future retention and accession by creating higher separation rates compared to the High-Three system, especially if higher opt-in rates are observed in MOSs that either are critical or align with civilian sector jobs that pay higher wages. Chapter III provides an overview of military retirement reform literature as well as the existing relationships between job mobility, turnover, and private sector employee retirement choices.

III. LITERATURE REVIEW

A. EFFECTS OF RETIREMENT COMPENSATION ON TURNOVER

1. Job Search and Turnover

A vast amount of academic literature exists on voluntary turnover and job search. Empirical evidence suggests that job search is often included in turnover models and has been shown to be a good predictor of voluntary turnover (Swider et al., 2011). In Steel's research conducted in 2002, he contends that job search is a continuous process that occurs over a period of time, even in a passive state for individuals who are not actively searching for jobs. In a 2010 study on the effects of internal and external employment opportunities on Air Force enlisted retention, he finds that the relationship of external opportunities (alternative opportunities of employment) and voluntary turnover is greater in the military than the relationship between external opportunity and turnover in the civilian sector (Steel & Landon, 2010).

While military members may not be actively searching for a job at all times, due to the nature of military contracts, members decide either to continue service or separate. This is the case for all enlisted Marines as well as officers; however, officers follow a slightly different path that is contingent upon the career designation (CD) board. The CD board is a competitive selection board process where the Marine Corps selects officers of all MOSs for continued service. If selected for CD, the officer can choose either to accept and continue service indefinitely (contingent upon continued promotion) until they decide to separate, or choose to decline CD and opt to separate, a decision that typically happens at the three-and-a-half-year mark and separation at the four-year mark. If not selected for CD, then the officer will typically be involuntarily separated at four years of service, regardless whether he/she wants to continue serving or not.

Career designation, then, is the point at which an officer must accept to continue or not continue service. Job search and turnover is no different for service members themselves. Because of the four-year contract and CD boards, within the first few years, members must make a decision to continue or not continue service. Job search and turnover theory can be applied during these important moments for service members because it is at points leading up to these career milestones that they either must search for alternative employment or continue service, which supports Swider et al.'s (2011) and Steel's (2011) arguments that job search is a continuous process and precedes turnover.

2. Mobility Tendencies of 401(k) Participants

To understand how the BRS opt-in decisions may have been affected by the change in the retirement system, i.e., from a defined benefit system to defined contribution/hybrid system, I reviewed previous literature on how employee mobility is affected by changes in their 401(k) structure. Specifically, as Goldhaber, Grout, and Holden (2017) suggest, employees who are more mobile are likely to select the defined contribution plan. This analysis supports the views of Goda, Jones, and Manchester (2017) in that employees with higher mobility tendencies self-select into defined contribution plans.

If these views hold true and are applied to the military, then it can be inferred that members who opt into the BRS may have a higher propensity to do so because of their higher mobility tendency, whether they realize it or not. Moreover, military members who are more mobile may take on a more active role in job search. This may contribute to an increased understanding of alternative employment opportunities and the effects and benefits of having a more mobile retirement plan, which may cause these particular members to have higher observed BRS opt-in rates.

B. MILITARY RETIREMENT REFORM STUDIES

1. Survival Analysis of the Modernized Retirement System

Moynihan (2016) uses a Kaplan-Meier survival analysis model to study how the Modernized Retirement System (MRS) would affect the career survival of Marine Corps officer and enlisted Marines and a probit regression model to predict their opt-in rates for the MRS (MRS was used at the time for what we know now as the BRS). To conduct a survival analysis for service members' expected length of service, Moynihan created an online survey that elicited responses to questions regarding one's risk tolerance, especially as it relates to investing, as well as their understanding of the legacy retirement system and TSP. The survey further presented hypothetical information of the MRS retirement plan and asked participants to make choices based on this information. This survey was sent out to approximately 28,000 Marines in I Marine Expeditionary Force, and he received approximately 1,100 responses.

Once Moynihan obtained the data, he conducted survival analysis for both officer and enlisted Marines and finds that enlisted Marines' length of service is longer under the MRS for years 5 to 8, but their service is shorter under the MRS above 16 years of service. For officers, their expected length of service under the MRS is shorter throughout all years. He notes that differences in expected survival for enlisted Marines is 2 percent while officers exhibit a 15 percent difference between the two retirement systems, being longer under the legacy system. Moynihan then uses a probit regression model to determine optin rates for both officer and enlisted Marines, finding that ceteris paribus, younger Marines are more likely to opt into the MRS as compared to older Marines. This finding is consistent with other research, especially considering younger Marines have more time to realize the full effects of government matching to members contributions and the compounding effects over time, while older Marines have missed out on those compounding effects.

2. Retention Effects of the Military Retirement System

Asch et al., in their 2017 study, assesses retention and estimates the cost of implementing the BRS for all DOD service components while identifying optimal continuation pay multipliers and its associated effect on active duty retention. In their study, they use a stochastic dynamic programming model, known as the Dynamic Retention Model (DRM). This model simulates compensation and retirement policy changes using service members' historical participation and transition rates as well as data on their transition from the active component to either the reserves or civilian sector. This simulation model contained 25,000 observations by using 20–21 years of service member history beginning from 1990/1991 to 2010/2011 (Asch et al., 2017).

Using their retention model, they predict that, while holding the continuation pay multiplier at 2.5 percent (the expected multiplier at the time and the rate currently in effect), the opt-in rate is 0 percent for officers with greater than five years of service, 5 percent at

four years of service, 9 percent at three years of service, 13 percent at two years of service, and 100 percent at one year of service. Additionally, they identify the "optimized" continuation pay multiples and find that the percentages of officers who opt in substantially increases to approximately 80 percent for those who have four years or less of service and approximately 60 percent for those who have greater than four years of service but less than 10 years of service. Further, they find that 10 to 12 years of service, the opt-in rates fell drastically to near-zero-level rates, which is attributed to the higher likelihood of an officer to reach 20 years of service once they reach this mid-career milestone (Asch et al., 2017).

Their DRM also simulates career retention survival at an "optimized" continuation pay multiplier that would need to be set to for retention under the BRS to mirror that of the legacy retirement system. They find that a continuation pay multiplier of 9.71 for Marine Corps officers is needed for the BRS to sustain similar legacy retirement system retention numbers. Further, the BRS opt-in rates would increase under these optimized levels. Optin rates for officers with one year time in service (TIS) is 100 percent, approximately 80 percent between two and four years TIS, 60 to 70 percent for five to eight years TIS, 50 percent for nine years of service, but would sharply decline to approximately 6 percent for officers with 10 years TIS, 0 percent for 11 years of service, and approximately 3 percent for 12 years TIS. The 3 percent of officers who opted-in at 12 years of service would be eligible for continuation pay within a relatively short time after opting in, which may have contributed to their decision to opt in (Asch et al., 2017).

3. Behavioral Economics Analysis of BRS Opt-in Decisions

Brockert (2018) studies the effects of irrational decision-making for members who opted-in to the BRS. His research differs from Asch et al. and Moynihan's research in that he uses the BRS data that includes actual opt-in and opt-out rates whereas previous research attempts to predict retention and opt-in rates based on simulation and via a survey. Brockert's study of irrational behavior focuses on tying a member's opt-in decision to certain life events such as marriage, promotion, child birth, etc., and attempts to analyze their decision to opt in based on those events. Particularly, as the data reveals, members who had greater than 5 years of service and even up to 10 and 11 years opted-in to the BRS at a higher rate than forecasted under previous research.

Moynihan (2016) projects opt-in rates to be approximately 10 percent at the eight, nine, and eleven-year mark and approximately 5 percent at the ten-year mark. Asch et al. projects (at the 2.5 percent continuation pay floor) that officer opt-in rates for anyone over five years of service would not opt in. Because actual opt-in rates were significantly higher than these estimates, Brockert analyzes service member decisions to opt in and finds that these higher-than-anticipated opt-in decisions may be attributed to irrational behavior.

Using a linear probability model, Brockert identifies certain variables that correlate to higher opt-in rates. Of particular importance, he examines opt-in rate differences amongst the various communities in the Marines Corps, those being combat arms, combat service support, and aviation. Of these three different communities, he finds that being in the aviation community resulted in higher opt-in rates as compared to combat arms and combat service support. Additionally, he examines how career designation and rank affect opt-in rates and finds that being career designated lowered the likelihood that one would opt into the BRS and that company grade officers opt in at higher rates than field grade officers.

Brockert's findings are consistent with previous research in that company grade officers and thus, younger service members, opt in at higher rates due to the ability to realize greater compounding effects of the TSP and its overall retirement value (Asch et al., 2017; Moynihan, 2016). The difference in his model is that he examines the BRS opt-in rates across the different Marine Corps communities (combat arms, combat service support, and aviation) as well as how accepting career designation, among other life events, affects opt-in decisions.

4. Effects of Australian Military Retention Reform

Cunha, Menichini, and Crockett (2015) provide real-world empirical evidence of the retention effects of removing cliff-vesting pensions in favor of one-year vesting retirement plans. In their study of the Australian Army's retention reform implemented in 1991, they find that removing cliff-vesting and implementing a defined contribution plan (essentially what the BRS is to the U.S. military) significantly increases attrition before the vesting period as well as decreases the career survival probabilities for those who opted-in to the defined contribution plan. This research is consistent with Goda, Jones, and Manchester's (2017) views that more mobile individuals self-select into defined contribution plans.

C. SUMMARY AND IMPLICATIONS

Previous literature on job search, turnover, and 401(k) mobility suggests that individuals are constantly looking for employment while on the job and that having greater employment alternatives increases one's likeliness to turnover. Additionally, those who are mobile tend to self-select into defined contribution retirement plans. Past research on the effects of removing cliff vesting pensions in favor of defined contribution plans reveals that it will have a negative effect on retention (Cunha et al., 2015). However, given that the study focuses only on the Australian Defense Force, it would be difficult to draw conclusions based on this study alone. Looking further at other studies on military retirement reform—to include survival analysis, dynamic retention modelling, and irrational decision making, as covered previously—helps to form a collective picture of how military retirement reform may affect retention; however, the exact reasons for opting in or opting out of the BRS have yet to be determined.

Academic literature supports the argument that changing from the High-Three to the BRS may imply a shorter career survival time and that the aviation community (in particular, pilots) opt in at higher rates (Asch et al., 2017; Brockert, 2018.; Moynihan, 2016). Past research then would likely indicate that changing from the High-Three retirement system to BRS would cause higher opt-in rates from those individuals who have higher mobility tendencies, greater external job opportunities, and potentially those with more technical or critical skills, such as pilots or even communications and intelligence MOSs that may demand higher wages in the private sector. Higher opt-in rates, then, may indicate an individual's willingness to separate from the service earlier which, if true, demands that the Marine Corps—as well as all services—pay particular attention how this may affect retention. In the next chapter, I discuss the data and methodology used throughout the conduct of my research.
IV. DATA AND METHODOLOGY

In this chapter, I use data obtained from the U.S. Marine Corps Total Force Structure Division (TFDW) to construct my econometric models. I first describe the data and variables I use in each model followed by my methodology for implementing each model.

A. DATA

My data includes all active component Marine Corps commissioned officers who were eligible to opt-in to the BRS during calendar year 2018. To be eligible to opt-in or opt-out of the BRS, members must have had less than 12 years of total active component service as of 31 December 2017, according to their PEBD. All members who had greater than 12 years of active component service as of this date were not eligible to opt in or opt out of the BRS and are not included in the data. Additionally, any members who entered the service on or after 1 January 2018 were automatically enrolled in the BRS and were not eligible to opt in or opt out of the BRS. As such, I exclude them from this analysis.

1. Data Cleaning

Approximately five percent of the original sample had incomplete General Classification Test (GCT) scores so I exclude those from my dataset as well as an erroneous member who was ineligible to opt in to the BRS. I further exclude the 10 percent of Marines with MOSs that do not have matched civilian SOC codes, as described further below. Because warrant officers are typically older and have more time in service due to the nature of their career, I also exclude them from my analysis because they are closer to retirement which may cause biased regression estimates. After cleaning the data by removing duplicate entries, there are 8,544 observations remaining in my dataset from the original 11,250 TFDW provided.

2. Dependent Variable

The sole dependent variable, *OPT_IN*, is an indicator variable that equals 1 if a Marine opts in and 0 otherwise. All other variables are independent X variables and are further explained below.

3. Key Independent Variables

Military members who search for alternative employment may look for veteranfocused resources to help them transition to the civilian workforce. One such resource that was developed by Occupational Information Network (O*NET) uses military occupational codes and job descriptions to match to similar civilian occupations using SOC codes. By using O*NET, military members are able to search for similar civilian jobs and obtain current and future projected job outlooks, to include industry growth and forecasted wages. This process of matching military-to-civilian occupations is called a "crosswalk," and Zunic uses the crosswalk in her research on gender composition in the Marine Corps. She uses a combination of O*NET's military crosswalk, the Marine Corps MOS Manual, and her own interpolation of military MOSs to match each MOS to similar civilian occupations (Zunic, 2018).

I use the same crosswalk Zunic developed to match MOSs with SOC codes and use civilian wage data obtained from the BLS to identify median national wages for each SOC and match those wages to each of the 17 OccFlds. The *LN_CIV_WAGE* variable is the natural log of the 2018 median annual civilian wages obtained from the Bureau of Labor Statistics (BLS). Each MOS that has a matching SOC code using Zunic's 2018 military-to-civilian crosswalk is assigned civilian wages according to the BLS table. I use the natural log of the civilian wage rate to account for differences in wage rates (low versus high, for example) and the associated effects of increasing wages as a percentage rather than as an absolute value. This ensures that increases in wage rates are represented as a percent increase of one's wages and is a better metric to use than absolute wage increases that does not take into account the perceived effect of wage changes on low versus high absolute wages. *Critical_MOS* is an indicator variable that is equal to 1 if the MOS is having

difficulty meeting target inventory. This data is according to the 2020 MOS status report generated by the Marine Corps' Manpower Plans and Policies Division.

4. Independent Variables

The *AGE* variable is the age of a service member during the BRS election period in 2018, the mean being 28.5 years old, and *YOS* is the amount of active component years of service (YOS) the member had during this same time, the mean being approximately 6 years. The mean YOS is important to note because serving 6 years typically requires officers to have been selected and accepted for career designation. This may suggest intent to serve in the Marine Corps for longer than the initial obligated four years of service. However, the mean YOS may be biased due to contract length, especially when considering that pilots typically have an eight-year contracts at the beginning of their service.

I create the *FEMALE* indicator variable to show opt-in rate differences between gender and take note that females represent approximately 10 percent of the observations. Other independent variables I create are *CO_GRADE* to designate company grade officers apart from field grade officers, *MARRIED* to indicate those who are married, and *NUMB_DEPEND* for number of dependents which range from 0 to 4 and above. I create the natural log variable of GCT scores since one-unit changes to a GCT score (increasing by one point, for example) has little effect on the BRS opt-in rate probability, and creating a log simplifies it as a percentage change. I further identify races as indicator variables: *WHITE*, *BLACK*, *ASIAN*, and *OTHER* for all other races, including those who have no race identified in the dataset.

5. Interaction Variable

I create an interaction variable, *Crit_Wage*, by interacting the *LOG_CIV_WAGE* and *Critical_MOS* variables for use in my models. This allows me to estimate the effects of an MOS that is both critical and has higher civilian wages.

6. Model Fit

The AGE and YOS variables as well as the MARRIED and NUMB_DEPEND variables are highly correlated according to Table 1 below, the correlation matrix. I compare models using a combination of these variables, in addition to the race variables, to determine the most optimal model to use in my analysis. I use a combination of the pseudo R-squared, Akaike Information Criterion, Bayesian Information Criterion, and log likelihood values to choose the best model and include the following demographic variables for my models: AGE, YOS, FEMALE, LN_GCT, CO_GRADE, NUMB_DEPEND, and WHITE. Table 2 below describes the summary statistics of the Key_X, Demographic, and Interaction variables I use in my econometric model.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Age	1.000						
(2) Years of Service	0.807	1.000					
(3) Female	-0.047	-0.078	1.000				
(4) Log GCT Score	0.073	0.096	-0.081	1.000			
(5) Company Grade	-0.394	-0.383	0.011	-0.081	1.000		
(6) Married	0.383	0.398	-0.086	0.039	-0.155	1.000	
(7) Dependents	0.473	0.467	-0.173	0.042	-0.240	0.704	1.000

Table 1. Correlation Matrix

Variable	Obs	Mean	Std.Dev.	Min	Max
Opt-in	8544	.58	.494	0	1
Log Civilian Wage	8544	11.384	.198	11.011	11.71
Critical MOS	8544	.465	.499	0	1
Age	8544	28.476	3.253	22	38
Years of Service	8544	5.843	3.042	0	11
Female	8544	.101	.301	0	1
Log GCT Score	8544	4.806	.08	4.317	5.037
Company Grade	8544	.94	.237	0	1
Dependents	8544	.899	1.142	0	4
White	8544	.838	.369	0	1

Table 2. Summary Statistics

In Table 3, I list the MOSs that I group together using two-digit OccFld identifiers. I create this list by using Primary Military Occupational Specialty (PMOS) OccFld identifiers as indicator variables and grouping the MOSs using their two-digit PMOS numbers. For example, all 01XX officer MOSs (again, not including warrant officers) include the 0101 and 0102 MOSs. 0101 MOSs are members in a student status who have not yet completed primary MOS training. However, because 0101s obtain the 0102 MOS after completion of primary MOS school, I group student MOSs and school-trained members together into one OccFld variable. In the case of the 01XX MOS, they are grouped under the *Manpower* variable. Not all PMOSs are used in this study; as such they are excluded from Table 3 and this thesis, either due to small sample sizes or not aligning with the military-to-civilian crosswalk, as I later describe.

I further lay out the military-to-civilian crosswalk, similar to Zunic's 2018 study, but I include the associated MOS-SOC wages obtained from the BLS. This crosswalk is listed in Table 4.

OccFld	Included PMOSs	OccFld	Included PMOSs
Manpower and Administration	0101, 0102	Financial Management	3401, 3404
Intelligence	0202, 0203, 0204, 0206, 0207	Communication Strategy and Operations (CommStrat)	4301, 4501, 4502
Infantry	0301, 0302, 0370	Legal Support	4401, 4402
Logistics	0401, 0402	Military Police, Investigations, and Corrections	5801, 5803
Communications	0601, 0602	Aircraft Maintenance	6001, 6002
Field Artillery	0801, 0802	Aviation Logistics	6601, 6602
Engineer, Construction, Facilities, and Equipment	1301, 1302	Aviation Command and Control Operations	7202, 7204, 7208, 7210, 7220
Tank, Assault Amphibious Vehicle and Amphibious Combat Vehicle	1801, 1802, 1803	Pilots/Naval Flight Officers	7507, 7509, 7516, 7518, 7521, 7525, 7531, 7532, 7543, 7556, 7560, 7562, 7563, 7566, 7567 7568, 7578, 7588, 7599
Supply Chain Material Management	3001, 3002		

 Table 3.
 Military Occupational Specialties by Occupation Field

PMOS	SOC	Civilian	PMOS	SOC	Civilian
	Code	Wage		Code	Wage
0101	11-3121	\$106,910	3001	11-3061	\$111,590
0102	11-3121	\$106,910	3002	11-3061	\$111,590
0202	11-1021	\$99,310	3401	11-3031	\$121,750
0203	33-1021	\$74,540	3404	11-3031	\$121,750
0204	33-1012	\$84,840	4301	11-2031	\$107,320
0206	33-1012	\$84,840	4401	23-1000	\$115,050
0207	11-1021	\$99,310	4402	23-1000	\$115,050
0301	33-1021	\$74,540	4501	11-2031	\$107,320
0302	33-1021	\$74,540	4502	11-2031	\$107,320
0370	47-1011	\$62,980	5801	33-1011	\$60,560
0401	13-1081	\$74,170	5803	33-1011	\$60,560
0402	13-1081	\$74,170	6001	49-1011	\$63,540
0601	11-1021	\$99,310	6002	49-1011	\$63,540
0602	11-1021	\$99,310	6601	11-3071	\$89,190
0801	47-1011	\$62,980	6602	11-3071	\$89,190
0802	47-1011	\$62,980	7204	53-2020	\$96,870
1301	11-9021	\$89,300	7208	53-2020	\$96,870
1302	11-9021	\$89,300	7210	53-2020	\$96,870
1801	33-1021	\$74,540	7220	53-2020	\$96,870
1802	33-1021	\$74,540	75XX	53-2010	\$105,720
1803	33-1021	\$74,540			

 Table 4.
 Military-to-Civilian Crosswalk with Median Annual Civilian Wages

B. METHODOLOGY

Because my dependent variable is dichotomous, I use a logistical regression model to determine opt-in rate probabilities and estimate six models to use in my analysis. The first two models, Model 1 and Model 2, identify differences in opt-in rate probabilities between members who made a deliberate choice to opt in or opt out versus those who made no decision at all. If a member made no decision, the member effectively chose to opt out of the BRS, as opting in required a deliberate choice whereas a member could choose to do nothing and automatically be opted out of the BRS.

I submit these two models to compare the associated effects of making deliberate decisions versus taking no action on the probability of opting in to the BRS. For Model 1, I include all observations who either made a deliberate decision or who did not make a deliberate decision. Model 2 omits those who did not make a deliberate decision. The equation for both Models 1 and 2 is listed below. Model 2 differs from Model 1 in the *OPT_IN* variable only, where Model 1 includes 8,544 observations that represent all opt-in decisions, and Model 2 includes 7,719 observations that represent only deliberate decisions.

Pr (*OPT_IN*) = $\alpha_0 + \alpha_1 * Key_X + \alpha_2 * Demographic + \alpha_3 * Interaction + \varepsilon$ Where: Key_X = Log Civilian Wage, Critical MOS *Demographic* = years of service, gender, GCT score, rank, married, number of

dependents, race

Interaction = interaction between Log Civilian Wage and Critical MOS variables

I then compare the two models to identify differences in opt-in probabilities when determining whether to capture deliberate decisions versus non-deliberate decisions in the opt-in variable. Table 5 shows the comparison of the two models and reveals slight statistically significant differences between both models. However, I offer that while some variables are slightly more significant in Model 2 than Model 1, I use Model 1 as the base model for my remaining models because it includes more observations that capture the true opt-in decisions that occurred. I also argue that perhaps a decision to take no action could also be interpreted as a deliberate decision to opt-out, which may suggest that Model 1 better represents the data (opt-in decisions) more so than Model 2.

				-	
Table 5.	Model 1	versus	Model	2	Comparison

	Model 1	Model 2
Key X variables:		
Log Civilian Wage	0.097 (0.030)**	0.116 (0.031)***
Critical MOS	-0.535 (0.004)***	-0.543 (0.004)***
Demographic variables:		
Age	-0.030 (0.003)***	-0.027 (0.003)***
Years of Service	-0.048 (0.003)***	- 0.046 (0.003)***
Female	-0.024 (0.016)	-0.026 (0.016)
Log GCT Score	$0.121 (0.058)^{*}$	0.090 (0.059)
Company Grade	0.159 (0.033)***	0.154 (0.033)***
Dependents	-0.023 (0.004)***	-0.029 (0.004)***
White	0.021 (0.012)	$0.027 (0.013)^{*}$
Interaction variable:		
Crit Wage	0.256 (0.050)***	0.177 (0.049)***
Num. obs.	8544	7719
Log Likelihood	-4306.909	-3634.032
Deviance	8613.818	7268.064
AIC	8635.818	7290.064
BIC	8713.401	7366.529

Marginal Effects Models 1 vs. 2

"p < 0.001, "p < 0.01, p < 0.05

Model 3 is built from Model 1 but I include OccFld variables, as described below. While this model includes similar variables to Brockert's 2018 research, I differentiate from his model by including different key X variables as a means to control for civilian wages and critical MOSs. I further omit other variables that he used in his model such as career designation, promotion, and enlisted and warrant officer ranks. Listed below is the equation for Model 3: Pr (*OPT_IN*) = $\alpha_0 + \alpha_1 * Key_X + \alpha_2 * Demographics + \alpha_3 * MOS + \alpha_4 * Interaction + \varepsilon$ Where: $Key_X = \text{Log Civilian Wage}$, Critical MOS indicator

Demographics = years of service, gender, GCT score, rank, married, number of dependents, race

MOS = MOS Community or two-digit MOS OccFld

Interaction = Interaction of Log Civilian Wages and Critical MOS

Model 3 includes all variables included in Model 1 with the addition of three MOS community variables, which are mos_combat, mos_combat_spt, and mos_aviation, as well as the interaction variable. The *mos_combat* variable includes combat OccFlds, which are: infantry; field artillery; and tank, assault amphibious vehicle and amphibious combat vehicle. The *mos_combat_spt* variable includes the following OccFlds, which are listed in Table 3: manpower and administration; intelligence; logistics; communications; engineer, construction, facilities, and equipment; supply chain material management; financial management; communications strategy and operations; legal support; and military police, investigations, and corrections. The mos aviation variable includes the following OccFlds: aircraft maintenance; aviation logistics, aviation command and control operations; and pilot and Naval flight officers (hereby referred to as pilot OccFld). Model 4 is the same model as Model 3, except I exclude the pilot MOS from the model. For Model 5, I omit the community variables and instead include all MOSs separated by their two-digit OccFld, where Model 5 includes all OccFlds and Model 6 includes all OccFlds with the exception of the pilot OccFld. Additionally, I remove the interaction variable in Models 5 and 6 due to multicollinearity.

In each of my models, I'm most interested in the effects of the *LN_CIV_WAGE* and *Critical_MOS* variables on the probability of opting in to the BRS. For Model 3, the statistically significant independent variables consist of *LOG_CIV_WAGE*, *AGE*, *YOS*, *CO_GRADE*, *NUMB_DEPEND*, and *mos_combat_spt*. For Model 4, the statistically significant independent variables are *AGE*, *YOS*, *CO_GRADE*, and *NUMB_DEPEND*. Model 5 statistically significant independent variables are *Critical_MOS*, *AGE*, *YOS*, *CO_GRADE*, *NUMB_DEPEND*, and all individual MOSs. Model 6 statistically significant independent variables are *AGE*, *YOS*, *CO_GRADE*, *NUMB_DEPEND*, and the law MOS.

I separate the pilot OccFld from Models 3 and 5 and show the results in Models 4 and 6 show changes in the level of significance of my key X variables (*LN_CIV_WAGE* and *Critical_MOS*) since pilots, on average, opt in to the BRS at higher rates and also have higher civilian wages than all other OccFld. Additionally, because of multicollinearity, I remove the *Crit_Wage* interaction variable from Models 5 and 6. I describe these four models and the results of my findings in the following chapter using a combination of graphs and regression tables. For the majority of my graphs, I use R programming code written by Hlavac (2018); all other graphs use the basic R programming packages. All regression tables use R programming code written by Ludecke (2018).

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V. RESULTS

I first describe the general characteristics of my data followed by explanation of each model and significant findings of each. The results of my analysis are explained below.

A. BRS POPULATION

Figure 1 displays the overall population of those who opted in versus those who opted out. Because I chose Model 1 (as described in Chapter III), this data contains the total population for those who were eligible and made a deliberate decision as well as those who did not make a deliberate decision. Those who made a deliberate decision to opt in comprise 58 percent of the total population. Individuals who made a deliberate decision make up 42 percent of the total population. Brockert's 2018 research also shows that 58 percent of officers opted in, but his data contains warrant officers whereas my data does not, suggesting that either warrant officers opt in and opt out at relatively the same rates or that there were so few in his data that it did not impact the overall opt-in rate for officers. In any case, my data, like his, show that more individuals of the total population opted in to the BRS than those who opted out.



Figure 1. Overall BRS Decision Rates

In Figure 2, I segregate the total BRS population into the three MOS communities: aviation, combat, and combat support. Opt-in and opt-out decision rates are further represented in Figure 3 to show the opt-in and opt-out rates by MOS community. Figure 2 shows the proportion of those who only opted-in, segregated by community. Figure 3 provides a bit more detail by separating the population by communities, as a whole, opt in or opt out of the BRS. Going back to Figure 1, the overall opt-in rate was 58 percent. When looking at each community individually, aviation opted-in at approximately 57.9 percent, whereas the combat MOS community trended higher at 60.4 percent and combat supported trended lower at 56.7 percent.



Figure 2. MOS Community Population



Figure 3. BRS Decision Rates by MOS Community

B. DEMOGRAPHIC AND KEY X VARIABLES

1. Demographic Variables

Figure 4, graph A, provides a snapshot of the density of each of the three MOS communities by total YOS. The mean YOS is 5.84 years and is depicted by the vertical dashed line. Of note, both the combat and combat support communities have lower years of service (5.21 and 5.53 YOS, respectively) compared to the aviation community (6.92 YOS). As alluded to in Chapter IV, this statistic corresponds to the fact that, on average, pilot MOSs generally have longer commissioning contracts as compared to all other MOSs. In turn, this increases the average YOS of the aviation community as a whole.

In Figure 4, graph B, the percentage of opt-in rates declines with each unit of increase in years of service, which fits Brockert's 2018 research but contradicts Asch et al.'s 2017 research in which their DRM predicted that officers with greater than five YOS will not opt in to the BRS. Their prediction that 100 percent of officers with one YOS will opt in to the BRS aligns closely with my findings that 92 percent of officer opt in at one

YOS. Conversely, their predicted opt-in rates for officers between one and five years of service vastly underestimated actual observed opt-in rates. However, some degree of differences may be attributed to the use of historical—and likely—different data, although these differences should not yield such great disparities in opt-in rates by YOS.



Figure 4. Years of Service by MOS Community and BRS Decision

Figure 5 depicts a similar image as Figure 4; however, in this figure, I show age density by MOS community as well as the BRS opt-in and opt-out rate by the same *AGE* variable. Similar to the *YOS* variable, age has the same effect on opt-in and opt-out rates. The percent of opt-in rates declines as one gets older, and therefore the opposite is also true and noted by Brockert (2018): being younger is positively correlated with a member's decision to opt in to the BRS. It is interesting to note, however, that individuals who are 36 and 38 years old appear to have an uptick in opt-in rates. While I'm not certain of the exact cause, this anomaly may be attributed to the smaller sample size of those individuals which may bias the estimates, or it could be attributed to those individuals approaching 12 YOS and being eligible for the continuation pay multiplier—as mentioned in Asch et al.'s 2017 research—or other unobservable factors.



Figure 5. Age by MOS Community and BRS Decision

2. Key X Variables

In Figure 6, I present a density plot of the *LOG_CIV_WAGE* as well as a bar chart that depicts the opt-in and opt-out rates by the same key X variable. What is interesting to note is that unlike the previous density charts listed in Figures 4 and 5, the density plot for the *LOG_CIV_WAGE* variable is not uniform. Instead, the densities for the aviation and combat MOSs are heavily skewed to the right and left, respectively, where the combat MOS is more distributed below the mean and the aviation MOS is distributed above the mean. The combat support MOS is more uniform in nature, signifying a more even distribution of wages across the combat support MOSs.

Looking at the BRS decision by the *LOG_CIV_WAGE* variable in Figure 6, graph B, the most telling observation from the bar chart is it appears that the opt-in and opt-out rates remain relatively unchanged as the *LOG_CIV_WAGE* variables increases. Because the densities of the *LOG_CIV_WAGE* variable are skewed for the aviation and combat MOS communities, this skewness likely affects the data depicted in the bar chart as well. While this graph shows opt-in and opt-out rates with respect to the *LOG_CIV_WAGE* variable, it doesn't provide a complete picture of the effects of the *LOG_CIV_WAGE* variable on opt-in rates. It also does not reveal statistically significant results from which

to draw conclusions. However, it does give at least some indication that the *LOG_CIV_WAGE* variable may have no effect on the BRS opt-in rate.



Figure 6. Log Civilian Wage by MOS Community and BRS Decision

Figure 7 depicts my other key X variable, *Critical_MOS*, and its total proportion relative to each MOS community as well as BRS opt-in and opt-out decisions if an MOS within the community is a critical MOS. If an MOS is not considered critical, that data is omitted from these figures. As alluded to in Chapter IV, to be considered a critical MOS, the MOS must have had difficulty meeting target inventory according to the 2020 MOS status report. As revealed in graph A of Figure 7, the aviation and combat support MOS communities comprise the majority of the *Critical_MOS* variable.

Turning back to the mean opt-in rate of 58 percent, graph B of Figure 7 shows optin and opt-out rate decisions by MOS community. Of note, in each of the MOS communities, being in a critical MOS does not appear to significantly affect the BRS decision, although the combat MOS community opts in to the BRS at a significantly lower rate than the two other MOS communities. Like Figure 6, Figure 7 data does not reveal statistically significant results to draw conclusions from. However, it is interesting to note that the combat MOS community opts in at lower rates comparatively.



Figure 7. Critical MOS Population and BRS Decision by MOS Community

C. REGRESSION RESULTS

Table 6 displays the results of the remaining four regression models, Models 3 through 6, using marginal effects. Because I use a logistic regression model for my estimation, simply estimating results without using the marginal effects would produce less meaningful results. By using marginal effects and reporting average partial effects, I am able to observe predicted probabilities of opting in to the BRS for a one-unit change in each covariate while holding all other covariates constant. Models 4 and 6 are similar to Models 3 and 5, respectively, with the exception of the pilot MOS which is removed from the data. I remove the pilot MOS from Models 4 and 6 to demonstrate that statistical significance is considerably affected and causes most estimates to become statistically insignificant. Additionally, I removed the *Crit_Wage* variable in models 5 and 6 due to multicollinearity with the *LOG_CIV_WAGE*, *Critical_MOS*, and some other MOS variables.

Model 3 Model 4 Model 5 Model 6 Key X variables: Log Civilian Wage 0.175 (0.045)*** 0.060 (0.045) -0.162 (0.118) -0.194 (0.113) Critical MOS -0.326 (0.527) -0.215 (0.702) -0.047 (0.022)* -0.010 (0.027) Interaction variable: Critiwage 0.033 (0.061) 0.018 (0.003)*** -0.032 (0.003)*** -0.031 (0.003)*** Years of Service -0.048 (0.003)*** -0.050 (0.003)*** -0.046 (0.003)*** -0.046 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.04)*** -0.016 (0.005)*** -0.020 (0.064)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: Combat Arms -0.036 (0.020) 0.042 (0.021) Combat Service Spt -0.089 (0.013)*** -0.234 (0.036)*** -0.026 (0.036) Intelligence -0.234 (0.043)*** -0.037 (0.051) Compt (0.045)*** <th></th> <th>Madal 2</th> <th>Madal 4</th> <th>Madal 5</th> <th>Madal 6</th>		Madal 2	Madal 4	Madal 5	Madal 6
Rey X variables: 0.175 (0.045)*** 0.060 (0.045) -0.162 (0.118) -0.194 (0.113) Critical MOS -0.326 (0.527) -0.215 (0.702) -0.047 (0.022)* -0.010 (0.027) Interaction variable: 0.033 (0.061) 0.018 (0.064) -0.028 (0.003)** -0.032 (0.003)** -0.031 (0.003)** Years of Service -0.048 (0.003)** -0.050 (0.003)** -0.046 (0.003)** -0.048 (0.003)** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)** -0.018 (0.055)** -0.020 (0.004)** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) Mos variables: Combat Arms -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** -0.024 (0.030) Infantry -0.236 (0.021) 0.032 (0.019) -0.234 (0.036)*** -0.026 (0.037) Manpower -0.234 (0.043)*** -0.026 (0.037) -0.175 (0.021)** 0.026 (0.037) Infantry -0.248 (0.043)*** -0.256 (0.037)* -0.036 (0.02	Var V variablas	Model 3	Model 4	Niddel 5	Niodel o
Log Civitian Wage 0.158 (0.043) 0.060 (0.045) -0.162 (0.118) -0.194 (0.113) Critical MOS -0.326 (0.527) -0.215 (0.702) -0.047 (0.022)* -0.010 (0.027) Interaction variable: Crit Wage 0.033 (0.061) 0.018 (0.064) -0.032 (0.003)*** -0.031 (0.003)*** Years of Service -0.048 (0.003)*** -0.050 (0.003)*** -0.046 (0.003)*** -0.048 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.099 (0.040)* Company Grade 0.154 (0.033)*** 0.097 (0.040)* -0.010 (0.004)** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) Mapower -0.028 (0.020) 0.042 (0.021) Combat Arms -0.036 (0.020) Commanications -0.039 (0.013)*** 0.032 (0.030) -0.116 (0.040) Intelligence -0.248 (0.043)*** -0.026 (0.037) Artillery -0.248 (0.043)*** -0.026 (0.032) Communications </td <td>Key X variables:</td> <td>0 175 (0 045)***</td> <td>0.0(0.0045)</td> <td>0.1(2.(0.110)</td> <td>0.104 (0.112)</td>	Key X variables:	0 175 (0 045)***	0.0(0.0045)	0.1(2.(0.110)	0.104 (0.112)
Interaction variable: -0.326 (0.527) -0.513 (0.702) -0.014 (0.022) -0.016 (0.027) Interaction variable: -0.033 (0.061) 0.018 (0.064) -0.032 (0.003)*** -0.031 (0.003)*** Years of Service -0.048 (0.003)*** -0.028 (0.003)*** -0.046 (0.003)*** -0.048 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.159 (0.033)*** 0.099 (0.040)* Ompany Grade 0.154 (0.033)*** 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.013 (0.013) MOS variables: Combat Arms -0.036 (0.020) 0.042 (0.021) 0.013 (0.013) 0.012 (0.012) 0.013 (0.037) Manpower -0.234 (0.036)*** -0.024 (0.040)** -0.244 (0.043)*** -0.024 (0.040) Logistics -0.248 (0.043)*** -0.037 (0.051) 0.045 (0.037) 0.051 (0.032) Communications -0.175 (0.021)*** 0.043 (0.046) -0.228 (0.043)*** -0.040 (0.048) Ground Supply -0.211 (0.033)*** 0.051 (0.0	Log Civilian Wage	0.1/5(0.045)	0.060 (0.045)	-0.162(0.118)	-0.194 (0.113)
Interaction Variable: Crit Wage 0.033 (0.061) 0.018 (0.064) Demographic variables: -0.030 (0.003)*** -0.028 (0.003)*** -0.032 (0.003)*** -0.048 (0.003)*** Years of Service -0.048 (0.003)*** -0.050 (0.003)*** -0.046 (0.003)*** -0.048 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.068 (0.064) Company Grade 0.154 (0.033)*** -0.017 (0.005)** -0.020 (0.004)** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: Combat Arms -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.036) Intelligence -0.208 (0.013)*** -0.248 (0.043)*** -0.024 (0.040) -0.024 (0.040) Logistics -0.248 (0.043)*** -0.037 (0.051) Communications -0.175 (0.021)*** 0.044 (0.037) Artillery -0.224 (0.043)*** -0.248 (0.043)*** -0.056 (0.057) Engineer -		-0.326 (0.527)	-0.215 (0.702)	-0.047 (0.022)	-0.010 (0.027)
Chi Wage 0.035 (0.061) 0.018 (0.064) Demographic variables: -0.030 (0.003)*** -0.028 (0.003)*** -0.032 (0.003)*** -0.048 (0.003)*** Years of Service -0.048 (0.003)*** -0.050 (0.003)*** -0.046 (0.003)*** -0.048 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.099 (0.004)* Company Grade 0.154 (0.033)*** 0.097 (0.040)* 0.159 (0.033)** 0.099 (0.040)* Dependents -0.022 (0.004)** -0.017 (0.005)** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: Combat Arms -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.030) Infantry -0.234 (0.036)*** 0.027 (0.041)** -0.224 (0.043)*** -0.027 (0.040) Logistics -0.248 (0.043)*** -0.027 (0.045)** -0.026 (0.037) Communications -0.175 (0.021)*** -0.046 (0.032) -0.176 (0.023)*** -0.056 (0.057) Engineer -0.269 (0.032)*** -0.040 (0.048	Interaction variable:	0.022 (0.061)	0.019 (0.064)		
Demographic variables: -0.030 (0.003)*** -0.032 (0.003)*** -0.031 (0.003)*** Years of Service -0.048 (0.003)*** -0.050 (0.003)*** -0.046 (0.003)*** -0.048 (0.003)*** Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.099 (0.040)* Company Grade 0.154 (0.033)*** 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: Combat Arms -0.036 (0.020) 0.042 (0.021) 0.026 (0.036) Combat Service Spt -0.089 (0.013)*** 0.032 (0.019) 0.032 (0.030) Infantry Mapower -0.224 (0.044)*** -0.024 (0.040) Logistics -0.248 (0.043)*** -0.037 (0.051) Communications -0.175 (0.021)*** 0.045 (0.037) -0.116 (0.032) -0.016 (0.032) Tanks AAVs -0.248 (0.049)***	Crit wage	0.033 (0.061)	0.018 (0.064)		
Age -0.030 (0.003) -0.028 (0.003) -0.032 (0.003) -0.031 (0.003) Years of Service -0.048 (0.003) -0.050 (0.003) -0.046 (0.003) -0.048 (0.003) Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.097 (0.040) 0.159 (0.033) 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.089 (0.013)*** 0.032 (0.021) -0.234 (0.036)*** 0.026 (0.036) Intelligence -0.089 (0.013)*** 0.032 (0.019) -0.248 (0.043)*** -0.037 (0.051) Logistics -0.248 (0.043)*** -0.036 (0.020) -0.248 (0.043)*** -0.036 (0.037) Communications -0.175 (0.021)*** 0.045 (0.037) -0.156 (0.057) Engineer -0.226 (0.032)**** -0.040 (0.048) -0.221 (0.043)**** -0.056 (0.057) Inance -0.222 (0.044)**** -0.040 (0.048) -0.222 (0.044)**** -0.040 (0.048) -0.224 (0.057) Law </td <td>Demographic variables:</td> <td>0.020 (0.002)***</td> <td>0.000 (0.000)***</td> <td>0.022 (0.002)***</td> <td>0.021 (0.002)***</td>	Demographic variables:	0.020 (0.002)***	0.000 (0.000)***	0.022 (0.002)***	0.021 (0.002)***
Years of Service -0.048 (0.003) -0.036 (0.003) -0.048 (0.003) Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: - - -0.036 (0.020) 0.042 (0.021) Combat Arms -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.036) Manpower -0.039 (0.013)*** 0.032 (0.019) -0.244 (0.040) -0.024 (0.040) Logistics -0.244 (0.043)*** -0.037 (0.051) -0.045 (0.037) Communications -0.175 (0.021)*** -0.045 (0.037) -0.175 (0.021)*** -0.046 (0.043) Ground Supply -0.211 (0.033)*** -0.056 (0.057) -0.166 (0.032) -0.016 (0.032) -0.016 (0.032) Tanks AAVs -0.240 (0.058)*** -0.0269 (0.032)*** -0.016 (0.032) -0.016 (0.032) -0.016 (0.032) -0.016 (0.032) -0.016 (0.032) </td <td>Age</td> <td>-0.030 (0.003)</td> <td>-0.028 (0.003)</td> <td>-0.032(0.003)</td> <td>-0.031(0.003)</td>	Age	-0.030 (0.003)	-0.028 (0.003)	-0.032(0.003)	-0.031(0.003)
Female -0.016 (0.016) 0.001 (0.017) 0.002 (0.016) 0.007 (0.017) Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.068 (0.0664) Company Grade 0.154 (0.033)*** 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** 0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.036) Combat Arms -0.089 (0.013)*** 0.032 (0.019) -0.239 (0.029)*** 0.032 (0.030) Infantry -0.261 (0.041)*** -0.024 (0.040) -0.204 (0.040) Logistics -0.276 (0.032)*** -0.037 (0.051) Communications -0.175 (0.021)*** 0.045 (0.037) Artillery -0.294 (0.058)*** -0.056 (0.057) Engineer -0.269 (0.032)**** -0.016 (0.032) Tanks AAVs -0.288 (0.049)*** -0.040 (0.048) Ground Supply -0.211 (0.033)*** 0.043 (0.046) CommStrat -0.149 (0.045)*** -0.12	Years of Service	-0.048 (0.003)	-0.050 (0.003)	-0.046 (0.003)	-0.048 (0.003)
Log GCT Score 0.087 (0.058) 0.091 (0.064) 0.014 (0.058) 0.008 (0.064) Company Grade 0.154 (0.033)*** 0.097 (0.040)* 0.159 (0.033)*** 0.099 (0.040)* Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.089 (0.013)*** 0.032 (0.019) -0.234 (0.036)*** 0.026 (0.036) Combat Arms -0.089 (0.013)*** 0.032 (0.019) -0.234 (0.040)*** 0.026 (0.030) Intelligence -0.234 (0.040)*** -0.024 (0.040) -0.224 (0.040) -0.224 (0.040) Logistics -0.248 (0.043)*** -0.037 (0.051) Communications -0.175 (0.021)*** -0.046 (0.032) Artillery -0.288 (0.049)*** -0.040 (0.048) -0.040 (0.048) -0.021 (0.033)*** -0.040 (0.048) Ground Supply -0.211 (0.033)*** 0.014 (0.035)** 0.014 (0.077) -0.149 (0.045)*** 0.016 (0.032) Tanks AAVs -0.280 (0.049)*** -0.240 (0.046)*** -0.149 (0.035)** -	Female	-0.016 (0.016)	0.001 (0.017)	0.002 (0.016)	0.007 (0.017)
Company Grade 0.154 (0.033) 0.097 (0.040) 0.159 (0.033) 0.099 (0.040) Dependents -0.022 (0.004)*** -0.018 (0.005)*** -0.020 (0.004)*** -0.017 (0.005)** White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.036 (0.020) 0.042 (0.021) 0.012 (0.013)*** 0.026 (0.036)*** Combat Arms -0.036 (0.020) 0.042 (0.021) 0.022 (0.040)*** 0.026 (0.036) Manpower -0.234 (0.036)*** 0.026 (0.030) 0.024 (0.040) -0.029 (0.029)*** 0.032 (0.030) Infantry -0.248 (0.043)*** -0.024 (0.040) -0.024 (0.040) -0.024 (0.040) Logistics -0.175 (0.021)*** 0.045 (0.037) -0.056 (0.057) Communications -0.175 (0.021)*** -0.046 (0.032) -0.056 (0.057) Artillery -0.288 (0.049)*** -0.046 (0.032) -0.056 (0.057) Engineer -0.288 (0.049)*** -0.040 (0.048) -0.051 (0.033) Ground Supply -0.211 (0.033)*** 0.051 (0.034) -0.149 (0.045)*** 0.073 (0.051)	Log GCT Score	0.087 (0.058)	0.091 (0.064)	0.014 (0.058)	0.068 (0.064)
Dependents -0.022 (0.004) -0.018 (0.005) -0.020 (0.004) -0.017 (0.005) White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.036 (0.020) 0.042 (0.021) 0.012 (0.012) 0.013 (0.013) Combat Arms -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.036) Manpower -0.234 (0.036)*** 0.026 (0.030) -0.209 (0.029)*** 0.032 (0.030) Infantry -0.209 (0.029)*** 0.037 (0.051) -0.204 (0.040) Logistics -0.248 (0.043)*** -0.037 (0.051) Communications -0.175 (0.021)*** 0.045 (0.037) Artillery -0.288 (0.049)*** -0.056 (0.057) Engineer -0.288 (0.049)*** -0.056 (0.057) Tanks AAVs -0.288 (0.049)*** -0.040 (0.048) Ground Supply -0.211 (0.033)*** 0.043 (0.046) CommStrat -0.149 (0.045)*** 0.073 (0.051) Law -0.016 (0.035)** 0.149 (0.031)*** Military Police -0.350 (0.060)*** -0.124 (0.077) <t< td=""><td>Company Grade</td><td>0.154 (0.033)</td><td>0.097 (0.040)</td><td>0.159 (0.033)</td><td>0.099 (0.040)</td></t<>	Company Grade	0.154 (0.033)	0.097 (0.040)	0.159 (0.033)	0.099 (0.040)
White 0.019 (0.012) 0.015 (0.013) 0.012 (0.012) 0.013 (0.013) MOS variables: -0.036 (0.020) 0.042 (0.021) -0.234 (0.036)*** 0.026 (0.036) Combat Service Spt -0.089 (0.013)*** 0.032 (0.019) -0.234 (0.036)*** 0.026 (0.036) Manpower -0.239 (0.029)*** 0.032 (0.030) -0.248 (0.043)*** -0.024 (0.040) Intelligence -0.248 (0.043)*** -0.037 (0.051) -0.045 (0.037) Logistics -0.175 (0.021)*** 0.042 (0.040) -0.294 (0.058)*** -0.056 (0.057) Communications -0.175 (0.021)*** 0.046 (0.032) -0.056 (0.057) -0.269 (0.032)**** -0.016 (0.032) Tanks AAVs -0.228 (0.049)**** -0.040 (0.048) -0.222 (0.044)**** -0.040 (0.048) Ground Supply -0.211 (0.033)**** 0.051 (0.034) -1.18 (0.035)*** 0.073 (0.051) Law -0.091 (0.035)*** 0.149 (0.031)**** -0.324 (0.066)**** -0.124 (0.077) Air Maintenance -0.326 (0.031)**** -0.022 (0.044)**** -0.002 (0.053) AirChurSupplyATC -0.222 (0.044)**** <th< td=""><td>Dependents</td><td>-0.022 (0.004)</td><td>-0.018 (0.005)</td><td>-0.020 (0.004)</td><td>-0.017 (0.005)</td></th<>	Dependents	-0.022 (0.004)	-0.018 (0.005)	-0.020 (0.004)	-0.017 (0.005)
MOS variables:Combat Arms $-0.036 (0.020)$ $0.042 (0.021)$ Combat Service Spt $-0.089 (0.013)^{***}$ $0.032 (0.019)$ Manpower $-0.234 (0.036)^{***}$ $0.026 (0.036)$ Intelligence $-0.209 (0.029)^{***}$ $0.032 (0.030)$ Infantry $-0.261 (0.041)^{***}$ $-0.024 (0.040)$ Logistics $-0.248 (0.043)^{***}$ $-0.037 (0.051)$ Communications $-0.175 (0.021)^{***}$ $0.045 (0.037)$ Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.016 (0.032)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.179 (0.051)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{**}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Supply $-0.228 (0.031)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ $-0.022 (0.044)^{***}$ Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6664.296 8508.474 6611.878 AIC 8590.077 6666.296 8508.474 6611.878 BIC 8681.765 6754.787 8691.851 6832.0	White	0.019 (0.012)	0.015 (0.013)	0.012 (0.012)	0.013 (0.013)
Combat Arms $-0.036 (0.020)$ $0.042 (0.021)$ Combat Service Spt $-0.089 (0.013)^{***}$ $0.032 (0.019)$ Manpower $-0.234 (0.036)^{***}$ $0.026 (0.036)$ Intelligence $-0.209 (0.029)^{***}$ $0.032 (0.030)$ Infantry $-0.261 (0.041)^{***}$ $-0.024 (0.040)$ Logistics $-0.248 (0.043)^{***}$ $-0.037 (0.051)$ Communications $-0.175 (0.021)^{***}$ $0.045 (0.037)$ Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.016 (0.032)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{**}$ $0.116 (0.066)$ Air Maintenance $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Supply $-0.228 (0.031)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ $-0.002 (0.053)$ Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6664.296 8508.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	MOS variables:				
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Intelligence $-0.209 (0.029)^{**}$ $0.032 (0.030)$ Infantry $-0.261 (0.041)^{***}$ $-0.024 (0.040)$ Logistics $-0.248 (0.043)^{***}$ $-0.037 (0.051)$ Communications $-0.175 (0.021)^{***}$ $0.045 (0.037)$ Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.222 (0.044)^{***}$ $-0.092 (0.053)$ AirChtrSupplyATC $-0.258 (0.31)^{***}$ Num. obs. 8544 6681 Log Likelihood -4282.038 -3320.148 -4282.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 661.878 BIC 8681.765 6754.787 8691.851 6832.054	Manpower			-0.234 (0.036)***	0.026 (0.036)
Infantry $-0.261 (0.041)^{***}$ $-0.024 (0.040)$ Logistics $-0.248 (0.043)^{***}$ $-0.037 (0.051)$ Communications $-0.175 (0.021)^{***}$ $0.045 (0.037)$ Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{**}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.222 (0.044)^{***}$ $-0.092 (0.053)$ AirChtrSupplyATC $-0.258 (0.031)^{***}$ Num. obs. 8544 6681 8544 Log Likelihood -4282.038 -3320.148 -4228.237 AIC 8590.077 6660.296 8508.474 6611.878 AIC 8590.077 6666.296 8508.474 661.878 BIC 8681.765 6754.787 8691.851 6832.054	Intelligence			-0.209 (0.029)***	0.032 (0.030)
Logistics $-0.248 (0.043)^{***}$ $-0.037 (0.051)$ Communications $-0.175 (0.021)^{***}$ $0.045 (0.037)$ Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{**}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.228 (0.041)^{***}$ $-0.002 (0.053)$ AirChtrSupplyATC $-0.258 (0.031)^{***}$ Num. obs. 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 AirC 8590.077 6660.296 8508.474 6611.878 AIC 8590.077 6666.296 8508.474 661.878 BIC 8681.765 6754.787 8691.851 6832.054	Infantry			-0.261 (0.041)***	-0.024 (0.040)
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Artillery $-0.294 (0.058)^{***}$ $-0.056 (0.057)$ Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{***}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.228 (0.031)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ $-0.002 (0.053)$ Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	Communications			-0.175 (0.021)****	0.045 (0.037)
Engineer $-0.269 (0.032)^{***}$ $-0.016 (0.032)$ Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{**}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.222 (0.044)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ $-0.002 (0.053)$ Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	Artillery			-0.294 (0.058)****	-0.056 (0.057)
Tanks AAVs $-0.288 (0.049)^{***}$ $-0.040 (0.048)$ Ground Supply $-0.211 (0.033)^{***}$ $0.051 (0.034)$ Finance $-0.222 (0.044)^{***}$ $0.043 (0.046)$ CommStrat $-0.149 (0.045)^{***}$ $0.073 (0.051)$ Law $-0.091 (0.035)^{***}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.222 (0.044)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ Num. obs. 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 AIC 8590.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	Engineer			-0.269 (0.032)***	-0.016 (0.032)
Ground Supply -0.211 (0.033)*** 0.051 (0.034) Finance -0.222 (0.044)*** 0.043 (0.046) CommStrat -0.149 (0.045)*** 0.073 (0.051) Law -0.091 (0.035)** 0.149 (0.031)*** Military Police -0.324 (0.066)*** -0.124 (0.077) Air Maintenance -0.350 (0.060)*** -0.116 (0.066) Air Supply -0.222 (0.044)*** -0.002 (0.053) AirCntrSupplyATC -0.258 (0.031)*** -0.002 (0.053) Num. obs. 8544 6681 8544 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	Tanks AAVs			-0.288 (0.049)***	-0.040 (0.048)
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$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Finance			-0.222 (0.044)***	0.043 (0.046)
Law $-0.091 (0.035)^{**}$ $0.149 (0.031)^{***}$ Military Police $-0.324 (0.066)^{***}$ $-0.124 (0.077)$ Air Maintenance $-0.350 (0.060)^{***}$ $-0.116 (0.066)$ Air Supply $-0.222 (0.044)^{***}$ $-0.002 (0.053)$ AirCntrSupplyATC $-0.258 (0.031)^{***}$ $-0.258 (0.031)^{***}$ Num. obs.854466818544Log Likelihood -4282.038 -3320.148 -4228.237 AIC8564.0776640.2968456.4746611.878AIC8590.0776666.2968508.4746661.878BIC8681.7656754.7878691.8516832.054	CommStrat			-0.149 (0.045)***	0.073 (0.051)
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Air Maintenance -0.350 (0.060)*** -0.116 (0.066) Air Supply -0.222 (0.044)*** -0.002 (0.053) AirCntrSupplyATC -0.258 (0.031)*** -0.002 (0.053) Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	Military Police			-0.324 (0.066)***	-0.124 (0.077)
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Num. obs. 8544 6681 8544 6681 Log Likelihood -4282.038 -3320.148 -4228.237 -3305.939 Deviance 8564.077 6640.296 8456.474 6611.878 AIC 8590.077 6666.296 8508.474 6661.878 BIC 8681.765 6754.787 8691.851 6832.054	AirCntrSupplyATC			-0.258 (0.031)****	
Log Likelihood-4282.038-3320.148-4228.237-3305.939Deviance8564.0776640.2968456.4746611.878AIC8590.0776666.2968508.4746661.878BIC8681.7656754.7878691.8516832.054	Num. obs.	8544	6681	8544	6681
Deviance8564.0776640.2968456.4746611.878AIC8590.0776666.2968508.4746661.878BIC8681.7656754.7878691.8516832.054	Log Likelihood	-4282.038	-3320.148	-4228.237	-3305.939
AIC8590.0776666.2968508.4746661.878BIC8681.7656754.7878691.8516832.054	Deviance	8564.077	6640.296	8456.474	6611.878
BIC 8681.765 6754.787 8691.851 6832.054	AIC	8590.077	6666.296	8508.474	6661.878
	BIC	8681.765	6754.787	8691.851	6832.054

 $\overline{}^{***}p < 0.001, \, {}^{**}p < 0.01, \, {}^{*}p < 0.05$

1. Models 3 and 4

Models 3 and 4 depicted in Table 6 display the regression results where I include each MOS community as an independent variable with the aviation community being the reference group. As indicated in Model 3, the following variables are statistically significant below the one percent level: *LN_CIV_WAGE, AGE, YOS, CO_GRADE, mos_combat_spt*. However, when transitioning from Model 3 to Model 4 (when the pilot MOS is removed from the aviation community), only the *AGE, YOS, CO_GRADE*, and *NUMB_DEPEND* variables remain statistically significant, which is supported by previous research conducted by Brockert (2018). With a one-year increase in age, the probability of opting in decreases by 3 percentage points. With one additional year of service, the probability of opting in decreases by 4.8 percentage points. Being a company-grade officer increases the probability of opting in by 15.4 percentage points, and having dependents decreases the probability of opting in to the BRS by 2.2 percentage points.

Figure 8 below depicts the predicted probabilities of opting in to the BRS by MOS community, using the *LOG_CIV_WAGE* variable to predict opt-in probabilities. The mean value of the *LOG_CIV_WAGE* variable is represented by the black line and associated confidence interval bars. As observed, the *LOG_CIV_WAGE* variable has a positive impact on the predicted probability. As the *LOG_CIV_WAGE* variable increases, so, too, does the predicted opt-in probability for all MOS communities. However, as reflected in Figure 6, compared to the aviation community as the reference group, only the combat support MOS community is statistically significant. Figure 9 reveals the same predicted probabilities as Figure 8 but instead, I remove the individual pilot MOS from the data. By removing the pilot MOS, all MOS community variables become statistically insignificant.

The above data is somewhat interesting but not at all surprising. In his 2018 research, Brockert finds that that company grade officers opt in at higher rates than field grade officers, Marines who have more time in service opt in at lower rates, and the aviation MOS community opts in at higher rates than combat arms and combat service support.

Two likely reasons that opt-in rates a higher for company grade officers than field grade is likely due to age and years of service, both favoring company grade officers who elect to opt in to the BRS. Because they are younger and have less time in service, company grade officers are able to contribute to the TSP and receive matching government contributions for a longer duration than field grade officers. In turn, the monetary value of the BRS makes it a more attractive option for company grade officers than it does for field grade officers.

It is also not surprising that the aviation community opts in to the BRS at higher rates, especially when considering that pilots, who comprise a majority of the aviation community population in my data, has historically had manpower shortages. To help alleviate this issue, the Marine Corps, over the past several years, has had to offer substantial monetary incentives to certain pilot MOSs to help maintain the force. Considering these shortages, it is understandable, then, that the pilot MOS causes the aviation community to have higher observed opt-in rates if those same pilots decided to opt in to the BRS with the intention of separating before reaching retirement age under the High-Three.

Additionally, it is also interesting to observe the negative relationship between dependents and opt-in rates. This could be attributed to the possibility that those with dependents perhaps take a longer view on their career and expect to make it to retirement and thus have lower mobility tendencies. Those with dependents may believe they have a stable career in the military and do not want to risk separating and needing to seek employment elsewhere while still having to care for their dependents. It may also be likely that lower opt-in rates for those with dependents are, again, because of age. Those who opted in and have dependents have a mean age of 28.2 while those who opted in who have zero dependents have a mean age of 26.4.



MOS Community

Figure 8. Predicted Probability of BRS Opt-in by MOS Community and Mean Log Civilian Wage (from Model 3)



MOS Community

Figure 9. Predicted Probability of BRS Opt-in by MOS Community and Mean Log Civilian Wage, Pilot MOS Omitted (from Model 4)

2. Models 5 and 6

Models 5 and 6 differ from Models 3 and 4 in that I separate each MOS individually, while continuing to include all other key X variables and demographic variables but removing the interaction variable. In Model 5, the statistically significant variables are: *Critical_MOS, AGE, YOS, CO_GRADE, NUMB_DEPEND*, and all MOS variables, where the pilot MOS is the reference group. Being a critical MOS decreases the probability of opting in by 4.7 percentage points, and all other demographic variables affect the probability of opting in to the BRS similarly to their probabilities as depicted in Model 3. All MOS variables are statistically significant and opt in at lower rates compared to the pilot MOS, which is the reference group.

When removing the pilot MOS from the regression in Model 6, the majority of the individual MOSs become statistically insignificant. The *Critical_MOS* variable is no longer statistically significant; however, the *AGE*, *YOS*, *CO_GRADE*, and *NUMB_DEPEND* continue to remain statistically significant below the five percent significance level and in line with the previous three models' estimated effects on the probability of opting in. While interesting, it is not at all surprising since the pilot MOS has a higher comparable Log Civilian Wage than the majority of other MOSs, as depicted in Figure 6. By removing the pilot MOS, the *AirCntrSupplyATC* MOS becomes the references group, and all MOSs with the exception of the law MOS becomes statistically insignificant.

Figures 10 and 11, displayed below, which reflect similar predicted probabilities of opting in to the BRS similar to Figures 8 and 9 above, the exception being that these figures reflect Models 5 and 6 where individual MOSs are represented. When removing the pilot MOS from Model 5 to produce Model 6, each individual MOS becomes no longer statistically significant with the exception of the law MOS. In Figure 11, this is reflected as well, and the predicted probabilities (with exception to the law MOS) become statistically insignificant.

MOSs

Figure 10. Predicted Probability of BRS opt in by MOS and mean Log Civilian Wage (from Model 5)

MOSs

Figure 11. Predicted Probability of BRS Opt-in by MOS and Mean Log Civilian Wage, Pilot MOS Omitted (from Model 6)

D. MODEL FIT

Table 7 represents Models' model misclassification rates obtained by developing confusion matrices for Models 4 through 6. I use the confusion matrix to test the performance of all models against each other by calculating misclassification rates of each. This enables me to understand whether one model performs better than another or if all models perform relatively the same. The objective of the confusion matrix is to closely align predicted values (test set) with actual values (training set).

I calculate the confusion matrix by splitting my data set into a training set (80 percent of the data) and test set (20 percent of the data) with a 20 percent threshold. The threshold level is a tradeoff between sensitivity and specificity in model. Sensitivity is the degree to which the model reports true positives accurately, and specificity is where the model reports true negatives. I choose 20 percent as the threshold to ensure that the model guards against false negatives more so than false positives. As observed in Table 6, all models perform nearly identical with misclassification rates ranging between 30 and 33 percent. The purpose of producing a confusion matrix is not to achieve 0 percent misclassification rates but rather to compare all four models against each other to identify whether any model performs better than another. Because the misclassification rates all fall within close proximity, I declare that no model is better (or worse) at predicting than another. Additionally, because the test set and training set misclassification rates are nearly identical, I do not find that any of the models have issues with overfitting.

 Table 7.
 Confusion Matrices, Misclassification Rates

	Model 3	Model 4	Model 5	Model 6
Training Set	32.60%	31.74%	31.09%	31.39%
Test Set	30.78%	30.78%	30.72%	30.31%

E. SUMMARY

This thesis brings together civilian wage data, a military-to-civilian occupational crosswalk, as well as the most recent MOS status report to explore how BRS opt-in decisions vary across occupational communities in the Marine Corps. I construct and estimate six models and test their performance relative to each other by using confusion matrices and misclassification rates, which reveals that no model is overfit nor performs significantly better than another. After executing each model, I am able to analyze and compare the results of each, which reveal somewhat interesting results.

Each model shows that both civilian wages, *LOG_CIV_WAGE* (in Model 3), and indicator for critical MOS, *Critical_MOS* (in Model 5), initially appear to be statistically significant predictors of opting in. However, when removing the pilot MOS indicator, both of these variables become statistically insignificant. In addition, indicators for the *combat_svc_spt* and all individual MOSs (with the exception of the law MOS), in Models 4 and 6, respectively, also become statistically insignificant when removing the pilot MOS as the reference group.

Although interesting, it is not at all surprising when one understands how the models execute the regressions. Specifically, Models 3 and 5 select the pilot MOS as the reference group. The pilot MOS community, on average, has larger proportions of critical MOS compared to most other MOSs communities, as well as having higher comparable civilian wages. Statistical significance is then removed once pilots are excluded as the reference group from the models, given the lack of variance remaining.

Finally, the estimated models show the following demographic and other characteristics that are consistently statistically significant across all models: *AGE*, *YOS*, *NUMB_DEPEND* and *CO_GRADE*.

The *AGE* and *YOS* variables are highly correlated, which makes sense as the younger one is, the higher likelihood of having fewer years of service. Additionally, and while not highly correlated, company grade officers compared to field grade also are younger and have less time in service. Perhaps as Asch et al. points out, younger Marines have the ability to reap more benefits of the BRS than do older Marines due to realizing

the full compounding effect of the TSP and time, which may contribute to higher BRS optin rates among younger Marines overall.

VI. CONCLUSION

The purpose of my research is to identify whether civilian wages, using a militaryto-civilian crosswalk and corresponding BLS wage data, are statistically significant factors that may have influenced the BRS opt-in or opt-out rate. Additionally, my research explores whether critical MOSs opted-in or opted-out at higher (lower) rates than noncritical MOSs to determine whether being in a critical MOS has any impact on opt-in rates.

A. FINDINGS, DISCUSSION, AND LIMITATIONS

The results of my research suggest that civilian wages have no effect on the BRS opt-in rate. My expectations of these results, however, suggest the opposite given the previous literature reviewed in Chapter III. Perhaps it is other unobserved factors not accounted for that effect the BRS opt-in decision that I was unable to capture in my models or that the civilian wage is not a proxy for job mobility or alternative employment decisions, at least with respect to the BRS decision. Additionally, while not statistically significant, being in a critical MOS has no effects on the BRS opt-in rate.

However, my findings did reveal variation of opt-in rates across MOS communities and individual MOSs, and that the aviation community opts in at higher rates than both the combat arms and combat service support communities, consistent with Brockert's 2018 research. While initially statistically significant, however, removing the pilot MOS from the models causes the MOS variables to become insignificant (with the exception of the law MOS). This is likely due to the pilot MOS having a higher comparable civilian wage as well as a higher proportion of critical MOSs within the OccFld.

With respect to other independent variables, I find that younger Marines opt in at higher rates than do older Marines, also consistent with Brockert's research. There is also a similar distinction for YOS: the longer an individual remains in the service, the probability of opting in continues to decrease. Further, Marines with dependents also opt in at lower rates compared to those who do not have dependents.

My research did not come without limitations. The ability to correctly align civilian SOC codes to similar Marine Corps occupations is one such limitation. The military-to-

civilian crosswalk is one method of identifying a military member's skillset and how it may transfer or fit into similar civilian occupations. Further, using the military-to-civilian crosswalk and corresponding civilian wages is a mere generalization of expected wage rates. As such, the wage data used in this analysis is generalized and assumed to be an average of what one can expect to make in the civilian sector.

This research also doesn't capture other unobserved factors such as current economic conditions during the opt-in period such as employment, job growth, etc., nor does my use of the crosswalk factor in the member's location, either the duty station where the member was stationed or their home of record. Location may be an important factor that is a limitation in this report, as local economic conditions or the member's home of record may have influenced their opt-in decision, if it was a factor in their BRS decision at all.

An additional limitation was the method by which I was able to classify critical MOSs. The MOS status report provided me with data on MOS target and fill rates as of January 2020. This limited my ability to capture the true target and fill rates in 2018 when the BRS election occurred. Further, while it's possible that the Marine Corps actually classifies some MOSs as critical, the data I obtained did not clearly define these MOSs as being critical. This required me to make my own interpretations on the MOS status report, where I define a critical MOS according to the MOS target and fill rates, according to the data I obtained from the Marine Corps' Manpower Plans and Policies Division.

B. RECOMMENDATIONS AND FURTHER RESEARCH

Although my findings suggest that civilian wages or critical MOSs may not influence one's decision to opt in or opt out of the BRS, it may be that other unobserved factors other than simply being younger or having dependents. Perhaps a member's propensity to opt in or opt out of the BRS is dependent upon job mobility or other alternative employment opportunities, but civilian wage rates, from what I find, may not be the correct variable from which to test this hypothesis. Conducting more research into job mobility and alternative employment may provide meaningful data that can better explain or help predict BRS opt-in rate behavior and the associated effects on retention. Additionally, an alternative would be to conduct a survey on all Marines who were eligible to opt in to the BRS. By conducting a survey, information with respect to career intent, job mobility, search for alternative employment, etc., can be collected and analyzed to obtain a more robust and thorough account of BRS opt-in behavior. While decisions to continue service or separate may change after the BRS decision, the survey can at least provide insight on members' opt-in rate decisions and, ultimately, retention decisions. Because the BRS is already in effect and members who enter the service on or after 1 January 2018 are already enrolled in the BRS, this would only be able to provide retention or separation propensity with regard to the eligible population. Nonetheless, exploring this avenue may still provide the Marine Corps with a better understanding of future retention issues that may occur due to the BRS.

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LIST OF REFERENCES

- Asch, B. J., Mattock, M. G., & Hosek, J. R. (2015). Reforming military retirement: analysis in support of the Military Compensation and Retirement Modernization Commission (Report No. RR-1022-MCRMC). RAND. https://www.rand.org/ pubs/research_reports/RR1022.html
- Asch, B. J., Mattock, M. G., & Hosek, J. R. (2017). The blended retirement system: retention effects and continuation pay cost estimates for the armed services (Report No. RR-1887-OSD/USCG). RAND. https://www.rand.org/pubs/ research_reports/RR1887.html
- Brockert, N. D. (2018). Blended retirement system opt-in decisions: A behavioral economics analysis [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://calhoun.nps.edu/handle/10945/62233
- Christian, J. (2006). An overview of past proposals for military retirement reform (Report No. TR-376-OSD). RAND. https://www.rand.org/pubs/technical_reports/ TR376.html
- Commandant of the Marine Corps (CMC). (2016, December 9). Blended retirement system (BRS) opt-in eligible population notification (MarAdmin 644/16). https://www.marines.mil/News/Messages/Messages-Display/Article/1025916/ blended-retirement-system-brs-opt-in-eligible-population-notification/
- Cunha, J. M., Menichini, A. A., & Crockett, A. (2015). The retention effects of high years of service cliff-vesting pension plans. *Economics Letters*, 126, 6–9. https://doi.org/10.1016/j.econlet.2014.11.005
- Department of Defense (DOD). (2008). *Report of the Tenth Quadrennial Review of Military Compensation, volume II: Deferred and noncash compensation.* https://militarypay.defense.gov/Portals/3/Documents/Reports/ 10th_QRMC_2008_Vol_II.pdf
- Department of Defense (DOD). (2015). Report of the Military Compensation and Retirement Modernization Commission. https://docs.house.gov/meetings/AS/ AS00/20150204/102859/HHRG-114-AS00-20150204-SD001.pdf
- Department of Defense (DOD). (2017). A guide to the uniformed services blended retirement system. https://militarypay.defense.gov/Portals/3/Documents/ BlendedRetirementDocuments/ A%20Guide%20to%20the%20Uniformed%20Services%20BRS%20December% 202017.pdf?ver=2017-12-18-140805-343

- Department of Defense (DOD). (n.d.). *Military compensation*. Retrieved December 31, 2019, from https://militarypay.defense.gov/Pay/Retirement/
- Goda, G. S., Jones, D., & Manchester, C. F. (2017). Retirement plan type and employee mobility: The role of selection. *Journal of Human Resources*, *52*(3), 654–679. https://doi.org/10.3368/jhr.52.3.0315-6997R1
- Hlavac, M. (2018). Stargazer: Well-formatted regression and summary statistics tables. R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
- Jeszeck, C. A., & Todisco, F. (2019). *Military pensions: Servicemembers need better information to support retirement savings decisions*. (GAO-19-631). Government Accountability Office. http://www.gao.gov/products/gao-19-631
- Jowers, K. (2018, April 14). Will new retirement system entice more service members to leave early? Officials are watching. *Military Times*. https://www.militarytimes.com/pay-benefits/2018/04/13/will-new-retirementsystem-entice-more-service-members-to-leave-early-officials-are-watching/
- Kamarck, K. N. (2019). Military retirement: background and recent developments (CRS Report No. RL34751). Congressional Research Service. https://fas.org/sgp/crs/ misc/RL34751.pdf
- Ludecke, D. (2018). "ggeffects: Tidy data frames of marginal effects from regression models." *Journal of Open Source Software*, 3(26), 772. doi: 10.21105/joss.00772.
- Military Officers Association of America. (2018, April 20). Personnel chiefs talk retention concerns as the pentagon rolls out its new retirement system. https://www.moaa.org/content/take-action/top-issues/currently-serving/personnelchiefs-talk-retention-concerns-as-the-pentagon-rolls-out-its-new-retirementsystem/
- Moynihan, G. T. (2016). Survival analysis of the modernized retirement system for the United States Marine Corps [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://calhoun.nps.edu/handle/10945/48570
- Reiley, M. (2017, August 7). New "blended retirement" puts retention at risk. Marine Corps Times. https://www.marinecorpstimes.com/pay-benefits/militaryretirement/2017/04/09/new-blended-retirement-puts-retention-at-risk/
- Steel, R. P. (2002). Turnover theory at the empirical interface: Problems of fit and function. *The Academy of Management Review*, 27(3), 346–360. https://doi.org/ 10.2307/4134383
- Steel, R. P., & Landon, T. E. (2010). Internal employment opportunity and external employment opportunity: Independent or interactive retention effects? *Military Psychology*, 22(3), 282–300. https://doi.org/10.1080/08995605.2010.492692

- Swider, B. W., Boswell, W. R., & Zimmerman, R. D. (2011). Examining the job search– turnover relationship: The role of embeddedness, job satisfaction, and available alternatives. *Journal of Applied Psychology*, 96(2), 432–441. http://dx.doi.org/ 10.1037/a0021676
- Zunic, A. S. (2018). Improving the gender composition of the United States Marine Corps through military occupational specialty crosswalk examination [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://calhoun.nps.edu/handle/10945/59631

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