2019-06

Retention Analysis Model (RAM) For Navy Manpower and Personnel Analysis

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NPS-GSBPP-19-006

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

RETENTION ANALYSIS MODEL (RAM) FOR MANPOWER AND PERSONNEL ANALYSIS

by

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May 2019

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Prepared for: OPNAV N81 Assessment Division

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE ***(DD-MM-YYYY)***
June 2019

2. REPORT TYPE
Final Technical Report

3. DATES COVERED ***(From-To)***
OCT 2017 to DEC 2018

4. TITLE AND SUBTITLE
RETENTION ANALYSIS MODEL (RAM) FOR NAVY MANPOWER AND PERSONNEL ANALYSIS

5a. CONTRACT NUMBER

5b. GRANT NUMBER
Naval Research Program

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
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5d. PROJECT NUMBER
NPS-18-N139-A

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) AND ADDRESS(ES)
Naval Postgraduate School
School: Graduate School of Business and Public Policy/ Dept: Manpower & Economics
1 University Circle, Monterey CA 93943

8. PERFORMING ORGANIZATION REPORT NUMBER
NPS-GSBPP-19-006

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited

13. SUPPLEMENTARY NOTES
The views expressed in this technical report are those of the authors and do not reflect the official policy or position of the Department of Navy, Department of Defense, or the U.S. Government.

14. ABSTRACT

This report addresses deficiencies in our understanding of service members' career trajectories. The insights generated will be used to construct more sophisticated and useful models of long run manpower projections, allowing complex simulations to predict the impact of personnel policy changes. This will allow Navy leadership to avoid unanticipated shocks to service member supply and quality.

This report proceeds along two lines. First, we collect a dataset of Navy officers and examine their career trajectory, paying particular attention to their educational background and sociodemographic characteristics. Using long-term trend, as well as regression analysis, we find significant retention rate differences over the long run across gender, marital and dependent status, race, and education level. While the long run trends and regression results are illuminating, we should be wary of drawing definite conclusions about the innate ability or desire of officers to stay or separate based on these analyses. Without a formal model to distinguish between correlation and causation, we should recognize that the findings in this study primarily help direct our modeling efforts in subsequent years.

Second, we provide an in-depth description of dynamic programming models, demonstrating their usefulness and internal consistency for predicting rational, forward-looking agents making choices that affect their future. We provide a detailed technical description of the model, defining value functions, Bellman's equations, and other concepts necessary to program, estimate, solve, and simulate a dynamic programming model. We then propose the path forward to examine how service members in different communities may make different career choices.

15. SUBJECT TERMS
Retention Modeling, Force Structure Modeling; Retention Bonus; Reenlistment Bonus; Logistic Regression; Retention Auction

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			
Unclassified	Unclassified	Unclassified	UU	65	Sae Young (Tom) Ahn
					19b. TELEPHONE NUMBER ***(include area code)*** 831-656-2470

Standard Form 298 (Rev. 8-98)

Prescribed by ANSI Std. Z39.18

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The report entitled Retention Analysis Model (RAM) For Navy Manpower and Personnel Analysis was prepared for OPNAV N81, Assessment Division, and funded by the Naval Research Program at the Naval Postgraduate School.

Further distribution of all or part of this report is authorized

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NRP FY18 TECHNICAL REPORT

Retention Analysis Model (RAM) For Navy Manpower and Personnel Analysis

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Keywords: *Retention Modeling, Force Structure Modeling; Retention Bonus; Reenlistment Bonus; Logistic Regression; Retention Auction*

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EXECUTIVE SUMMARY

The most critical resource of the United States Navy is its personnel. Despite this importance to the Navy, relatively little is known about the career trajectories of its officers. This lack of knowledge is especially problematic for long-term planning and introduction of attempts to attract and retain the best and brightest. Indeed, the Navy has been more reactive, rather than proactive, in enacting personnel policy.

The difficulty the Navy faces in forecasting manpower and simulating expected impacts of policy changes in retention rates is expected to be compounded by generational shifts in the sociodemographic makeup of the population, increased competition from the civilian sector, and large-scale compensation changes, such as the Blended Retirement System (BRS).

The goal of this report, as well as our first report issued last year, is to address current deficiencies in our understanding of the career trajectories of naval officers. The expectation is that the insights generated in this report will be used as a basis to construct more sophisticated and useful models of long run projections of manpower, allowing complex simulations to predict the impact of personnel policy changes. This should allow the Navy leadership to plan further ahead with greater confidence so that it will not be surprised by unanticipated shocks to the supply and quality of officers.

Below, we summarize the findings of the two reports, and suggest directions forward in subsequent reports.

In the first report issued for our Retention Analysis Modeling project last year:

- We surveyed the literature for economic theory and econometric models that had been or could be adapted to examine policy levers affecting the reenlistment rates of officers and enlisted sailors. These models included various ad-hoc, average cost of leaving (ACOL), and dynamic programming models (also known as dynamic retention models [DRMs]).
- We found that various econometric problems, such as reverse causality, measurement errors, omitted variable bias, etc., make many of the examined models unsatisfactory for forecasting retention rates in response to policy levers. Policies based on such models could yield outcomes that are greatly different from expectations, requiring further adjustments to correct for such mistakes.
- One candidate model that was recommended for further study was the dynamic programming or DRMs. One flavor of these models was created by RAND and has been

used since the 1980s to forecast officer retention rates in the Army and Air Force. While the RAND DRM yielded a myriad of useful predictions, limited computing power at the time of the model's creation necessitated extreme parsimony in the model.

- We recommended exploiting the many advances in econometric techniques, better data, and exponentially increased modern computing power (by using high performance computing [HPS] cluster servers) to build new DRMs from the ground-up. Such a model could be used alongside other previously used models to provide additional insights and predictive power.

In this second report, we proceed along two lines:

First, we collect a rich administrative dataset of Navy officers and examine their career trajectory, paying particular attention to their educational background and sociodemographic characteristics. Using long-term trend, as well as regression analysis, we find the following:

- Significant retention rate differences arise, especially over the long run, across gender, marital and dependent status, race, and education level.
- Married males with graduate degrees who have children, on average, have the longest career with the Navy.
- Somewhat surprisingly, officers with a STEM background seem to be no more likely to separate from the Navy compared to those without a STEM background.
- For gender, race, and marital and dependent status, differences in retention rates widen sharply relatively early in the officers' careers (until approximately year of service 5) and stabilize from then onward.
- For graduate degree status, the gap in retention rates opens up quickly and continues to widen through 20+ years.
- While the long run trends and regression results are illuminating, we should be wary of drawing definite conclusions about innate ability or desire of officers to stay or separate based on these analyses. In particular, if leadership identifies good officer candidates for further advancement and subsidizes graduate education, it should not be shocking to find that officers with graduate degrees enjoy a longer career in the Navy due to rapid/on-time promotion.
- We do not yet differentiate whether separation was voluntary or forced.
- The observed trends could be impacted by Department of Defense (DoD) policy, cultural influences, and outside economic forces that may act differently on each sub-group under analysis.

- Without a formal model to distinguish between correlation and causation, we should recognize that the findings in this study help to direct our modeling efforts in subsequent years.

Second, we provide an in-depth description of dynamic programming models:

- We start with a general description of dynamic programming, demonstrating the usefulness and internal consistency of the model in being able to predict rational, forward-looking agents making choices that affect their future. We then describe some of the technical difficulties of computing such a model and survey recent advances in the literature that may help to alleviate these problems.
- Next, we provide a more detailed technical description of the model, defining value functions, Bellman's equations, and other concepts necessary to program, estimate, solve, and simulate a dynamic programming model.

Synthesizing these two lines of examination, we finally propose the path forward:

- We will collect additional data on officers, and program the dynamic programming model taking into account the unique labor market circumstances of naval officers.
- We will account for monetary and non-monetary compensation policies that may affect individual decisions to remain or separate from the Navy.
- We will "condition" on the observable quality characteristics of the officers (such as education level, major of study, Fitness Report (FITREP) scores, etc.) to assess whether the Navy is losing its best and brightest.
- We will incorporate the state of the economy, such that officers are not making career-altering decisions in a vacuum.
- We will perform these analyses for separate Military Occupational Specialties (MOSs) to examine how officers in different communities may make different career choices.

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I. INTRODUCTION

Our military and civilian workforce is our greatest resource. ... The organization will capitalize on its best talent today, retain that talent over the long term, and find ways to continue to recruit the best people for the mission of the future.

— Richard V. Spencer, The Secretary of the Navy (Memorandum re: Department of Navy Mission, Vision, and Priorities, August 29, 2017)

It is well-established that the most important resource of the U.S. Navy is its personnel. Despite advances in lethal weapons systems, new innovative platforms, proposed increases in the number of ships, massive increases in computing power, and the introduction of machine learning and artificial intelligence, the Navy's ultimate edge in maintaining superiority against our adversaries and providing protection and cooperation with our allies continues to be highly trained, capable, and motivated officers.

While recruiting, training, and retaining high quality officers has always been a challenge, talent management has become progressively more difficult within the past few decades. Recent substantive changes to DoD and Navy personnel policy as well as generational shifts in the sociodemographic make-up of the population has in turn led to large changes in the size and composition of the officer corps.

Some of these factors, such as the force drawdown in the 1990s, the introduction of the Blended Retirement System (BRS), increasing difficulty in finding and recruiting candidates (with acceptable physical conditioning and/or without misdemeanor offenses such as drug possession), and a strong economy leading to tougher competition for highly qualified candidates (enlisted and commissioned officers) from the civilian sector as well as the other services, are well-known and well-studied in other reports (Asch, Hosek, & Warner, 2007). In addition, the unique nature of training and promotion within the Navy (as well as the other services) means that the internal labor market is highly silo-ed, with little possibility of lateral entry from the civilian sector to plug any gaps in manpower or expertise. Due to these factors, it is imperative that the Navy become smarter in attracting desirable candidates and nurturing its own talent pool.

While we have now accumulated a specific, in-depth understanding of the impact of many of the above listed issues, these are parts of a larger, much more complex and interrelated personnel management puzzle. Pulling one or more policy lever(s) based on a partial equilibrium understanding of how all of the pieces fit together risks, at best, an inefficient deployment of resources, and at worst, unintended consequences that make the initial problem worse. We still lack a holistic understanding of who the current Navy officers are, what characteristics of the profession (monetary as well as non-monetary) or family circumstances induces them to stay or leave, and how career decisions of individual officers now and in the future will affect the shape of the force.

To address current deficiencies in our understanding of the career of Naval officers, this report has two main goals:

First, this study serves to broadly outline the lifetime career trajectory of Naval officers using a comprehensive administrative dataset. Before a specific dynamic retention model can be selected, created, estimated, and run through simulations, we must have a clearer understanding of who is impacted by changes to monetary and non-monetary compensations and by how much. Much of this can be accomplished through the judicious analysis of summary statistics, trend-lines by socioeconomic characteristics, and simple reduced-form econometric analysis, including ordinary least squared, logistic regressions, and difference-in-difference analysis.

The bulk of the empirical analysis of this report carefully describes the career trajectory of officers and lays the groundwork for the dynamic programming model to be created and estimated in a future report. Although the analysis in this report may be termed *preliminary* in the sense that we will only attempt to show correlative relationships between officer characteristics and career outcomes, the report will fill in large gaps in our knowledge of officers' career decisions.

Indeed, long run, descriptive analyses of officers' careers, especially as they pertain to non-monetary characteristics of the job, have not been extensively studied. Focusing on monetary levers to induce change in retention rates ignores potentially more effective and cheaper policy changes that may have greater effect on size and quality of the officers corps.

Second, the study describes dynamic programming models in some detail. While dynamic programming models have become the workhorse of long-term personnel policy decision analysis in other parts of the DoD (as well as academia), the Navy has consistently relied on older models that have some well-documented significant shortcomings. We briefly review these problems before describing the strengths (and weaknesses) of our proposed analysis framework. In subsequent reports, we expect to fully develop the dynamic programming model of the Naval officers corps. Note that we interchangeably use the terms "dynamic programming models" and "Dynamic Retention Model (DRM)" throughout this report.

II. WHAT WE KNOW SO FAR FROM PRIOR STUDIES

It would be impossible to have complete coverage of all major factors that impact retention/promotion/attrition decisions of naval personnel. In this abbreviated review, we summarize some of the literature on the chronology of the military career trajectory, split into recruitment, advancement and evaluation, and retirement.

A. RECRUITMENT

Throughout the ’90s, the attractiveness of a military career among male high school seniors declined precipitously. Research showed that most military recruiting efforts were largely ineffective, and family (parental) characteristics largely determined the propensity of a high school graduate to be open to enlisting (Warner, Simon, & Payne, 2001, 2003). Some education-based recruitment incentives have been shown to be effective. (Kraus, Griffis, & Golfin, 2000; Asch, Schonlau, & Du, 2004). Most alarming was the observed trend of recruiting becoming more insular: a strong predictor of recruiting success was whether the candidate had family who was already in the military. Such a trend may widen the gap between civilian and military, which may have detrimental impacts, not only on recruiting, but also on political issues such as propensity to deploy troops by Congress (McGirk, Hilger, & Miller, 2017).

Demographic changes and shifting political and cultural winds have also caused the leadership to pay more attention to recruiting from traditionally under-represented groups. Most prominently, the perceived gender gap (at least compared to the labor market) on average, and especially in the combat MOSs, have resulted in political pressure and studies (Strauss et al., 2012; Yeung, Steiner, Hardison, Hanser, & Kamarck, 2017).

Large scale changes the demography of the United States and stiffer competition from the civilian market, along with the limited efficacy of traditional monetary recruiting bonuses led some researchers to evaluate using a myriad of lesser explored personnel policy (Dertouzos & Garber, 2006). Examining what makes for a successful recruiting experience has revealed that correctly matching and incentivizing the recruiter may yield more success.

B. EVALUATION, RETENTION, COMPENSATION, AND PROMOTION

Several studies attempt to find factors that predict promotion. Identifying what makes an officer promotable would mean that the Navy could focus on recruiting and rewarding candidates with the desirable characteristics. Beyond common sense factors, such as academic achievement, research has yielded somewhat inconsistent results isolating the elements that lead to promotion. Personnel economics studies have shown that the best predictor of success is to allow the candidate to show his or her ability via job performance. Studies of Navy personnel have shown similar results, with FITREPS scores being predictive of job performance and success. See Phillips and Clemens (2011) for a review of prior research.

Many models address retention issue from a dynamic context: upon application of some policy lever, such as a bonus or change in promotion rate, the change in propensity of personnel to stay or leave the service sometime in the future is estimated. Older research relied on the ACOL and ACOL-2 models, which attempted to predict the optimal time for an officer to retire (Warner & Asch, 1995; Goldberg, 2001). Recent research has used dynamic programming models to evaluate the impact of various policy changes on retention rates (Gotz & McCall, 1984; Asch & Warner, 2001; Daula & Moffitt, 1995).

Many traditional studies attempted to estimate the elasticity of military pay. That is, how much more likely is an officer or sailor to choose to separate if wage decreases by, say, one percent? There is no wide-spread agreement on this value, as many studies have estimated very different values (Hosek & Peterson, 1985; Hattiangadi, Lee, & Quester, 2004; Hansen & Wenger, 2005). Still other studies have estimated the value of statistical life using retention incentives and mortality rates in the military (Greenstone, Ryan, & Yankovich, 2014).

C. RETIREMENT

A more complete look at the career trajectory of Naval officers requires us to seriously consider life after the Navy. Many researchers have examined the labor market experiences of veterans. Studies of the effect of the draft (and deployment during the Vietnam War) on lifetime earnings, veteran labor force participation rates, and the impact of more recent military service on earnings and education have been examined, yielding mixed results on whether military service harms or benefits the labor force outcome of the worker (Angrist, 1990; Coile, Duggan, & Guo, 2015; Martorell, Miller, Daugherty, & Borgshulte, 2013).

Changes from the legacy cliff-vesting retirement system to the new BRS has been studied with dynamic programming models (Asch, Mattock, & Hosek, 2017). Simulations show that most of those who have the option to opt-in will, in fact, choose not to, because the BRS yields less generous payouts to those who would prefer to stay longer in the service. The authors suggest drastically increasing continuation pay (a one-time bonus to induce longer service within the BRS) to make it more attractive. How the change to the retirement system affects the young, recent cohort of officers and the enlisted soldier who does not have the option to select the legacy system, remains an open question.

D. FAMILIES

More recently, many studies have centered on the impact of the military life on the families of service members. Adverse impacts on the health and educational achievement of children, and potential connections between domestic violence and deployment to war zones have been studied (Engel, Gallagher, & Lyle, 2008; Cesur & Sabia, 2016). Most studies have shown small to moderate detrimental impacts of the military lifestyle on dependents.

As the officer will be making career decisions in a joint-household-utility framework, closer attention must be paid to how military lifestyle will affect the spouse and children. This may be of particular concern to female officers and one of the reasons why we see higher attrition (as well as low absolute numbers) of women in the military.

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III. DATA AND DESCRIPTIVES

We obtained the data from three different sources: the Bureau of Naval Personnel, the Navy Personnel Command, and the Defense Manpower Data Center (DMDC). The dataset contains individual demographics on all the Navy officers commissioned in the period 1999–2003. We observe each service member annually until his/her 10th year of service or until separation, whatever happens first. The dataset initially consists of 23,334 observations. We require the observations to contain information on the usual demographics (age, gender, race, etc.), including educational background and service-related characteristics for all officers commissioned at an O-1 grade. We exclude Navy Limited Duty Officers (LDO) or Warrant Officers. These data restrictions reduce the size of the dataset to 16,143 observations.

A. VARIABLE DESCRIPTIONS

i. Dependent Variables: Retention Measures

Officer retention is studied annually during officers' initial career years, starting a year after commissioning until 10 years of service (YOS) or until separation, if the latter happens first. This is analogous to Maugeri (2016) and Tick et al. (2017), who analyze officers' retention at six YOS, which is the end of the minimum service requirement and officers can make their leave-or-stay decision. This study is also similar to Menichini and Tick (2018), who examine the retention and promotion outcomes of Navy officers at six and 10 years of service. Table 1 shows the definition of each dependent variable used in this study.

Table 1. Dependent Variable Definitions

Dependent Variable Name	Dependent Variable Definition
T Year Retention	= 1 if the officer is still in the Navy at *T* years from commissioning; 0, otherwise
Retention at quarter *t*	= 1 if the officer is still in the Navy at *t* quarters from commissioning; 0, otherwise

ii. Independent Variables

The independent variables are organized into four categories: demographics (gender, marital status, dependent status, etc.), commissioning source, Navy community, and commissioning/cohort year. We include cohort dummy variables for the five cohorts entering between 1999 and 2003 in all the multivariate models examined in this article. These dummy variables help us to isolate unobserved factors that may impact officer retention and promotion differently for each cohort. Table 2 displays the variable names and definitions for all the independent variables.

Table 2. Independent Variable Definitions

Independent Variable Name	**Independent Variable Definition**
Demographic Characteristics	
Age	Age at commissioning
Female	= 1 if Female; 0, otherwise
Male	= 1 if Male; 0, otherwise
Dependent Children at 2 YOS	= 1 if the officer has dependent children 2 years after commissioning; 0, otherwise
No Dependent Children at 2 YOS	= 1 if the officer no dependent children 2 years after commissioning; 0, otherwise
Black	= 1 if Black (race) & Non-Hispanic (ethnicity; 0, otherwise
White	= 1 if White (race) & Non-Hispanic (ethnicity); 0, otherwise
Asian	= 1 if Asian; 0, otherwise
Hispanic	= 1 if Hispanic; 0, otherwise
Unknown Race	= 1 if Race is not known; 0, otherwise
Married at 2 YOS	= 1 if married 2 years after commissioning; 0, otherwise
Not Married at 2 YOS	= 1 if not married 2 years after commissioning; 0, otherwise
Commissioning Sources	
Naval Academy	= 1 if commissioned from USNA; 0, otherwise
ROTC	= 1 if commissioned from ROTC; 0, otherwise
OCS	= 1 if commissioned from OCS; 0, otherwise
Direct	= 1 if direct commissioning; 0, otherwise
Other Commissioning	= 1 if commissioned from other sources; 0, otherwise
Navy Community	
Surface Warfare	= 1 if Surface Warfare Officer; 0, otherwise
Submarine	= 1 if Submarine Officer; 0, otherwise
Aviation	= 1 if Naval Pilot; 0, otherwise
Special Operations	= 1 if Special Operations Officer; 0, otherwise
General Unrestricted Line	= 1 if Unqualified Line; 0, otherwise
Restricted Line	= 1 if Restricted Line Community; 0, otherwise
Staff	= 1 if Staff Community; 0, otherwise
Commissioning Cohorts	

Cohort FY99	= 1 if commissioned during fiscal year 1999; 0, otherwise
Cohort FY00	= 1 if commissioned during fiscal year 2000; 0, otherwise
Cohort FY01	= 1 if commissioned during fiscal year 2001; 0, otherwise
Cohort FY02	= 1 if commissioned during fiscal year 2002; 0, otherwise
Cohort FY03	= 1 if commissioned during fiscal year 2003; 0, otherwise

B. DESCRIPTIVE STATISTICS

Table 3 exhibits the descriptive statistics for the independent variables used in all the multivariate retention models analyzed in this study. As in Table 2, we separate those variables into four

Table 3. Descriptive Statistics, Larger Data Set, by Community

Variables	All Communities (n=16,143)	URL (n=12,225)	RL/Staff (n=3,918)
Independent Variables			
Demographic Characteristics			
Age	24.84	24.04	27.33
Female	0.184	0.138	0.327
Dependent Children at 2YOS	0.239	0.197	0.371
Married at 2YOS	0.339	0.305	0.442
White	0.753	0.759	0.733
Black	0.071	0.062	0.099
Asian	0.051	0.043	0.073
Hispanic	0.094	0.105	0.061
Unknown Race	0.032	0.031	0.034
Commissioning Sources			
Naval Academy	0.240	0.302	0.046
ROTC	0.265	0.317	0.104
OCS	0.324	0.287	0.439
Direct	0.078	0.005	0.306
Other Commissioning	0.071	0.068	0.083
Navy Community			
SWO	0.233	0.308	-
SUB	0.098	0.129	-
Aviator	0.285	0.376	-
Special Operations	0.017	0.022	-

General Unrestricted Line	0.125	0.166	-
Restricted Line	0.059	-	0.243
Staff	0.184	-	0.757
Commissioning Cohorts			
Cohort FY99	0.183	0.181	0.192
Cohort FY00	0.208	0.206	0.214
Cohort FY01	0.211	0.207	0.224
Cohort FY02	0.206	0.208	0.198
Cohort FY03	0.192	0.199	0.172

categories: demographics, commissioning source, Navy community, and commissioning/cohort year. We further disaggregate the data into three groups: all communities (i.e., the entire population), unrestricted line officers (URL), and restricted line and staff officers (RL/Staff).Regarding all communities, we can observe that the average age at commissioning is around 25 and, as usual, less than 20% of officers are female and around 75% of officers are white. The Naval Academy, ROTC, and OCS are the largest commissioning sources—close to 30% each. Within the Navy, Aviators and SWO are the two largest communities, followed then by Staff and General Unrestricted Line. Finally, we can observe that each of the five cohorts represents roughly 20% of the total population of officers.

Considering the full sample, Figure 1 shows that male officers who are not married have an average of 76% retention rate at 60 months from commissioning (i.e., the end of the minimum service requirement [MSR]), which is higher than the retention rates for female officers who are not married (58%). The retention means of male and female officers are significantly different from each other at a significance level of $p<0.01$. Similarly, for male and female officers who are married, males have higher mean retention rates at MSR when compared with mean retention rates of their female counterparts (83% vs. 63%). These retention rates are also significantly different from each other at the 1% significance level.

Among male officers, the mean MSR retention rate among married male officers (83%) is statistically larger than that of unmarried male officers (76%). However, the mean MSR retention rates are statistically the same for female officers, whether married or not (63% vs. 58%).

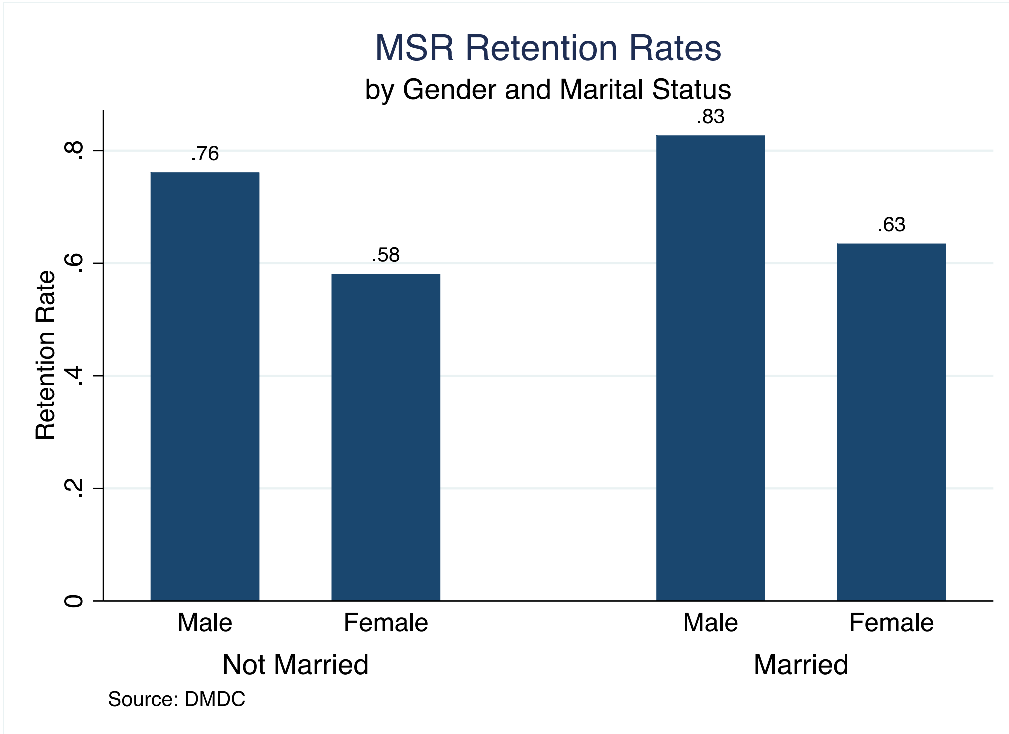

Figure 1. Retention at MSR by Gender and Marital Status for All Navy Officers

Figures 2 and 3 show the retention outcomes separated by URL Officers (without Aviators, who have longer MSR than five years) and RL/Staff officers, respectively. We can observe that the results are similar to the ones above, in the sense that the mean retention rates are indeed higher for male than for female officers, regardless of their marital status (i.e., married and unmarried). In addition, among male officers, the mean MSR retention rate among married male officers is statistically larger than that of male officers who are not married. The mean MSR retention rates for married female officers is marginally larger (at a p=0.05 percent level) than that of female officers who are not married.

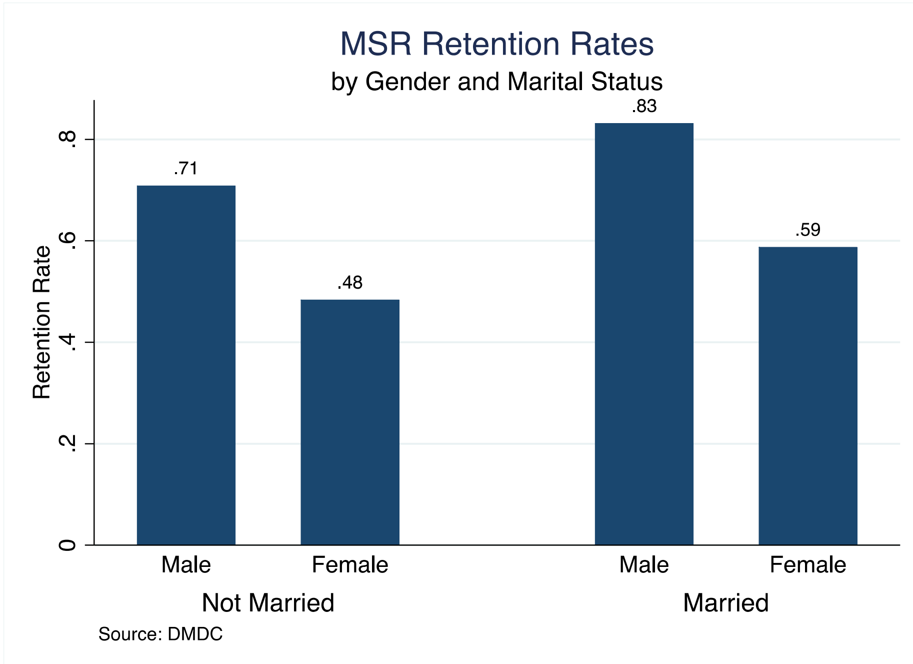

Figure 2. Retention at MSR by Gender and Marital Status for URL Officers (Excluding Aviators)

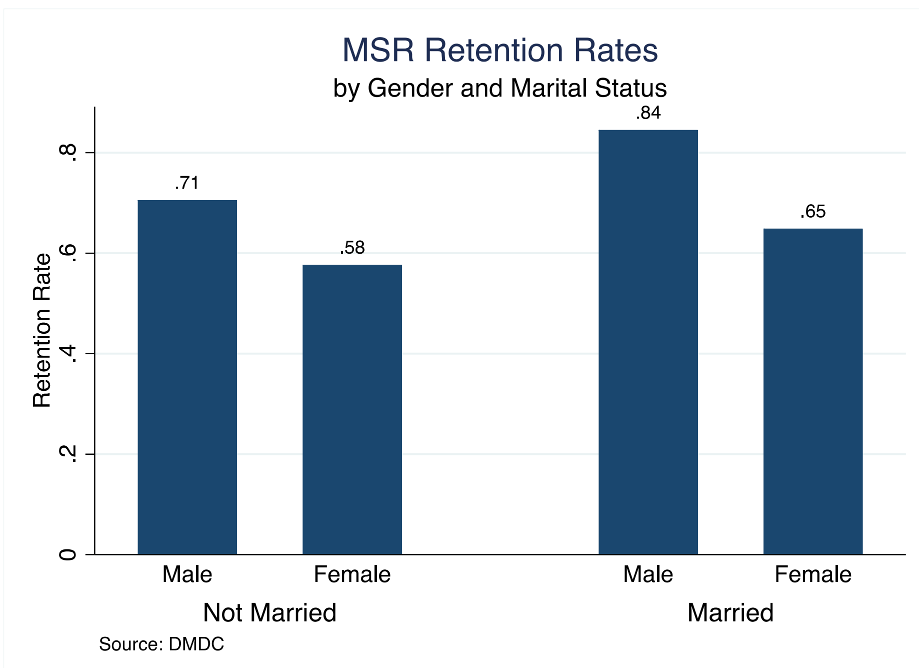

Figure 3. Retention at MSR by Gender and Marital Status for RL and Staff Officers

Figure 4 shows the retention rates at MSR by race and ethnicity for the full sample. Black and Hispanic officers have higher retention rates, while Asians have the lowest retention rates. However, the mean retention rates among these groups are statistically no different from each other.

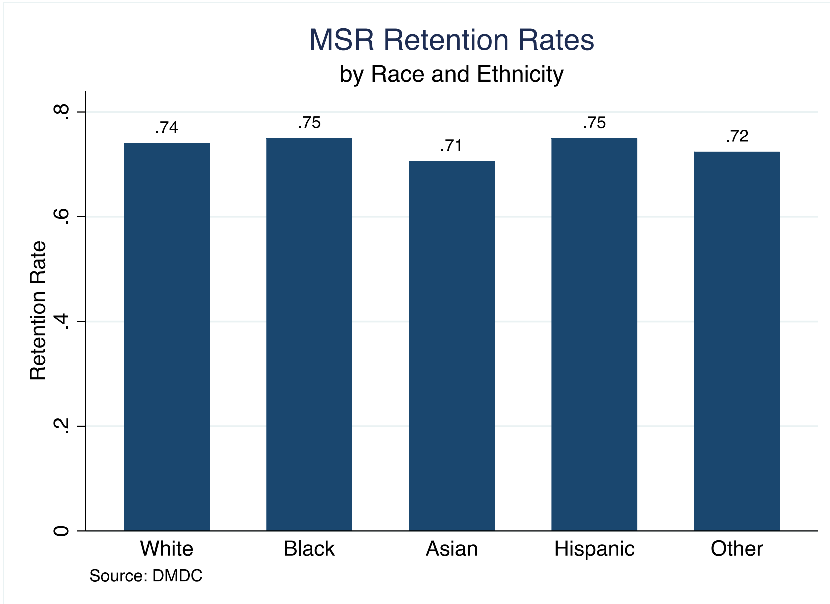

Figure 4. Retention at MSR by Race and Ethnicity

We next repeat the retention analysis showed above at 10 YOS. We can observe in Figure 5 that, for the full sample, the retention rates for male officers is higher than that of their female counterparts, regardless of their marital status (i.e., married and unmarried). In addition, married officers have higher retention rates at 10 YOS than the unmarried ones, both for males and females.

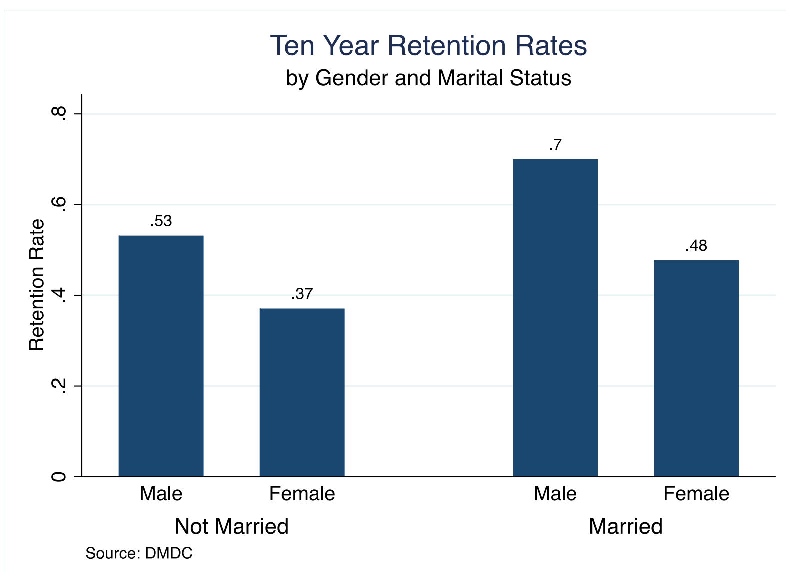

Figure 5. Retention at 10 Years, by Gender and Marital Status for All Navy Officers

All the patterns just described for the full sample also hold when we separate the observations in URL officers and RL/Staff officers, as Figures 6 and 7 show, respectively.

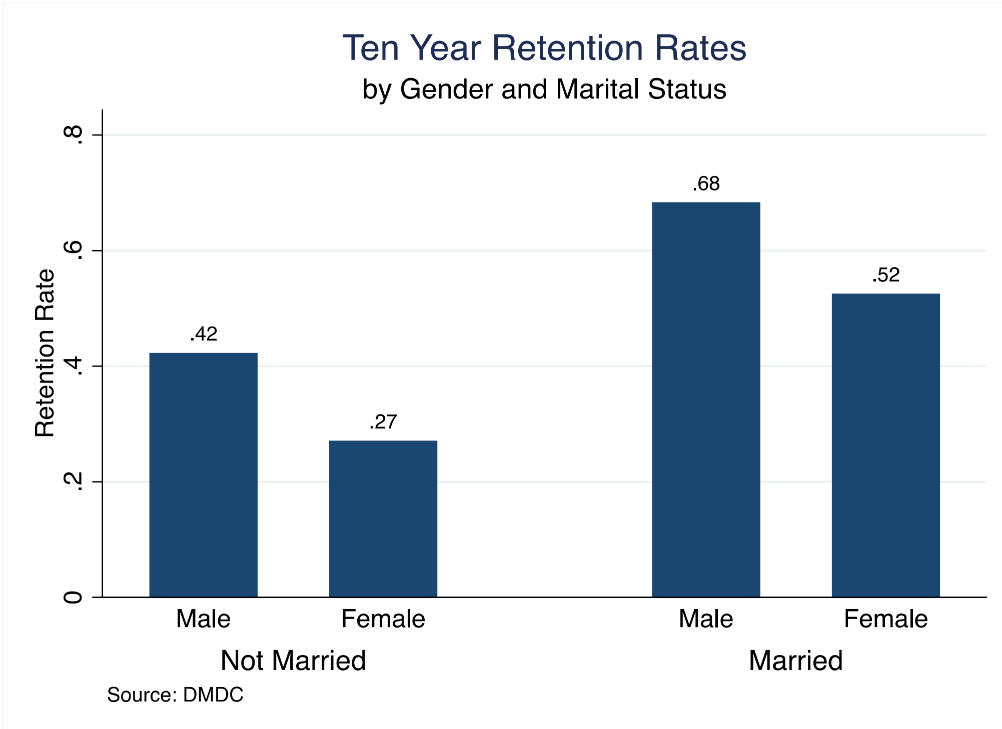

Figure 6. Retention at 10 Years, by Gender and Marital Status for URL Officers

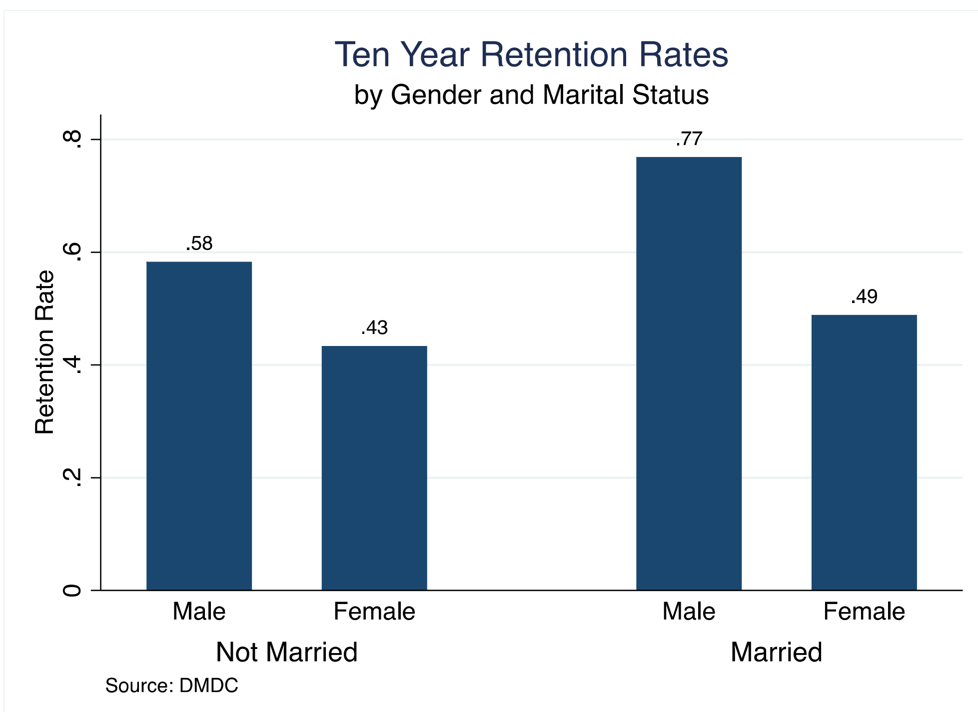

Figure 7. Retention at 10 Years, by Gender and Marital Status for RL and Staff Officers

Finally, Figure 8 shows the retention rates by race and ethnicity for the full sample at 10 YOS. Black officers continue to have highest retention rates, but, contrary to the outcomes at MSR, Hispanic officers have the lowest retention rates. However, as before, the mean retention rates across these groups are statistically no different from each other.

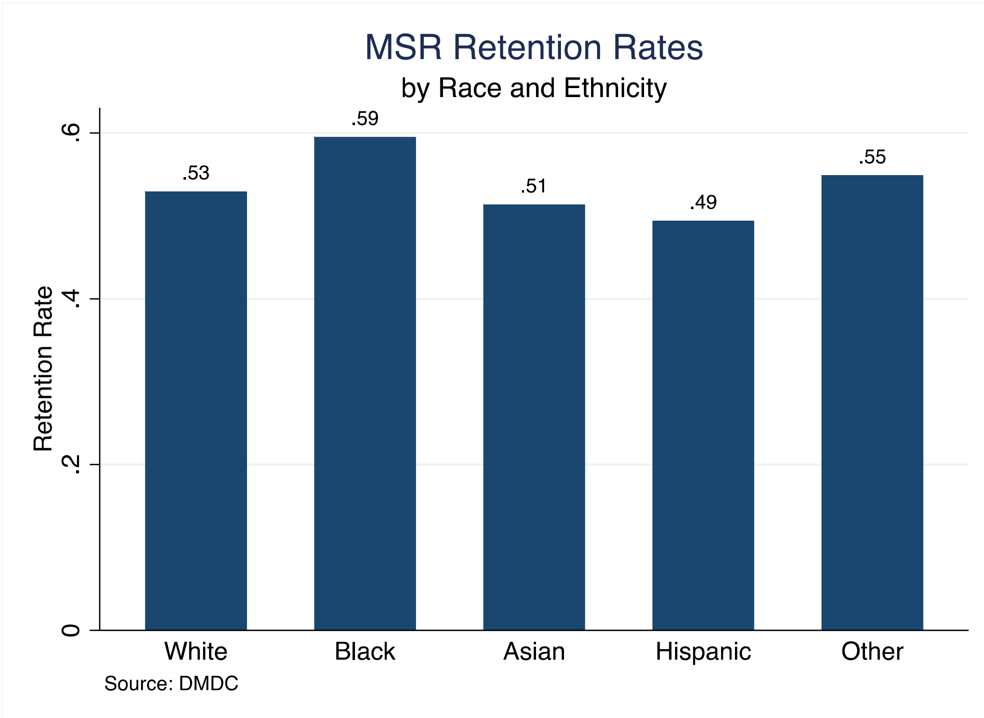

Figure 8. Retention at 10 Years, by Race and Ethnicity

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IV. EMPIRICAL ANALYSIS

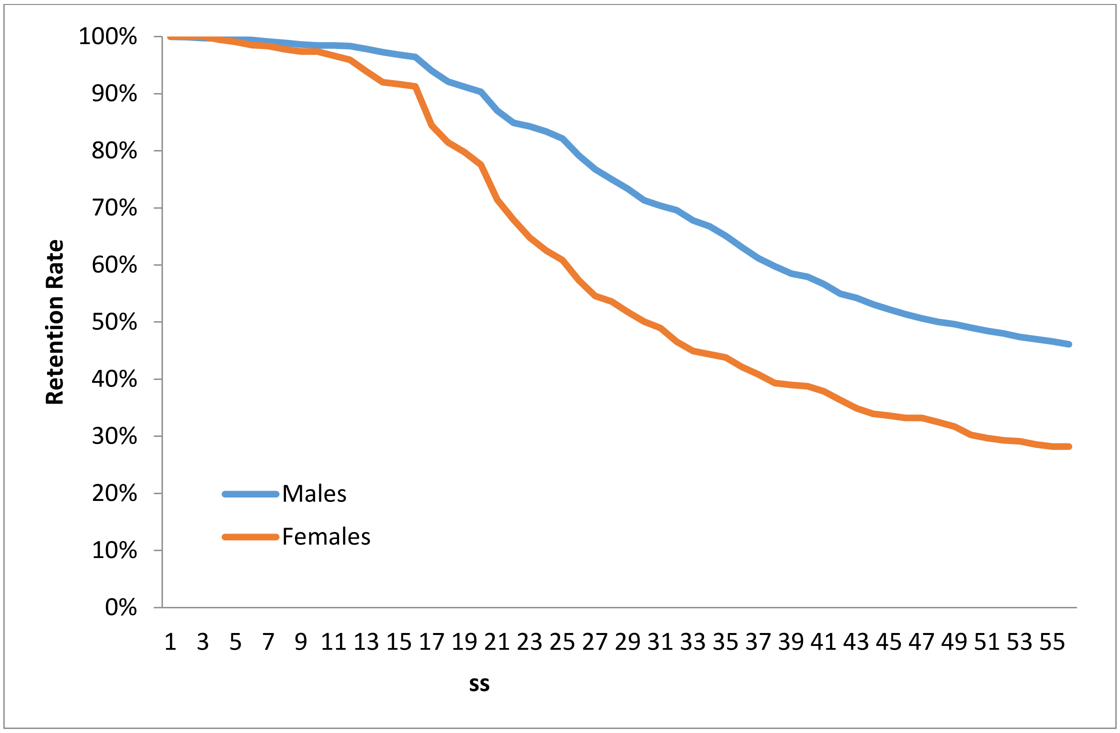
Our focus in this empirical section is to provide a long run perspective of Naval officers choosing to remain or separate from the Navy. While separation may be voluntary or involuntary, for this study we do not distinguish between the two outcomes. Voluntary separation may be due to (1) a preference for civilian life (or general distaste for military life), (2) strong earning potential in the civilian market (that the Navy cannot adequately compete against), or (3) realizing that he or she is unlikely to be promoted in the up-or-out system and opting to leave the Navy at the time of his or her choosing. This third reason is functionally equivalent to involuntary separation. It is outside the scope of this report to distinguish among these three potential reasons. Future research may focus more heavily on these issues.

We also choose not to emphasize the impact of monetary incentives on retention. Clearly, most prior research has focused on the ability of bonuses or pay increases to induce officers to serve longer. Our complete model in subsequent reports will also incorporate salary and examine the efficacy of various compensation schemes. In this report, we purposely restrict our attention to the career trajectory of officers who differ in socioeconomic, academic, and family characteristics. Because military pay has smaller variance compared to civilian sector pay (even accounting for various bonuses), most officers at similar points in their careers, with the exception of a smaller number of MOSs such as aviation, will be receiving largely the same annual salary. With little difference in income, if officers all had identical preferences, then they would have very similar career trajectory that would be easy to forecast. However, as we demonstrate below, separating officers by very broad socioeconomic categories such as gender and race reveal some large differences in retention behaviors. We hope to demonstrate that estimation of a singular career trajectory for officers (as has been done in the past in dynamic programming models) may be incomplete and inaccurate. We need to account for the substantive differences across officers (demographic and otherwise), to create a more nuanced, accurate, and ultimately useful model for the Navy.

A. LONG-TERM TREND ANALYSIS

Figure 9 shows stark differences in retention rates across gender. Male and female officers begin to diverge in their career trajectories very quickly in their careers. By the third year beyond commissioning, female officers separate at a noticeably higher rate compared to their male counterparts. By about year seven, approximately half of the female officers have attrited. Even at

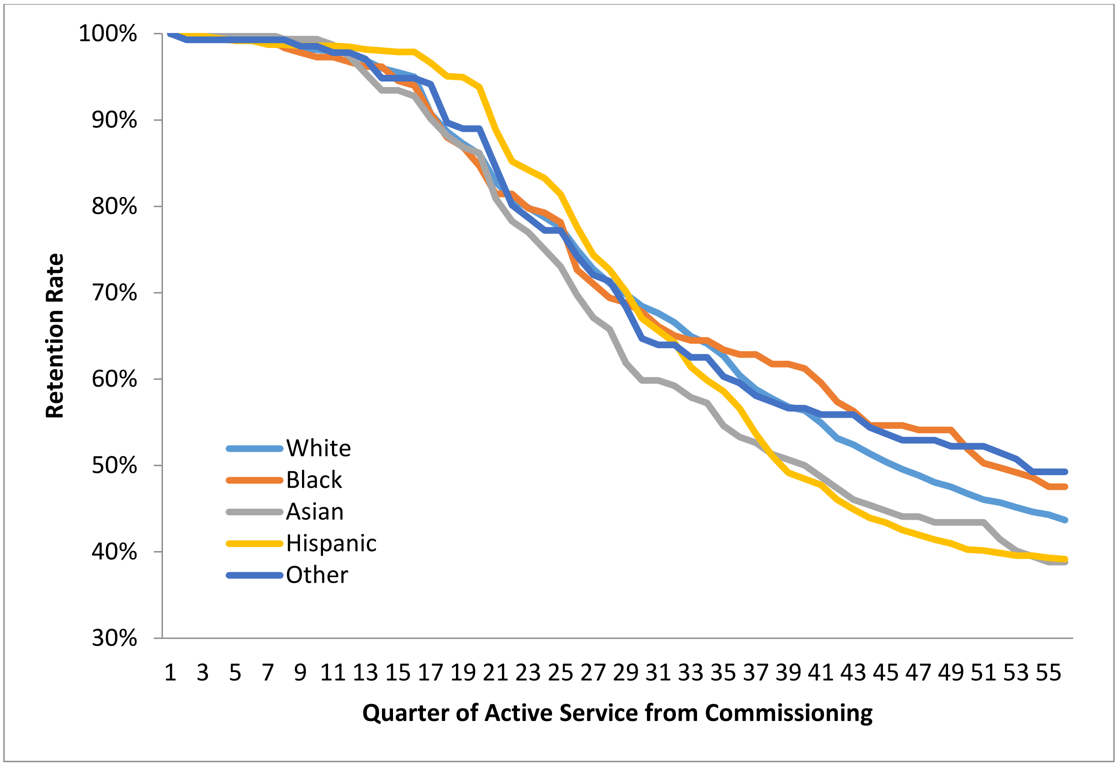
10-plus years, more than 50% of the male officers remain in the Navy. A naïve conclusion to be drawn from the figure may be that since male officers tend to stay longer, it is in the Navy's interest to focus on recruiting and training male officer candidates.



Source: DMDC

Figure 9. Quarterly Retention Rates among Naval Officers Commissioned in FY1999, by Gender

Figure 10 traces out the representative career trajectories of officers from different ethnic groups. While differences in attrition rates are not as stark as in Figure 9, the difference between Hispanic and African-American officers is interesting. Hispanic officers have a much higher propensity to remain in the Navy early in their careers. Hispanic officers experience almost zero attrition across the first five years. In contrast, almost 10% of African-American officers will have left the service by year five. This trend dramatically flips at about year seven, beyond which retention among Hispanic officers craters. Whether Hispanic officers are self-selecting out of the Navy, or they are experiencing involuntary separation due to failure to be promoted is another issue to be explored in our subsequent studies. This is particularly important because the Hispanic population in the United States is expected to grow in the future. The lack of success in retaining these officers may point to a lack of training and/or mentoring, better outside options relative to African-American officers, or existence of discrimination (perceived or real).

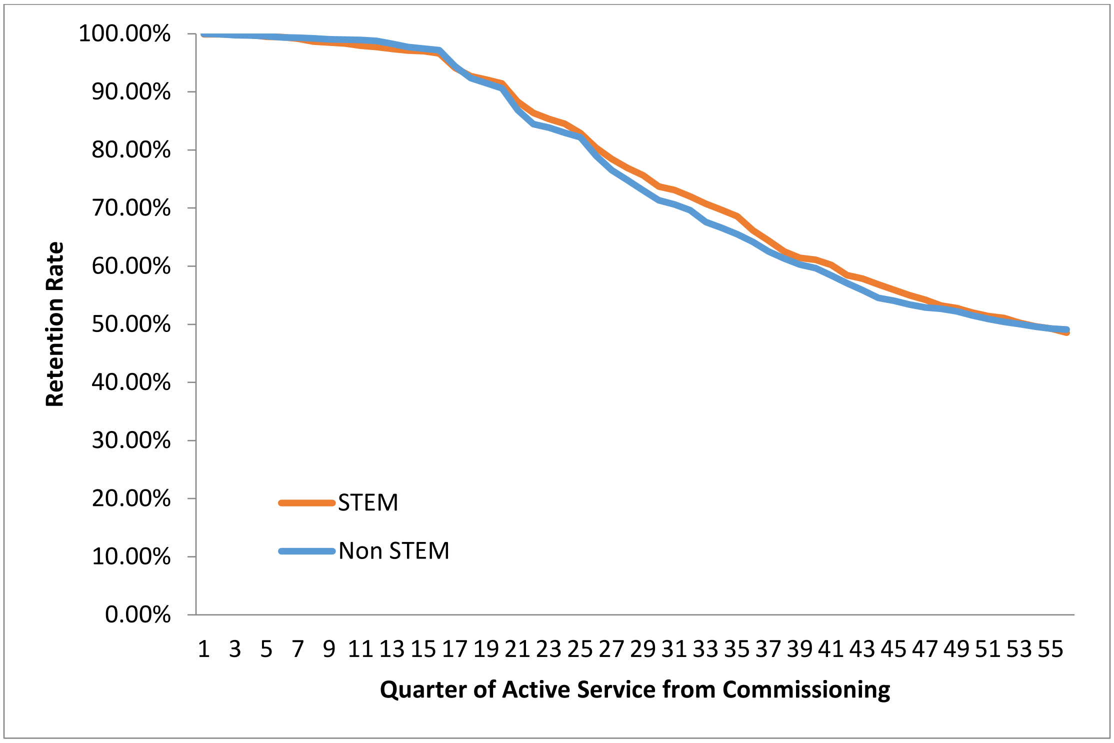


Source: DMDC

Figure 10. Quarterly Retention Rates among Naval Officers Commissioned in FY1999, by Race/Ethnicity

In contrast to difference in attrition across gender and race, educational background of officers seems to play little role in affecting career trajectories. We use the same STEM definition as in Maugeri (2016). Figure 11 shows that officers with STEM backgrounds remain in the Navy at about the same rate as officers without a STEM background. This may be encouraging news for the Navy.

Ex ante, officers with STEM backgrounds are expected to have more attractive civilian options. It would not be surprising, then, to observe higher attrition rates from this group. While we do not yet definitively understand why STEM officers do not leave at a higher rate, some caution should be exercised in interpreting this figure. We note that approximately 15% of the sample of officers did not have information on their STEM background in our dataset. A subset of officers who go on to receive graduate degrees will be identified as having a STEM background or not, due to information being collected by the Navy itself. Some officers choose to self-report their background, while others refrain from doing so. The unidentified group (although not shown in Figure 11) have much lower retention rate. Without being able to identify officers in this third group, it is difficult to say definitively that the Navy does not have problems in retaining STEM officers.



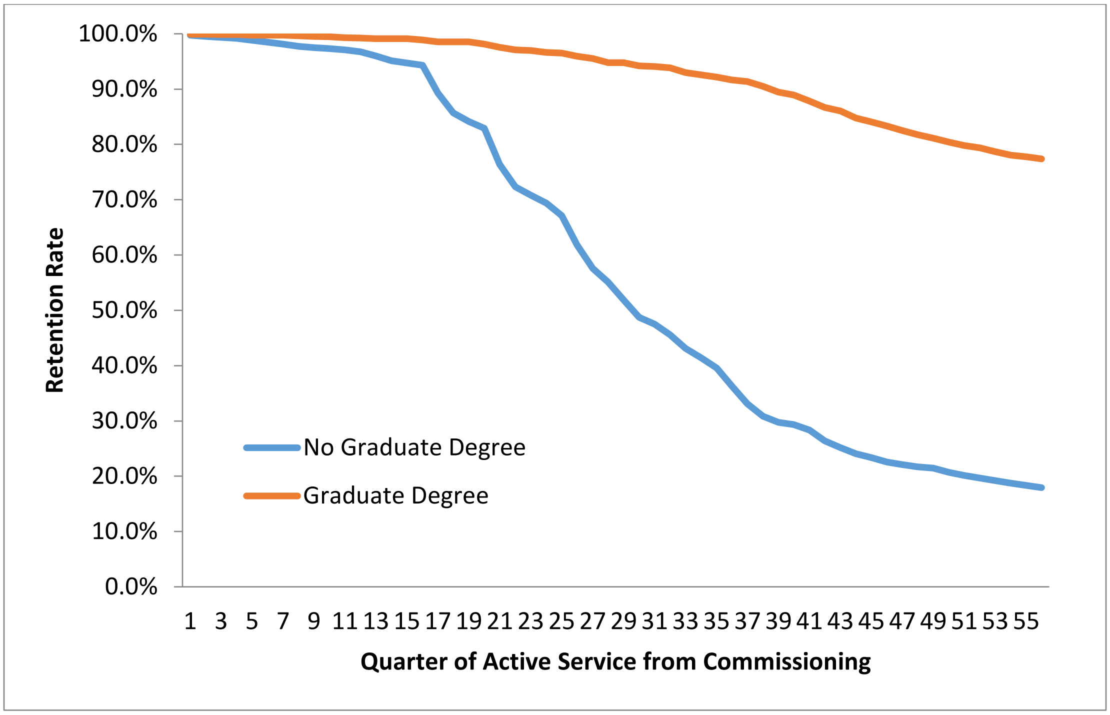
Source: DMDC. N=2, 469

Figure 11. Quarterly Mean Retention Rates among Naval Officers Commissioned in FY1999, by STEM/Non-STEM College Major

Even if retention rates are similar across STEM and non-STEM officers, we may be in a sub-optimal situation if more high-ability STEM officers leave (due to more attractive options in the civilian sector) and low-ability STEM officers remain. Our dynamic programming model should contain finer measures of ability than has been previously done.

In contrast with the STEM/non-STEM divide, Figure 12 examines the career trajectory of officers who do or do not obtain graduate degrees and reveals very stark differences. Starting at about 20 quarters in, the two series rapidly diverge. By approximately 10 years of service, the gap in retention rate between the two groups is over 50 percentage points.

While the Navy's ability to retain officers with graduate degrees is encouraging, we should note that interpreting this figure is difficult, because those officers who obtain graduate education with funding from the Navy can do so because they were selected by the Navy leadership. Since these officers were designated as being particularly good fits with the Navy, perhaps it is not a big surprise most choose not to separate. On the other hand, those who are not selected for graduate education would face involuntary separation earlier, or would choose to exit voluntarily to find an organization where they are better fits.

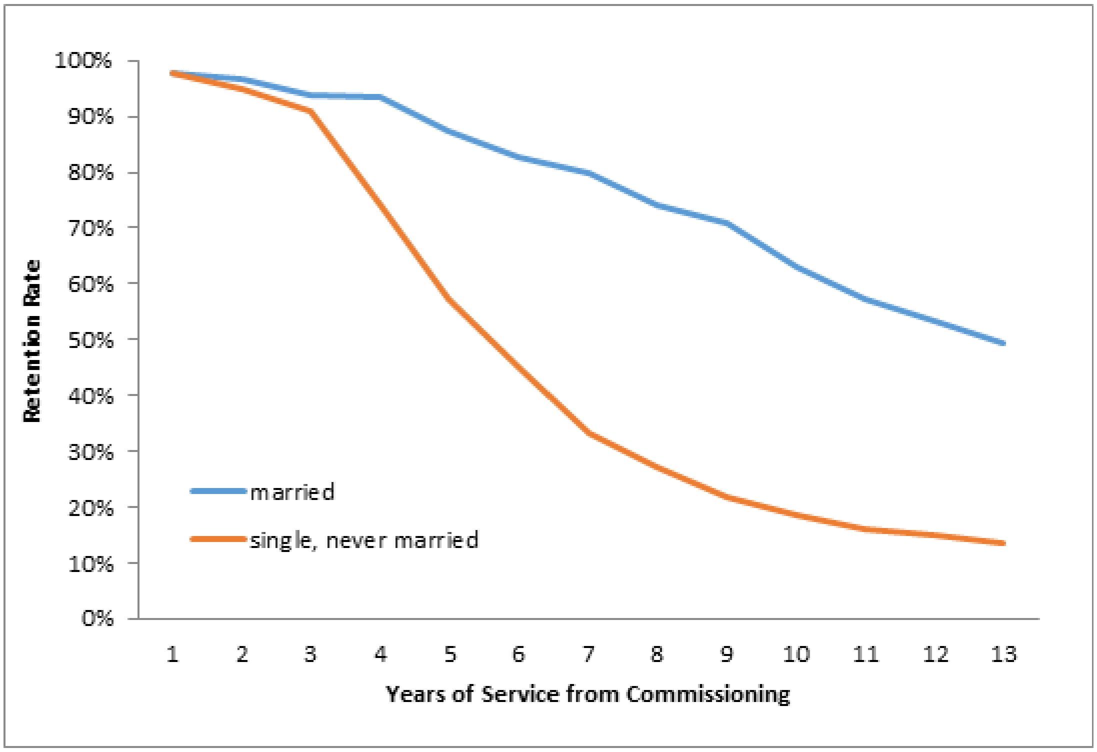


Source: DMDC. N=2,475. Dropping officers with unknown education variables from the sample.

Figure 12. Quarterly Mean Retention Rates among Naval Officers Commissioned in FY1999, by Graduate Education Attainment

Figure 13 shows, for each year, the percentage of officers who choose to remain or separate, by marriage status. It seems immediately clear that the Navy has a serious problem in retaining officers who are unmarried. According to the figure, by 12 to 13 years, the Navy has lost virutally all officers who are single.

In fact, the figure is somewhat misleading. The marriage sample are officers who were married at commissioning and remained married up to year 13. The unmarried sample are officers who were single at commissioning and remained single up to year 13. Those who switched status between years one and 12 (due to marriage or divorce) are excluded from analysis. The excluded group in fact is more than half of the sample.

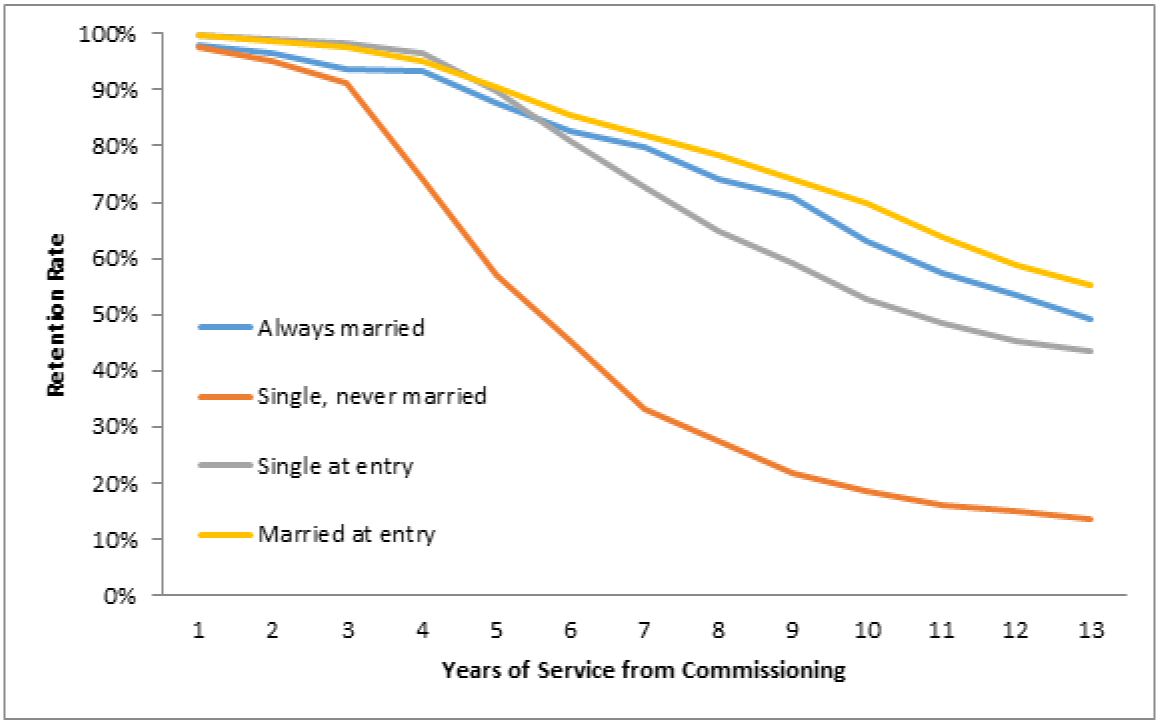


Source: DMDC. N=2, 953 for Cohort FY1999 sample. N=408 officers who are married from entry to YOS13 or until separation. N=842 officers who are single, never married, from entry to YOS13 or until separation.

Figure 13. Annual Mean Retention Rates among Naval Officers Commissioned in FY1999, by Annual Marital Status

To more accurately describe what a married or single officer's career trajectory may look like, it is more informative to follow a cohort based on their marital status at a certain point in time. In Figure 14, we define the married/single cohorts as those who are/are not married at the point of commissioning into service. Once they have been classified into the status, we keep track of their career decisions without altering their classification, even if they later decide to marry or divorce.

We see that once this adjustment is made, the retention rates of the two groups track closely, although the married (at year two) cohort is always more likely to stay in the Navy. The reason is that the two cohorts begin to look more like each other through the years. More of the single group marry, and some of the married group divorce. These groups never collapse into the same retention rate, most likely due to inherent differences (in preference for when to get married) in the two groups. While timing of marriage may seem inconsequential, it is intimately tied to timing of children and professional ambitions. A complete model of career trajectory will then have to explicitly account for marriage status.

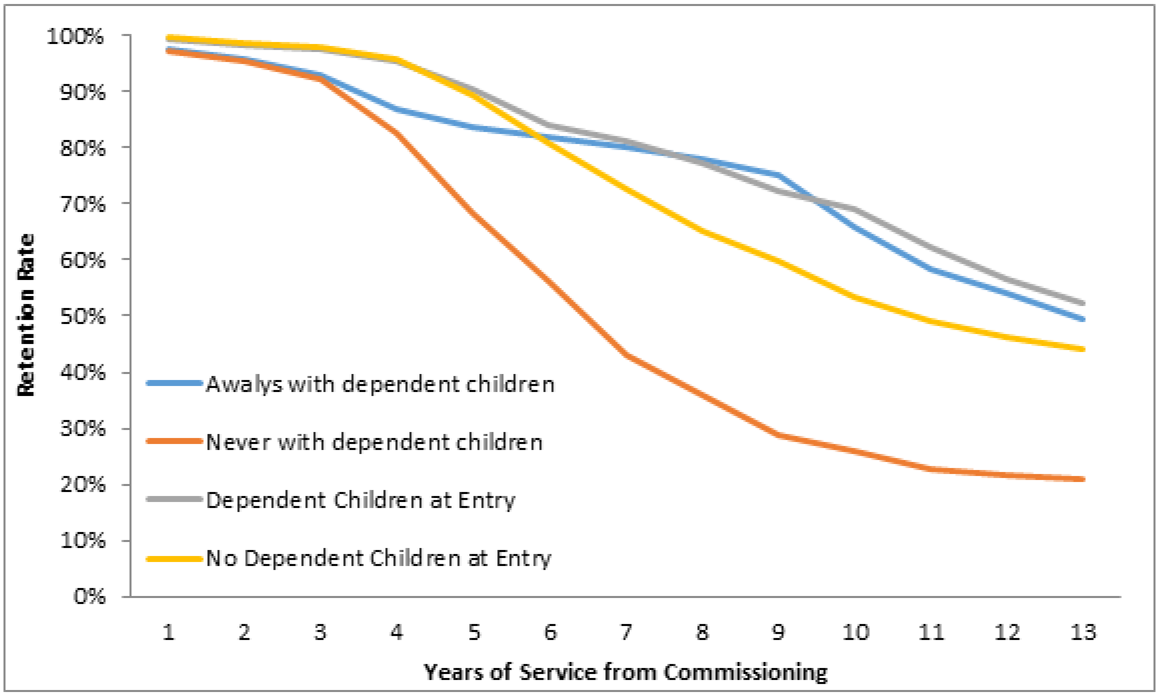


Source: DMDC

Figure 14. Quarterly Retention Rates among Naval Officers Commissioned in FY1999, by Marital Status Always/Never Married, Married/Single at Entry

Similar to Figure 14, Figure 15 tracks the retention rate of officers who always have children at commissioning vs. those who never have children (at least up to year 13), as well as those who have/do not have children at commissioning. Note that the difference between those who "always" have children and those who have children at commissioning is that an officer may have children who age out of dependent status.

Retention rates are much higher for officers who had dependents at commissioning. Whether this is due to financial responsibilities of providing for the family or inherent preference differences, the Navy seems to be more successful in retaining officers in marriages with children. We note that these trends are in line with civilian labor studies. Average quit rates decline with age, martial, and dependent status.



Source: DMDC

Figure 15. Annual Mean Retention Rates among Naval Officers Commissioned in FY1999, by Annual Dependent Children Status

B. REGRESSION ANALYSIS

We conclude the analysis section complementing the previous trends with regression results showing retention behavior at different points of service members' careers. Table 4 displays the regression results for the FY99 cohort sample. The first column contains the retention results after 20 quarters of service (i.e., at 5 YOS) for those officers that were in active duty at 2 YOS. This point in an officer's career is close to the end of the minimum service requirement (i.e., around 6 YOS). The second column exhibits the regression outcomes at 35 quarters of service (i.e., around 9 YOS) for those officers who were in active duty at 5 YOS. This is the time in an officer's career in which he/she is close to being evaluated for promotion to O-4 rank, when promotion becomes much more selective. Finally, the third column shows the officer retention behavior at 55 quarters of service (i.e., around 14 YOS) for those officers who were in active duty 35 quarters of service. At this time, most remaining officers have decided to stay in the military at least until 20 YOS. We note that officers in our data set are making career decisions prior to the BRS. Therefore, all officers are being impacted by the cliff-vesting aspect of the legacy pension system. Once an officer has gone past 14–15 YOS, there is very little sound economic argument to voluntarily leave the service before the pension vests.

The analysis is simple ordinary least squares, with sample sizes decreasing at each dependent variable due to attrition.[1] We include a myriad of socioeconomic characteristics, including gender, ethnicity, education, marital and dependent stauts, and commissioning method. Of particular note is that we do not include income information. While income is clearly important in an officer's decision to stay or leave the Navy, most officers with similar YOS will have very similar annual salaries, which could lead to some collinearity problems. In addition, a true measure of total income should include bonuses and other non-standard pay received. In addition to the difficulties in tracking down these payments, a much more complex problem is how to account for prior payments. For example, if an officer received a one-time retention bonus last year, should that be included in the compensation? For our current study, we abstract away from these difficult and complex issues. The impact of compensation (monetary and non-monetary) will be more formally addressed in reports to follow.

Consistent with our findings in Figure 9, Table 4 shows that female officer retention is lower compared to their male counterparts, specifically at 20 and 35 quarters of service. The impact of having dependent children at 2 YOS on retention is also significantly negative at 55 quarters of service, while having dependent children at 2 YOS and being a female officer is strongly negatively associated with retention at 20 quarters of service. As discussed in Figure 9, the latter outcome is most likely related to female service members serving as the primary caretaker of dependent children.

Relative to white officers, ethnicity seems to play an insignificant role on retention at the three career marks. This is in contrast to some of the trends observed in the previous section. This may be pointing to the fact that the average white officers look substantively different (along gender, education, marriage and dependent status) compared to the average non-white officer. While recruiting and retention policy can never be based on race, the implied sociodemographic differences across ethnicity may imply that policies to encourse a longer career in the Navy may have differential impacts.

Being married at 2 YOS is significantly and positively correlated with retention at 35 quarters of service, but being married at 2 YOS and female seems to have a mixed impact on retention. Traditional gender roles may still be playing a part in the long-term career trajectory of married couples.

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[1] We considered other, more sophisticated regression techniques, but ultimately decided in favor of the simpler method with easier to interpret parameter estimates. Subsequent research studies will build out much more complex and robust dynamic programming models.

Table 4. Regression Results for FY99 Cohort

Variable	*Retention at 20 Quarters*	*Retention at 35 Quarters*	*Retention at 55 Quarters*
Intercept	0.817***	0.858***	0.745***
	(0.000)	(0.000)	(0.000)
Female	-0.065***	-0.105***	-0.045
	(0.000)	(0.000)	(0.250)
Dependent Children at 2 YOS	0.019	0.026	-0.088***
	(0.184)	(0.241)	(0.001)
*Dependent Children at 2 YOS * Female*	-0.104***	0.07	-0.061
	(0.001)	(0.189)	(0.389)
Black	-0.02	0.018	0.03
	(0.401)	(0.623)	(0.483)
Asian	-0.024	-0.036	0.011
	(0.345)	(0.364)	(0.826)
Hispanic	0.001	0.005*	-0.01
	(0.953)	(0.086)	(0.782)
Married at 2 YOS	0.019	0.073***	0.003
	(0.167)	(0.000)	(0.912)
*Married at 2 YOS * Female*	0.088**	-0.171***	-0.057
	(0.012)	(0.002)	(0.456)
Age	0.006**		
	(0.012)		
USNA	0.033	-0.264***	-0.077*
	(0.138)	(0.00)	(0.055)
ROTC	-0.09***	-0.225***	0.056*
	(0.000)	(0.000)	(0.058)
Direct Other Commissioning	-0.01	-0.004	0.105***
	(0.583)	(0.893)	(0.001)
STEM College Major	0.008	-0.003	0.032
	(0.495)	(0.863)	(0.143)
Unknown College Major	-0.163***	-0.395***	-0.329***
	(0.000)	(0.000)	(0.000)
RL/Staff	-0.075***	0.036	0.005
	(0.000)	(0.118)	(0.868)
Number of Observations	2,896	2,598	1,808
Adjusted R^2	0.093	0.149	0.062

*Note: *,**,*** denote statistical significance at the 10%, 5%, 1% levels, respectively. P-values in parentheses*
Omitted group: Male, No Children at 2 YOS, White, Single at 2 YOS, OCS, URL

As expected, the officer age is significantly and positively associated with retention at 5 YOS, outcome that is consistent with the large military literature. We speculate that part of the story is that junior officers who enter service later in life may be more sure that they want a career in the Navy (possibly after experimenting with career(s) in the civilian sector or after serving for a period of time as an enlisted sailor). Another possibility is that a late start to one career necessarily closes off (or reduces the) the possibility of switching to a different career, even if one learns that they are a poor fit. If older officers are staying for the former reason, this is good news for the Navy, not just in terms of filling billets but in retaining an enthusiastic and happy officers corps. At this point, more research is required to determine the true motivating factors.

In line with Figure 11, having a STEM college major has no impact on retention at the three career points, while, on the contrary, having no information on the college major has a significantly negative association with officer retention at the three career marks. It seems likely that those with unidentified majors are officers who are not selected by the Navy for graduate education, sending a signal that they do not have a high likelihood of promotion beyond entry ranks. These candidates may then self-select out faster to pursue opportunities in the civilian sector. Finally, relative to URL officers, retention of RL/Staff officers is significantly lower only at 20 quarters of service.

We also note the significant amount of attrition of officers from USNA and ROTC programs beyond 5 YOS. Many of these officers will move on to more lucrative careers in the civilian sector. Indeed, this is a common observance across academy graduates in all services. While the Navy will not be able to compete against civilian firms on salary, it is imperative that we try and retain these highly qualified (and highly invested) assets as much as possible by implementing monetary and non-monetary benefits.

Table 5 displays the analogue regression results for all the sample cohorts (i.e., FY99 through FY03). Confirming results from the previous table, being female is significantly and negatively correlated with officer retention at the three career points. Relative to White officers, Black, Asian, and Hispanic officers have significantly lower retention rates at 20 quarters of service. Officers that are married at 2 YOS have significantly higher retention rates at 20 and 35 quarters of service relative to single officers at 2 YOS. While STEM college major has mixed impact on officer retention, having no information on the officer's college major, as before, is significantly and negatively correlated with retention at the three career marks. As in Table 4, relative to URL officers, RL/Staff officers exhibit lower retention rates, especially at 20 and 35 quarters of service. Finally, it is worth noting that, relative to the FY99 cohort, the other sample cohorts have significantly negative retention rates at 20 quarters of service.

Table 5. Regression Results for All Cohorts

Variable	*Retention at 20 Quarters*	*Retention at 35 Quarters*	*Retention at 55 Quarters*
Intercept	0.872***	0.848***	0.736***
	(0.000)	(0.000)	(0.000)
Female	-0.093***	-0.108***	-0.020*
	(0.000)	(0.000)	(0.065)
Dependent Children at 2 YOS	0.003	0.052***	-0.024***
	(0.730)	(0.000)	(0.001)
*Dependent Children at 2 YOS * Female*	0.02	0.031	-0.012
	(0.245)	(0.205)	(0.509)
Black	-0.025**	0.033**	0.006
	(0.019)	(0.026)	(0.583)
Asian	-0.030**	-0.009	0.009
	(0.016)	(0.599)	(0.482)
Hispanic	-0.027***	0.006	-0.004
	(0.005)	(0.574)	(0.674)
Married at 2 YOS	0.048***	0.052***	0.010
	(0.000)	(0.000)	(0.107)
*Married at 2 YOS * Female*	-0.010	-0.043*	-0.003
	(0.512)	(0.061)	(0.866)
Age	0.004***		
	(0.000)		
USNA	-0.003	-0.217***	-0.070***
	(0.755)	(0.000)	(0.000)
ROTC	-0.103***	-0.214***	-0.01
	(0.000)	(0.000)	(0.180)
Direct Other Commissioning	0.013	0.056***	0.019**
	(0.157)	(0.000)	(0.024)
STEM College Major	0.014**	-0.017**	0.009
	(0.024)	(0.032)	(0.133)
Unknown College Major	-0.248***	-0.394***	-0.093***
	(0.000)	(0.000)	(0.000)
RL/Staff	-0.044***	-0.025**	-0.01
	(0.000)	(0.014)	(0.156)
FY00 Cohort	-0.033***	-0.035***	-0.542***
	(0.000)	(0.003)	(0.000)
FY01 Cohort	-0.046***	0.005	-0.709***
	(0.000)	(0.662)	(0.000)
FY02 Cohort	-0.080***	0.038***	-0.707***
	(0.000)	(0.002)	(0.000)
FY03 Cohort	-0.051***	0.058***	-0.703***
	(0.000)	(0.000)	(0.000)
Number of Observations	15,610	13,264	9,334
Adjusted R^2	0.114	0.133	0.524

*Note: *,**,*** denote statistical significance at the 10%, 5%, 1% levels, respectively. P-values in parentheses*
Omitted group: Male, No Children at 2 YOS, White, Single at 2 YOS, OCS, URL, FY99 Cohort

V. GENERAL DESCRIPTION OF DYNAMIC PROGRAMMING

Dynamic programming models are complex mathematic and econometric model of dynamic, optimal decision making through time. Although several versions of dynamic programming models have been created and examined in the academic literature for at least 50 years, the most well-known variant to the DoD is the Dynamic Retention Model (DRM), developed in the 1980s by the RAND Corporation. It was/is the primary tool used by the DoD to evaluate the impact of the proposed talent management/personnel policy changes on service member retention. Dynamic programming reduces a complex, multi-period problem (such as an officer's lifetime labor market decisions) into a series of simpler, one-period sub-problems in a backward recursive manner. Solving a single-period problem that contains future decisions that the officer will make, allows us to estimate and forecast complex, decades-long behavior in a more tractable empirical framework.

The primary benefit of the DRM then is its ability to estimate a lifetime behavior model of officers and enlisted men and women where they would make logical choices at each point in time. The set-up of the model allows researchers, once estimation of the econometric model is finished, to simulate how changes in policy regarding salaries, retirement, and bonuses would affect the decisions of a representative (or average) officer or enlisted soldier. Recently, researchers have explored the potential impact of the BRS on military retention. The DRM and its extensions have been the workhorse of manpower/retention analysis in the military for the past 30-plus years, yielding valuable insights into the labor market decisions of officers and enlisted personnel.

The strength of the model from RAND was that it was able to accomplish this feat with such limited computing power from the 1980s. The substantive trade-off for the computational tractability was in the high degree of abstraction from the real world. Ultimately, this parsimony in modeling has meant that the DRM is attempting to characterize the very complex motivations and behaviors of soldiers and officers in making life-altering labor market decisions with a small number of regression parameters. It achieves this impressive feat by aggressively shrinking the state space (e.g., the set of information considered when making decisions) and drastically simplifying the model. As an example, imagine trying to predict the decision of an officer to retire or not without knowing his/her gender, marital status, number of dependents, education-level, health-status, or professional ability. The model predicts retention behavior for officers and enlisted members by service, but not by specialty area, and not adjusted based on the strength of the economy or service member quality. Furthermore, the model does not adjust for non-monetary compensation, which is becoming increasingly important under the current talent management initiatives. Nor does the model address the quality of the service members retained.

The principal of dynamic programming can be simply demonstrated in the following manner: A person has two choices, whether to select high (H) or low (L) across two periods. If choices are unconnected, the person selects whatever yields the greatest payoff at each period as depicted in Figure 16. So in periods 1 and 2, to maximize pay out the person would select (H,H) = $300.

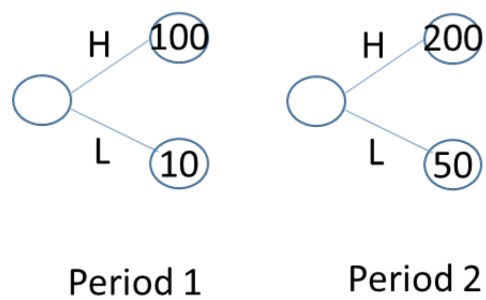

Figure 16. Independent Choices

Now, assume that choice in period 1 impacts possible choices in period 2, as in Figure 17. When there are a small number of periods and a limited number of choices, we can "brute force" solve for the solution by calculating the payoff for every path. Since (H,H) = $300, (H,L) = $150, (L,H) = $60, and (L,L) = $1,010, we select (L,L) to attain the maximum pay out.

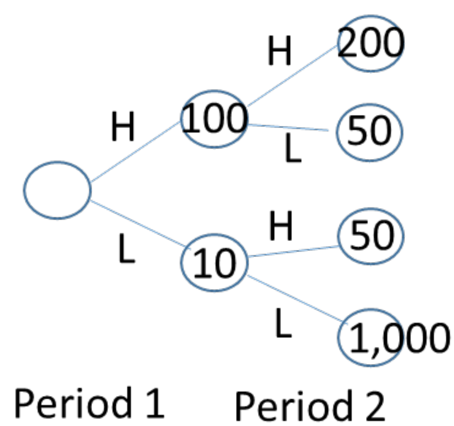

Figure 17. Dependent Choices

As the number of periods and/or the number of choices increase, the problem becomes more complex. For example, keeping the number of choices at two (the simplest possible scenario), with one period, there are two possible outcomes. With two periods, four possibilities, and with three periods, eight. Over a 30-period span, there are 1,073,741,824 possible outcomes.[2] It would be inefficient to calculate all 1+ billion outcomes. Economists realized that it was possible to exploit a mathematical representation of this dynamic discrete choice problem by breaking the payoff from one choice into the component received today plus a future term that is constructed by assuming that rational, optimal decisions will continue to be made by the individual into the final period. This is also called Bellman's principle of optimality (or Bellman's equation).

The logic is as follows. If we are at period 30 (the terminal period) and choose between H and L, the problem is simple. We simply select the option that yields the highest payoff. If we pull back one period to 29, we solve another easy problem, because we already know what choice we will make in 30 (the optimal one). We continue this logic back to the initial period. This is called backward recursion. Note the utility of this methodology. Assume instead we are myopic and attempt to select the best option in each period, without looking forward. Then, going back to our simple two-period example, we would choose (H, H) and attain \$300 instead of the maximum possible \$1,010.

An additional difficulty arises in evaluating the behavior of officers to stay in the Navy or retire in this framework arises from the fact that we are not simply evaluating monetary payoff as in the simple example above. While there are undoubtedly monetary considerations, the retirement decision is inextricably tied to family, health, geographic, and professional reasons that are very difficult to monetize.

In a simple one-period framework, if an officer is faced with the decision to retire or not, he/she will be comparing the monetary benefit of staying (quantifiable as \$A) and the non-monetary benefits (not necessarily quantifiable as B) against the monetary benefits (\$C) and non-monetary benefits of leaving (D). If the officer is observed to stay in the Navy, then we know that

$$\$\mathrm{A} + \mathrm{B} \geq \$\mathrm{C} + \mathrm{D}.$$

If he/she opts to leave, we know that

$$\$\mathrm{A} + \mathrm{B} < \$\mathrm{C} + \mathrm{D}.$$

So while we would be able to tell that the sum of benefits from one option is more attractive than the other, it is difficult to know by how much: we need an "exchange rate" between the non-monetary characteristics and salary. We need to rely on the econometric technique to translate B or D into dollars in order to make policy recommendations. So then, a DRM must not only solve the

[2] It should be noted that a stay-or-leave model, where leaving implies permanent exit, is much simpler in terms of the potential number of outcomes, as long as staying leads deterministically to one and only one state.

backward recursion problem, but it must also distinguish how officers value money in relation to other non-monetary characteristics of the job.

Possibly, the first full-blown DRM in the military economics literature is the one developed by Gotz and McCall (1984) working at RAND. They analyzed the stay/leave decisions of Air Force officers facing diverse compensation incentives at different moments in their careers. The DRM has been extended in various ways to tackle a myriad of other topics in military manpower policy. Asch, Johnson, and Warner (1998) and Asch and Warner (2001) analyze how changes to the retirement benefit system and basic pay would impact retention. The latter paper also adds individual ability and effort to the model. Hosek, Asch, Fair, Martin, and Mattock (2002) extend the model to include the initial decision to enlist, looking specifically at IT workers in the military. Mattock and Arkes (2007) examine retention for Air Force officers. Asch, Mattock, and Hosek (2013) extend DRM to calculate retention cohort size as new policies are introduced and follow them through time, estimating the transition path until the new stable equilibrium. Asch, Mattock, and Hosek (2017) examine the potential impact of changes to the BRS across the services. Gotz (1990) contains a detailed discussion of the advantages of DRM over other models of employee retention behavior, such as the traditional ACOL model.[3]

In estimating a dynamic programming model, we deal with two persistent problems:

First, note that our example only deals with two potential "states" each period. The agent can choose H to get to one state, or L to get to the other. Even in such a simple problem, across 30 periods, the number of states explodes to more than a billion. If there is a third choice available, there will be 205,891,132,094,649 states at the 30th period. With small increases in the number of states/periods (say, by including race/gender), we easily approach such a number of required calculations that approach and surpass the number of atoms in the universe. This rapid growth in "state space" is called the curse of dimensionality.[4]

Second, even the substantial simplification by the use of Bellman's equation requires us to calculate the future value of the subsequent choices to be made each period. This future term is traditionally derived through a nested-fixed-point-algorithm. This relies on a mathematical concept called contraction mapping which starts with a random guess at the value and loops through the

[3] This is not an exhaustive list of extensions and applications of the original Gotz-McCall model, but it does represent a good cross-section of the ways in which the model has been pushed forward.

[4] The retention problem is usually cast as an "optimum stopping problem," where the decision to separate is an absorbing state. Once that decision is made, the individual receives the outside option and the problem is terminated. This reduces potential state space significantly, but not enough to allow "brute forcing" the solution.

problem continuously, at each iteration getting a better estimate of the future value until the difference in future value across iterations shrinks to some very small number. The computational burden to solve a modest model would traditionally require weeks of computing time at a supercomputer. Any alteration of the model would require calculations to be redone. Together, this has meant that any dynamic discrete choice model would have to walk a fine line between computational tractability and fidelity of the model to the real world.

The literature in the recent past has attempted to overcome the computational burdens of dynamic programming by abandoning *exact* value function calculations and focusing on approximate solutions that can reduce computational time. Among full-solution methods, which still require the explicit calculation of the value function using the nested-fixed-point-algorithm, authors have successfully reduced the time to estimate the model through discretization, approximation and interpolation of the "Emax" function, and randomization.

Recently in the literature, estimation methods that do not require solving the full dynamic programming problem have been applied across a range of labor economics problems. The most promising is the CCP method, pioneered by Hotz and Miller (1993). The model cleverly uses nonparametric estimations of the choice and transition probabilities (how likely are individuals to make certain career choices and how likely is the state space to change?) to circumvent the need to calculate the value functions. Some recent examples that have used the CCP method includes Slade (1998), Aguirregabiria (1999), and Sanchez-Mangas (2002).[5]

An important limitation of CCP was its inability to accommodate permanent unobserved heterogeneity. If the individuals differed in an important way leading them to make different choices given identical pay structure, but we lacked the ability to observe how these individuals were different, the model would be unable to account for these behaviors. Advances in estimation have enabled the incorporation of finite mixture models to extend models to accommodate permanent unobserved heterogeneity (Aguirregabiria & Mira, 2007; Arcidiacono & Miller, 2011; Kasahara & Shimotsu, 2008: Arcidacono & Ellikson, 2011).

[5] There have also been advances in using Bayesian statistical techniques to lessen computational burden. These techniques are newer and have not been as robustly applied (Imai, Jain, & Ching, 2009).

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VI. TECHNICAL DESCRIPTION OF DYNAMIC PROGRAMMING MODELS

In this section, we parsimoniously describe a simplified version of the DRM appropriate for analysis of the Navy.

We assume officers are fully rational agents that make career choices to maximize their lifetime utility. In particular, we suppose that the individual weighs all the costs and benefits in each decision, including both the monetary and non-monetary components. At the end of each period (e.g., year), the officer decides to either stay in the Navy for another period or leave. The complete model will attempt to intelligently account for periods in a career where voluntary separation is not possible. We assume (for now) that returning to the Navy after leaving is not possible, so the leave decision is irreversible.

Note that the assumption of the fully rational agent is a very high standard. Officers must, in theory, be able to correctly predict professional outcomes (in and out of the Navy) at every point in their career, as well as changes to personal status, and make the optimal decision at every point in time. Considering the fact that we will require the use of a cluster server (the Hamming supercomputer at the Naval Postgraduate School) to solve this model, our model may appear to be unrealistic. However, there are four reasons to choose dynamic programming as the modeling framework.

The first reason is that the fully rational assumption can be supported in a more modest sense when we consider that people do try to think through important choices, gather advice from friends, family, and senior officers, and the Navy itself has out-reach programs to try to educate personnel on making smart retirement decisions. Even if a naval officer making retirement decisions is not a supercomputer, as long as he or she is making rational decisions following best-practices and good advice from experts, dynamic programming models are expected to have good predictive powers. The second reason is that dynamic programming models have been shown in the academia to have good performance in actually modeling and predicting dynamic systems in a number of different labor markets, as well as industrial organization problems. The third reason is that with the estimates from the model, we are able to generate powerful simulation exercises to explore a myriad of policy changes. The final reason is that prior models used to generate predictions or recommendations are fundamentally flawed. We discuss shortcomings of these other models later in the report.

The monetary components that the individual considers include the following: (1) regular compensation, military pension, and bonuses and (2) outside compensation (e.g., potential income in the private sector). The non-pecuniary components can include the individual's taste or preference for military life (or equivalently, preference for civilian life).

The basic notation includes the following:

- W_t^m indicates the regular compensation that the individual can obtain in period t (including bonuses).
- W_t^c denotes the compensation that the officer can obtain in the civilian sector in period t (including retirement).
- T represents the time horizon of the decision problem (e.g., the expected number of periods until final retirement).[6]
- $\beta = \frac{1}{1+r}$ indicates the discount factor, and r is the subjective discount rate of the officer.
- ω^c denotes the taste parameter that captures the monetary equivalent of the preference for the civilian life.
- ω^m denotes the taste parameter that captures the monetary equivalent of the preference for the AWF and military work.
- $E_t[.]$ is the expectation operator given the information in period t.
- ε_t^c and ε_t^m are random variables with zero mean.

We let super-index L denote the decision to voluntarily separate and super-index S refer to the decision to remain. Then, the officer's problem can be written as follows:

$$V_t^L = W_\tau^c + \omega^c + \beta E_t[V_{t+1}^L] + \varepsilon_t^c = \sum_{\tau=t}^{T} \beta^{\tau-t}(W_\tau^c + \omega^c) + \varepsilon_t^c, \quad (1)$$

$$V_t^S = W_t^m + \omega^m + \beta E_t[V_{t+1}] + \varepsilon_t^m, \quad (2)$$

$$V_t = Max[V_t^L, V_t^S] \quad (3)$$

where V_t^S denotes the present value of staying for another period while V_t^L indicates the present value of leaving to pursue a civilian career. According to this setup, the officer will remain as long as the value of staying, V_t^S, exceeds the value of leaving, V_t^L. This decision problem refers to a specific officer and, thus, all variables and parameters are individual specific.

Future work will begin developing a new augmented DRM for the Navy. The modeling effort will include both model development and investigations into different questions regarding retention, which directly relates to force size and shape, officer quality, and other talent management initiatives. The answers to these specific questions will support personnel policy decision makers in both the short and long run.

[6] To avoid further complexities, we assume that income after retirement (i.e., beyond horizon T) is the same regardless of his/her stay/leave choices. Thus, we can disregard this stream of payments.

While the original DRM has served the DoD well, since the 1980s there have been substantial gains in computing power, and research into dynamic programming techniques has pushed the frontier vastly forward in terms of what is estimable and predictable. We can now take into account important sociodemographic characteristics of the agents (such as gender, race, education level, marital status, etc.) or accommodate potential changes to personnel policy that are not easily monetized.

A. PRIOR ALTERNATIVE RETENTION MODELS

One of the main features of the DRM described above is the correct way of solving the agent's maximization problem from the point of view of rationality, which results in a time consistent behavior. Unfortunately, an undesired consequence of that feature is the difficult solution and estimation of the model. In an attempt to make the latter easier, different simplifications of the DRM have been proposed. The main departure from the DRM is the way of solving the military members' maximization problem. In those models, the maximization operation is performed in different ad-hoc, non-rational ways, potentially yielding time-inconsistent behaviors. This means that the "optimal" plan of action determined in a given year becomes (most likely) suboptimal in the future. This fundamental problem does not occur with the DRM.

The ACOL model appeared in the academic literature at the beginning of the 1980s (Enns, Nelson, & Warner, 1984; Warner & Goldberg, 1984), and became the most well-known alternative model to the DRM in the military retention literature. This fast success was partly due to its simplicity in the estimation of the model parameters. However, as mentioned above, its predicted behavior is most likely time inconsistent. Policy changes based on recommendations from these older models with inaccurate forecasts will suffer from at best inefficiency, and at worst outcomes contrary to the desired effect.[7]

[7] See Arkes, et al., (2019) for a more thorough review of the literature and prior models.

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VII. CONCLUSIONS AND THE PATH FORWARD

With the background analysis completed in this study, we plan to create a new DRM from the ground up to custom fit the particular structure and needs of the Navy. Our long-term research objectives are aimed towards building a DRM that ultimately will better address the retention impacts of monetary and non-monetary incentives. In the future, our goal is to develop a model that, relative to existing models, can accomplish the following:

(1) Better predict the impact of changes in monetary compensation.

It is simple enough to reason that an increase in monetary compensation through pay raises or bonuses will increase the *average* tenure of officers in the Navy and decrease attrition. However, it is often difficult to forecast the response of officers who are at different points in their careers. As an example, the implementation of the BRS in FY 2017 greatly altered the potential income streams of those who had not planned to stay in the Navy until their pensions vested at 20 years. Indeed, it may have also altered the career paths of those who had planned remaining until (and past) 20 years of service. Simulations using a dynamic programming model will be able to better forecast retirements of the entire officer corps to allow decision makers a better sense of the long-term trajectory of the force. Furthermore, when a shortage or surplus of the workforce is predicted to arise in the future, simulation exercises with various incentives (one-time and permanent changes) can assist in crafting policies to delay or accelerate retirement or attrition.

(2) Evaluate the effects of various non-pay policies.

In addition to inducing changes in retention behavior by the use of monetary compensation, the leadership may have additional policy levers in the form of non-monetary benefits. For example, more generous family or sick leave policies, flexibility in deployment location and time period, access to education or training may all impact an officer's decision to stay or go. Careful construction of the model may allow us to elucidate potential effects of these policies.

(3) Assess the impact on employee quality.

When the leadership identifies deficits or surpluses in the number of officers to fill the required billets, it may alter monetary and non-monetary policies to impact retention behavior. However, care must be taken to ensure that negative self-selection does not occur. Negative self-selection in this case refers to the economic theory that workers who have the worst outside options (lowest level of skills, training, or education) are those who are easiest to persuade into staying longer at their current position. Dynamic programming models, correctly specified, will be able to investigate retention of officers with different ability characteristics.

(4) Incorporate the effects of the state of the economy.

The officer corps does not exist in a vacuum. Retention of the military workforce, especially one so highly educated and motivated, is impacted by the state of the economy, such as economic booms and recessions. For example, the United States currently enjoys historical lows in unemployment with an expanding private sector that demands more employees. Furthermore, the rise of the gig economy has lowered the bar for individual entrepreneurial ventures. These factors are expected to lead to difficulties in recruiting and retaining high quality officers. Our proposed future work will incorporate economy-wide factors.

(5) Perform the above analyses for separate MOSs.

The naval officer corps is not uniform. Different MOSs all have their unique workforces with differing skillsets, requirements, and short-run and long run objectives for recruitment and retention. The dynamic programming model will attempt to custom-fit each group's needs to analyze policies for each career field separately.

One note of caution in these proposed simulation exercises is that the predictions we will generate rely on the labor market system remaining in a relatively stable equilibrium. If drastic changes in the economy occur within a short period of time, similar to the Great Recession leading to massive increases in unemployment or the tech-bubble in the early 2000s, driving rapid growth of wage and labor demand, such that they significantly alter the labor market of civilian workers and firms, the spillover is expected to impact not only the career trajectory of mid-career officers, but also recruiting efforts.

In conclusion, our future proposed DRM model will allow the leadership to be proactive in identifying potential long-term problems in the shape and quality of the workforce, arising from the changing economy, demographics, and competition from the civilian sector. The simulation capabilities of the model will allow the leadership to forecast the impact of potential monetary and non-monetary incentives to counteract “brain drain” and retain the best and brightest of the workforce.

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