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Attrition Among the DoD Civilian Workforce

October 29, 2019

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Graduate School of Defense Management

Naval Postgraduate School

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Executive Summary

This study examines the determinants of attrition among the Department of Defense civilian workforce. We follow a cohort of civilian employees newly appointed in 2009 and track their separations through 2017. Using personnel records obtained from Defense Manpower Data Center (DMDC) master files, we model the career life-cycle characteristics of employees and how those characteristics influence individual behavior. This research strategy generates a series of survival curves that illustrate differences in attrition behavior across a variety of workforce subpopulations.

The primary finding of the analysis relates to sex-based survival differentials for employees in different types of job categories. The Department of Defense (DoD) maintains a strong interest in ensuring that its workforce possesses the technical skills necessary to sustain a technological advantage over its adversaries (Asch, 2002). The study used a job classification code to identify whether employees are in career fields related to science, technology, engineering, and math (STEM). Separate survival analyses were conducted for men and women within each job classification While non-STEM employees exhibited higher attrition among women, no sex-based attrition differential existed for the employees in STEM career fields. This finding highlights the need for increased recruitment efforts and education campaigns to increase representation among women in STEM job categories within the DoD civilian workforce.

Another important finding is that there is a significant gender gap in appointees that have prior active duty service. Our analysis of the 2009 cohort reveals how the DoD relies on a large influx of employees that have retired from active duty military service and wish to pursue secondary careers as civilians. Women make up a disproportionately small share of these new hires. As the DoD considers its future recruitment strategies for civilian positions, it should consider how these jobs are advertised and communicated to retiring active duty personnel and seek to identify how it can increase the visibility of these positions to women.

This findings from this analysis are especially relevant because there is a lack of studies using actual employee attrition behavior in the public sector human resource

management literature. The data used in this analysis describing and following the 2009 employee cohort is a major step forward in making use of available personnel data to generate information that can help guide human resource management for the DoD. Much of the prior research has had to rely on agency average attrition rates as well as inaccurate proxies for actual employee behavior. Additionally, the focus of this study on the civilian workforce makes these findings more generally externalizable to other public sector employees. Managers outside of the DoD may find value in these results as they consider how to manage workforce attrition in other public-sector contexts.

Acknowledgments

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This work was performed in collaboration with NPS faculty supported by the Department of Defense Office of People Analytics. The views expressed in written materials or publications, and/or made by speakers, moderators, and presenters, do not necessarily reflect the official policies of the Department of Defense or the Office of People Analytics, nor does mention of trade names, commercial practices, or organizations imply endorsement by the U.S. government.

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Introduction

Purpose

This study is an analysis of attrition among civilian employees of the Department of Defense (DoD). This research is sponsored by the Acquisition Research Program[1] (ARP) at the Naval Postgraduate School. The study uses employee personnel data accessed through the Army Analytics Group's (AAG) Person-Event Data Environment (PDE). These data are used to observe employee separation behavior and then model how individual employee and organizational attributes are statistically associated with separation behavior. The attributes used to model separation behavior include age, years of service, job classification, and prior active-duty service. These data describe the career life cycle of civilian employees and help reveal the factors associated with the probability of separating from civil service.

Understanding the determinants of attrition within the civilian workforce is an important concern for the DoD. Maintaining the skills and competencies necessary for job classifications associated with science, technology, engineering, and math (STEM) is a strategic requirement if the United States is going to maintain a technological advantage over its adversaries (Asch, 2002; National Academy of Engineering et al., 2012). By determining how separation behavior among employees in STEM career fields differs from the rest of the workforce, this study may help DoD officials improve their strategic management of human resource assets.

This research can also help inform DoD efforts to ensure that it develops a workplace environment that offers equal opportunities for all persons and that hostile factors for women and minorities are mitigated. There is a long history of studying how diversity affects and even improves workplace performance within the DoD (Knouse & Dansby, 1999). This study furthers this research by examining specifically how gender differentials in employee attrition vary across STEM and non-STEM job categories. The primary finding of this analysis is that, if the DoD is concerned with increasing women's

[1] Project number FY-036 *An Analysis of Employee Satisfaction Measures and Workforce Attrition Rates*

representation in STEM-related fields, recruitment efforts rather than turnover mitigation strategies would be more effective. While women experience higher turnover rates in non-STEM and medical job classifications, our analysis reveals no significant gender differential in the survival of STEM civilian employees.

Background

This project was carried out in collaboration with a research team located at the Naval Postgraduate School in the Operations Research Department. That team is sponsored by the Department of Defense Office of People Analytics (OPA). This report and another report (Buttrey, Whitaker, & Klingensmith, 2019) authored by the research team describe the same research activities, data collection efforts, and research methodologies. The technical report delivered to the OPA is much more focused on describing the methodology and technical features of survival analysis for workforce attrition modeling. Part of its mission is to enable the OPA to adapt the survival analysis methodology to its own work, as well as give a technical assessment of the feasibility of using the PDE data environment for applied research. This report focuses on the managerial implications of attrition modeling. This study also develops more fully the implications of the empirical findings for professional practice. Because both studies describe the same data cleaning and quantitative analytic procedures, significant portions of the sections of the OPA report describing those technical aspects of the study are quoted in this document.

Team Members:

- Dr. Lyn R. Whitaker, Associate Professor, NPS
- Dr. Samuel E. Buttrey, Associate Professor, NPS
- Dr. Spencer T. Brien, Assistant Professor, NPS
- Dr. Andrew Anglemyer, Assistant Professor, NPS
- MAJ Kurt Klingensmith, Combat Analyst, TRAC-MTRY

This analysis of workforce attrition was also supported by five NPS students that have either completed or continue work on master's theses using the project data:

- CPT Racheal Mwangi, MS, Management Defense Systems Analysis, December 2018.

- LT Brittany Morgan, MS, Operations Research, March 2019.
- LCDR Anthony Urech, MS, Operations Research, March 2019.
- LCDR Stephanie Paone, MS, GSDM, Expected March 2020.
- LT John McCauley, MS, GSDM, Expected March 2020.

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Scope

The objective of this study is to examine the factors associated with attrition among the DoD civilian workforce. This study will pursue this purpose by developing a survival model of the length of time individuals remain employed following their appointment. A cohort of all individuals appointed to positions in 2009 is constructed from the personnel master files maintained by the Defense Manpower Data Center (DMDC). We use a machine-learning algorithm to identify the factors that are most closely associated with workforce attrition at different lengths of employee service.

This analytic exercise generates two outputs that can help DoD officials gain a better understanding of workforce attrition and eventually inform policy and practice. The first is a set of survival curves that illustrate the relationship between the length of time since the current appointment and the probability that an individual will experience attrition, or separation from DoD employment. These survival curves illustrate how the probability of attrition changes at different points in time, from a relatively high rate of separation during the first few years of employment, to a more stable mid-career period, and then transitioning into a higher rate of attrition as retirement eligibility becomes a driving factor in voluntary separations.

These survival curves can also be used to differentiate between subpopulations within the DoD civilian workforce. It is this differentiation that allows this project to pursue its secondary goals of examining how gender and participation in STEM-related career paths interact and influence turnover outcomes. The findings from this analysis strongly suggest that if the DoD is interested in increasing women's participation in STEM-oriented occupations, its resources would be best spent on recruitment and outreach efforts, rather than retention efforts. The findings of this analysis reveal little to no gender-based differential in employee survival once other factors related to career life cycle are incorporated into the model.

An additional product of the survival analysis methodology is a "survival tree" that illustrates the subdivisions within the workforce and how attrition within each "branch" of the population is driven by different sets of variables. The survival tree approach demonstrates the limited subgroup of the non-STEM workforce where gender does appear to be statistically associated with higher attrition rates. Another benefit is that survival trees can use categorical variables, such as age groups or organizational subdivisions, to reveal where the overall workforce splits in its observed attrition behavior. This methodology can help DoD officials to understand the similarities and the differences in the behaviors across different elements of the civilian workforce.

Literature Review

An essential part of adequately resourcing the DoD is ensuring that its human resources are sufficient to meet its operational requirements. Understanding workforce attrition, defined here as either the voluntary or involuntary separation of an employee from service, is an essential component of maintaining necessary workforce levels. Researchers interested in defense management have for years examined attrition among uniformed military personnel (Baldor, 2018; Buddin, 1984, 2005; Gebicke, 1998, 1999; Rabkin, 2000; U.S. General Accounting Office, 1997). The Department of Defense is also reliant, however, on civilian employees for a variety of functions, and attrition among the civilian component of the DoD workforce has received much less attention. Despite the lack of research on the determinants of civilian attrition, researchers have been aware for decades that factors such as pay freezes, furloughs, and other federal policies add significant volatility to the size and structure of the civilian workforce change (Fernadez, Gotz, & Bell, 1985).

Among the research that does exist on the civilian DoD workforce, two studies are most relevant to the issue of workforce turnover. The first describes the RAND Corporation's "dynamic retention model (DRM)" (Fernandez, Gotz, & Bell, 1985). This model seeks to identify how changes to fiscal policies, including pay and other benefits, influence voluntary attrition. The results of their analysis of the civilian workforce highlights the behavior of veterans who enter civilian employment after retiring from a uniformed military career. One major limitation of the RAND analysis is that the DRM model does not incorporate demographic attributes of individual employees that influence voluntary separation.

Another study of turnover among the DoD civilian population was conducted by the Partnership for Public Service (2014), a non-profit think tank. Their study examined attrition rates reported by the Army and National Labor Relations Board and found that the DoD civilians experienced higher attrition rates than civilian employees in other federal agencies. Their findings also identified gender differentials in attrition rates that showed women separating from federal employment at higher rates than men. This study shares a limitation with the RAND analysis in that it focuses on aggregate behaviors and does not study individual employee-level personnel data.

Although attrition studies of the DoD civilian workforce are relatively sparse, there is broad public-sector human resource management literature that may inform this analysis. An important subset of this literature examines the factors associated with gender differentials in employee attrition. In the public-sector human resource literature employee attrition is discussed using the term *turnover*. Although the term *turnover* may include an assumption that any employee losses will be immediately replaced, for the purposes of this study, we will use attrition and turnover as synonyms.

Historically, researchers studying the public sector workforce at federal, state and local levels have observed women separating from public service at higher rates (Lewis & Park, 1989). Understanding the roots of this disparity is important for maintaining an adequate DoD workforce. Eliminating discriminatory practices is necessary for compliance with Equal Employment Opportunity laws. It is also important from a managerial perspective to develop an employment environment that enables qualified and productive employees to remain in public service. Given the costs associated with hiring and training qualified personnel, it is important to ensure that employee attrition is not increased by inequitable practices.

Early research on gender differentials in employee turnover date from the 1970s. These early studies examine the factors that lead employers to invest less in training and retaining female employees (Bartholomew, 1979; Mancke, 1971; Sawhill, 1973). A primary assumption in this literature is that gender itself is the primary factor driving differential outcomes for women’s separation behavior in the workforce.

A new branch of literature that began in the 1980s began to challenge the hypothesis that attrition among women is driven by gender. These studies were driven by more robust quantitative analyses of employee pay and demographics. Their primary theoretical contribution is the development of a concept of the employee life cycle (Blau & Kahn, 1981; Kellough & Osuna, 1995; Lewis & Park, 1989; Moynihan & Landuyt, 2008;). The concept of the employee life cycle recognizes that employee separation behavior is largely driven by where an individual person is in his or her career path. At different periods in a person's career, whether it be soon after starting a new job, or as he or she approaches retirement eligibility, there are broad patterns associated with the likelihood that an individual will separate from public employment. Controlling for pay and other benefits also contribute to this model of separation behavior. The primary findings of these studies revealed that once factors such as age, years of service, type of work, and pay are taken into consideration, the effect of sex on attrition becomes statistically insignificant. In other words, controlling for the employee life cycle, women and men make similar choices about when to separate from their employment.

The repeated finding that sex is not statistically significant in public sector attrition models has not gone unchallenged. Workforce studies about the challenges that women face in careers associated with STEM have obtained a variety of specific results that identify persistent forms of sex discrimination that contribute to higher turnover for women. This branch of research examines women working in academic positions at universities in STEM-related fields. Surveys of women in these careers revealed a variety of conditions that are detrimental to women's careers (McCullough, 2011; Xu, 2008). One study found that, controlling for measures of academic productivity, women in STEM academic positions perceived that they received lower performance evaluations (Riffle et al., 2013). The same study by Riffle et al. (2013) also found that women perceive that they are less included in intra-departmental discussions. This lack of collegiality can harm women's professional performance and subsequently increase the likelihood of attrition. These results may carry over to other public-sector STEM careers where collaboration and mentorship are important factors to professional success.

Another important component of the public sector human resource management literature is its analysis of research methodologies for analyzing attrition. Nearly all of the research covered in this discussion has suffered from a lack of access to individual employee personnel records. Without these data to identify individual employees separate from public employment, researchers have been forced to rely on various proxies. One of these approaches has been to use "turnover intention," or an employee's stated intention to separate from their employment in the near future. Surveys of employee characteristics have included turnover intention to investigate the broader issue of why people quit their jobs. A recent study has called research relying on the turnover intention as a proxy for actual workforce attrition (Cohen, Blake, & Goodman, 2016). The authors obtained both turnover intention data with actual turnover behavior for the same workforce. Their analysis of the two measures found that turnover intention only describes approximately 4.2% of actual turnover behavior. They also used intention and behavior as dependent variables in two models of employee separation. This revealed that a model which explains 59% of the variation in actual attrition behavior only explains 12% of turnover intention responses. The findings of Cohen et al. (2013) bring a major challenge to the validity and explanatory power of prior studies that have used turnover intention to proxy for actual behavior. Employees' stated beliefs on their likelihood of leaving their jobs in the near future do not appear to be closely associated with their actual behavior.

The problems with turnover intention are critical because this variable has been the best available option for many human resource researchers. Individual-level employee personnel data have not been widely available due to privacy concerns. There is an urgent need in both the academic and the practitioner community for new studies of workforce attrition that examine how actual employee behavior is affected by factors associated with the employee career life cycle. Additionally, questions associated with Equal Employment Opportunities deserve more robust analysis using actual behavior rather than turnover intention. This may help resolve some of the tension between the broader empirical studies that found little impact of sex on turnover and the more focused analysis of how women in STEM fields suffer from adverse environmental factors that increase their likelihood of separating from public service.

Methodology

This section describes the methods used in this analysis to examine workforce attrition. This methodology is shared with the parallel civilian attrition report "Civilian Department of Defense Attrition Analysis" conducted through TRAC-Monterey (Buttrey et al., 2019).

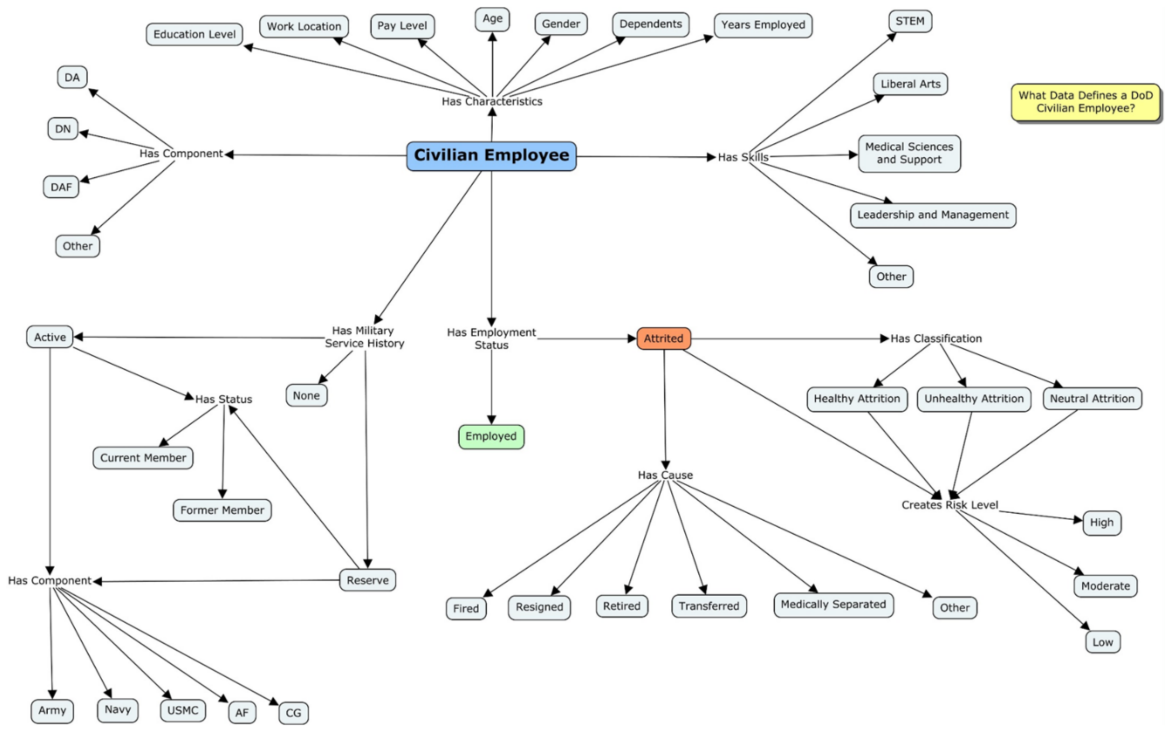

Figure 1. Civilian Employee Concept Map

(Buttrey et al., 2019, p. 25).

The first step in the analysis was to develop a Concept Map of DoD Civilian employees. This concept map provides a framework for understanding the factors associated with attrition. Concept Maps are visual depictions of the relationships that exist between concepts (Novak & Cañas, 2008). Figure 1 depicts the concept map the civilian attrition team developed to describe the relationships between the available data fields obtained from personnel records and attrition behavior. The upper half of the concept map describes the personnel characteristics of the civilian employee. These include individual characteristics that describe the employee career life cycle (age, years of service, pay) and other demographic characteristics. It also describes the branch of service within the armed forces and the career type attributes of the employee.

The southwest quadrant of the figure describes prior military service of civilian employees. As shown later, a significant share of the DoD civilian workforce has prior military service that is counted separately from their civilian years of service. Age at entry is much later for this subset of the civilian workforce, and therefore the relationship between civilian years of service and voluntary separation behavior is categorically different. The southeastern quadrant of the concept map describes whether the employee separates from employment status, or “attrited.” It also describes the various types of separation codes associated with separation and the degree of risk the separation creates for the DoD enterprise.

Data Structure

The primary data source for this analysis are the personnel records contained in the civilian master files maintained by the Defense Manpower Data Center. Access to these data is managed through the Person-Event Data Environment, which is maintained by the Army Analytics Group (AAG). The cleaning and structuring work done by the research team on the DMDC civilian master files is described in detail in the TRAC-Monterey report:

> These datasets, maintained by DMDC, contain demographic and detailed information found in an employee’s personnel file. We merge the civilian transaction files with the civilian master files to catch all the data transactions that take place within each employee’s record. These transactions are changes in the employee’s career, which include salary changes, changes of appointment, and, most importantly, separation. We flag those employees with separation transactions to determine which employees attrite during the eight years of our study. We also classify employees as “disappeared” who do not have a separation transaction file, but their master file quarterly snapshots end during the research period, indicating they are no longer employed.
>
> Next, we add the records from the active duty master file. The active duty master file contains dependent quantity, dependent type, and marital status information, which is not present in the civilian master or transaction files. The data also includes the Armed Forces Qualification Test (AFQT) scores

> and enlisted career status codes. We then add the active duty transaction files to this subset of prior active duty employees to gain insights about their discharge from active duty service.
>
> Lastly, we add the records from the reservist master and transaction files. We merge these files to gain information about the employees who had served or are currently serving in the reserves upon entering employment. These files also contain dependent quantity and marital status information, but no dependent-type information. The records also include AFQT scores and a prior active duty service indicator. We also use the reserve transaction files to gain insights about their discharge from reserve service. (Buttrey et al., 2019, pp. 29–30)

Using this approach, the data from the DMDC were extracted from the raw master files and converted to a unified format that would facilitate analysis. The next stage in data construction involved developing a fixed cohort of individuals employed at a given period of time that would then allow for a legitimate comparison across time periods. We construct this cohort using the personnel data of all DoD employees that were appointed in 2009. This group includes employees with no prior federal service as well as individuals with service in other federal agencies, or that had breaks in their federal employment. Of the 808,925 individuals that appear in DMDC records of DoD civilian employees in 2009, 102,009 are part of the cohort of newly appointed employees (12.6%).

Prior federal service is identified using the Federal Creditable Service (FCS) field. This identifies the date used to determine retirement eligibility, annual leave accrual, and other administrative statuses.

Several stages of additional data cleaning were conducted to prepare for the statistical analysis. First, 4,355 individuals were dropped from the cohort because their initial records had either missing or inconsistent transaction record dates, or their birth date field was missing.

The second stage of data cleaning establishes an employee survival period that starts from the first time we observe them in 2009. The beginning of this period is defined as either the first transaction date observed in the master file, or the appointment date, whichever comes first. This variable starts at zero and measures the length of time that the employee remains in service. This variable is separate from the

FCS period because it does not include prior service to current DoD civilian employment. The object of the analysis is how long the employee remains in their current period of continuous service with the DoD. Variation in prior service helps explain the length of continued employment for the 2009 cohort, but that prior service is separate from the current length of tenure.

This approach to creating a starting date for the period of analysis revealed several hundred additional records with anomalous data. A total of 841 individuals have problems associated with the alignment of their start and end date. These problems include starting and separation dates that fall on the same date, end dates that occur before the starting date, and others have transaction records that appear after their termination date. We correct these records by either requiring that the length of service be at least one day, or for the final type of error, setting the end date to the last observed transaction record. We also observed in the data a handful of individuals that separate from service and then are immediately reappointed. We treat these brief gaps in employed status as continuous periods of service, rather than counting them as attrition events.

The final group excluded from the cohort consists of all employee that are in temporary or fixed term appointments. Since administrators already have a clear end of performance date for these employees, there is no point in trying to statistically model their attrition. While many temporary employees have their contracts renewed, DoD officials similarly have the ability at that renewal period to decide how to manage their workforce. Survival analysis and other forms of attrition modeling gives more value to the management of the full time/permanent workforce that does not have a clear end date. See Figure 2 for a graphical depiction of the employees excluded from the 2009 cohort.

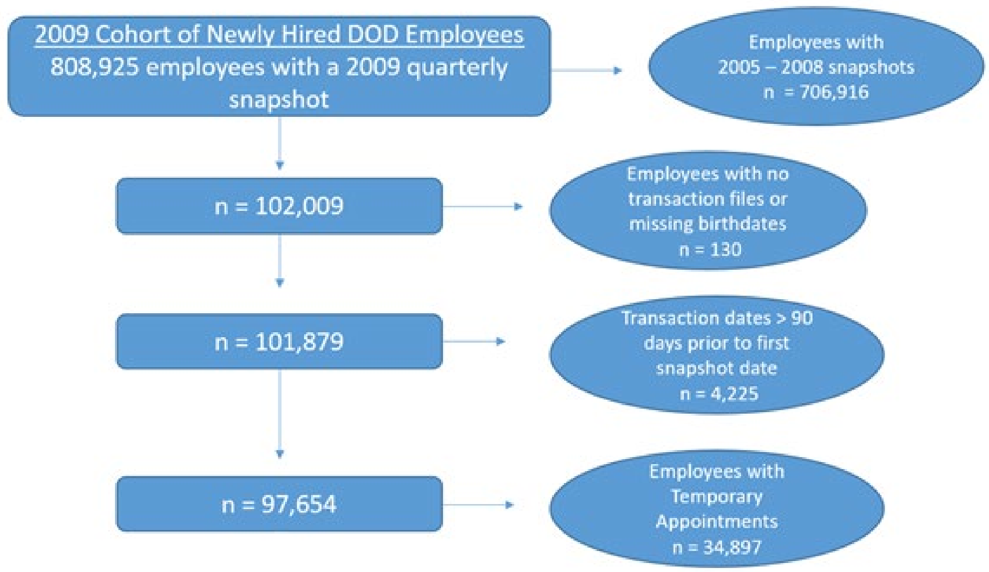

Figure 2. Employees Omitted from the 2009 Cohort.

(Buttrey et al., 2019, p. 37).

Data Elements

The features of the 2009 cohort are described by a variety of variables. These variables primarily describe the career life-cycle characteristics of each employee. These include age, years of service, education and prior military service. Participation in a STEM-related job field is identified using an occupational category code. This field describes whether, at the time of appointment, the employee was in a STEM job, a medical job, or a non-STEM job type. There is another designation that separates out social science and psychology job types, but there were so few employees with this designation that we excluded them from the analysis.

Several variables, such as age and years of service, are numeric values. The non-parametric methodology used for this analysis generally performs better when numeric values are converted to categorical groups. We generated categorical variables for each of the numeric fields. Age at time of appointment, for example, is converted into 10 age groups. Table 1 describes the initial data fields and the secondary categorical values constructed from the raw data.

Table 1. Description of the Variables.

(Buttrey et al., 2019, p. 40-41).

Name	Type	R class	Description
BirthDate*	date	Date	Birth month and year.
Age	numeric	numeric	Age at appointment in years
Age.group	categorical	factor	Ten age approximately uniform age groups [14,20], (20,23], (23, 27], (27,30], (30,34], (34,39], (39,43], (43,52], (52, 84].
Sex*	categorical	factor	Male (M) or female (F)
service	categorical	factor	Component at appointment Army, Navy, Marine Corps, Air Force, DoD.
education	ordinal	numeric	Time-varying education code 0 – 3 corresponding to less than high school, graduated high school, a four-year degree, a graduate degree respectively.
StemCode.1*	categorical	factor	Job type at appointment: STEM ("S"), social science and psychology ("C"), medical ("M") and other ("N").
priorAD	categorical	logical	TRUE if active duty service prior to appointment, FALSE otherwise.
ActSvc*	numeric	numeric	Number of years of active duty service prior to appointment (0 if no active duty service).
priorAD20	categorical	factor	None, active duty with less than 20 years of service, active duty with 20+ years.
FCS_DateMod*	date	Date	Approximate credited federal service at appointment date.
yearsFS	numeric	numeric	Years of federal service credited towards retirement at appointment date.
yearsIR	numeric	numeric	Number of years from appointment date until eligible for immediate retirement.
yearsIRgroup	categorical	factor	yearsIR grouped into intervals [-15,0], (0,1], (1,2], (2,3], (4,5], (5,10], (10,45].

Kaplan-Meier Survival Analysis

The quantitative technique used to examine workforce attrition is known as survival analysis, or analysis of failure-time data. For a comprehensive technical review of this method see Collet (2015). Survival analysis is generally used when estimating the time until some terminal event occurs, such as the failure of a mechanical part, or the death of a patient after receiving a given type of treatment. For this study, the duration of an employee's service following their appointment is their "lifetime," and the terminal event is their attrition or separation from DoD civilian service.

The following passage is quoted from the companion technical report prepared by the research team for the Office of People Analytics. It describes how survival analysis is used in this study to examine DoD civilian attrition:

> The result of a survival analysis is a survival (or survivor) function. This function shows the proportion of survivors as a function of time. Often it is represented as a curve that starts at y = 1 at time t = 0, indicating that everyone in the data set is alive right after they have started, and decreases steadily with increasing t. In the usual case the survival curve (often denoted by S(t), a function of t, where S(0) = 1) can never increase, since this would indicate individuals transitioning from a dead to an alive state. In our case, we can envision an employee who "dies" (i.e., leaves federal service) and then "comes back to life" after being re-hired. These are fairly rare and we continue without considering these small numbers of employees. In our work, we take their lifetimes to be the total time in a sequence of DoD positions.
>
> The survival function can also be characterized by the hazard function, which measures the instantaneous death rate. The survival and hazard functions carry the same information. Unlike the survivor function, the hazard function can increase, even above the value 1, and decrease across time. We mention the hazard function only in preparation for the description of analysis techniques that follows.
>
> Survival analysis differs from ordinary regression-type analyses in several important ways. First, most survival analyses involve censored data. That is to say, for many employees, their employment lifetimes cannot be fully measured, since the employees are still in service at the end of the study period. If we observe an active employee who has eight years of tenure, we know her lifetime is at least eight years, but we do not know whether her tenure will exceed eight years. In that sense, her (final) tenure lifetime is unknown—it has been censored. In this case we have right-censoring, meaning that the censoring takes place at the right-hand end of the employee's timeline (where time increases from left to right.) Censored

data, particularly this right-censored kind, is a very common attribute of survival analysis; a number of methods for handling it commonly used and survival analysis software is widely available.

A second and perhaps more subtle problem is that of truncation. This refers to the fact that the set of employees present in the first snapshot makes up a biased sample from among all prior employees, with the bias being towards longer-serving employees. Consider, for instance, the set of employees who were hired in 1995. Among all those employees, the only ones we have any information on are the ones whose tenure survived at least ten years (since this project's data starts in 2005). Employees who left before 2005 are lost without a trace. Therefore, only the longer-serving members of the cohort of 1995 are visible—and of course this will be true for all other years as well. Not all survival analysis software accommodates left-truncation.

Problem three concerns time-varying covariates. Time-varying covariates are covariates whose values for a particular individual can change over the course of the study period. These include educational status, service (Army, Navy, Air Force, Marine Corps, or DoD), paygrade, etc. For this study, time-varying covariates remain constant for most individuals over the study period. These we treat as time-constant using their values at time of appointment for cohorts and at the cross-section date for cross-sectional data. To show how time-varying covariates are used in survival analysis, we treat education as a time-varying covariate in the next section. In principal, time-varying covariates are fairly easily incorporated into a survival analysis as long changes only depend on the past and not knowledge of future events. Recently, researchers (Therneau, Crowson, & Atkinson, 2017) published an R vignette that introduces common mistakes made when using time-varying covariates and tools (used in our work) to handle them. Incorporating time-varying covariates involves reshaping the dataset. In the new dataset each individual is represented by one of more items, one item for each change in their time-dependent covariates. Under this scheme, a new 2009 hire with a high-school education who goes on to earn a high-school diploma in 2010, and a Bachelor's degree in 2016, and then leaves DoD in 2017 will contribute three items to the analysis. The first item is the record of his employment up to his first change in educational status, i.e., education is less than a high-school education and the item is right-censored at 1 year; the second item (with a high-school education) is left-truncated with one year of service, and right-censored at seven years; the final item (with a four-year degree) is left-truncated at seven years with a separation at eight years of service. Survival functions can then be fit to the new dataset using any survival analysis software that allows for left-truncated observations. (Buttrey et al., 2019, pp.40–41)

Survival analysis using the Kaplan-Meier (KM) estimation procedure facilitates an analysis of how employee characteristics influence the probability of individual employees remaining in service as time passes. We implement a non-parametric KM model, meaning that we do not impose assumptions on the model about the behavior of individual employees. For a large and diverse workforce such as the DoD civilian cohort, this approach avoids arbitrary assumptions that individuals in widely different personal and professional circumstances would engage in similar behavior. Instead, this approach attempts to take a more neutral approach that allows the data to reveal which factors generate the greatest predictive power for this cohort.

A second component of the empirical strategy is to develop survival trees. Survival trees are a machine-learning approach to data analysis that use algorithms to iteratively select model components that generate the greatest predictive power for forecasting attrition. Additionally, survival trees produce powerful visualizations of the resulting model that help illustrate the variation in the factors contributing to attrition across population subgroups.

> Survival trees are constructed much like classification and regression trees (Breiman, 2017). A tree algorithm partitions the data into subsets (leaves or terminal nodes) where the observations in each terminal node are used to produce a survival function fit. We use the non-parametric KM estimate rather than parametric estimates of terminal node survival functions. The tree algorithm begins at the root, with all data in one set. It splits the data into two subsets or nodes, and then at each subsequent branch splits a node into two more nodes. The survival tree algorithm chooses the covariate and its values to be used at each split. Numeric covariates are split at a single value (e.g., at a split, all observations with age less than 21 might form one child node and all observations with age at least 21, the other). Categorical covariates are split according to their levels (e.g., if one child node is STEM $\in$ {"C","N"}, the other will be STEM $\in$ {"S", "M"}). The splitting criteria is defined so that the split yields subsets that are as homogeneous as possible.
>
> For the algorithms used in this report, the splitting criteria is based on a hypothesis test. The split with the smallest p-value (i.e., the strongest evidence against the null hypothesis that the survival functions in the two child nodes are the same) is chosen. Splitting is stopped when there is no strong reason to estimate the observations in a node with two different survival functions. This may be because the p-values for all possible splits of a node are large, indicating that there is not enough evidence to use two different survival functions for that node, or because there are too few observations to warrant a split. The 2009 cohort, with education treated as time-varying, has over 1 million records, yielding very small p-values and survival trees that are quite deep. In future work, especially if the results of

> survival trees are used for forecasting civilian end-strength, we suggest that survival trees based on such large cohorts be pruned using a criteria other than p-values. In our experience, fitting the 2009 cohort survival tree in the PDE requires overnight computation; we suspect that such a criteria will involve setting aside a random validation set rather than the more computationally intensive cross-validation.
>
> Survival trees exploit the many nice properties of trees in general. The splitting is automatic and non-parametric; we can estimate the survival function with left-truncated and right-censored data in each terminal node non-parametrically using KM. A tree algorithm allows numeric, nominal and ordinal categorical, and time-varying covariates. The results are not heavily influenced by extreme covariate values (e.g., an 84 year old new hire); and it is invariant to monotonic transformations of numeric values (e.g., age versus log[age]). (Buttrey et al., 2019, pp.43–45)

The combination of KM survival curves and KM survival trees generates visualizations of how employee attrition behavior differs across the subgroups within the 2009 cohort that are identified with the DMDC personnel records. The following section describes the results of the statistical analysis.

Analysis of Kaplan-Meier Survival Analysis

The first KM survival model we estimate divides the 2009 cohort by age and sex. Of the 97,654 individuals included in the cohort, 51.7% of them separate from DoD civilian employment before 2017. The remainder continued their employment through at least the first quarter of annual year 2017. Controlling for differences in individuals' appointment time in 2009, the probability that an employee hired in 2009 would remain in service for at least eight years is 0.508. The KM curve for the survival function of the entire cohort is displayed in Figure 3.

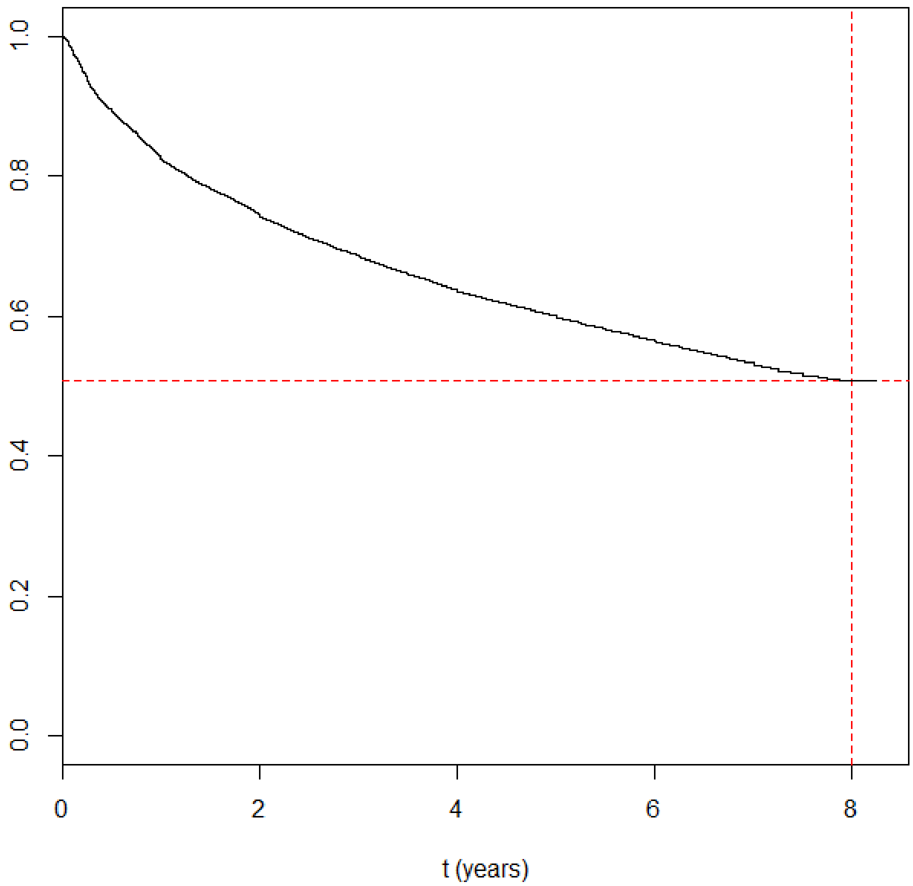

Figure 3. KM Estimated Survival Function for the Entire 2009 Cohort with Dashed Lines Indicating the Estimated Probability of Separation After Eight Years.
(Buttrey et al., 2019, p. 76).

A KM survival curve is interpreted by examining the descending slope of the curve as it moves to the right. The X-axis represents time, while the Y-axis represents the probability that an individual would "survive" a given length of time. At time period 0, the curve intersects 1 on the Y-axis, meaning that no employees have separated yet. No error-bars bracket the KM curves presented in this analysis because we use the entire population of the 2009 cohort, rather than a randomly selected sample.

The survival curve shown in Figure 3 shows the pace of attrition within the 2009 cohort. Its relative steepness during the first two years reflects a higher rate of attrition among new hires. Once employees have more than two years of service since their appointment their rate of attrition flattens. At 8 years, the survival curve interests the horizontal checked red line, showing the expected 50.08% expected survival rate.

Age and Sex Distribution

After examining the attrition of the entire cohort, we generate survival curves for subpopulations identified in the cohort with the demographic and administrative characteristics. Our first division separates the cohort on the basis of age and sex. Table 2 provides a numeric description of the age categories we generated and age distribution across sex. Before showing the KM curves, we present some descriptive analysis of the distributions of sex and age. Figure 4 depicts the same age and gender distribution in a stacked histogram. Several important features of the cohort are revealed in these depictions. First, 64.25% of new appointees in 2009 were male. Within age categories, this percentage ranges from 55.3% to 73.45%. Each of the three highest age categories were more than 70% male. This suggests that recruitment for higher grade civilian positions tends to bring in a higher proportion of men than women when compared to overall recruitment.

Table 2. Distribution of Age and Gender

	14-20	21-23	24-27	28-30	31-34	35-39	40-43	44-47	48-52	53-84	All Ages	Gender Percentage
Males	5,536	6,137	7,852	5,175	5,078	6,090	6,734	7,288	6,541	6,315	62,746	64.25%
Females	4,477	3,443	4,921	3,354	3,640	4,111	3,098	2,901	2,681	2,282	34,908	35.75%
Total	10,013	9,580	12,773	8,529	8,718	10,201	9,832	10,189	9,222	8,597	97,654	100.00%
Percent	10.25%	9.81%	13.08%	8.73%	8.93%	10.45%	10.07%	10.43%	9.44%	8.80%	100%	

Another interesting feature of the age distribution is the bi-modal distribution of age across both men and women. Figure 4 shows one peak in the age distribution of new hires at around 24 years, which would be consistent with new hires recently out of college or graduate programs. The second mode begins around 39 years of age and continues through the mid-40s. This later peak in civilian recruitment is consistent with new appointees entering DoD civilian employment after retiring from a 20-year military career.

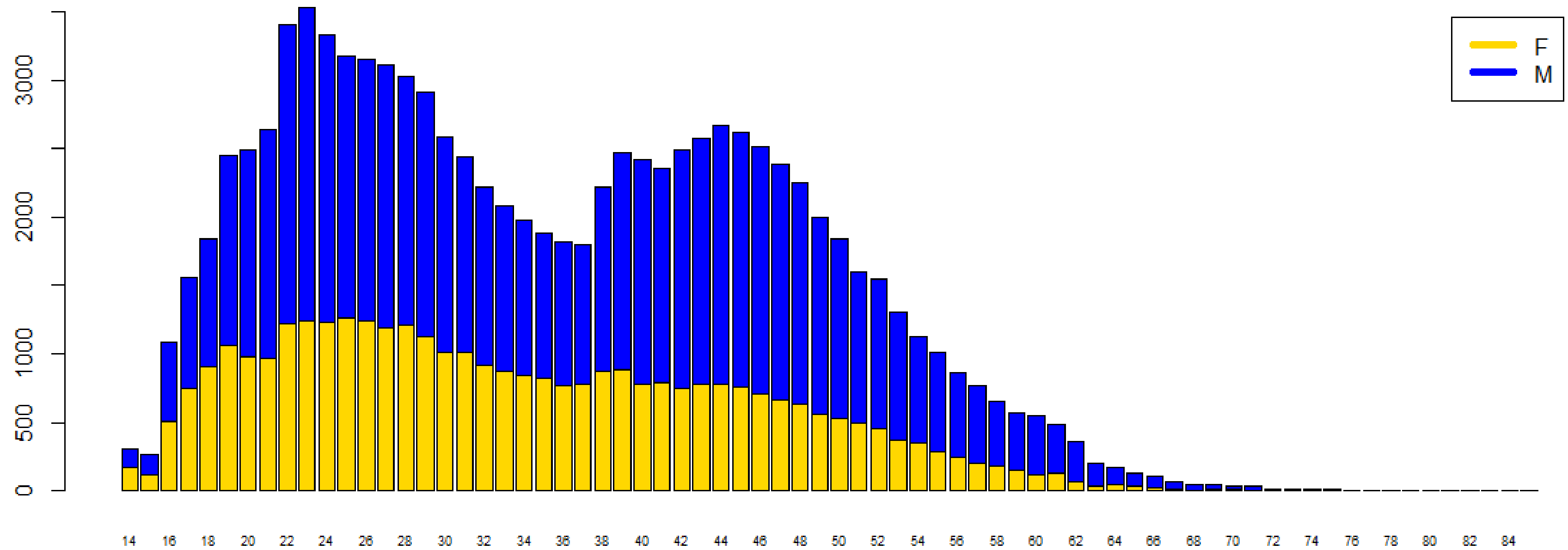

Figure 4. Distribution of Ages Colored by Sex.
(Buttrey et al., 2019).

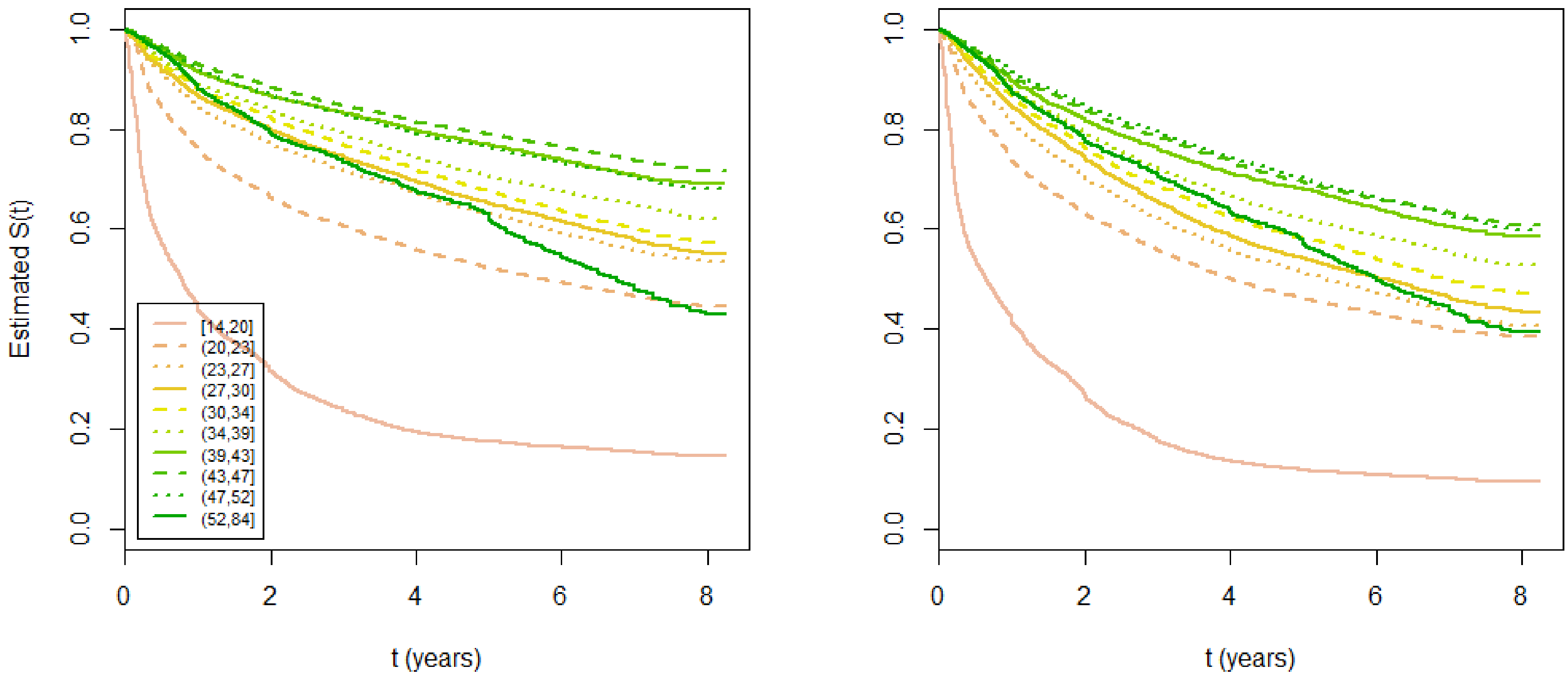

Figure 5. KM Estimated Survival Functions by Age and Sex.
(Buttrey et al., 2019, p. 70).

Estimating KM survival functions by age and gender allows us to compare how attrition rates vary across employees who are appointed at different ages. We also separate these survival curves for men and women. Figure 5 depicts these curves. The lowest curve for both men and women belongs to employees who were between 14 and 20 years of age when initially appointed. Many of these employees were presumably interns or summer employees, and the survival curves reveal that approximately 60% of them attrite before reaching one year of service. Approximately 20% of male young hires remain employed for at least eight years; for young female hires approximately 14% remain the entire period.

As the age at appointment increases the survival rate appears to increase, at least until the last two age categories. At the age group [47,52], the upward trend is reversed, and these employees have a slightly lower attrition rate than the prior age group. The survival in the final age group [52,84] is much lower. Its trajectory is similar to the other older age groups for the first year, but then steepens and becomes comparable to employees that were initially higher in the [23,27] age group. Then, after approximately five years of service, this older group's attrition rate sharply increases. Men end the 8-year period with the second highest overall attrition rate, while women in this age group had the third highest attrition rate. Although this pattern of attrition is not intuitively surprising, it is reassuring that survival model is identifying patterns of behavior that are consistent with practice-based experience.

Attrition by DoD Component

The next set of divisions within the 2009 cohort that we examine are tied to the organizational component of the DoD the employees reside within and their prior active duty service. Figure 6 depicts KM curves for each of branch of military service, as well as "purple" DoD-wide employees. This figure reveals that the Navy appears to have relatively higher survival rates among its civilian workforce than all other DoD components. Additionally, civilians working for the Marine Corps experience higher attrition rates in the first few months of employment, and then flattens out to have a survival curve that runs parallel to the other service branches. Although we excluded most temporary employees from the cohort, it may be that the USMC relies on some other type of fixed or limited term employment that our initial data cleaning exercise omitted. Before dropping them, it would be necessary to determine how much control and predictability the USMC has over the expected separation date of these employees.

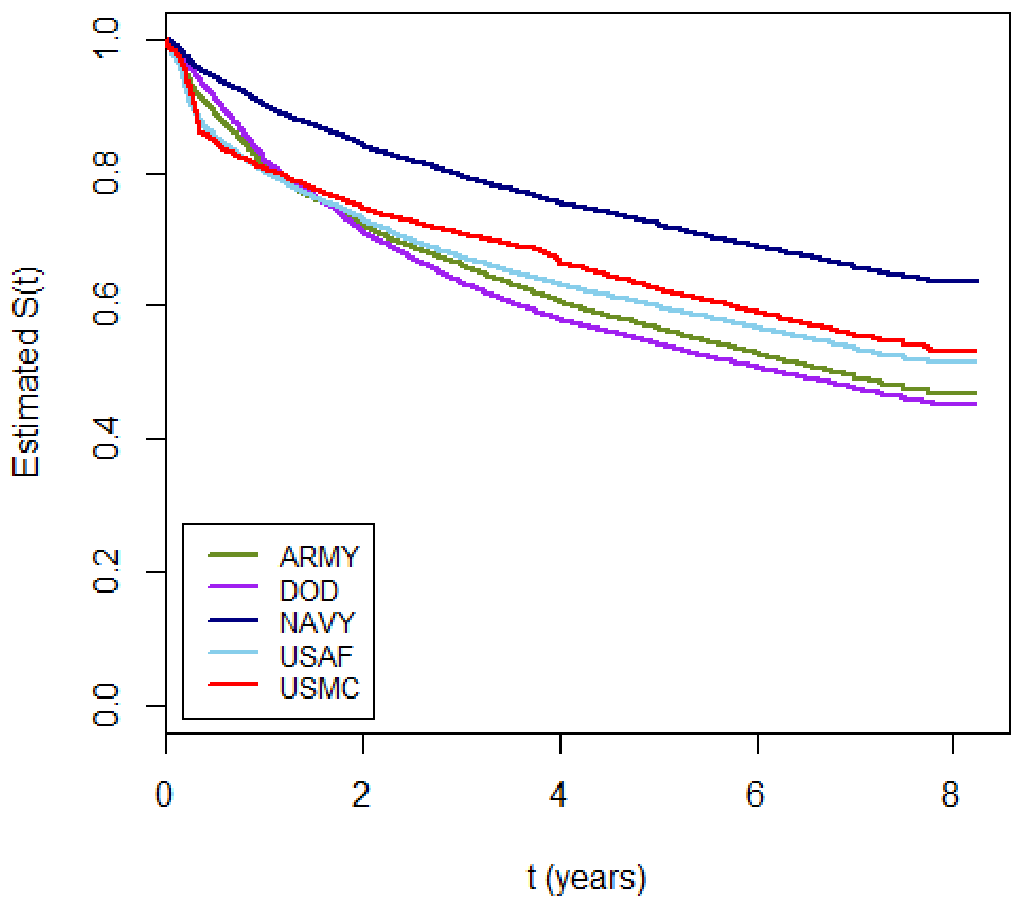

Figure 6. KM Survival Curves Divided by Service Component.
(Buttrey et al., 2019, p. 53).

Dividing the DoD component survival curves by gender reveals significant variation in the size of the gender survival differential across service branches. Figure 7 reveals that while women in the Navy have a higher attrition rate than Navy men, particularly during the first two to three years of service, overall, Navy women have higher survival rates than all other women working in the DoD. Additionally, Navy women have comparable attrition to men in the USMC, the USAF, and the DoD headquarters, and they have higher survival rates than Army men. The DoD headquarters has the highest sex-based survival gap relative to all other DoD components. Furthermore, the gap between male and female attrition in DoD headquarters continues to widen until approximately year 4 of employment, while the gap for all other service components appears to have stabilized by year 2. In contrast, while both males and females in the Army experience higher attrition than the other components, the gender differential is the smallest within the Army relative to the other service branches. This important finding invites further comparative research into the workforce climates for civilian women across different DoD service components.

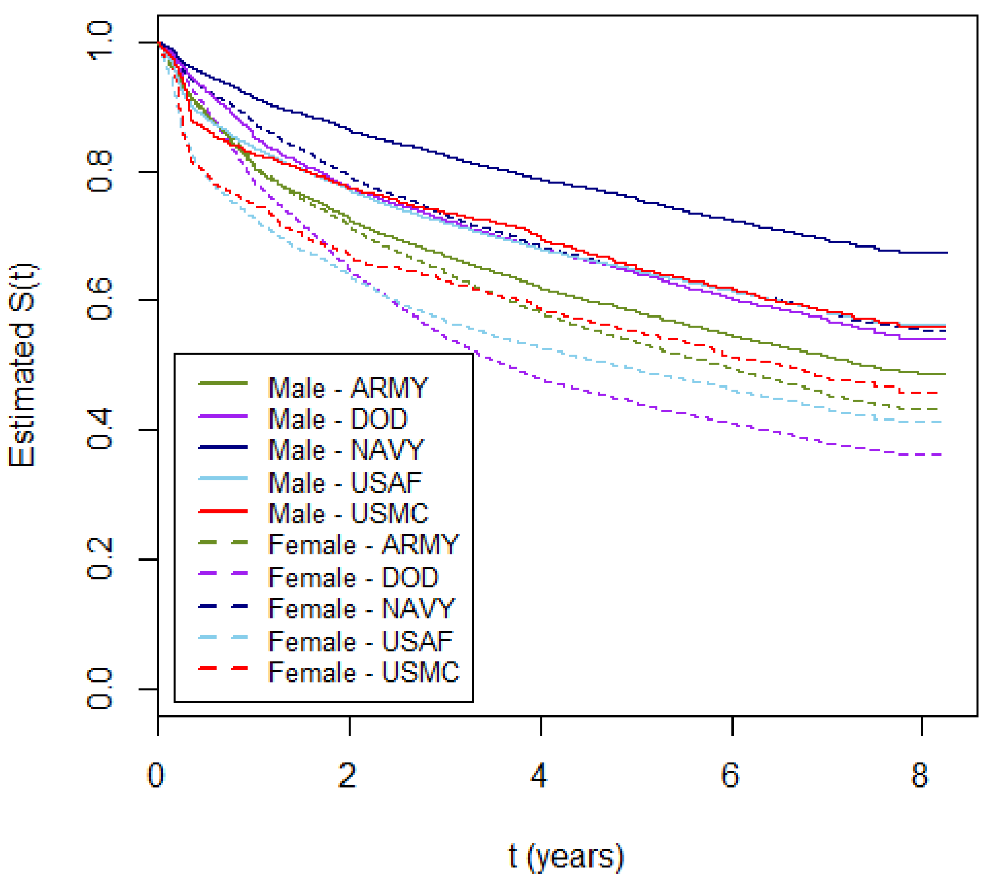

Figure 7. KM Curves Divided by Sex and DoD Service Component.

Attrition by Prior Active Duty Service

To examine the relationship between prior active duty (AD) status and attrition, we first subdivide the histogram of age and gender presented in Figure 4 with the prior active duty variable. This new table, presented in Figure 8 reveals how prior active duty is distributed across the age and gender of new appointees. Figure 8 reveals that the bulk of new appointees entering civilian employment with prior AD status are men. This gender differential is especially sharp in at the start of the "second career" bump starting at age 39 when retirees with 20 years of AD service would begin to enter the civilian workforce. The gender differential is so sharp that it may be worth investigating in a separate study how female active duty soldiers approaching retirement eligibility perceive transitions to civilian service. It may be that the way that these career opportunities are advertised and communicated leave men more aware and interested in subsequent civil service and could contribute to this gender gap.

The intersection between prior AD service, sex, age and attrition is depicted in a series of KM curves depicted in Figure 9. In the three youngest age groups, people with prior active duty service have slightly higher attrition rates, but these differences don't manifest until after at least four years of service. This is indicated by the slightly lighter blue and yellow lines hovering above their darker-colored counterparts. Appointees that entered civilian DoD employment in all age groups 34 and above show a sharply different pattern, with prior AD service leading to longer survival. Additionally, in each of these older age groups there is an immediate divergence in survival between prior-AD and non-prior-AD employees that was not present for the three youngest age groups. This difference may represent a form of commitment to the DoD, or a recognition that these employees have invested in relatively non-transferrable skills that are less valued outside the DoD.

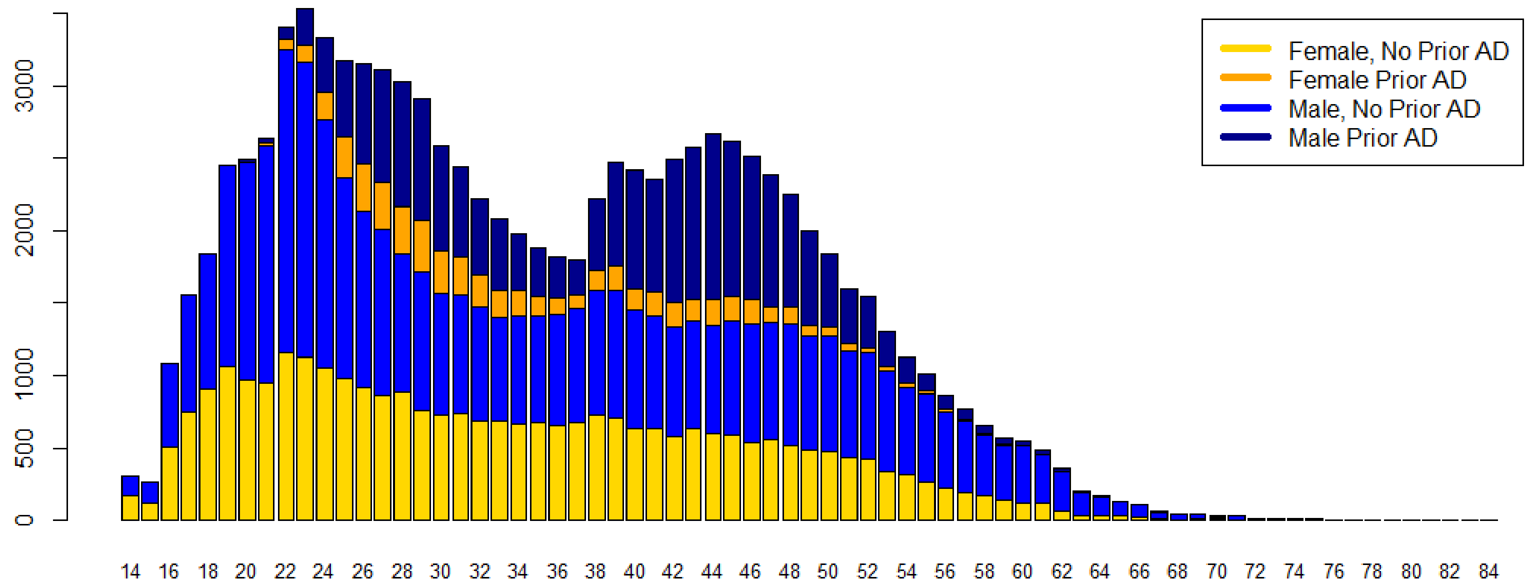

Figure 8. Distribution of Age, Sex, and Prior Active Duty Service.
(Buttrey et al., 2019, p. 55).

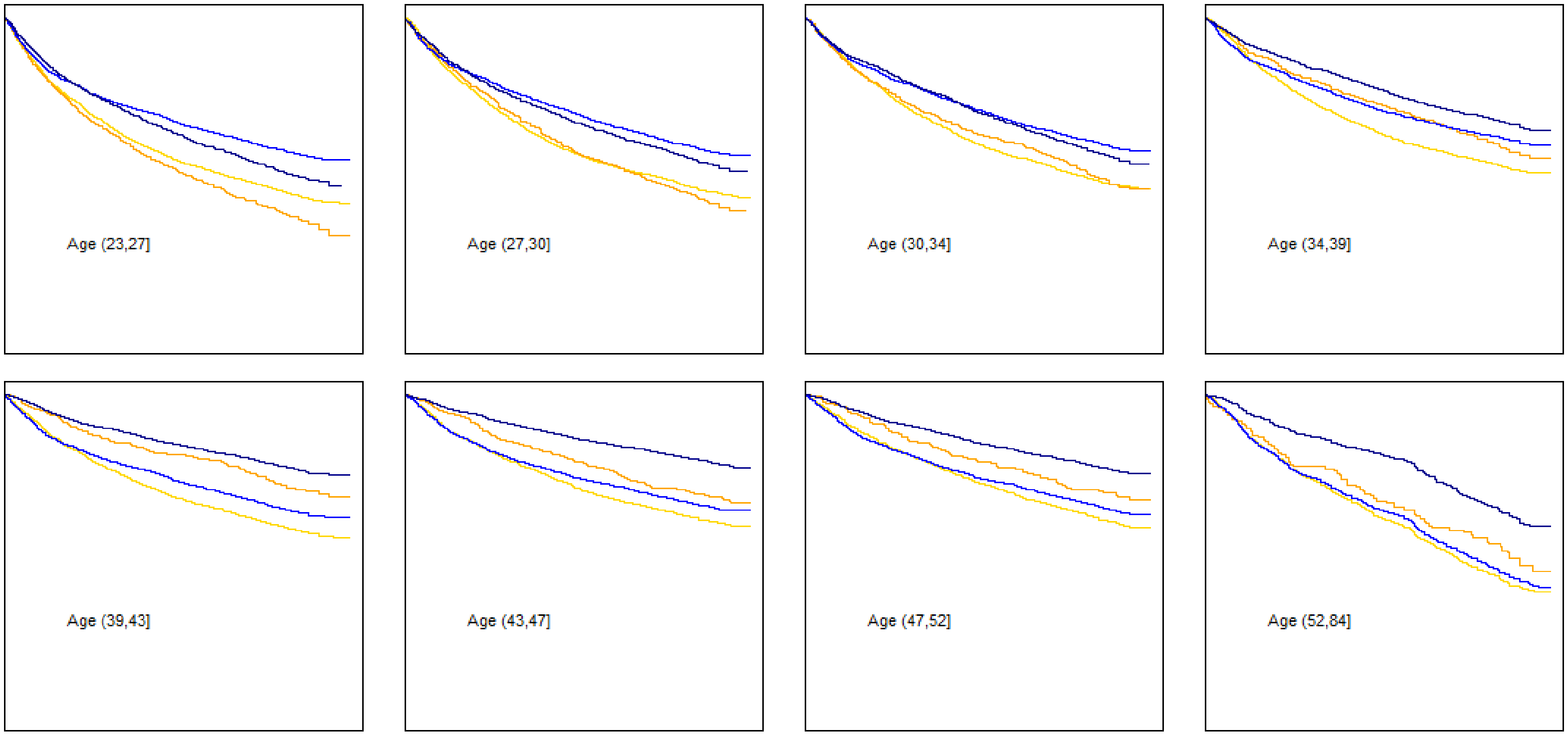

Figure 9. KM Estimated Survival Functions for Each Age Group by Sex (Blue Male and Gold Female) and Prior Active Duty Service (Darker Colors) or Mot (Lighter Colors).
(Buttrey et al., 2019, p. 82).

Attrition in STEM Job Classification

As discussed in the literature review, maintaining a technically skilled and adaptive workforce is crucial to modern security needs. To this end, understanding attrition among employees in STEM-related job fields is important to defense strategy. Within the 2009 cohort, STEM affiliation is identified through a categorical variable that identifies employees as STEM, social science and psychology, medial and non-STEM. Table 3 depicts the percentages of each DoD component's workforce that falls into each STEM classification code. The "C" code that represents Social Scientists and Psychologists is a very small proportion of the overall workforce and is only included in the analysis for completeness. The Navy civilian workforce is the most STEM intensive, with more than 23% of its employees receiving that designation. The other military branches rely on little more than 10% of their civilian employees to perform STEM-related jobs, and the DoD agency is the least STEM-intensive at 7.4%.

Table 3. Distribution of STEM Classification across DoD Components.
(Buttrey et al., 2019, p. 82).

	ARMY	DOD	NAVY	USAF	USMC
Social Science/Psychology	0.90	0.32	0.53	0.45	0.46
Medical	6.00	0.34	2.96	1.07	0.26
Non-STEM	82.07	91.93	73.40	88.05	88.65
STEM	11.03	7.40	23.11	10.44	10.62

The KM curves displayed in Figure 10 describe, for each STEM classification group, the gender attrition differential. In both the Medical and non-STEM categories there is a broad attrition gap that begins to open after approximately one year of service. For both categories, at eight years of service, women have experienced more than 10% higher attrition than men. This means that an additional 10% of the women in a starting pool of employees would have left civilian service eight years after their initial appointment. For both non-STEM and medical professional fields, efforts to retain employees and mitigate the environmental conditions that may induce women to separate at a higher rate may help to close this gap.

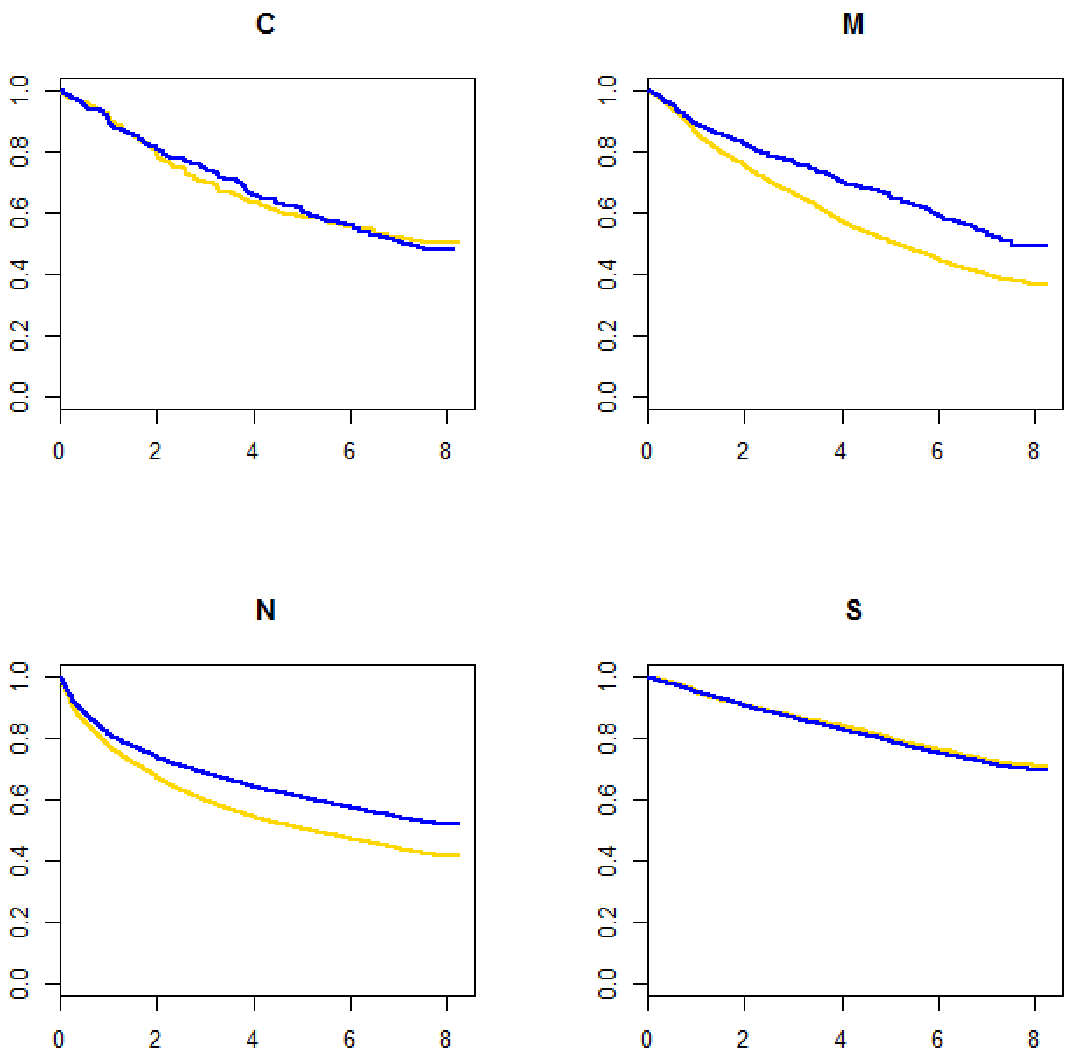

Figure 10. KM Survival Curves by STEM Category and Sex.
(Buttrey et al., 2019, p. 86).

C: Social Science/Psychology; M: Medical; N: Non-STEM; S: STEM

Alternatively, for employees in the STEM job classification, we observe no meaningful sex-based differential in attrition behavior. This is an extremely notable finding in light of the broad literature examining sex differentials in the public sector workforce reviewed earlier in this report. The academic workforce literature that has identified a variety of important environmental factors that harm the career trajectories of women in STEM-related academic disciplines. Alternatively, the federal agency turnover literature found that, once employee life-cycle measures are controlled for, gender itself has little to no impact on turnover behavior. This paper greatly improves on the empirical work performed in that turnover literature by using individual employee attrition behavior rather than agency level averages or turnover intention proxies.

Survival Tree Methodology

While KM survival functions are excellent at depicting the relationship between attrition and a few variables, they only are able to effectively display one to three variables at a time. In this section, we describe the results of our survival tree analysis. This approach helps reveal more complex relationships among several variables within the diverse population of the 2009 cohort. As described in the methodology section, survival trees use an algorithmic model to partition the cohort into subgroups. Figure 11 depicts the survival tree for the entire 2009 cohort.

The branching divisions flow from the top of the tree to the bottom. Each branch depicts a categorical division in the data that the algorithm identified as having the greatest statistical strength.[2] The first division identified by the algorithm was the age variable identifying whether people are older than 21 years of age. All those that are older than 21 are in the right branch, all that are 21 or younger fall under the left branch. Each of these two groups then repeat the subdivision process and create additional "branches" until a cutoff condition is reached that shows the survival curves of the subpopulations within the branches are sufficiently similar that no more branches are created.

[2] The algorithm selects the division that minimizes the p-value for a statistical test rejecting the null that the two survival curves generated from a given division are identical.

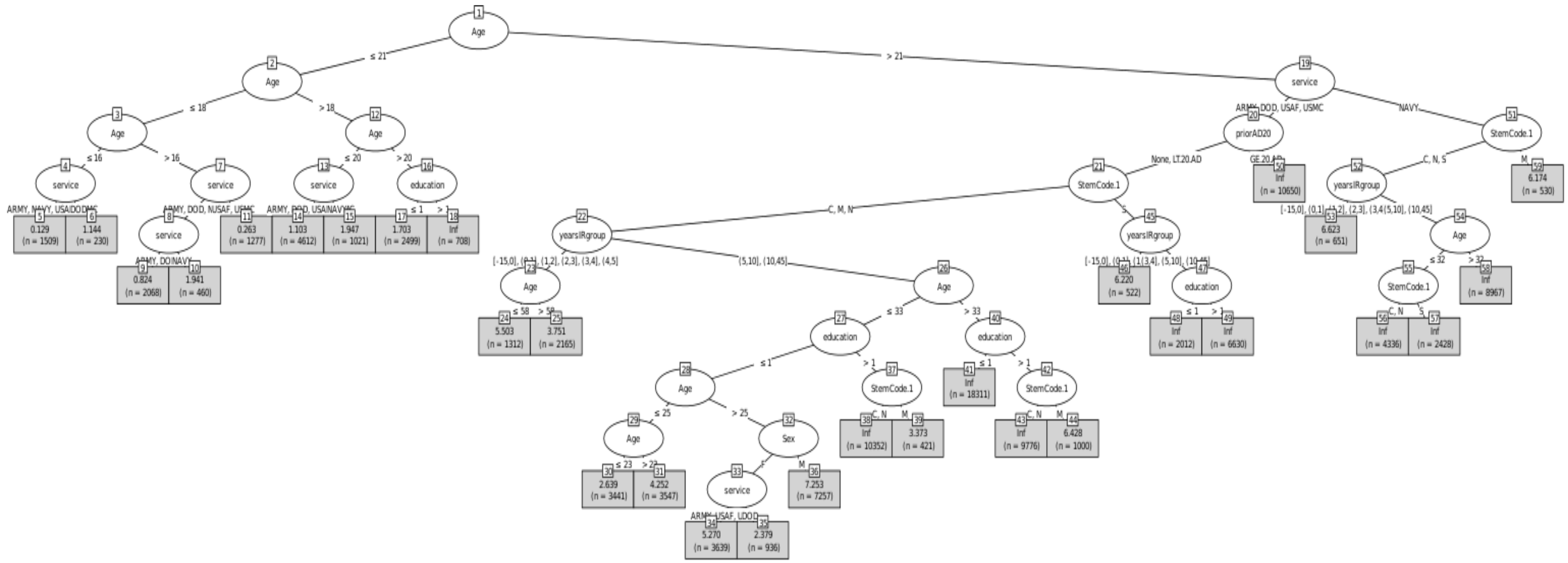

Figure 11. Survival Tree of Entire 2009 Cohort

This approach helps identify the variables that are most important in determining and describing attrition behavior. One of the primary concerns of this analysis is the relationship between sex and attrition. The left-hand branch of the tree, pertaining to all individuals 21 and younger, does not include sex at all. The right hand branch only includes sex in a smaller branch that only includes 12% of the cohort. For the remaining 88% of the cohort, workforce survival is not significantly differentiated by sex. This 12% cohort consists of non-Navy employees between the ages of 25 and 33 with a high-school diploma or less education. These individuals are not in the STEM career path and had either no prior active duty service, or less than a full 20-year AD career.

Overall, the features of the survival tree support the career life-cycle models in the vein of Lewis and Park (1989). When age, years of service, and retirement eligibility, education, and other personal employee characteristics are accounted for, sex has little to no impact on attrition behavior.

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Discussion

One of the key findings of this analysis is that, within the DoD, the gender differential in attrition rates observed broadly across the civilian workforce is not present for women participating in STEM-related career fields. The descriptive data reveal, however, that women remain relatively underrepresented in these career areas. If the DoD is interested in increasing and maintaining a diverse and innovative STEM workforce, it will need to carefully consider how these empirical results reflect on its available policy options. While private sector firms and academic institutions may have environmental conditions that reduce the duration of women's employment relative to men, this analysis reveals no such differential within STEM-affiliated job paths.

Given this finding, the DoD may consider refocusing its efforts on recruitment strategies to increase the share of women that are initially hired into these positions. Examining how the DoD conducts its outreach to universities may reveal that some of these strategies are more targeted toward men, leaving women less informed about the types of career opportunities for DoD civilians in STEM. Additionally, this analysis revealed that there is a significant differential in the proportion of women with prior active duty status that choose to have a second career as a DoD civilian following their retirement. This would appear to be a significant untapped potential labor force that the DoD should pursue.

Further research is needed to further investigate the environmental differences between STEM careers in the DoD or other federal agencies and the academic and for-profit workforces. From an administrative perspective, it would be important to differentiate between whether required Equal Employment Opportunity training for the federal workforce is having an impact at increasing employment survival for women in STEM, or this is the result of sex not affecting attrition after adequately controlling for career life-cycle effects. Untangling this question may require the integration of survey data with this form of survival analysis to describe other factors that are associated with their attrition behavior that are outside of the career life cycle.

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