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Examining Turnover Behavior, Gender, and STEM Participation in the Federal Civil Service

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Abstract

How does turnover behavior vary across demographic and organizational subgroups of the federal workforce? This study uses personnel data describing the civilian segment of the Department of Defense (DoD) workforce to perform a survival analysis of factors associated with turnover behavior. The analysis focuses on interactions between retirement eligibility, gender, and participation in STEM career fields. Results indicate that, while gender differences in the likelihood of employee separation persist within the DoD, for STEM job categories, the gender differential largely disappears. Refocusing managerial strategies toward recruitment and advertisement of job openings may be more effective at achieving higher gender diversity in STEM than new retention initiatives.

Evidence for Practice

- This research presents an analysis of the turnover behavior of a cohort of civilian employees of the Department of Defense who joined the agency in 2009. Their careers were tracked through 2017 using individual personnel records obtained from the Defense Manpower Data Center.
- This analysis measures how turnover behavior varies across gender and STEM career participation.
- The findings reveal that while women experience higher turnover rates in the civilian DoD workforce at large, employees in STEM-related careers do not exhibit a gender-based turnover differential.
- Refocusing managerial strategies toward recruitment and advertisement of job openings may be more effective at achieving higher gender diversity in STEM than new retention initiatives.

This study examines the intersection of three challenges in human resource management: 1) turnover in federal government employment, 2) gender differentials in turnover behavior, and 3) women's participation in Science, Technology, Engineering, and

Math (STEM) career fields. Turnover, or the separation of an employee from the civil service, has long been a concern of public managers due to the cost of replacing and retraining new employees (Congressional Budget Office, 1986; Pitts, Marvel, & Fernandez, 2011; Schlesinger & Heskett, 1991). Exploring the factors driving differential turnover rates between women and men has been an important component of this literature for decades (Bartholomew ,1979; Blau & Kahn, 1981; Dolan, 2004; Lewis & Park, 1989; Mancke, 1971; Sawhill, 1973). Research articles examining the factors that contribute to higher exit rates for women in STEM career fields, particularly in academia, have made important contributions in recent years (McCullough, 2011; Oh & Lewis, 2011; Riffle et al., 2013; Y. Xu, 2015; Y. J. Xu, 2008). Understanding the determinants of sex-based turnover differentials is of great importance to modern organizations that seek a representative public sector workforce. Turnover disparities may reveal an inability to effectively hire the right talent from the broadest pool possible or an inability to create an equitable work environment for existing employees.

A limitation of prior turnover research has been the lack of access to data on actual turnover behavior of individual employees. Much of the prior empirical research has relied on turnover intention, or the stated intention to separate from public employment in the near future as a proxy for actual employee behavior (Pitts, Marvel, & Fernandez, 2011). Some earlier meta-analyses of psychological research were cautiously optimistic about turnover intention as a proxy for behavior, primarily on the basis that it was more closely related to behavior than other cognitive measures of employee satisfaction (Dalton, Johnson, & Daily, 1999; Steel & Ovalle, 1984; Tett & Meyer, 1993). More recent research, however, has produced findings that question the overall value of intention as a useful proxy (Cohen, Blake, & Goodman, 2016; Jung, 2010). Cohen et al. (2016) test intention versus validity at the agency level and find that turnover intention describes only approximately 4.2% of quit-rate variance. Also, they find that a given set of factors that explain 59% of actual turnover behavior explains only 12% of the variance in turnover intention. They conclude that, “at the organizational level at least, agencies’ actual turnover rate and turnover intention rate are distinct and contrarily explained constructs” (Cohen et al., 2016). This result challenges the validity of extending the results of much of the turnover literature to actual employee behavior.

This study takes advantage of unique access to a database of Department of Defense (DoD) civilian employee personnel data to explore actual turnover behavior at the individual employee level. A cohort of civilian DoD employees that were hired by the agency in 2009 is identified, and then their retention behavior is followed through 2017. The study employs a non-parametric survival analysis model to examine how factors associated with the career life cycle influence turnover behavior. The results of the analysis indicate that, after controlling for a broad set of employee life-cycle factors, gender remains associated with higher turnover rates for the civilian DoD workforce at large. For employees in STEM-related careers, however, the gender differential disappears. This finding suggests several things: first, the protections of public sector employment may overcome or at least mitigate some of the forms of adverse environmental factors that women in academia and private sector STEM career paths continue to endure. Second, refocusing managerial strategies toward recruitment and advertisement of job openings may be more effective at achieving higher gender diversity than new retention initiatives. Third, this survival analysis methodology helps depict the turnover rate differentials at different points in the career life cycle and may help managers target retention efforts to subpopulations of the civil service that do experience higher turnover rates.

Employee Behavior and the Career Life Cycle

Recent studies of public sector turnover have organized the determinants of employee separation into three categories: individual attributes, environmental conditions, and organizational characteristics (Moynihan & Landuyt, 2008; Pitts, Marvel, & Fernandez, 2011). Individual attributes encompass a variety of characteristics including age, years of service, sex, compensation, and education. These factors are collectively used to describe the life cycle of a career.[1] Career life cycle refers to the changing probability that someone will quit their job at different points in their career. For example, an employee only a few years away from retirement eligibility would presumably have a much lower rate of voluntary turnover than someone who is already retirement-eligible. Similarly, an employee that opts out of employer-provided health care may have a higher rate of voluntary turnover than an employee that depends on their job to provide health care for their dependents.

Environmental conditions may encompass a broad set of economic characteristics, such as the overall state of the economy and the impact that either IRA fund balances or alternative employment opportunities may have. Federal employees working for agencies in areas with other federal employment opportunities may take their years of service and benefits to another federal job, and therefore federal employers located in those areas may experience higher overall rates of turnover.

Organizational characteristics describe the policies, practices, and other structures of public agencies that influence employee turnover behavior. Turnover intention models have used these variables to seek to understand how managerial choices affect employee experiences. These characteristics have been especially important in attempts to understand how women and minorities have been affected by work culture and climate in the public sector (Blau & Kahn, 1981; Grissom, Nicholson-Crotty, & Keiser, 2012). They have also helped clarify the specific barriers to women's career advancement and longevity in federal civil service (Dolan, 2004).

Increasing public managers' access to projections of workforce turnover can help promote organizational objectives. Local governments have demonstrated willingness to use this information for workforce planning and financial management (Goodman, French, & Battaglio, 2015). Along with the broader national security policy community, the DoD has maintained an ongoing interest in studying turnover among its civilian workforce, particularly among employees in critical STEM job classifications (Asch, 2002; Buttrey, Klingensmith, & Whitaker, 2018; National Academy of Engineering and National Research Council, 2012). Ensuring an adequate workforce skilled in technical areas is perceived as an essential part of the national security strategy of the United States (Kreisher, 2019).

Department of Defense Civilian Cohort

This study overcomes the data limitations of much of the prior human resource turnover literature by examining individual-level turnover behavior over an extended duration. A cohort of all federal employees appointed by the DoD to civilian positions during

[1] Labor economics has long studied the relationship between tenure and employee separation. Becker (1962) developed a model of firm-specific capital that increases the return the employee can receive from their current employer. Ippolito (1987) examined the cost of losing retirement benefits in quit behavior.

2009 is identified. These individuals are then tracked until 2018, and Kaplan-Meier survival curves are estimated for a variety of subpopulations to determine how environmental attributes and career life-cycle attributes impact turnover behavior. One limitation of this study is that it does not incorporate organizational attributes that reflect how individuals perceive the climate and characteristics of their workplaces. Instead, this study is based on analyzing personnel records and the linked attributes that describe the type of work the individual performs.

All personnel data for both uniformed and civilian DoD employees are maintained by the Defense Manpower Data Center (DMDC), the DoD agency responsible for storing and maintaining human resource data archives. These data include personnel attributes like age, years of service, job category, retirement eligibility, physical location, and other employee attributes. Taken together, these fields can identify the career life-cycle factors that influence employee turnover.

The U.S. Army Analytics Group Research Facilitation Lab (AAG-RFL) has developed a data system designed to allow scholars access to DMDC employee personnel records while protecting the privacy and autonomy of employees and meeting ethical standards for research. This system, known as the Person-Event Data Environment (PDE), is "a secure, collaborative research environment, to warehouse and study health, military service, and demographic information" (Vie, Griffith, Scheier, Lester, & Seligman, 2013, p. 1). The PDE structures the data to maintain employee privacy by de-identifying personal records and assigning secure identification numbers. Research conducted using the PDE personnel data is reviewed through Institutional Review Board protocols at the academic institution the scholar resides within. The PDE provides access to actual public sector turnover data that has not been widely available to prior public personnel scholars.

Data Structure

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 and individuals with service in other federal agencies or who 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. Although the cohort consists of new appointees, many have prior federal service outside the DoD that is reflected in their FCS value.

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 established an employee survival period that starts from the first time an employee is observed 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 0 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 service prior to current DoD civilian employment. The object of the analysis is to determine 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. The final cohort contains 97,654 individuals. Figure 1 depicts the data cleaning process

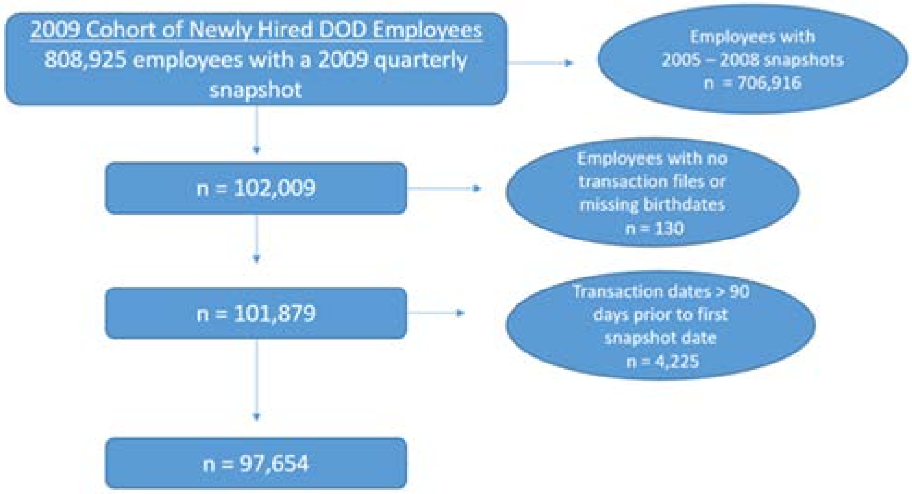

Figure 1. Employees Omitted from the 2009 Cohort

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 and end dates that occur before the starting date, and others have transaction records that appear after their termination date. These records are accounted for 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. A handful of individuals that separate from service and then are immediately reappointed were also observed in the data. These brief gaps in employed status are treated as continuous periods of service, rather than as attrition events.

The DMDC data contain a variety of fields that 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 position was in one of the following four categories: STEM, social science and psychology, medical, or non-STEM.

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. Categorical variables were generated 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. 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%	

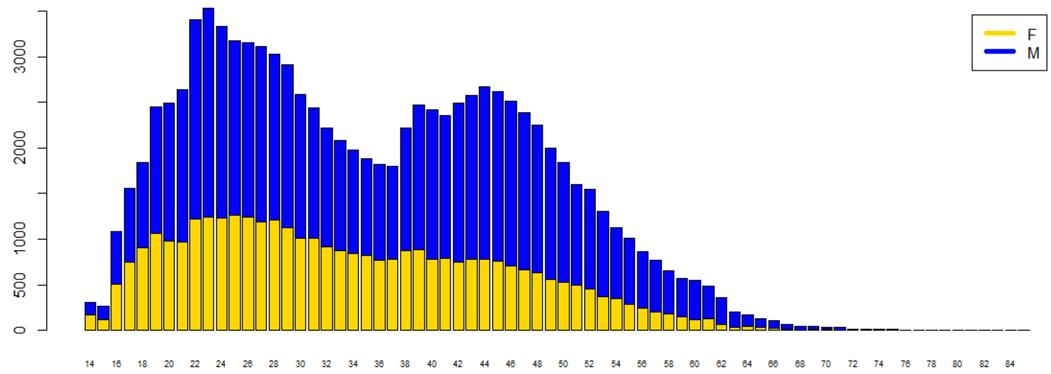

Figure 2. Age and Sex Distribution of 2009 Cohort Appointees

Table 1 provides a numeric description of the age categories generated and age distribution across sex. Figure 2 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 was more than 70% male. If older appointees enter civilian service at higher grades on average, then relatively more men are entering employment at these higher-level managerial positions.

Applicants for federal employment with prior military service can receive preferential consideration in the hiring process. "By law, veterans who are disabled or who served on active duty in the Armed Forces during certain specified time periods or in military campaigns are entitled to preference over others in hiring from competitive lists of eligibles and also in retention during reductions in force (Office of Personnel Management, 2020)." The individual personnel records used in this analysis identify whether the new employee has prior uniformed active duty (AD) service in the U.S. military. Figure 3 augments the age and gender distribution displayed in Figure 2 with this AD variable. The bulk of new appointees entering civilian employment with prior AD status are men. This gender differential is especially sharp 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. Part of this differential reflects the much higher percentage of men in uniformed military service than women. Pew Research Center reported that in 2010, women filled 16.1% of officer positions and 14.1% of enlisted roles (Patten & Parker, 2011). The sharp gender differential depicted in Figure 3 does suggest 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.

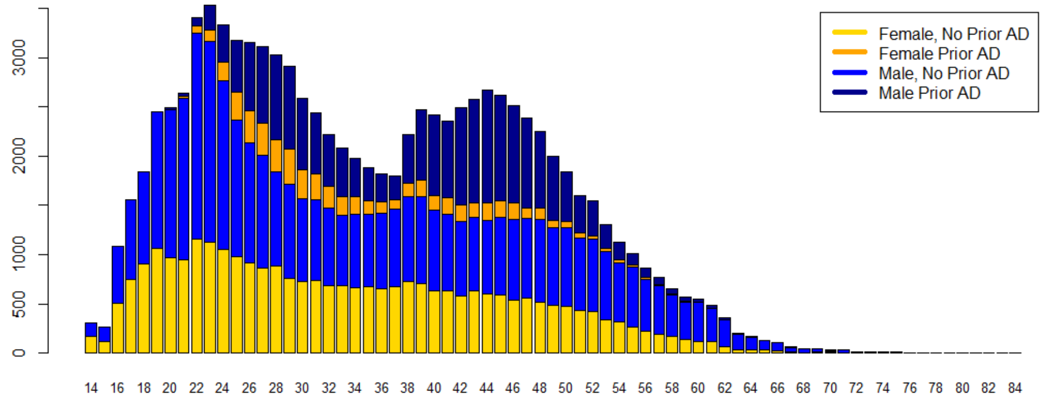

Figure 3. Age and Sex Distribution of 2009 Cohort Appointees by Prior Active Duty (AD) Service

Using a combination of the age and the years of service, it is possible to calculate the retirement eligibility of federal employees. There are three separate eligibility pathways for a full retirement under the Federal Employee Retirement System (FERS).[2] Employees are identified as being eligible for retirement at the earliest possible date under each rule system. Using the retirement eligibility age, the number of years until the employee is retirement eligible is calculated. This factor is important because individuals that are close to retirement eligibility are expected to have a lower likelihood of separating. The full list of descriptive variables included in the model is depicted in Table 2.

Survival Analysis of Employee Tenure

"Survival analysis" (or "analysis of failure-time data" or "analysis of lifetime data") is the branch of data analysis concerned with modeling lifetimes. In the context of this article, a "lifetime" is the length of tenure of a federal employee. Following the usual convention, "death" is used to indicate the end of an employee's tenure, even though this is only rarely because the employee actually died.

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 each employee in the data set is alive right after they have started and decreases steadily with increasing t. In the usual case, the survival curve can never increase, since this would indicate individuals transitioning from a dead to an alive state. In this case, it is possible to have an employee who "dies"—leaves

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[2] There are three formulas for determining retirement eligibility under FERS: 1) age of at least 62 years and five years of federal service, 2) minimum age of 60 years and 20 years of federal service, and 3) meeting the Minimum Retirement Age with 30 years of federal service. MRA is set depending on year of birth and ranges between 55 and 57 years.

federal service—and then “comes back to life” after being rehired. This is fairly rare, and this small number of employees is not considered further.

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. The hazard function is mentioned only in preparation for the following description of analysis techniques.

Survival analysis differs from ordinary regression-type analyses in several important ways. First, most survival analyses may involve censored data. This refers to the fact that, for many employees, their lifetimes cannot be 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 their lifetime is at least eight years, but we do not know whether they will continue to nine or 12 or 20 years. So in that sense, their (final) lifetime is unknown—it has been censored. “Right-censoring” is present in this example, 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 are in common use, and survival analysis software is widely available.

Table 2. Characteristics Included in the Model

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 toward 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].

A second and perhaps subtler 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 toward longer-serving employees. Consider, for instance, the set of employees who were hired in 1995. Among all those employees, the only ones for which information is available are the ones who survived at least 10 years (since this project's data starts in 2005). Employees who left before 2005 are lost without a trace. So 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. Figure 4 shows examples of censoring and truncation.

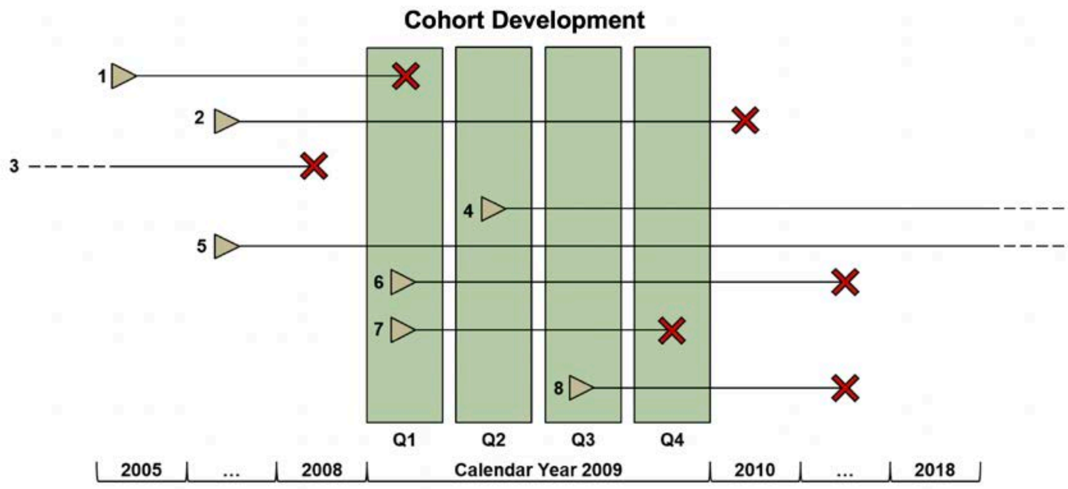


Figure 4. Illustration of Truncation

A third issue arises with time-varying covariates. Time-varying covariates are covariates whose values for a particular individual can change over the course of the study period. In this data set, these include educational status, service (Army, Navy, Air Force, Marine Corps, or DoD), and paygrade. For this study, time-varying covariates remain constant for most individuals over the study period. Then they are treated as time-constant using their values at time of appointment for cohorts and at the cross-section date for cross-sectional data. In principle, time-varying covariates are fairly easily incorporated into a survival analysis as long as changes depend only on the past and not the future. By reshaping data with time-varying covariates, survival analysis software that allows for left-truncation can be used for right-censored data with time-varying covariates.

Approaches to Survival Analysis

Traditional survival analyses fall into one of several camps. In a "parametric" survival analysis, the hazard rate is assumed to take on a particular functional form, like, for example, that of a Weibull distribution. A small number of parameters of the function are estimated from the data, and the parametrized hazard function then determines the survival function. For anything more complicated than a small manufactured part, real hazard functions are much more complicated, and this type of analysis is not pursued here.

Particularly when people are the subjects, a "non-parametric" approach called Kaplan-Meier ("KM") is very commonly used. Here the probability of surviving to time 3, for example, is computed through a product of simple conditional probabilities. In particular,

Pr (survive until t = 3) = Pr (survive until t = 1)

× Pr (survive until t = 2, given survival until t = 1)

× Pr (survive until t = 3, given survival until t = 2).

More precisely, the probability of survival until any time t, $S(t)$, is computed as a product of probabilities computed at all the times of death preceding t. Where no death is observed, the model claims no probability of dying. So, the resulting survival function estimates take on a stairstep appearance, with vertical drops where deaths occur and horizontal stretches where no deaths occur. Despite the unusual staircase look, this model is widely used and successful. Where more than one curve is specified, the data are broken into groups, which are treated separately; there is no "sharing of information" between groups.

A KM analysis can therefore require lots of data if many predictors are included in the model. The basic KM model does not handle continuous predictors or time-varying covariates, although scholars have described methods by which to handle these complications.

One such method, a survival tree (Negassa, Ciampi, Abrahamowicz, Shapiro, & Boivin, 2005), is used in this analysis. Survival trees are constructed much like classification and regression trees (Segal, 1997). The resulting tree partitions the data into subsets (terminal nodes) where survival functions are fit using the records in each terminal node. The non-parametric KM estimate is used rather than parametric estimates to determine the split points. 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., all observations with age less than 45 and all observations with age at least 45); categorical covariates are split according to their levels. The splitting criteria is defined so that the split yields subsets that are as homogeneous as possible.

Survival trees have a fairly long history, starting with Gordon and Olshen (1985). The splitting rule used in these trees (the log-rank test) is an implementation of the conditional inference procedure by Hothorn, Hornik, and Zeileis (2006). This article's implementation of survival trees is also influenced by the research of Fu and Simonoff (2016), who extend survival trees to handle left-truncated data. This extension also lets for the handling of time-varying covariates. Their R package LTRCtrees is also used (Fu & Simonoff, 2017).

The algorithm iteratively splits each node into two subgroups by each of the remaining categorical variables. It then conducts a log-rank test to determine whether the survival curves in the test and null groups are different. Of all the tests conducted, the split that generates the lowest p-value for the log-rank test is kept. The algorithm then repeats on each of the two newly created subpopulations. The algorithm continues until no subsequent split reaches a given p-value threshold.

For survival trees, the criterion is a "goodness of fit" measure to capture how well the survival function is estimated in each subset. Trees are grown so that they are not too shallow, where the resulting survival function estimates are biased because the data in the leaves are too heterogeneous (under-fitting). Splitting is stopped before the resulting survival function estimates fit the data so well that they their ability to predict survival probabilities for new observations is compromised (over-fitting). Of the many nice properties of trees, trees are chosen because the splitting is automatic and non-parametric; by using KM, the survival function with left-truncated and right-censored data in each leaf can be estimated non-parametrically; this methodology allows numeric, categorical, and ordinal and time-varying covariates; missing values are handled gracefully; the results are not unduly influenced by extreme covariate values (e.g., the 84-year-old new hire); and this approach is invariant to monotonic transformations of numeric values (e.g., age versus log(age)).

Results

Of the 97,654 individuals included in the cohort, 51.7% of them separated 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 5.

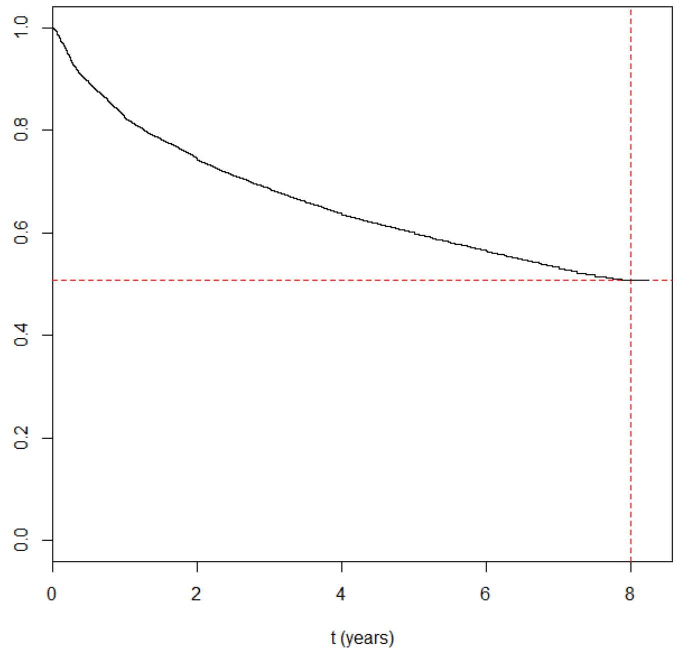


Figure 5. KM Estimated Survival Function for the Entire 2009 Cohort with Dashed Lines Indicating the Estimated Probability of Separation After Eight Years

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 the entire population of the 2009 cohort is used, rather than a randomly selected sample.

The survival curve shown in Figure 5 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. Two years after their initial appointment, the survival curve had dropped to approximately 0.75, meaning that 25% of the new hires had left by that point in time. The managerial implication of this turnover rate is that administrators seeking to replace retiring workers need to expect a share of new hires to separate while they are relatively new to their positions. Once employees have more than two years of service since their appointment, their rate of attrition flattens. At eight years, the survival curve intersects the horizontal checked red line, showing the expected 50.08% expected survival rate.

Estimating KM survival functions by age and gender allows for comparison of how attrition rates vary across employees who are appointed at different ages. These survival curves are also separated for men and women. Figure 6 depicts these curves. The lowest curve for both men and women belongs to employees who were between 13 and 19 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 young male hires in that 13 to 19 age range remain employed for at least eight years, while only 14% of young women in that same age group remain over the same eight-year period.

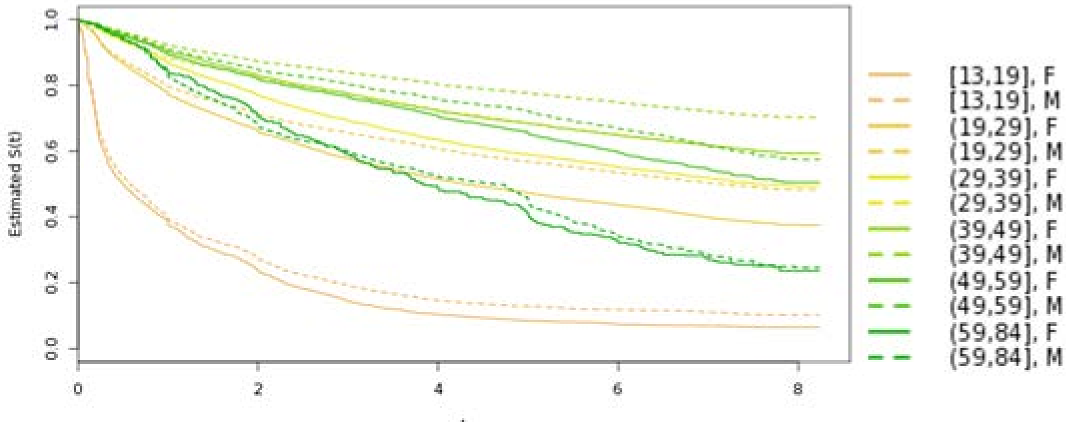


Figure 6. KM Estimated Survival Functions by Age and Sex

As the age at appointment increases, the survival rate appears to increase, at least until the last two age categories. For adults hired in the age range of 47 to 52 years of age, [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 of 52 to 84 years of age [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 eight-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 the survival model is identifying patterns of behavior that are consistent with practice-based experience.

The gender distribution across the four job categories is depicted in Table 3. This table shows that while, overall, 35.75% of the new appointees in the 2009 cohort were identified as female, only 19.19% entered STEM job categories. At the other extreme, women made up 76.42% of new appointees in the civilian medical job categories. Non-STEM positions closely mirrored the overall gender distribution with 36.42% identified as female.

Table 3. Distribution of Sex and Job Category in the 2009 Cohort

	Social Science (C)	Medical (M)	Non-STEM (N)	STEM (S)	Total	Percent
Female	333	2573	29,658	2,344	34,908	35.75%
Male	296	794	51,786	9,870	62,746	64.25%
Total	629	3367	81,444	12,214	97,654	
Percent Female	52.94%	76.42%	36.42%	19.19%	35.75%	

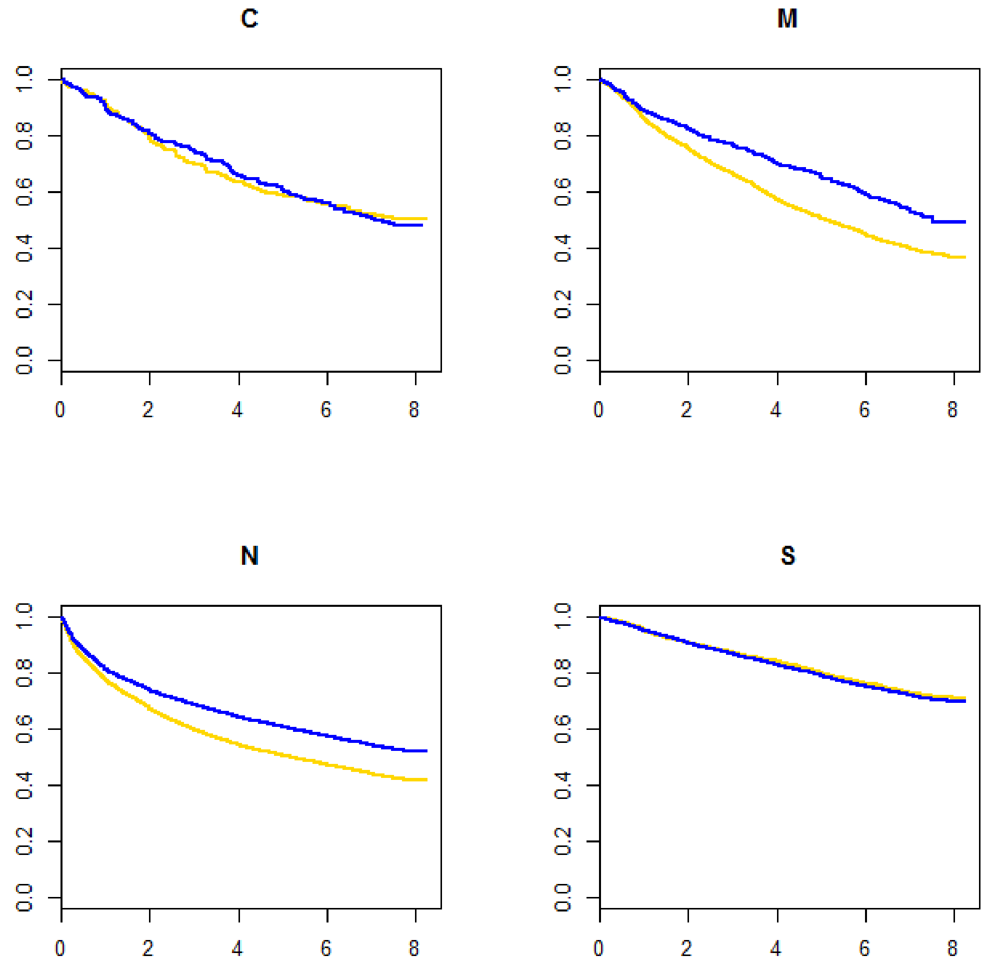


Figure 7. KM Survival Curves by STEM Category and Sex

The KM curves displayed in Figure 7 describe, for each STEM classification group, the gender attrition differential. In both the Medical (M) and non-STEM (N) 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 in these employment categories have experienced more than 10% higher attrition than men. This is observed on Figure 7 as the vertical distance between the two lines at 8 years in both the M and N graphs. 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.

Within the STEM employment category, both male and female employees appear to follow the same survival path. The lack of a sex-based survival difference in the behavior of STEM professionals is an important empirical finding. It may be that the professional protections and norms for advancement under federal civilian employment offer a better environment than other employment environments for female STEM professionals. Additionally, it should be noted that the hostile and discriminatory factors identified in qualitative research on women in academia (e.g., Xu, 2008) may still be present in the federal context and are harmful in ways that are not expressed in survival rates.

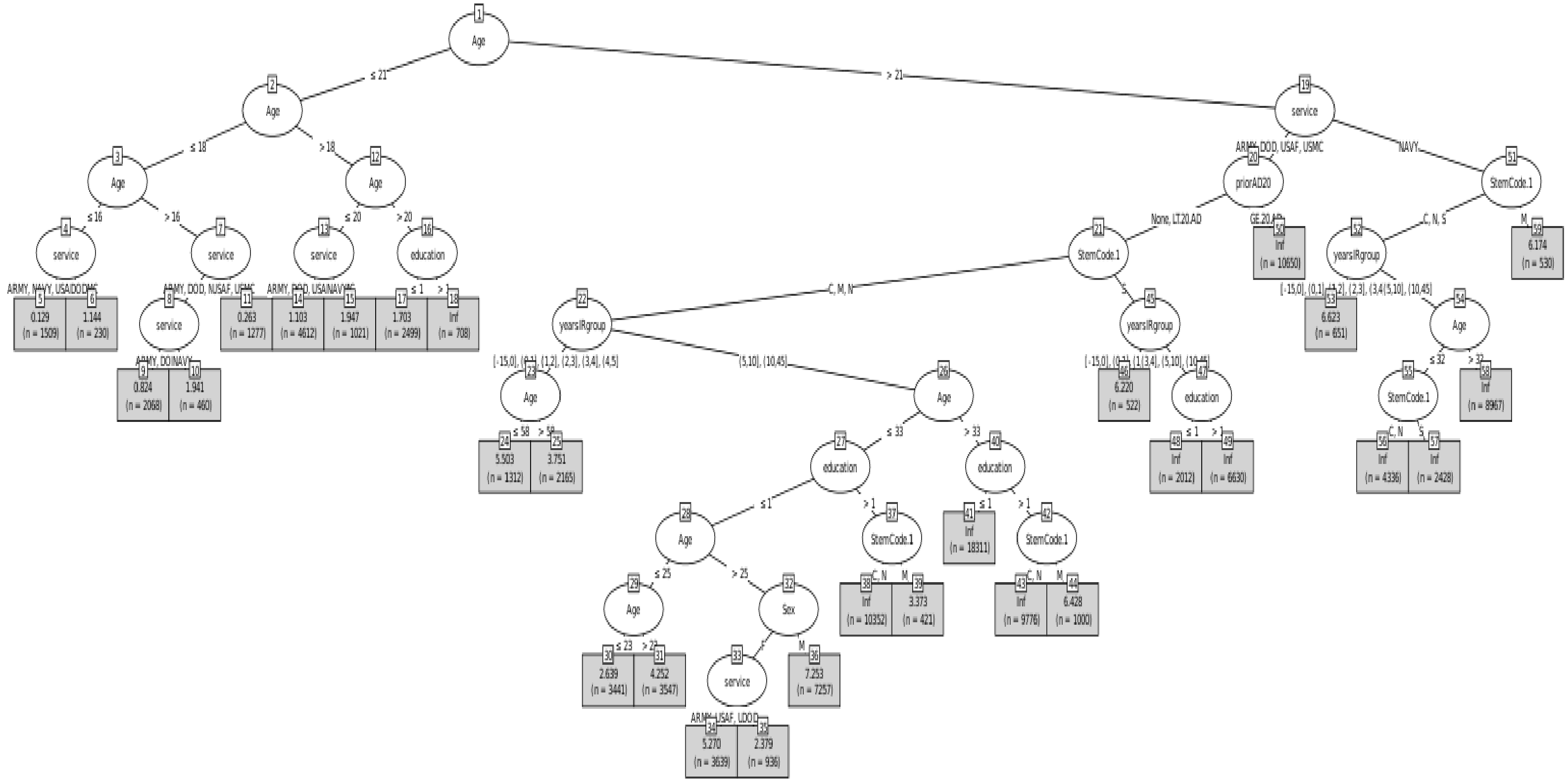
Survival Tree Results

While KM survival functions are excellent at depicting the relationship between attrition and a few variables, they are only able to effectively display one to three variables at a time. In this section, the results of the survival tree analysis are described. This approach helps reveal more complex relationships among several variables within the diverse population of the 2009 cohort.

Figure 8 depicts the survival tree generated for the 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.[3] The first division identified by the algorithm was the categorical 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. The subdivision process is repeated for each of these two groups to create additional "branches." This process repeats 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.

This approach identifies 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 includes only 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.

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



1 Age
≤ 21
> 21
2 Age
≤ 18
> 18
3 Age
≤ 16
> 16
4 service
7 service
12 Age
≤ 20
> 20
13 service
16 education
19 service
NAVY
20 priorAD20
51 StemCode.1
21 StemCode.1
None, LT.20.AD
GE.20.AD
50 Inf (n = 10650)
52 yearsIRgroup
C, N, S
M
59 6.174 (n = 530)
5 0.129 (n = 1509)
6 1.144 (n = 230)
8 service
9 0.824 (n = 2068)
10 1.941 (n = 460)
11 0.263 (n = 1277)
14 1.103 (n = 4612)
15 1.947 (n = 1021)
17 1.703 (n = 2499)
18 Inf (n = 708)
22 yearsIRgroup
C, M, N
S
45 yearsIRgroup
53 6.623 (n = 651)
54 Age
≤ 32
> 32
23 Age
≤ 58
> 58
24 5.503 (n = 1312)
25 3.751 (n = 2165)
(5,10], (10,45]
26 Age
≤ 33
> 33
46 6.220 (n = 522)
47 education
48 Inf (n = 2012)
49 Inf (n = 6630)
55 StemCode.1
C, N
S
56 Inf (n = 4336)
57 Inf (n = 2428)
58 Inf (n = 8967)
27 education
40 education
≤ 1
> 1
28 Age
≤ 25
> 25
37 StemCode.1
41 Inf (n = 18311)
42 StemCode.1
29 Age
≤ 23
> 23
30 2.639 (n = 3441)
31 4.252 (n = 3547)
32 Sex
F
M
33 service
36 7.253 (n = 7257)
38 Inf (n = 10352)
39 3.373 (n = 421)
43 Inf (n = 9776)
44 6.428 (n = 1000)
34 5.270 (n = 3639)
35 2.379 (n = 936)

STEM classification appears at several points in the survival tree. Unsurprisingly, STEM classification only appears in the right half of the tree for employees that were older than 21 at the time of their appointment. Most of the 21 and younger subset would not have the education to enter the medical and STEM career fields. The first branch to the lower right of initial age division leads to node 19, which divides Navy employees from all other organizational groups in the Department of Defense. Following the Navy branch to node 51 shows that the subgroup is then divided based on STEM classification code. This node separates the medical employees from the remaining three groups. The next division within the Navy where STEM is a significant factor is three nodes lower on the tree. Nodes 52 and 54 isolate a subgroup that has between five and 45 years of employment remaining before they would become retirement eligible, and is 32 years of age or younger. Node 55 reveals that the STEM employees in this subgroup exhibit a different survival curve than the social science and non-STEM employees.

The survival tree illustrates the specific subpopulations where turnover behavior differs across employment categories. Each of the terminal points on the survival tree represents a distinct KM survival curve. Although we do not display all of the resulting curves in this analysis, they are available and can be provided upon request. In a practical administrative exercise, public managers and human resource officers could use the various resulting survival curves to observe differences in projected turnover rates for specific components of the agency workforce.

Overall, the features of the survival tree are consistent with the career life-cycle models estimated at the agency level (e.g., Lewis & 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. Age and retirement eligibility are the strongest predictors in the mode. Agency-level differences, here represented by the different military service branches, are also important branch points in the survival tree. The role of agencies suggests that culture and other managerial practices are important in attrition behavior. While it seems unlikely that a subsequent study could merge the individual-level data with individual employee satisfaction responses, it may be possible in future scholarship to pair average responses from organizational units to measure the aggregate climate of employee satisfaction. This may help untangle the organizational factors from the individual life-cycle factors.

Conclusion

The goal of this analysis has been to examine actual employee turnover behavior to determine how survival rates vary across different subpopulations of the civilian workforce. The primary empirical result was that the gender differential observed in non-STEM job categories disappears for STEM workers. This empirical finding raises several questions that should be followed by subsequent research. First, the finding that the gender differential disappears for federal civil servants in STEM differs from the findings in the academic STEM context as reported by Xu (2008). This quantitative finding should be followed by qualitative studies of the working environment for women in STEM careers in the federal environment to see whether the hostile environmental effects found in academia are present. Similarly, the private tech sector has been criticized for its hostile and discriminatory practices toward women (Funk & Parker, 2018; Pew Research Center, 2018). Are the protections for federal workers mitigating these effects?

Another important implication of this research is that it illustrates the differences in turnover behavior at different points in public service career trajectories. By identifying how attrition rates changes at different points in the early years of a career, this research illustrates the rates of recruitment that agencies must achieve to adequately backfill projected attrition. If after three years of employment, 20–30% of employees have separated, administrators should compensate by hiring at a proportionately higher rate to replace projected losses over this same period.

One of the primary practical implications of this analysis is the implication for managers seeking to increase representation of women in different career areas. The DoD may consider refocusing its efforts on recruitment strategies to increase the share of women who 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.

The primary contribution of this analysis is that it investigates these issues of turnover behavior with individual employee record data that has not been previously available in studies of public sector human resource management. Prior studies have used aggregate averages of agency turnover or relied on problematic proxies of turnover intention. Continuing this form of quantitative analysis of personnel records paired with studies of qualitative factors will help develop a better understanding of the determinants of employee turnover in the future.

References

Asch, B. J. (2002). *Paying, promoting and retaining high-quality workers in the Department of Defense* (RB-7550-OSD). Santa Monica, CA: RAND. Retrieved from https://www.rand.org/pubs/research_briefs/RB7550.html.

Bartholomew, D. J., Forbes, A. F., & McClean, S. I. (1991). *Statistical techniques for manpower planning* (2nd ed.). New York, NY: John Wiley and Sons.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy, 70*(5, Part 2), 9–49.

Blau, F. D., & Kahn, L. M. (1981). Race and sex differences in quits by young workers. *ILR Review, 34*(4), 563–77. Retrieved from https://doi.org/10.1177/001979398103400406.

Buttrey, S., Klingensmith, K., & Whitaker, L. (2018). Civilian Department of Defense attrition. Unpublished technical report.

Cohen, G., Blake, R. S., & Goodman, D. (2016). Does turnover intention matter? Evaluating the usefulness of turnover intention rate as a predictor of actual turnover rate. *Review of Public Personnel Administration, 36*(3), 240–263. Retrieved from https://doi.org/10.1177/0734371X15581850.

Congressional Budget Office. (1986). *Employee turnover in the federal government*. Washington, DC: Author.

Dalton, D. R., Johnson, J. L., & Daily, C. M. (1999). On the use of ‘intent to ...’ variables in organizational research: An empirical and cautionary assessment. *Human Relations, 52*(10), 1337–1350. Retrieved from https://doi.org/10.1177/001872679905201006.

Dolan, J. (2004). Gender equity: Illusion or reality for women in the federal executive service? *Public Administration Review, 64*(3), 299–308. Retrieved from https://doi.org/10.1111/j.1540-6210.2004.00374.x.

Fu, W., & Simonoff, J. S. (2016). Survival trees for left-truncated and right-censored data, with application to time-varying covariate data. *Biostatistics, 18*(2), 352–369.

Fu, W., & Simonoff, J. S. (2017). LTRCtrees: Survival trees to fit left-truncated and right-censored and interval-censored survival data (R Package Ver. 0.5. 0). Retrieved February 12, 2019.

Funk, C., & Parker, K. (2018, January 9). Women and men in STEM often at odds over workplace equity. Retrieved from https://www.pewsocialtrends.org/2018/01/09/women-and-men-in-stem-often-at-odds-over-workplace-equity/.

Goodman, D., French, P. E., & Battaglio, R. P. (2015). Determinants of local government workforce planning. *The American Review of Public Administration, 45*(2), 135–152. Retrieved from https://doi.org/10.1177/0275074013486179.

Gordon, L., & Olshen, R. A. (1985). Tree-structured survival analysis. *Cancer Treatment Reports, 69*(10), 1065–1069.

Grissom, J. A., Nicholson-Crotty, J., & Keiser, L. (2012). Does my boss's gender matter? Explaining job satisfaction and employee turnover in the public sector. *Journal of Public Administration Research and Theory, 22*(4), 649–673. Retrieved from https://doi.org/10.1093/jopart/mus004.

Hothorn, T., Hornik, K., & Zeileis, A. (2006). Unbiased recursive partitioning: A conditional inference framework. *Journal of Computational and Graphical Statistics, 15*(3), 651–674. Retrieved from https://doi.org/10.1198/106186006X133933.

Ippolito, R. A. (1987). Why federal workers don't quit. *Journal of Human Resources, 22*(2), 281–299.

Jung, C. S. (2010). Predicting organizational actual turnover rates in the U.S. federal government. *International Public Management Journal, 13*(3), 297–317. Retrieved from https://doi.org/10.1080/10967494.2010.504124.

Kreisher, O. (2019, November 14). Navy Under Secretary Modly touts E4S education initiative during forum. *Seapower* [Blog]. Retrieved from https://seapowermagazine.org/navy-undersecretary-modly-touts-e4s-education-initiative-during-forum/.

Lewis, G. B., & Park, K. (1989). Turnover rates in federal white-collar employment: Are women more likely to quit than men? *The American Review of Public Administration, 19*(1), 13–28. Retrieved from https://doi.org/10.1177/027507408901900102.

Mancke, R. B. (1971). Lower pay for women: A case of economic discrimination? *Industrial Relations, 10*(3), 316–326. Retrieved from https://doi.org/10.1111/j.1468-232X.1971.tb00029.x.

McCullough, L. (2011). Women's leadership in science, technology, engineering and mathematics: Barriers to participation. *Forum on Public Policy Online, 2011*(2). Retrieved from https://eric.ed.gov/?id=EJ944199.

Moynihan, D. P., & Landuyt, N. (2008). Explaining turnover intention in state government: Examining the roles of gender, life cycle, and loyalty. *Review of Public Personnel Administration, 28*(2), 120–143. Retrieved from https://doi.org/10.1177/0734371X08315771.

National Academy of Engineering and National Research Council. (2012). *Assuring the U.S. Department of Defense a strong science, technology, engineering, and mathematics (STEM) workforce.* Washington, DC: National Academies Press.

Negassa, A., Ciampi, A., Abrahamowicz, M., Shapiro, S., & Boivin, J.-F. (2005). Tree-structured subgroup analysis for censored survival data: Validation of computationally inexpensive model selection criteria. *Statistics and Computing, 15*(3), 231–239. Retrieved from https://doi.org/10.1007/s11222-005-1311-z.

Office of Personnel Management. (2020). Vet guide for HR professionals. Retrieved from https://www.opm.gov/policy-data-oversight/veterans-services/vet-guide-for-hr-professionals/#content

Oh, S. S., & Lewis, G. B. (2011). Stemming inequality? Employment and pay of female and minority scientists and engineers. *The Social Science Journal, 48*(2), 397–403. Retrieved from https://doi.org/10.1016/j.soscij.2010.11.008.

Patten, E., & Parker, K. (2011). *Women in the U.S. military: Growing share, distinctive profile.* Washington, DC: Pew Research Center.

Pew Research Center. (2018). *Women and men in STEM often at odds over workplace equity*. Washington, DC: Pew Research Center.

Pitts, D., Marvel, J., & Fernandez, S. (2011). So hard to say goodbye? Turnover intention among U.S. federal employees. *Public Administration Review, 71*(5), 751–760. Retrieved from https://doi.org/10.1111/j.1540-6210.2011.02414.x

Riffle, R., Schneider, T., Hillard, A., Polander, E., Jackson, S., DesAutels, P., & Wheatly, M. (2013). A mixed methods study of gender, STEM department climate, and workplace outcomes. *Journal of Women and Minorities in Science and Engineering, 19*(3).

Sawhill, I. V. (1973). The economics of discrimination against women: Some new findings. *The Journal of Human Resources, 8*(3), 383–396.

Schlesinger, L. A., & Heskett, J. L. (1991). The service-driven service company. *Harvard Business Review, 69*(5), 71–81.

Segal, M. R. (1997). Features of tree-structured survival analysis. *Epidemiology, 8*(4), 344–346.

Steel, R. P., & Ovalle, N. K. (1984). A review and meta-analysis of research on the relationship between behavioral intentions and employee turnover. *Journal of Applied Psychology, 69*(4), 673.

Tett, R. P., & Meyer, J. P. (1993). Job satisfaction, organizational commitment, turnover intention, and turnover: Path analyses based on meta-analytic findings. *Personnel Psychology, 46*(2), 259–293. Retrieved from https://doi.org/10.1111/j.1744-6570.1993.tb00874.x

Vie, L. L., Griffith, K. N., Scheier, L. M., Lester, P. B., & Seligman, M. E. P. (2013). The person-event data environment: Leveraging big data for studies of psychological strengths in soldiers. *Frontiers in Psychology, 4*. Retrieved from https://doi.org/10.3389/fpsyg.2013.00934.

Xu, Y. (2015). Focusing on women in STEM: A longitudinal examination of gender-based earning gap of college graduates. *The Journal of Higher Education, 86*(4), 489–523. Retrieved from https://doi.org/10.1080/00221546.2015.11777373.

Xu, Y. J. (2008). Gender disparity in STEM disciplines: A study of faculty attrition and turnover intentions. *Research in Higher Education, 49*(7), 607–624. Retrieved from https://doi.org/10.1007/s11162-008-9097-4.

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