# Supplementary Materials

for

# The Career Advancement of Military Veterans in Recent Cohorts of the U.S. Executive Branch

Contents	Page
1. Analyses taking into account type of appointment and appointment authority	S2
2. Loss of observations due to data management procedures	S11
3. Comparison of estimated coefficients when using list-wise deletion v. no deletion	S12
4. Analysis of employees of who worked the same number of years before exit	S15
5. Analysis of employees by occupational category: administrative, professional, clerical	S20
6. Complete replication altering method of excluding part-time employees & duplicates	S24
7. Calibration of methods with Johnson (2015)	S41
8. Supplementary Materials References	S43

#### 1. Analyses taking into account Appointment Type and Appointment Authority

Veterans' preference applies in only a subset of openings in the U.S. federal service and managers can avoid preference via the use of certain hiring procedures (a.k.a. appointment authorities). Although Johnson (2015) and Lewis (2013) did not take empirical measures to account for these features of federal hiring, we do so in this section of the supplementary materials by drawing on two variables from the CPDF: Type of Appointment and Appointment Authority (a.k.a. "hiring" authority) at hire (see OPM, 2007). The variable Type of Appointment indicates whether employees were hired as a permanent employee, a temporary employee, or one of various other designations relating to the term of employment, the nature of the work to be conducted, and whether the hire is a political appointment (again, see OPM, 2007). Appointment Authority indicates the formal set of procedures that managers chose to use when recruiting, evaluating, and selecting candidates for the position to which an employee is hired; dozens of such "appointment authorities" exist (OPM, 2007). Each of these variables influence whether veterans' preference points can be applied in the hiring process; thus, controlling for them ensures that comparisons within our analysis only occur among veterans and nonveterans subject to the same degree to which veterans' preference could influence the hiring process. To incorporate these variables into our analysis, we performed the following procedures.

First, we added control variables to our analysis that indicate the *Type of Appointment* to which an employee was hired and the *Appointment Authority* that was used when selecting the employee. This approach statistically focuses comparisons on military veterans and nonveterans subject to the same degree to which veterans' preference could influence the hiring process. The third column of Table S1 (below) reports the results of this analysis. The analysis regresses employees' GS grades—from a given year of their career—on *both* the (i) indicator of veteran-status discussed in the main text (1=veterans, 0=nonveteran) and (ii) controls for employees'

#### -Supplementary Materials-

combination of workplace characteristics at entry-namely, entry occupation, agency, location, grade, and year—plus their Type of Appointment and Appointment Authority (note that appointment authorities are grouped into the categories used in MSPB [2008]). The second column of Table S1 reports the estimated coefficients and standard errors from our "baseline" analysis, which regresses GS grades on the veteran-status indicator and employees' combination of workplace characteristics at entry, but excludes Type of Appointment and Appointment Authority (i.e. it represents the focal analysis reported in the main text, estimated on the same data as the models in the third column of Table S1). The rightmost, fourth column of Table S1 reports, in each row, the p-value from a test of the hypothesis that the estimated coefficients in that same row do not differ from each other.<sup>1</sup> As one can see in the table, although the estimates from models that include *Type of Appointment* and *Appointment Authority* are often lower in value than the corresponding estimates in the second column, they and the coefficients reported in the adjacent column exhibit small magnitudes and possess notably large standard errors, thus raising the possibility that the apparent differences might be attributable merely to statistical variation, not attributable to a statistically significant difference. Indeed, the column of Bonferroni-adjusted *p*-values reported in the rightmost column of the table indicates that we cannot reject the null hypothesis of no difference in the coefficients in any year of employment under study. Across every year of employment, the p-value indicates that one would find

<sup>&</sup>lt;sup>1</sup> We perform a Bonferroni correction of the p-values in this and other tests throughout this response to address the increased likelihood of uncovering statistically significant results under multiple hypothesis testing (Miller, 1966). Although the Bonferroni correction generally involves dividing the critical threshold, alpha, by the number of hypothesis tests, m, and comparing this to the observed p-value,  $p^*$  (i.e.  $alpha/m < p^*$ ), this method makes presentation of the findings awkward because it requires the researcher to compute various critical values and report those critical values *in addition* to the relevant p-values. An equivalent, yet clearer, approach is to adjust the p-value, instead of the critical value, by multiplying the computed p-value in a given test by the number of comparisons then comparing it to the conventional critical value. This procedures is commonly implemented by statistical software (see IBM, 2018) and it prevents the reader from having to engage in uncommon practices to interpret statistical findings.

differences in coefficient estimates as large as those observed with virtual certainty (p=1.00) were it true that no difference actually existed between the coefficients.

To further understand the effect of appointment types and appointment authorities on our estimates, we performed a separate set of analyses on subsets of the data consisting of employees that we knew either *were* subject to the influence of veterans' preference or *were not* subject to veterans' preference (however, note that some might have been eligible for veterans' preference and, thus, the veteran status indicator—which is putatively derived from a veteran's preference eligibility [see Lewis 2013]—takes the value of 1 for some observations). These analyses provided further evidence to see if veterans' preference in the hiring process might have influenced our estimates of veterans' career advancement relative to that of nonveterans.

We first replicated our analysis solely on employees who entered federal service with their *Type of Appointment* designated as either "Career, Competitive Service Permanent" or "Career Conditional, Competitive Service Permanent"; focusing on these employees rules out political appointees and non-permanent employees hired in processes that do not involve veterans' preference. Results from this analysis appear in Table S2. Results from this analysis again return coefficients that take slightly lower values than those from the baseline analysis produced using the methods reported in the main text. Substantively, the differences are small. Furthermore, tests of the hypothesis of no difference in the coefficients shows that these apparent differences are not statistically significant. As in Table S1, the adjusted p-values reported in the final column of Table S2 vastly exceed conventional standards of statistical significance (e.g., p< 0.05) and they essentially suggested that one would certainly observe the coefficient differences we compute were there to be truly no difference in the coefficients (p=1.00).

Next, we examined employees whose appointment authorities indicated that they were selected either via competitive examination, which incorporates veterans' preference into the hiring process, or the direct hire authority, which allows managers to circumvent veterans' preference (though preference-eligible applicants can still apply; OPM 2017). Table S3 (below) compares our baseline results with analyses performed only on hires subject to competitive examination, whereas Table S4 (below) compares the baseline results with findings from employees entering via direct hire. Finally, Table S5 (below) compares estimates from competitively examined employees with those from employees subject to direct hire. Once again, as evident in the *p*-values reported in Tables S3, S4, and S5, we find no significant differences between (a) estimates produced in our baseline analysis versus those produced from data including only employees facing competitive examination; (b) estimates produced in our baseline analysis versus those produced from only employees selected via the direct hire authority; or, (c) estimates produced from data including only employees facing competitive examination versus those produced from only employees selected via the direct hire authority. These findings once again indicate that the degree to which veterans' preference applies in any given context has a very limited effect on our coefficients estimates. Substantively, this conclusion supports the inference we draw from the main findings reported in our manuscript: veteran status appears to be a poor predictor of career advancement once an employee's entry job is taken into account. Thus, it has a limited effect on federal workforce quality.

Year of Career	Type of Appointment and Appointment Authority Not Included	Type of Appointment and Appointment Authority Included	Bonferroni <i>p</i> -value for Coefficient Difference
Caleel			Coefficient Difference
2	0.01866 (0.00424)	0.01656 (0.00605)	1.00
3	0.02003 (0.00554)	0.01382 (0.00778)	1.00
4	0.01009 (0.00684)	0.0024 (0.00965)	1.00
5	0.01374 (0.00842)	0.00937 (0.01205)	1.00
6	0.02433 (0.01022)	0.01034 (0.01479)	1.00
7	0.03 (0.01233)	-0.01804 (0.01782)	0.56
8	0.02028 (0.01438)	-0.02768 (0.02077)	1.00
9	0.007 (0.01679)	-0.04102 (0.02376)	1.00
10	0.00882 (0.01907)	-0.05261 (0.02703)	1.00
11	0.01109 (0.0216)	-0.04197 (0.03067)	1.00
12	-0.00818 (0.02441)	-0.05757 (0.03484)	1.00
13	-0.03801 (0.02785)	-0.09837 (0.04008)	1.00
14	-0.04133	-0.09561	1.00
15	(0.03243) -0.02514 (0.03717)	(0.04629) -0.06662 (0.05240)	1.00
16	-0.07109	(0.05349) -0.11616 (0.06228)	1.00
17	(0.04348) -0.03649 (0.05003)	(0.06328) -0.12346 (0.07285)	1.00
18	-0.06194 (0.05731)	-0.21069 (0.08359)	1.00
19	-0.03765 (0.06396)	-0.20222 (0.09282)	1.00
20	0.00226	-0.22375	1.00
21	(0.08014) 0.21097	(0.11452) 0.15056	1.00
22	(0.09926) 0.31781 (0.14102)	(0.14689) 0.23414 (0.19596)	1.00

Table S1. Baseline analysis compared with models controlling for appointment-type and -authority

Year of Career	Analysis Including All Employees	Only Including Competitive Service Permanent	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.01866 (0.00424)	0.00979 (0.00526)	1.00
3	0.02003 (0.00554)	0.01373 (0.00729)	1.00
4	0.01009 (0.00684)	0.00277 (0.00945)	1.00
5	0.01374 (0.00842)	-0.00175 (0.012)	1.00
6	0.02433 (0.01022)	0.00367 (0.0147)	1.00
7	0.03 (0.01233)	-0.01719 (0.01773)	0.61
8	0.02028 (0.01438)	-0.02277 (0.02054)	1.00
9	0.007 (0.01679)	-0.03023 (0.02332)	1.00
10	0.00882 (0.01907)	-0.04807 (0.0264)	1.00
11	0.01109 (0.0216)	-0.02419 (0.02996)	1.00
12	-0.00818 (0.02441)	-0.04771 (0.03396)	1.00
13	-0.03801 (0.02785)	-0.07824 (0.03913)	1.00
14	-0.04133 (0.03243)	-0.08828 (0.04634)	1.00
15	-0.02514 (0.03717)	-0.07304 (0.05402)	1.00
16	-0.07109 (0.04348)	-0.13482 (0.06362)	1.00
17	-0.03649 (0.05003)	-0.13768 (0.07338)	1.00
18	-0.06194 (0.05731)	-0.20834 (0.08456)	1.00
19	-0.03765 (0.06396)	-0.13798 (0.09252)	1.00
20	0.00226 (0.08014)	-0.15485 (0.11394)	1.00
21	0.21097 (0.09926)	0.19429 (0.14473)	1.00
22	0.31781 (0.14102)	0.21038 (0.19126)	1.00

Table S2. Baseline analysis compared with analysis on subset of competitive-service, permanent employees

Year of Career	Analysis Including All Employees	Only Including Competitively Examined Employees	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.01866 (0.00424)	0.01995 (0.00588)	1.00
3	0.02003 (0.00554)	0.02687 (0.00808)	1.00
4	0.01009 (0.00684)	0.01566 (0.01044)	1.00
5	0.01374 (0.00842)	0.01748 (0.01313)	1.00
6	0.02433 (0.01022)	0.01713 (0.01617)	1.00
7	0.03 (0.01233)	-0.00515 (0.0195)	1.00
8	0.02028 (0.01438)	-0.02011 (0.02266)	1.00
9	0.007 (0.01679)	-0.03544 (0.02596)	1.00
10	0.00882 (0.01907)	-0.04176 (0.02939)	1.00
11	0.01109 (0.0216)	-0.03488 (0.03364)	1.00
12	-0.00818 (0.02441)	-0.03733 (0.03821)	1.00
13	-0.03801 (0.02785)	-0.09219 (0.04413)	1.00
14	-0.04133 (0.03243)	-0.08778 (0.05164)	1.00
15	-0.02514 (0.03717)	-0.05081 (0.06011)	1.00
16	-0.07109 (0.04348)	-0.10751 (0.07225)	1.00
17	-0.03649 (0.05003)	-0.11595 (0.08505)	1.00
18	-0.06194 (0.05731)	-0.25989 (0.09995)	1.00
19	-0.03765 (0.06396)	-0.22417 (0.11095)	1.00
20	0.00226 (0.08014)	-0.28803 (0.13676)	1.00
21	0.21097 (0.09926)	0.17158 (0.17728)	1.00
22	0.31781 (0.14102)	0.30104 (0.2687)	1.00

Table S3. Baseline analysis compared with analysis of competitively examined employees

Year of Career	Analysis Including All Employees	Only Including Appointments Made via Direct Hire Authority	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.01866 (0.00424)	0.07253 (0.02498)	0.71
3	0.02003 (0.00554)	0.05798 (0.03407)	1.00
4	0.01009 (0.00684)	0.04412 (0.04688)	1.00
5	0.01374 (0.00842)	-0.02171 (0.06343)	1.00
6	0.02433 (0.01022)	-0.01975 (0.07824)	1.00
7	0.03 (0.01233)	-0.05206 (0.08919)	1.00
8	0.02028 (0.01438)	-0.14762 (0.10189)	1.00
9	0.007 (0.01679)	-0.14727 (0.10987)	1.00
10	0.00882 (0.01907)	-0.13539 (0.12007)	1.00
11	0.01109 (0.0216)	-0.02278 (0.12384)	1.00
12	-0.00818 (0.02441)	-0.04032 (0.12972)	1.00
13	-0.03801 (0.02785)	-0.04631 (0.13681)	1.00
14	-0.04133 (0.03243)	-0.11203 (0.14614)	1.00
15	-0.02514 (0.03717)	-0.15796 (0.15571)	1.00
16	-0.07109 (0.04348)	-0.22104 (0.16714)	1.00
17	-0.03649 (0.05003)	-0.24023 (0.17684)	1.00
18	-0.06194 (0.05731)	-0.26974 (0.18855)	1.00
19	-0.03765 (0.06396)	-0.26167 (0.19597)	1.00
20	0.00226 (0.08014)	-0.22355 (0.22949)	1.00
21	0.21097 (0.09926)	0.03693 (0.26991)	1.00
22	0.31781 (0.14102)	0.06489 (0.29377)	1.00

 Table S4. Baseline analysis compared with subset of direct hire appointments

Year of Career	Only Including Competitively Examined Employees	Only Including Appointments Made via Direct Hire Authority	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.01995 (0.00588)	0.07253 (0.02498)	0.85
3	0.02687 (0.00808)	0.05798 (0.03407)	1.00
4	0.01566 (0.01044)	0.04412 (0.04688)	1.00
5	0.01748 (0.01313)	-0.02171 (0.06343)	1.00
6	0.01713 (0.01617)	-0.01975 (0.07824)	1.00
7	-0.00515 (0.0195)	-0.05206 (0.08919)	1.00
8	-0.02011 (0.02266)	-0.14762 (0.10189)	1.00
9	-0.03544 (0.02596)	-0.14727 (0.10987)	1.00
10	-0.04176 (0.02939)	-0.13539 (0.12007)	1.00
11	-0.03488 (0.03364)	-0.02278 (0.12384)	1.00
12	-0.03733 (0.03821)	-0.04032 (0.12972)	1.00
13	-0.09219 (0.04413)	-0.04631 (0.13681)	1.00
14	-0.08778 (0.05164)	-0.11203 (0.14614)	1.00
15	-0.05081 (0.06011)	-0.15796 (0.15571)	1.00
16	-0.10751 (0.07225)	-0.22104 (0.16714)	1.00
17	-0.11595 (0.08505)	-0.24023 (0.17684)	1.00
18	-0.25989 (0.09995)	-0.26974 (0.18855)	1.00
19	-0.22417 (0.11095)	-0.26167 (0.19597)	1.00
20	-0.28803 (0.13676)	-0.22355 (0.22949)	1.00
21	0.17158 (0.17728)	0.03693 (0.26991)	1.00
22	0.30104 (0.2687)	0.06489 (0.29377)	1.00

Table S5. Analysis of competitively examined employees compared with analysis of direct-hire appointments

#### 2. Loss of observations due to data management procedures

To make our analysis comparable to that of Lewis (2013) and Johnson (2015), we performed data management procedures that led to the loss of observations. Furthermore, we removed observations with corrupted or missing data. For the purposes of transparency and to clarify the sources of our substantial data loss, we created Table S6 (below), which reports the number of observations we lose each time we perform one of the operations required to make the data suitable for analysis. Although losing these data is unfortunate, it leaves us with enough observations to perform our analysis and we continue to have more observations than past research that uses the CPDF 1% sample (which suffers from the same missing data problems, but includes only a fraction of the observations) to study veterans' preference (e.g., Lewis 2013).

Data Management Action	Remaining Observations
Combine raw data into baseline data set*	47,333,165
Delete duplicate observations	46,794,951
Delete observations that do not work a full-time schedule	42,330,497
Delete observations who entered the data set before 1992	10,529,745
Delete observations not working under the General Schedule	7,538,357
Delete observations missing a value for first duty station	5,105,789
Delete observations missing a value for first occupation	5,104,692
Delete observations missing a value for first agency	5,104,692
Delete observations missing a value for first GS grade	5,104,374
Delete observations missing a value for first year in data set	5,104,374
Delete observations missing a value for veteran status	5,104,357
Delete observations missing a value for GS grade in any given year	4,701,925

 Table S6. Data management activities resulting in data loss

*Note*:\*Represents the complete data set before any loss of observations due to data management activities.

#### 3. Comparison of estimated coefficients using list-wise deletion v. no deletion

In the main text, we report an analysis in which we use list-wise deletion to scrub the data of any observation that is missing a value on one of the variables used in our empirical investigation. In this section of the supplementary materials, we compares those findings to analyses performed on a data set in which we did not delete observations that contained missing values. Instead, we treated the missing value codes used by OPM as if they were valid variable values, thus allowing our analysis to include all observations and make comparisons between observations that shared the same missing values on the same variables. For example, a military veteran with a missing value for the variable "occupation" who entered the federal service in Washington, D.C., in the Department of Labor, in 1987 at GS Grade 8 would be compared with a nonveteran who entered the federal service in Washington, D.C., in the Department of Labor, in 1987 at GS Grade 8 and who also possessed a missing value for the occupation variable. Some might contend that our analysis ought to utilize multiple imputation methods for correcting missing data, which have grown in popularity over the past several decades (King et al., 2001). Such methods would not apply in our data, however, given the explicit rationales for redacting sensitive data in OPM's population of personnel records. That is, were we to use such methods, we ultimately would replace missing values with non-sensitive data, which are the type of data that OPM allows in its public releases, even though we know that some portion of the missing values in our data reflect sensitive values not revealed to us. In lieu of making this error, it seems more plausible to regard missing values as sharing a common source (sensitivity of information, ease of identifying an employee) and, thus, treating them as if they were valid values, which we do in the analysis reported in Table S7.

The second column of Table S7 reports the "baseline" results that stem from the methods described in the main text—i.e. list-wise deletion of observations with missing values on the study variables—whereas column three of the table reports the results of models estimated on the data when no observations are removed (i.e. OPM's missing value codes are used in the estimation process). The analysis shows that coefficient estimates differ between the analysis involving list-wise deleted data and the analysis including all data, but none of the differences in coefficients is substantively noticeable or statistically significant. That is, on the latter note, the rightmost column of Table S7 presents the Bonferroni-adjusted<sup>2</sup> *p*-values of hypothesis tests of no difference between the coefficients in each row of column 2 and column 3. In no year does the *p*-value approach conventional levels of significance (p<0.05); to the contrary, all but one comparison indicates that there is near certainty (p=1) that we would observe the differences in the differences in coefficients between columns 2 and 3 of Table S7 were there truly no difference between them. Thus, our analysis suggests that the deletion of observations with missing values does not have a statistically significant effect on the coefficient estimates we report.

<sup>&</sup>lt;sup>2</sup> As mentioned earlier in our comments to R1, we perform a Bonferroni correction of the p-values in this and other tests throughout this response to address the increased likelihood of uncovering statistically significant results under multiple hypothesis testing (Miller, 1966). Although the Bonferroni correction generally involves dividing the critical threshold, alpha, by the number of hypothesis tests, m, and comparing this to the observed p-value, p\* (i.e. alpha/m < p\*), this method makes presentation of the findings awkward because it requires the researcher to compute various critical values and report those critical values *in addition* to the relevant p-values. An equivalent, yet clearer, approach is to adjust the p-value, instead of the critical value, by multiplying the computed p-value in a given test by the number of comparisons then comparing it to the conventional critical value. This procedures is commonly implemented by statistical software (see IBM, 2018) and it prevents the reader from having to engage in uncommon practices to interpret statistical findings.

Year of Career	Analysis Using List-wise Deletion	Analysis Using No Deletion	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.01866	0.02848	1.00
2	(0.00424)	(0.00271)	1.00
3	0.02003	0.03625	0.28
-	(0.00554)	(0.0035)	
4	0.01009	0.02213	1.00
	(0.00684)	(0.00421)	
5	0.01374	0.02141	1.00
	(0.00842)	(0.00505)	
6	0.02433	0.01857	1.00
	(0.01022)	(0.00596)	
7	0.03 (0.01233)	0.01899 (0.00689)	1.00
	0.02028	0.00962	
8	(0.01438)	(0.00777)	1.00
	0.007	-0.00591	
9	(0.01679)	(0.0094)	1.00
	0.00882	-0.01613	
10	(0.01907)	(0.01031)	1.00
	0.01109	-0.01036	
11	(0.0216)	(0.01138)	1.00
10	-0.00818	-0.0178	1.00
12	(0.02441)	(0.01286)	1.00
12	-0.03801	-0.01175	1.00
13	(0.02785)	(0.01445)	1.00
14	-0.04133	-0.00278	1.00
14	(0.03243)	(0.01611)	1.00
15	-0.02514	0.01066	1.00
15	(0.03717)	(0.01775)	1.00
16	-0.07109	0.00536	1.00
10	(0.04348)	(0.01973)	1.00
17	-0.03649	0.01867	1.00
	(0.05003)	(0.02252)	
18	-0.06194	0.012	1.00
	(0.05731)	(0.02624)	
19	-0.03765	0.01088	1.00
	(0.06396)	(0.03164)	
20	0.00226 (0.08014)	0.00394 (0.04016)	1.00
21	0.21097 (0.09926)	0.04907 (0.04926)	1.00
22	0.31781 (0.14102)	0.08963 (0.06664)	1.00
	(0.14102)	(0.0004)	

 Table S7. Comparison of coefficients produced from list-wise deletion versus no deletion

#### 4. Analysis of employees of who worked the same number of years before exit

In the CPDF, we observe many employees exiting the data set regularly and this raises the possibility that a form of attrition bias might emerge. If veterans or nonveterans of a particularly low/high quality leave the data set at disproportionately high rates, then our resulting estimates would not reflect these employees' performances and, thus, our estimates would not reflect the true consequences of veterans' preference. We can gain insight into the problem by analyzing subsets of the data that solely include employees who worked a given number of years. Among these subsets of the data, any bias from differential attrition between veterans and nonveterans is eliminated. In particular, we studied three sets of employees: those who worked in the federal government for exactly 5 years, 10 years, or 15 years, respectively. We then examined whether the estimated coefficients from analyses performed on these groups (which we refer to, respectively, as the "5-year cohort," "10-year cohort," and "15-year cohort") significantly differed from each other or from our baseline analyses that included all employees. The results of these analyses appear in Table S8, Table S9, Table S10, Table S11, Table S12, and Table S13 on the following pages.

The results offer some insight into the degree to which bias resulting from attrition might create problems for our estimates. In particular, the results of these analyses indicate the longer that veterans appear in the data, the greater the difference between their career advancement and that of nonveterans. For instance, Table S8 shows that coefficient estimates take larger values in the 10-year cohort than in the 5-year cohort, though these coefficient differences are not statistically significant; however, when comparing coefficients from the 5-year cohort with coefficients estimated on data concerning the 15-year cohort, we find substantively meaningful and statistically significant differences (see Table S9). Veterans with a 15-year career are

roughly one-fifth of a grade higher up the GS scale than nonveterans with careers of the same length by the fifth year of their career (Table S9, Column 3); on the other hand, veterans who stay in the federal service for only five years hold grades that are virtually no different from the grades held by nonveterans and, in fact, they may be slightly worse. Indeed, as Table S13 shows, veterans who stay in the federal service for 15 years shower faster career advancement over nonveterans in their first five years of employment than do veterans in the overall sample. These findings suggest that if attrition biases estimates, then it likely does so "upwardly" in later years of employees' careers—that is, were the lower performing veterans to remain in the sample, they would create downward pressure on coefficient estimates thus substantively making veterans appear less qualified.

One can take that reasoning too far, however, as we find only one statistically significant difference in the coefficients resulting from analyses of the 5-year and 10-year cohorts (Table S8), and we find no statistically significant differences in comparisons of coefficients from the 10-year and 15-year (Table S10), or from the baseline analyses and, respectively, the 5-year (Table S11) and 10-year cohorts (Table S12). Furthermore, in less than one-third of all career years do we find statistically significant differences between coefficients from the baseline analysis and coefficients from the 15-year cohort (see Table S13). These findings allay some of the concerns about attrition bias by signaling that the magnitude of such bias would appear to be sufficiently small that it does not significantly change coefficient estimates in most of the analyses we perform. However, the findings do indicate that attrition bias might emerge from lower-performing veterans exiting the federal service early (as shown in the significantly smaller coefficients in the 5-year cohort versus the 15-year cohort; Table S9), which would inflate the effect size in later years.

Year of Career	5-Year Cohort	10-Year Cohort	Bonferroni <i>p</i> -value for Coefficient Difference
2	-0.02883 (0.01337)	0.0168 (0.02413)	0.39
3	-0.0022 (0.016)	0.03046 (0.02919)	1
4	-0.01447 (0.01905)	0.03734 (0.0353)	0.79
5	-0.01657 (0.02145)	0.03143 (0.04077)	1

Table S8. Analyses on 5-year and 10-year cohorts

Table S9. Analyses on 5-year and 15-year cohorts

Year of Career	5-Year Cohort	15-Year Cohort	Bonferroni <i>p</i> -value for Coefficient Difference
2	-0.02883 (0.01337)	0.10298 (0.03368)	0.0011
3	-0.0022 (0.016)	0.14841 (0.04235)	0.0035
4	-0.01447 (0.01905)	0.16796 (0.04864)	0.0019
5	-0.01657 (0.02145)	0.19614 (0.05689)	0.0019

Year of Career	10-Year Cohort	15-Year Cohort	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.0168 (0.02413)	0.10298 (0.03368)	0.34
3	0.03046 (0.02919)	0.14841 (0.04235)	0.2
4	0.03734 (0.0353)	0.16796 (0.04864)	0.27
5	0.03143 (0.04077)	0.19614 (0.05689)	0.17
6	0.04009 (0.04542)	0.21646 (0.06336)	0.21
7	0.07212 (0.04957)	0.15992 (0.06931)	1
8	0.00917 (0.05245)	0.142 (0.0728)	1
9	0.03376 (0.05385)	0.12849 (0.07671)	1
10	0.0355 (0.05566)	0.14924 (0.08112)	1

-Supplementary Materials-

Year of Career	5-Year Cohort	All Employees	Bonferroni <i>p</i> -value for Coefficient Difference
2	-0.02883 (0.01337)	0.01866 (0.00424)	<0.01
3	-0.0022 (0.016)	0.02003 (0.00554)	0.76
4	-0.01447 (0.01905)	0.01009 (0.00684)	0.90
5	-0.01657 (0.02145)	0.01374 (0.00842)	0.75

Table S11. Comparison of Coefficient Estimates from 5-year Cohort and All Employees

Table S12. Comparison of Coefficient Estimates from 10-year Cohort and All Employees

Year of Career	10-Year Cohort	All Employees	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.10298 (0.03368)	0.01866 (0.00424)	1.00
3	0.14841 (0.04235)	0.02003 (0.00554)	1.00
4	0.16796 (0.04864)	0.01009 (0.00684)	1.00
5	0.19614 (0.05689)	0.01374 (0.00842)	1.00
6	0.21646 (0.06336)	0.02433 (0.01022)	1.00
7	0.15992 (0.06931)	0.03 (0.01233)	1.00
8	0.142 (0.0728)	0.02028 (0.01438)	1.00
9	0.12849 (0.07671)	0.007 (0.01679)	1.00
10	0.14924 (0.08112)	0.00882 (0.01907)	1.00

Year of Career	15-Year Cohort	All Employees	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.10298 (0.03368)	0.01866 (0.00424)	0.18
3	0.14841 (0.04235)	0.02003 (0.00554)	0.04
4	0.16796 (0.04864)	0.01009 (0.00684)	0.02
5	0.19614 (0.05689)	0.01374 (0.00842)	0.02
6	0.21646 (0.06336)	0.02433 (0.01022)	0.04
7	0.15992 (0.06931)	0.03 (0.01233)	0.91
8	0.142 (0.0728)	0.02028 (0.01438)	1
9	0.12849 (0.07671)	0.007 (0.01679)	1
10	0.14924 (0.08112)	0.00882 (0.01907)	1
11	0.10238 (0.08327)	0.01109 (0.0216)	1
12	0.12561 (0.08586)	-0.00818 (0.02441)	1
13	0.11563 (0.08732)	-0.03801 (0.02785)	1
14	0.08939 (0.08758)	-0.04133 (0.03243)	1
15	0.11245 (0.08777)	-0.02514 (0.03717)	1

 Table S13. Comparison of Coefficient Estimates from 15-year Cohort and All Employees

#### 5. Analysis of employees by occupational category

Some readers might wonder if we detect heterogeneous effects of veteran status across different types of occupations (e.g. administrative versus clerical positions). To examine this interesting possibility, we divided our data by PATCO category and repeated our most rigorous analysis on each of these PATCO subsets; we, then, compared coefficients from each analysis. Due to the detailed comparisons we make (i.e. controlling for entry occupation, grade, duty station, agency, and year), we could not make comparisons among veterans and nonveterans all occupational categories because we lacked adequate variation in the values of independent variables. However, in professional, administrative, and clerical categories, we were able to examine whether the coefficient estimates derived from employees in these categories differed significantly from each other. Tables S14, S15, and S16 (below) provide insight into that possibility. Across all of the analyses reported in these tables, we find no statistically significant differences between the estimated coefficients produced in each analysis. In fact, across each table, one once again sees that the *p*-values reported in the last column of each table indicate near certainty that we would observe the slight coefficient differences evident in the tables if there truly was no difference in the coefficients.

Year of Career	Analysis of Employees in Administrative Positions	Analysis of Employees in Clerical Positions	Bonferroni <i>p</i> -value fo Coefficient Difference
2	-0.00321 (0.00758)	0.01141 (0.00724)	1.00
3	0.0021 (0.00881)	-0.00264 (0.01092)	1.00
4	-0.01749 (0.01024)	-0.03342 (0.01448)	1.00
5	-0.03071 (0.01236)	-0.05279 (0.01812)	1.00
6	-0.04429 (0.01508)	-0.02746 (0.0226)	1.00
7	-0.04514 (0.01781)	-0.03249 (0.0282)	1.00
8	-0.04391 (0.02029)	-0.04118 (0.03468)	1.00
9	-0.06319 (0.02369)	-0.10136 (0.03999)	1.00
10	-0.09351 (0.02687)	-0.11841 (0.04753)	1.00
11	-0.0842 (0.02963)	-0.02485 (0.05707)	1.00
12	-0.10858 (0.03302)	-0.09391 (0.06487)	1.00
13	-0.09683 (0.0374)	-0.16847 (0.07543)	1.00
14	-0.11301 (0.04334)	-0.1737 (0.09534)	1.00
15	-0.11641 (0.04933)	-0.12135 (0.11344)	1.00
16	-0.20254 (0.05753)	-0.10467 (0.14198)	1.00
17	-0.20976 (0.06362)	-0.25897 (0.17995)	1.00
18	-0.22232 (0.07212)	-0.05337 (0.21576)	1.00
19	-0.31197 (0.0803)	0.02439 (0.28337)	1.00
20	-0.29524 (0.10286)	-0.24074 (0.37486)	1.00
21	-0.13437 (0.12126)	-0.23047 (0.33607)	1.00
22	-0.20156 (0.15784)	-0.41221 (0.3772)	1.00

 Table S14. Replication of analysis on administrative and clerical employees only

Year of Career	Analysis of Employees in Professional Positions	Analysis of Employees in Clerical Positions	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.00196 (0.01076)	0.01141 (0.00724)	1.00
3	-0.00359 (0.01253)	-0.00264 (0.01092)	1.00
4	-0.00642 (0.01348)	-0.03342 (0.01448)	1.00
5	-0.02579 (0.01502)	-0.05279 (0.01812)	1.00
6	-0.02324 (0.01728)	-0.02746 (0.0226)	1.00
7	-0.03538 (0.02016)	-0.03249 (0.0282)	1.00
8	-0.09967 (0.02257)	-0.04118 (0.03468)	1.00
9	-0.12023 (0.02504)	-0.10136 (0.03999)	1.00
10	-0.10069 (0.02686)	-0.11841 (0.04753)	1.00
11	-0.10023 (0.02968)	-0.02485 (0.05707)	1.00
12	-0.10093 (0.03251)	-0.09391 (0.06487)	1.00
13	-0.14071 (0.03592)	-0.16847 (0.07543)	1.00
14	-0.14464 (0.04085)	-0.1737 (0.09534)	1.00
15	-0.16783 (0.04634)	-0.12135 (0.11344)	1.00
16	-0.23119 (0.053)	-0.10467 (0.14198)	1.00
17	-0.2929 (0.06163)	-0.25897 (0.17995)	1.00
18	-0.31672 (0.07232)	-0.05337 (0.21576)	1.00
19	-0.19413 (0.08195)	0.02439 (0.28337)	1.00
20	-0.07784 (0.09967)	-0.24074 (0.37486)	1.00
21	0.09786 (0.13029)	-0.23047 (0.33607)	1.00
22	-0.14769 (0.20537)	-0.41221 (0.3772)	1.00

Table S15. Replication of analyses on professional and clerical employees only

	· · · ·	rofessional and administrative	<u> </u>
Year of Career	Analysis of Employees in Professional Positions	Analysis of Employees in Administrative Positions	Bonferroni <i>p</i> -value for Coefficient Difference
2	0.00196 (0.01076)	-0.00321 (0.00758)	1.00
3	-0.00359 (0.01253)	0.0021 (0.00881)	1.00
4	-0.00642 (0.01348)	-0.01749 (0.01024)	1.00
5	-0.02579 (0.01502)	-0.03071 (0.01236)	1.00
6	-0.02324 (0.01728)	-0.04429 (0.01508)	1.00
7	-0.03538 (0.02016)	-0.04514 (0.01781)	1.00
8	-0.09967 (0.02257)	-0.04391 (0.02029)	1.00
9	-0.12023 (0.02504)	-0.06319 (0.02369)	1.00
10	-0.10069 (0.02686)	-0.09351 (0.02687)	1.00
11	-0.10023 (0.02968)	-0.0842 (0.02963)	1.00
12	-0.10093 (0.03251)	-0.10858 (0.03302)	1.00
13	-0.14071 (0.03592)	-0.09683 (0.0374)	1.00
14	-0.14464 (0.04085)	-0.11301 (0.04334)	1.00
15	-0.16783 (0.04634)	-0.11641 (0.04933)	1.00
16	-0.23119 (0.053)	-0.20254 (0.05753)	1.00
17	-0.2929 (0.06163)	-0.20976 (0.06362)	1.00
18	-0.31672 (0.07232)	-0.22232 (0.07212)	1.00
19	-0.19413 (0.08195)	-0.31197 (0.0803)	1.00
20	-0.07784 (0.09967)	-0.29524 (0.10286)	1.00
21	0.09786 (0.13029)	-0.13437 (0.12126)	1.00
22	-0.14769 (0.20537)	-0.20156 (0.15784)	1.00

 Table S16. Replication of analyses on professional and administrative employees only

#### 6. Complete replication altering method of excluding part-timers and duplicates

As mentioned in the main text, our analysis required data management decisions about how we would handle the exclusion of employees not working a full-time schedule as well as observations possessing a unique, personal identifier that appeared twice in the same year (i.e. duplicate observations). Various methods of excluding these part-time employees and duplicate observations exist. In this section of the supplementary materials, we enumerate those various procedures and we report the results of analyses that examine whether our findings change when employing methods that differ from those used in the main text. Overall, we find no evidence that the data management decisions we employ influence the results of our analysis in a manner that would alter our substantive conclusions. Before presenting those results, we first describe the alternative data management procedures that we could employ in our study; then, on the subsequent pages, we present the results of these alternative procedures.

*Removing Part-Time Employees.* We remove part-time employees to remain consistent with the past literature and to ensure that any differences in grade advancement are not the product of an employee's work schedule. However, the fundamental challenge in removing part-time employees is that it can change how we count an employee's years in the federal service. If one removes part-time employees prior to creating a "counter" tallying the years an employee has worked in the federal service (as we do in the main text of the analysis), then the count of service years will warrant a different interpretation than a count of service years that takes place after removing those employees. In the former situation, only years of full-time service are included (i.e. on tracks an employee's "years of full-time service"). In the latter situation, if one removes part-time employees after creating the counter, then the years in which an employee works part-time will be removed from the analysis in a manner that appears to "skip" some years (e.g., an employee who works a part-time schedule in her third year of service over a five year career will only have service years one, two, four and five in the data set); this warrants an alternative interpretation—namely, "year of service, part-time years excluded"). In this section, we consider the consequences of both methods of removing part-time observations for our study's findings. Furthermore, we use each method in combination with alternative procedures for removing duplicate

-Supplementary Materials-

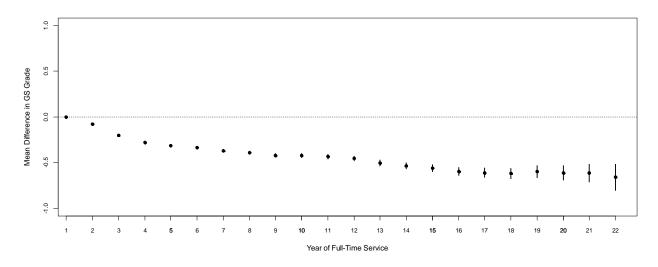
observations. For simplicity, we call the first procedure "counting after part-time exclusion" and the latter procedure "counting before part-time exclusion."

*Removing Duplicate Observations*. In the full population of CPDF records, we find numerous instances in which a unique, personal identifier appears twice in the same year. We have no way of knowing whether these duplicates represent legitimate duplications (e.g., an employee working two jobs in the same year) or whether they represent errors (e.g., two distinct employees given the same numeric, personal identifier). In the main text, we report analyses that result from data management procedures in which we pinpoint all identifiers that have appeared twice or more in the same year, then we exclude all observations—across all years of data—that possess those personal identifiers. We can conceive of two other ways of handling this problem: removing just one of those two identifiers or leaving the duplicate observations in the data. In this section, we report the results of pursuing each of these alternative data management procedures. We refer to the procedures as "All Duplicates Removed," "No Duplicates Removed."

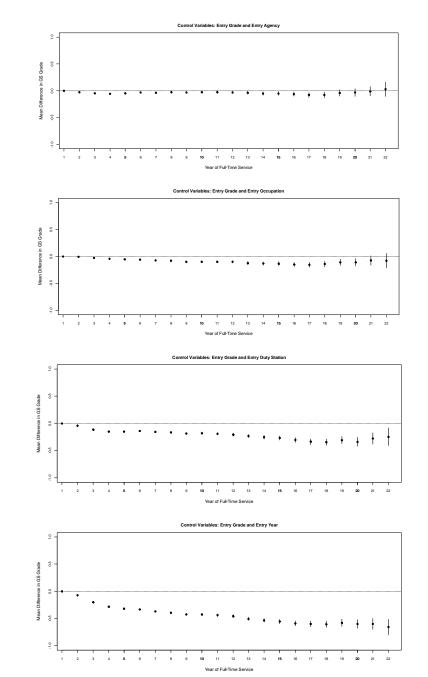
*Results*. As evident in the following pages, our results differ little according to the datamanagement methods that we use. Regardless of the method employed, we find that veterans appear to hold increasingly lower average grades, relative to nonveterans, across their careers when solely controlling for entry grade. Furthermore, across all methods, these average grade differences slightly diminish when controlling for an additional entry-job trait and they effectively disappear when controlling for all entry-job traits simultaneously. In the following pages, we report those findings.

# Figure S2. (A.) Counting After Part-Time Exclusion with One Duplicate Removed

[A1.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Entry Grade



#### Figure S2 (Cont.). (A.) Counting After Part-Time Exclusion with One Duplicate Removed

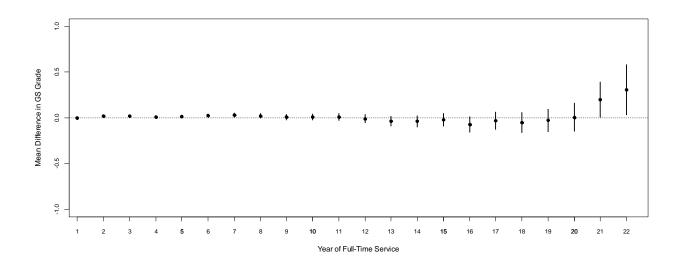


# [A2.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in Positions with Common Attributes

-Supplementary Materials-

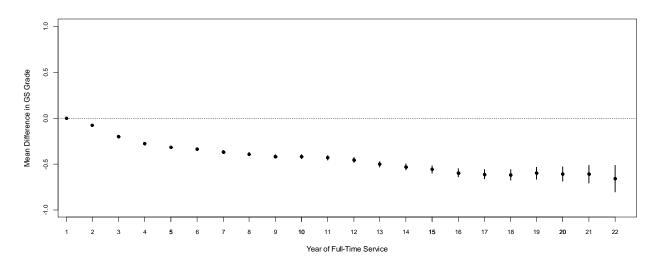
Figure S2 (Cont.). (A.) Counting After Part-Time Exclusion with One Duplicate Removed

[A3.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Positions (i.e. Occupation, Agency, Year, Grade, and Duty Station)

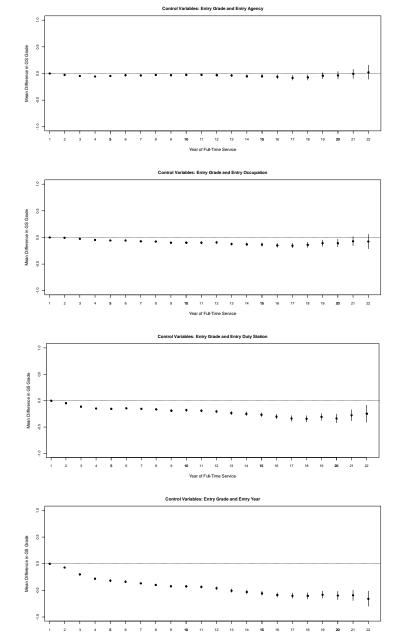


# Figure S2 (Cont.). (B.) Counting After Part-Time Exclusion with One Duplicate Removed

[B1.]. Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Entry Grade



#### Figure S2 (Cont.). (B.) Counting After Part-Time Exclusion with One Duplicate Removed



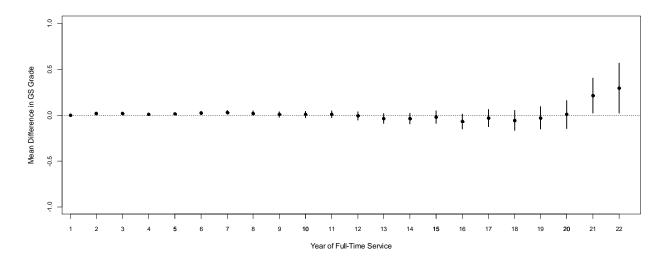
[B2.]. Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in Positions with Common Attributes

-Supplementary Materials-

Year of Full-Time Service

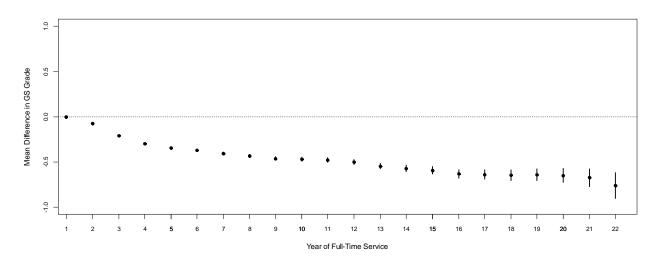
### Figure S2 (Cont.). (B.) Counting After Part-Time Exclusion with One Duplicate Removed

[B3.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Positions (i.e. Occupation, Agency, Year, Grade, and Duty Station)

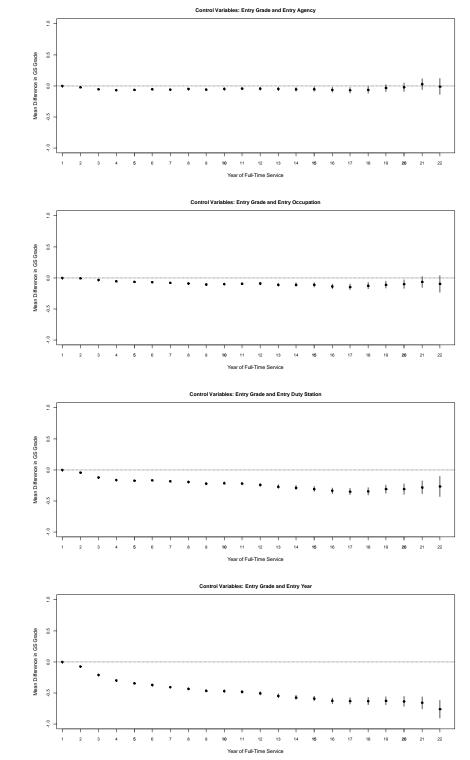


# Figure S2 (Cont.). (C.) Counting Before Part-Time Exclusion with All Duplicates Removed

[C1.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Entry Grade



# Figure S2 (Cont.). (C.) Counting Before Part-Time Exclusion with All Duplicates Removed

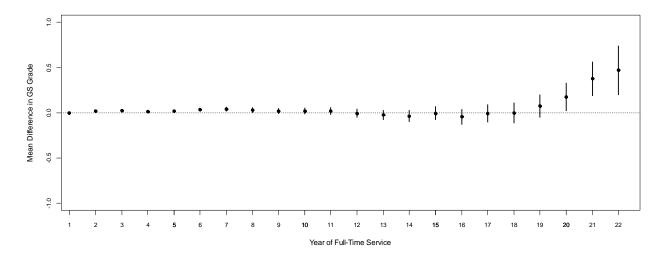


[C2.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in Positions with Common Attributes

-Supplementary Materials-

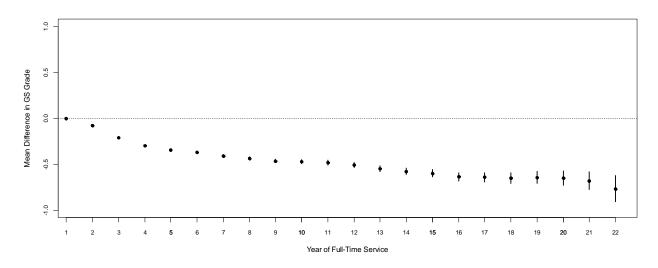
# Figure S2 (Cont.). (C.) Counting Before Part-Time Exclusion with All Duplicates Removed

[C3.]Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Positions (i.e. Occupation, Agency, Year, Grade, and Duty Station)

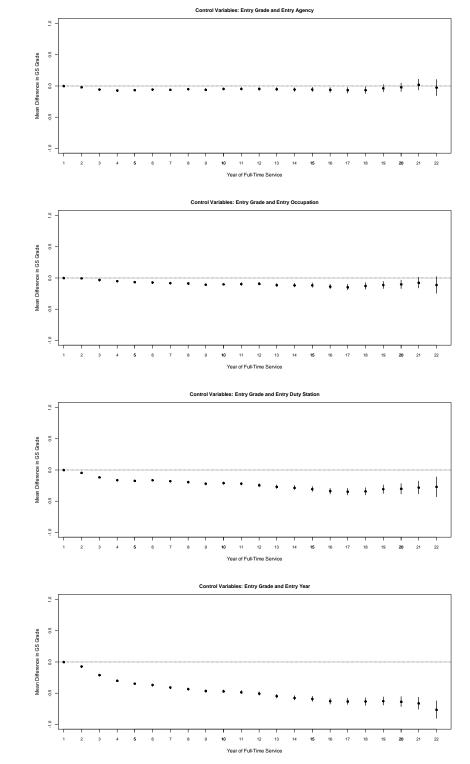


# Figure S2 (Cont.). (D.) Counting Before Part-Time Exclusion with One Duplicate Removed

[D1.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Entry Grade



# Figure S2 (Cont.). (D.) Counting Before Part-Time Exclusion with One Duplicate Removed

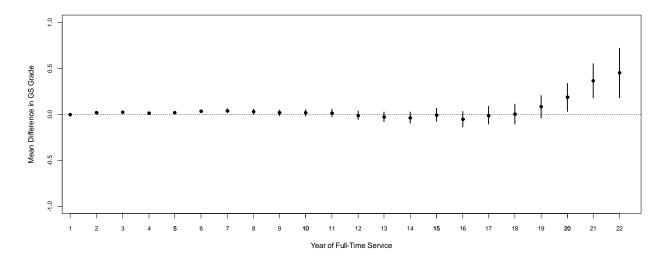


[D2.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in Positions with Common Attributes

-Supplementary Materials-

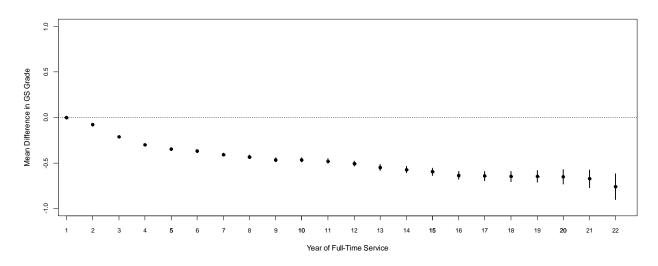
# Figure S2 (Cont.). (D.) Counting Before Part-Time Exclusion with One Duplicate Removed

[D3.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Positions (i.e. Occupation, Agency, Year, Grade, and Duty Station)

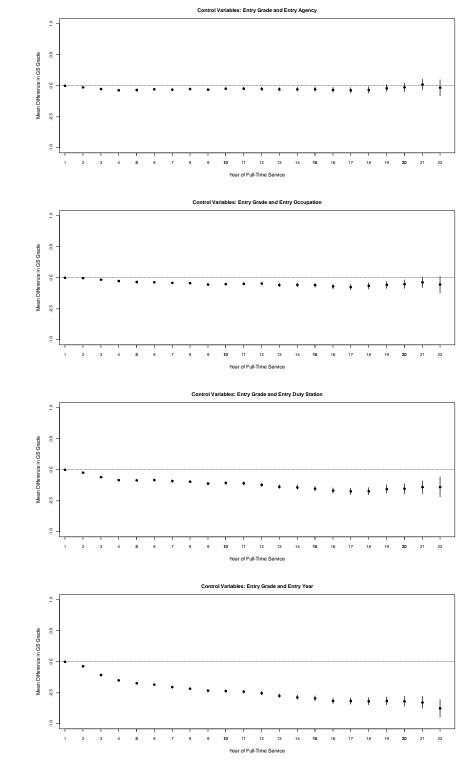


# Figure S2 (Cont.). (E.) Counting Before Part-Time Exclusion with No Duplicates Removed

[E1.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Entry Grade



#### Figure S2 (Cont.). (E.) Counting Before Part-Time Exclusion with No Duplicates Removed

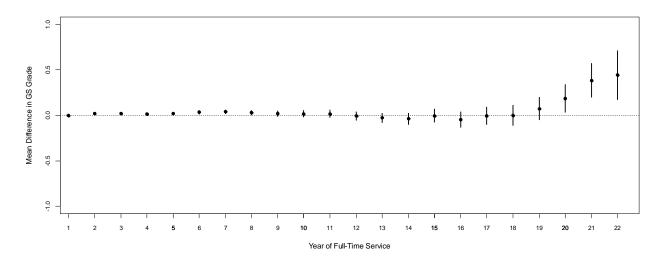


# [E2.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in Positions with Common Attributes

-Supplementary Materials-

# Figure S2 (Cont.). (E.) Counting Before Part-Time Exclusion with No Duplicates Removed

[E3.] Mean Grade Differences between Veterans and Nonveterans Entering Federal Service in the Same Positions (i.e. Occupation, Agency, Year, Grade, and Duty Station)



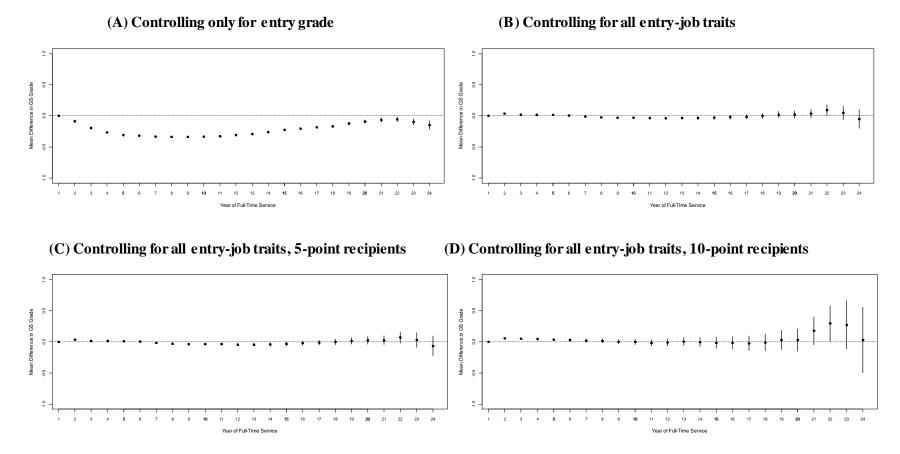
#### 7. Calibration of methods with Johnson (2015)

In order to assess the parity of methods used in the main text of this paper with those used in past investigations, we replicate our procedures from the main text on the data from Johnson (2015), which consists of a complete copy of the CPDF, from 1973-1997, including the Department of Defense. The results we uncover appear to differ little, in substantive terms, from the findings reported in Johnson (2015).

Johnson (2015) presented four sets of main results: results (i) when controlling only for employee's entry grade; (ii) when controlling for all entry-job characteristics (grade, duty station, occupation, agency, and year of entry); (iii) when controlling for all entry-job characteristics and comparing 5-point veterans' preference recipients with all non-recipients; and (iv) when controlling for all entry-job characteristics and comparing 10-recipients with non-recipients. In the forthcoming pages, we present the results of using our present methods of excluding part-time employees and duplicates in our analysis when using the data from Johnson (2015).

In substantive terms, we come to the exact same conclusions as Johnson (2015). When controlling solely for entry grade, we find that non-recipients gain higher average grades than preference recipients in all years, with the difference in average grades declining in absolute magnitude toward the end of the time period under study (Panel A of Figure S3, next page). However, once one controls for the various features of employees' entry positions, these differences effectively disappear (Panel B of Figure S3), which is a finding that resembles the findings of Johnson (2015) precisely. This same pattern appears when comparing 5-point preference recipients to non-recipients (Panel C of Figure S3) and when comparing 10-point preference recipients to non-recipients, although the latter comparison results in estimates of considerable uncertainty toward the end of employees careers (Panel D of Figure S3).

# Figure S3. Replicating Johnson (2015) Using the Procedures Reported in the Main Text



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Johnson, Tim. 2015. Service after Serving: Does Veterans' Preference Diminish the Quality of the US Federal Service? *Journal of Public Administration Research and Theory* 25: 669-696.

Lewis, Greg. 2013. The impact of veterans' preference on the composition and quality of the federal civil service. *Journal of Public Administration Research and Theory* 23:247–65.

Merit System Protection Board. 2008. *Federal Appointment Authorities: Cutting Through the Confusion*. Washington, D.C.: MSPB.