Military Service and Mortality: A Reappraisal Based on Frailty Models

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For more than two decades investigators have examined the influence of military service on men's life course trajectories, particularly educational, occupational, marital, and health outcomes (Elder 1974, 1986, 1987; Elder, Shanahan, & Clipp 1994, 1997; Hogan 1978a; 1978b; 1981; Laub & Sampson 2003; Parker et al. 2001; Pavalko & Elder 1990; Sampson & Laub 1996; Xie 1992). However, research on the impact of military service on mortality outcomes in later life has been limited.

Studies that have examined the experiences of World War II veterans have not systematically considered mortality in later life as an outcome, although Elder and his colleagues did find that combat exposure was related to a greater risk of mortality during the fifteen years after WWII (Elder, Shanahan, & Clipp 1997). Two studies of Vietnam War veterans, one based on U.S. data (Hearst, Newman, & Hulley 1986) and one based on Australian data (Adena et al. 1985), have come to differing conclusions about the effect of military service during the Vietnam War on mortality: the U.S. investigators concluded that veterans had a higher death rate primarily due to suicide and motor-vehicle accidents, while the Australian investigators reported no significant differences in the death rates of veterans and non-veterans. Other studies that focus exclusively on veterans have found death rates in midlife among veteran populations that are lower than in the general population (Dalager & Kang 1997; Kang & Bullman 1996; Rothberg et al. 1990). However, these analyses only considered mortality over the short term and they did not examine whether the effect of military service on mortality varied by race.

In our own research using the Health and Retirement Study (London and Wilmoth 2006), we found that military service was associated with a greater likelihood of death over the ten-year period 1992-2002. The findings of Liu et al. (2005), which focus only on the 70+ portion of the HRS sample, are consistent with our research: veterans were more likely than non-veterans to die over the two- to three- year interval between 1993 or 1994 and 1995. Liu et al (2005) conclude that these findings imply a mortality crossover prior to age 70. However, they do not attempt to empirically demonstrate the validity of this claim.

The HRS does contain data from subjects who are between the ages of 51 and 69 years, which could be used to determine if there is any evidence of a mortality crossover during those age ranges. However, for most sample members there have been many years between the completion of military service and entry into the HRS sample, which creates an initial-conditions problem (Hsiao 1986). First, if military service changes mortality risks during the pre-HRS years, then the chances of surviving from the completion of military service until the HRS baseline (1992) will differ between veterans and non-veterans. Second, if there are unobserved within-group factors that are correlated with mortality risks, then the conditional distribution of these unobserved factors will differ between groups at the point of entry into the HRS sample. Of course, these initial-conditions problems are not unique to the HRS: they plague any analysis that attempts to understand mortality outcomes in later life using samples drawn from the population of adults who have already reached mid- to late-life.

We address these two aspects of the initial-conditions problems in two ways. First, we employ nonsample information—in particular, estimates of pre-HRS survivorship based upon decennial Census data—to adjust mortality models estimated using HRS data. Second, we develop cohort mortality models that explicitly represent unmeasured heterogeneity, using the analytic machinery of fixed-frailty mortality dynamics (Vaupel, Manton, & Stallard 1979; Vaupel & Yashin 1985). The findings will test the robustness of previous findings based on the

HRS data regarding mortality differences by veteran status and provide insight in the existence of a mortality crossover between veterans and non-veterans. In addition, the methodology developed in this paper will have implications for other analyses that rely on data collected from older subjects.

Data and Methods

Health and Retirement Data

This analysis uses data from the Health and Retirement Study (HRS), specifically the original HRS cohort, whose members were ages 51 to 61 years in 1992. We do not include women because military service was rare among women in this cohort*:* only 45 female subjects in the HRS cohort report military service. We model the mortality experience of men from the HRS cohort over the period 1992-2002.

Measures

*Death***.** We have linked the HRS public-use data to the restricted HRS Cross-Year National Death Index (NDI) Cause of Death File. Staff at the National Center for Health Statistics (NCHS) created the restricted file by probabilistically matching respondents known to be dead, or whose status was unknown, to records in the NDI. Only reliable matches, as determined by the NCHS staff, are included in the file. The file contains the date of death and cause of death for respondents who died between the baseline interview and 2002.

Using these data we first created a duration variable that measures how long each subject survived before dying or being censored. For subjects who died, the duration variable is calculated using the first interview date and death date variables. For subjects who did not die, the duration variable is based on the first interview date and the last interview date. Then we created a variable that measures the status of each subject at the time recorded in the duration variable. The status variable equals 0 for censored cases and 1 for those who died.

Military service. The military service measure is based on the respondent's report of service in the military, where military service was defined as "active military service" not including service in the military reserves: 50.3% of the 1992 HRS sample reports having served in the military. For this analysis we employ a narrower measure of military service, one that indicates that the respondent had entered the military by 1960.

Race. Only whites and blacks are included in the analysis; approximately 16% of our sample is black.

Decennial Census Data

Our analysis employs estimates of group-specific survival probabilities based on samples from the public-use files of the 1960 and 1990 Censuses. Together these data sources allow us to compute 30-year survival probabilities that cover much of the period between the completion of military service and enrollment in the HRS study. In order to use the Census data, it is essential that a consistent measure of military service be applied in all these data sources. Specifically, we need to classify men as veterans or non-veterans ***as of 1960***. This, in turn, leads us to further restrict our analysis to the oldest half of the HRS cohort, namely the men born 1931-1935. Those men fall into the 25-29 age group in 1960, the 55-59 age group in 1990, and the 57-61 age group in 1992, at the start of the HRS study. Each Census file includes indicators of military service in each of several distinct peacetime and wartime periods. We coded men as "veterans" in 1960 if at that time they had previously served in the military or were, at the time of the Census, serving in the military. In the 1990 data, men were coded as veterans if they indicated service in World War II, the Korean War, the period 1955-1964, or an "other" period which, given the response categories available in the 1990 Census, is limited to the interwar years 1948 and 1949. Although the method requires that the variable “veteran” be consistently coded in both Censuses, we have little choice but to include the decade-spanning response field 1955-1964 in our “veteran” category in 1990. However, in order for someone in the 55-to-59 age group in 1990, whose military service falls within the 1955-64 period, to have served exclusively after 1960, he would have had to join the military for the first time after age 25, a relatively unlikely occurrence.

Analysis Sample

In order to maximize comparability of the three samples used in this analysis, we restricted the samples to native-born men. Our samples of native-born white and black males born during 1931-1935 include 1773 men from the HRS cohort, 50,641 from the 1960 Census and 44,703 from the 1990 Census. The counts of HRS respondents by racial, veteran, and vital status appear in Table 2, below.

Mortality Models

To date, we have estimated a number of group-specific mortality models. The novel feature of the work reported here is the use of external information from the Census data analysis to impose constraints on the HRS mortality models. Here we describe the modeling framework, as applied to a single such group; we first consider a “marginal” model in which unmeasured heterogeneity is ignored, and then a model that explicitly represents unmeasured heterogeneity.

Model without heterogeneity

For each possible grouping of our data—all men; whites and blacks considered separately; white non-veterans (WN), white veterans (WV), black non-veterans (BN) or black veterans (BV), considered separately—there is a baseline hazard, $h(a)$, a cumulative (integrated) hazard,

$$H(a) = \int_0^a h(x)dx,$$

and a survivor function

$$S(a) = \exp[-H(a)]. \quad (1)$$

In the present study we have used the Gompertz mortality function, i.e.,

$$h(a) = e^{b_0 + b_1 a},$$

for which the integrated hazard is

$$H(a) = \frac{e^{b_0}}{b_1}(e^{b_1 a} - 1)$$

provided that $b_1 \neq 0$. The chances of dying at age a are given by the product $h(a)S(a)$.

In order to align the HRS data with the Census data, we replace age with a^*, which equals time elapsed since 1960. In 1960, then, $a^* = 0$ (when the men in our HRS sample are, on average, roughly 27.5 years old). In the HRS data, which span the period 1992-2002, we observe deaths in the range $a^* = 32$ to $a^* = 42$ (corresponding to chronological ages 59.5-69.5). It is necessary to account for the fact that by definition the men in the HRS sample have survived from 1960 to 1992. We do this by replacing (1) with a ***conditional*** survivor function,

$$S(a^* \mid a^* > 32) = \exp[-\int_{32}^{a^*} h(x)dx];$$

the integrated hazard, in this case, becomes

$$H(a^*) = \frac{e^{b_0}}{b_1}(e^{b_1 a^*} - e^{32 b_1}).$$

Estimation of the model is by maximum likelihood; an individual observed to die at age a^* contributes $\ln[h(a^*)S(a^* \mid a^* > 32)]$ to the log-likelihood, while an individual observed to survive to age a^* contributes $\ln[S(a^* \mid a^* > 32)]$ to the log-likelihood. Because the model's parameters—the intercept and slope of the Gompertz mortality hazard—are expressed with reference to the

1960 time-origin of the process, they can be manipulated to produce an implied value of *S*(30)—the chances of surviving from 1960 to 1990—or of *S*(32)—the chances of surviving from 1960 to 1992. These implications can be derived despite the fact that the HRS includes no information on pre-1992 mortality within the HRS cohort. As noted already, we use Census data to develop an "observed" value for *S*(30), denoted $\hat{S}(30)$, and can compare the value implied by the HRS estimates to the observed value.

We can, however, go further, and require the HRS estimates to satisfy the equality

$$\hat{S}(30) = \exp\left[-\frac{e^{\hat{b}_0}}{\hat{b}_1}(e^{30\hat{b}_1} - 1) \right]. \qquad (2)$$

We do this by iterating over just one of the model parameters, b_1, at each iteration solving for the value of b_0 that satisfies (2). Thus we can force our model of mortality within the HRS cohort to be consistent with pre-HRS mortality experience observed in successive decennial Censuses.

Model with Unmeasured Heterogeneity

We now introduce unmeasured heterogeneity (or "frailty") into the mortality model. Each member of each group modeled is characterized by a strictly positive, time-invariant, person-specific but unmeasured frailty factor, z_i, which operates multiplicatively on the baseline hazard; thus $h_i(a) = z_i\, h_0(a)$ and

$$S_i(a) = \exp[-z_i H_0(a)].$$

The 0 subscripts attached to $h_0(a)$, $H_0(a)$, and $S_0(a)$ indicate that they now denote the "baseline" hazard, cumulative hazard, and survivor functions, respectively. Following Vaupel et al (1979), we assume that at time 0 the *z*s come from a gamma distribution with parameters *k* and λ, i.e.,

$$f_0(z) = \frac{\lambda^k z^{k-1} e^{-\lambda z}}{\Gamma(k)}.$$

For this distribution $E_0(z) = k/\lambda$ and $\text{var}(z) = k/\lambda^2$ (see also Lancaster 1990). We follow the usual practice of setting $k = \lambda$; i.e. setting the initial mean of z to one, and reducing by one the number of parameters requiring estimation.

By "integrating out" the heterogeneity, i.e. evaluating the expression

$$\int_0^\infty e^{-zH_0(a)} f_0(z)dz,$$

the cohort-level probability (i.e. the expected value of the probability) of surviving from time 0 to age a can be shown to equal

$$S(a) = \left[\frac{k}{k + H_0(a)}\right]^k. \tag{3}$$

Mortality selectively removes from the cohort individuals with high values of z. It can be shown that at any positive age a, the distribution of z among survivors is gamma with parameters k and $k + H_0(a)$. The mean of z among survivors to age a is, therefore, $\frac{k}{k + H_0(a)}$. Because the integrated hazard, $H_0(a)$, grows with a, the mean of z shrinks with a; survivors are, on average, successively more robust (less frail) at each successive age.

Using these results, we can express the probabilities of dying, or of surviving, within our left-censored HRS sample, as follows: $S(a^*| a^* > 32)$, the chances of surviving to a given age after surviving to 1992, is

$$S(a^* \mid a^* > 32) = \left[\frac{k + H_0(32)}{k + H_0(a^*)}\right]^k. \tag{4}$$

The chances of dying at age $a^* > 32$ equal $-\frac{\mathrm{d}}{\mathrm{d}a^*}\left[S(a^* \mid a^* > 32)\right]$, or

$$f(a^* \mid a^* > 32) = \left[\frac{kh_0(a^*)}{k + H_0(a^*)}\right]\left[\frac{k + H_0(32)}{k + H_0(a^*)}\right]^k. \tag{5}$$

As before, (4) and (5) form the basis for constructing the sample likelihood, from which maximum-likelihood estimation proceeds. As in the case of the model without heterogeneity, the parameters of the model for left-censored data are expressed with respect to the time origin of the process (a*=0).

Finally, we can again impose on the estimation a requirement that the parameters satisfy the condition

$$\hat{S}(30) = \left[\frac{\hat{k}}{\hat{k} + \hat{H}_0(30)} \right]^{\hat{k}}, \tag{6}$$

where $\hat{H}_0(30)$ indicates the value of the integrated baseline hazard implied by the estimates $\hat{b}_0$ and $\hat{b}_1$. In this case, we iterate over the parameters b_1 and k, at each iteration solving for the value of b_0 that satisfies (6).

Thirty-year Survival Probabilities Based on Census Data

Hill (1999) presents a method with which data from cross-sectional data collected at different times, such as two Decennial Censuses, can be combined so as to produce estimates of survival probabilities that condition on explanatory variables. For the estimates to be valid, the explanatory variables must be fixed before the first set of data is collected (for an application of this method see Lauderdale 2001).

The method employs a log-linear probability model,

$$\ln[S_x(a_2 \mid a_1)] = \alpha_0 + \alpha_1 x_1 + \ldots + \alpha_m x_m, \tag{7}$$

where $x_1, \ldots, x_m$ is the array of explanatory variables, a_1 measures age at the time of the first cross-section, and a_2 is age at the second cross-section; clearly the difference $a_2 - a_1$ must be the same as the time interval between cross-sections. Hill (1999) shows that if the two data sources are combined, and the indicator variable $Y_i = 1$ if individual i appears in the second cross-section, 0 otherwise, then the parameters of (7) can be estimated using logistic regression, with Y as the dependent variable and $x_1, \ldots x_m$ as independent variables.

The results of three models of 30-year survival probabilities appear in Table 1. Model (1) makes no distinctions by race or veteran status, and produces an estimate $S(30) = 0.883$. Model (2) introduces differences by race, and model (3) includes indicators of both race and veteran status. The coefficients are estimated with a high degree of precision, reflecting the relatively large samples available for this analysis. Models (2) and (3) indicate that blacks' 30-year survival probabilities are significantly lower than those of whites. In model (3) we find no differences by veterans status in whites' survival probabilities, but we find that black veterans have significantly higher survival probabilities than those of black non-veterans. The coefficients in model (3) imply the following estimates of survival probabilities: $S_{\mathrm{WN}}(30) = 0.8918$; $S_{\mathrm{WV}}(30) = 0.8946$; $S_{\mathrm{BN}}(30) = 0.7442$; and $S_{\mathrm{BV}}(30) = 0.8453$. For blacks, the advantageous survival associated with military service is not enough to counteract the disadvantage of being black.

Results

Results from four different modeling strategies—with and without unmeasured heterogeneity, and with and without imposing the constraint that the parameter estimates agree with the Census-based estimates of S(30)—applied to seven different sample subgroups appear in Table 2. Several conclusions can be reached based on the evidence presented in Table 2. First, although we have not estimated models in which individual parameters represent race differences, or veteran-status differences, in mortality, we can use likelihood-ratio tests to compare nested models and generate inferences on each of these potential differences. Using the "no heterogeneity, constrained" model specification, a likelihood-ratio test of separate models of mortality by race [columns (2) and (3)] versus a combined model—in each case, disregarding veteran status—produces a chi-square test statistic of 16.96 ($df = 2$); thus with $p = 0.0002$ we can reject the null hypothesis of equal mortality-model parameters for blacks and whites. However, when we conduct analogous tests of models that permit separate parameters for veterans and non-veterans, within racial groups [models (4) and (5) versus (2) for whites, and (6) and (7) versus (3) for blacks], we fail to reject the null hypothesis for either racial group. Thus, we fail to find evidence, using a global test, of differences by veteran status in mortality during the 10-year period spanned by the HRS data; this is in contrast with the findings for 1960-1990 using Census data, where there clearly were such effects for blacks (but not for whites). Moreover, our failure to find mortality differences by veteran status implies that there is no mortality crossover, at least for the ages spanned by the HRS data.

Second, imposing on the estimation the constraint that the model parameters reproduce exactly our estimates of 30-year survival probabilities derived from Census data, produces dramatic changes in the point estimates of model parameters. Within each of the 7 models estimated, the maximized value of the likelihood function (L in the table) is closer to zero without than with the constraint imposed, as we would expect. However, the standard errors of the parameters estimated are much smaller with the constraints imposed, again as we would expect. The point estimates themselves are very different with and without the constraints. For example, for the "all" model (without race or veteran-status distinctions recognized), the slope of the Gompertz mortality function is 0.224 in the unconstrained model but drops to 0.114 in the constrained model.

As a rough test on the performance of these models, we fitted a Gompertz curve to mortality rates found in cohort life tables produced by the Office of the Chief Actuary of the Social Security Administration. We pooled the death rates from the cohort life tables for all men born in 1931, 1932, 1933, 1934, and 1935. For each cohort, we included only the ages that correspond to the period 1960-2002, i.e., the same period represented in our analysis. Thus, for the men born in 1931, a^* = 0, … , 42 corresponds to ages 29, … , 71; for those born in 1932, a^* = 0, … , 42 corresponds to ages 28, … , 70; and so on. Our HRS-plus-Census data do not represent precisely the same populations—we restrict our attention to native-born whites and blacks, while the SSA tables pertain to men of all races and nativities—but the differences should be relatively small. The estimated equation based on the SSA life table data is

$$\ln(m_{a^*}) = -6.497 + 0.070a^*,$$
$$[0.017] \quad [0.0007]$$

(standard errors shown in square brackets). It is evident that our constrained-model estimates are much closer to the SSA data than are the unconstrained-model estimates.

Finally, we fail to find any evidence of the presence of unmeasured heterogeneity in mortality, in contrast to other applications of the same Gompertz-with-gamma-mixture model (e.g., Manton et al. 1981). For every group studied, the values of the maximized likelihood with and without heterogeneity are identical or nearly so, and in almost every case the k parameter (the inverse of the gamma variance) goes to infinity, implying that the mixture variance goes to zero (note: Table 2 reports estimates of $\ln(k)$ rather than of k). Two possible reasons for this result are (a) our use of data from a relatively limited part of the life cycle, and (b) modest sample sizes, especially for blacks. Somewhat paradoxically, it is for blacks that we come closest to finding evidence for unmeasured heterogeneity (the implied values of k are 4.33 for blacks as a whole and 2.43 for black non-veterans, respectively), but in both cases the estimated heterogeneity parameters are not significantly different from zero.

Next steps

We plan to extend the analysis reported here in several directions. First, despite the null results generated by the likelihood-ratio tests reported above, a more parsimonious model—for example, a proportional-hazards model incorporating intercept shifts for race and veteran status—may well produce evidence that favors the alternative hypothesis. Second, the HRS and AHEAD samples allow us to bring in additional age groups, although for each such group new problems of aligning the decennial Census data with the various birth cohorts emerge. Third, the constrained-estimation approach used here treats the Census-based estimates of $S(30)$ as nonstochastic. Those estimates are very precise, but do exhibit some sampling variability. A natural direction in which to take the estimation is to randomize over values of $S(30)$, investigating the sensitivity of model estimates to this source of variability.

Summary

We have presented new evidence on late-life health consequences of early-life military service for men in the 1931-1935 birth cohorts. Using HRS data for this cohort, in which mortality experiences over the period 1992-2002 are observed, fails to produce evidence of differential mortality by veteran status, although it does confirm that the overall patterns of age-specific mortality differ between blacks and whites. In contrast, our analysis of 1960 and 1990 Census data produces clear evidence that black veterans have lower death rates than black nonveterans over this 30-year period. It could be that the midlife consequences of military service for blacks dissipate by later in life, or it could be that our HRS sample is simply too small to detect the true differences. The estimation methods introduced here indicate the importance of recognizing the initial-conditions problems associated with studying life-cycle patterns using left-censored data. The preliminary results presented here leave open a number of issues for which further research would be fruitful.

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Table 1: Alternative Models of Survival from 1960 to 1990

Coefficient	Model (1)	(2)	(3)
Constant	-0.1246	-0.1124	-0.1145
	(0.0065)	(0.0068)	(0.0119)
Black		-0.1234 **	-0.1809 **
		(0.0217)	(0.0307)
Veteran			0.0031
			(0.0146)
Black × Veteran			0.1242 *
			(0.0439)

* $p < 0.01$
** $p < 0.001$

Table 2: Results of alternative estimators, for selected demographic groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				White		Black	
	All	White	Black	Nonvet	Veteran	Nonvet	Veteran
Observed S(30)	0.883	0.894	0.790	0.892	0.895	0.744	0.845
No heterogeneity, unconstrained							
b_0	-11.790	-11.621	-12.317	-12.163	-11.288	-11.808	-14.374
	(0.608)	(0.709)	(1.223)	(1.135)	(0.905)	(1.464)	(2.754)
b_1	0.224	0.217	0.251	0.231	0.208	0.237	0.307
	(0.016)	(0.019)	(0.032)	(0.030)	(0.024)	(0.038)	(0.073)
L	-1453.48	-1120.94	-322.18	-377.71	-743.05	-177.69	-144.11
Implied S(30)	0.972	0.973	0.967	0.977	0.970	0.962	0.982
No heterogeneity, constrained							
b_0 (using constraint)	-7.647	-7.726	-6.784	-7.700	-7.726	-6.287	-7.585
b_1 (estimated)	0.114	0.113	0.104	0.113	0.113	0.091	0.125
	(0.004)	(0.004)	(0.007)	(0.007)	(0.005)	(0.009)	(0.012)
L	-1474.02	-1134.40	-331.14	-384.47	-750.00	-183.77	-147.44
Heterogeneity, unconstrained							
b_0	-11.823	-11.621	-13.897	-12.164	-11.288	-14.663	-14.374
	(0.605)	(0.030)	(2.124)	(0.051)	(0.336)	(2.967)	(0.064)
b_1	0.225	0.217	0.295	0.231	0.208	0.317	0.307
	(0.016)	(0.002)	(0.058)	(0.051)	(0.009)	(0.080)	(0.004)
ln(*k*)	4.668	9.375	1.466	8.886	9.433	0.887	10.853
	(0.599)	(0.030)	(1.187)	(0.051)	(0.104)	(1.065)	(0.105)
L	-1453.48	-1120.94	-321.75	-377.72	-743.05	-177.08	-144.12
Implied S(30)	0.972	0.973	0.975	0.977	0.970	0.982	0.982
Heterogeneity, constrained							
b_0 (using constraint)	-7.647	-7.726	-6.784	-7.700	-7.726	-6.287	-7.585
b_1 (estimated)	0.114	0.113	0.104	0.113	0.113	0.091	0.125
	(0.004)	(0.004)	(0.006)	(0.012)	(0.005)	(0.074)	(0.012)
ln(*k*)	10.176	10.088	12.845	10.236	10.651	13.195	11.384
	(0.026)	(0.030)	(0.047)	(0.051)	(0.037)	(0.074)	(0.082)
L	-1424.02	-1134.40	-331.14	-384.47	-750.00	-183.77	-147.44
Sample size	1773	1485	288	502	983	153	135
Number of deaths	333	249	84	85	164	47	37

Note: Standard errors in parentheses.