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ABSTRACT

Soldiers who exit the Army before the end of their first term of service represent lost investments in terms of both direct costs (e.g., training costs) and indirect costs (e.g., force instability). The Army would benefit from pre-enlistment information that could identify those individuals most likely to complete their first term. This paper examines the relationship between first-term military attrition, information currently available to the Army (e.g., high school diploma graduate status), and three non-cognitive measures developed and administered during the Army's Project A/Building the Career Force research program (Campbell and Zook, 1990a; Campbell and Zook, 1992). Proportional hazards regression models were estimated for 4 job groups (roughly 49,000 first-term soldiers) using hierarchical and empirical "best-model" approaches. A battery of predictors is proposed for predicting attrition in all four job groups. The Army can improve prediction of attrition by gathering biodata and temperament information prior to enlistment and by better using information they currently possess. Nine figures and 16 tables present study information. (Contains 26 references.) (Author/SLD)

Prediction of First-Term Military Attrition Using Pre-Enlistment Predictors

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Abstract

Soldiers who exit the Army before the end of their first term of service represent lost investments in terms of both direct costs (e.g., training costs) and indirect costs (force instability). The Army would benefit from pre-enlistment information that could identify those individuals most likely to complete their first term. This paper examines the relationship between first-term military attrition, information currently available to the Army (e.g., high school diploma graduate status), and three non-cognitive measures developed and administered during the Army's Project A/Building the Career Force research program (Campbell & Zook, 1990a; Campbell & Zook, 1992). Proportional hazards regression models were estimated for four job groups using hierarchical and empirical "best-model" approaches. A battery of predictors is proposed for predicting attrition in all four job groups.

Prediction of First-Term Military Attrition Using Pre-Enlistment Predictors

Soldiers who fail to complete their first term of military service are costly to the Services. Klein, Hawes-Dawson, and Martin (1991) conservatively estimated the cost of first-term attrition to be 200 million dollars (in 1989 dollars). Such direct costs include lost investments such as training costs, recruiting costs, and compensation costs in the form of salary during enlistment and subsequent unemployment costs (e.g., Laurence, 1993; McCloy et al., 1992). Laurence further noted that attrition also results in significant indirect costs, both to the military (in the form of lowered morale and force instability) and to the individual (in the form of possibly reduced future employment opportunities and earning potential). As a result, significant benefits can accrue from better understanding the precursors of attrition and using this information to select those recruits who are less likely to exit the military prematurely.

The Services currently use high-school diploma graduate status as an indicator of a recruit's chances of completing his or her first term, a practice spurred by an initial Air Force technical report (Flyer, 1959) and since justified by years of supporting evidence. As Laurence (1993) stated, the Flyer study "was only the first in a very long line of research to conclude that high school graduates have lower attrition rates [than non-diploma graduates] . . . [and] similar findings have been echoed in countless reports over the past 30 plus years" (p. 5).

In contrast, very little relationship has been found between measures of cognitive ability and attrition. High-school graduates scoring in the lowest part of the distribution on the Armed Forces Qualification Test (AFQT) have lower rates of attrition than non-graduates in the uppermost part of the distribution. Laurence (1993) suggested that the relationship between first-term attrition and diploma status might be due to differences between the two groups on various non-cognitive characteristics. These characteristics, in turn, are typically assessed with instruments such as temperament, interest, or biodata inventories.

Indeed, although high-school diploma status is the single best predictor of first-term attrition, biodata instruments have demonstrated incremental validity (e.g., Steinhaus, 1988; Trent, 1993; White, Nord, Mael, & Young, 1993). Further, research from the Army's Project A (Campbell & Zook, 1990a) and the follow-on Career Force project (Campbell & Zook, 1992) has demonstrated the validity of non-cognitive measures for predicting the volitional, or "will-do," dimensions of Army job performance (e.g., effort, physical fitness and military bearing, personal discipline) -- dimensions that may impact attrition.

Building on this research, the goal of the present study was to determine the relationship between first-term Army attrition and various pre-enlistment predictors, including scores on three non-cognitive predictor instruments developed as part of the Project A/Building the Career Force research program -- a large-scale, multi-year research program intended to develop an improved selection and classification system for initial assignment of persons to U. S. Army occupations, or Military Occupational Specialties (MOS). The three inventories include a biodata and temperament measure, an interest measure, and a measure of job outcome preferences or values. The primary research question was which, if any, of the experimental non-cognitive measures would provide incremental prediction to the information already available to the Army: (1) test scores from the military enlistment test, the Armed Services Vocational Aptitude Battery (ASVAB), and (2) high school diploma graduate status.

Event History Analysis and the Proportional Hazards Model

The relationship between first-term attrition and the pre-enlistment predictors was addressed using proportional hazards modelling (Cox, 1972), a form of event history analysis (cf. Allison, 1984). Event history analysis allows a researcher to model whether or not an event occurs, and if so, when it occurs. In the present research, the event is attrition from the Army during the first term of enlistment. Specifically, a proportional hazards model allows one to determine the relationship between one or more predictor variables and the rate at which events occur over time:

$$\ln[h(t)] = \ln[h_0(t)] + \boldsymbol{\beta X} \qquad (1)$$

where ln is the natural logarithm, $h(t)$ is the hazard rate, $h_0(t)$ is a baseline hazard rate that can take any form (i.e., it is non-parametric), β is a vector of regression coefficients with a specific functional form (i.e., it is parametric), and $\mathbf{X}$ is a vector of predictor variables.

Working with event data presents several analytic difficulties that more conventional analytic methods do not handle well, including non-normal distributions, time-varying independent variables, and subjects who do not experience the event of interest during the observation period -- observations that are "censored" (cf. Allison, 1984; Lawless, 1982; Singer & Willett, 1991). Event history analysis does not rely upon normality assumptions, easily accommodates time-varying independent variables[1], and makes maximal use of the data provided by censored observations. Thus, event history analysis provides a proper analytic method for event data and is therefore ideal for the analysis of first-term military attrition. In particular, the proportional hazards model is very flexible in that it does not require the researcher to specify a particular distribution for the events across time. Consequently, the proportional hazards

[1] *Although the proportional hazards model discussed here easily incorporates time-varying independent variables, most event models that assume the event times to follow a specific distribution (i.e., parametric models) do not. Parametric models involving such variables can be estimated (e.g., Flinn & Heckman, 1982) but only with great difficulty.*

model was chosen to examine the relationship between attrition and several pre-enlistment predictors. (See McCloy, 1993, for a more detailed discussion of the fundamental properties of event history models.)

Method

Subjects

The subjects were the roughly 49,000 first-term soldiers from the Project A/Career Force Longitudinal Validation (LV) sample (Campbell & Zook, 1992). These soldiers were administered a four-hour Experimental Predictor Battery (Campbell & Zook, 1990a) within 2 days of their entry into the Army. The data were collected over a 14-month period (August 20, 1986 through November 30, 1987) at eight Reception Battalions. The soldiers represented the 21 MOS listed in Table 1.

- - - - Insert Table 1 About Here - - - -

Data checks for out-of-range values (e.g., impossible or incompatible entry and exit dates) reduced the sample to 48,308. Listwise deletion was performed on the pre-enlistment measures used to model attrition, yielding a final sample size of 31,032 soldiers.

Job groups. Rather than running analyses by MOS, job groups were formed by splitting the 21 MOS listed in Table 1 into two groups: Combat (MOS 11B, 13B, 16S, 19E, and 19K) and Non-Combat (all others). These two groups were further separated by enlistment terms.

In many applications of event history analysis, the endpoints and length of the observation period are arbitrary, being driven by convenience or a desire to observe a certain number of events. First-term attrition, however, has clear starting and ending points, beginning when the soldier enters the military and ending at the conclusion of the enlistment term agreed upon on the enlistment contract. Army enlistment terms typically range from two to six years, with three-year and four-year terms being the most common. The present study contains only those soldiers who agreed to three-year and four-year terms.

Because the two terms of enlistment provide meaningful observation periods of different duration, the two MOS groups were further split by term, yielding four analysis groups: soldiers in Combat and Non-Combat MOS with 3-year and 4-year enlistment terms (C3, C4, NC3, and NC4, respectively). Note that all six Combat MOS appear in both enlistment term groups (C3 and C4) because they contain many soldiers with three-year terms and many soldiers with four-year enlistment terms. Similarly, three of the Non-Combat MOS (76Y, 94B, and 95B) appear in both Non-Combat enlistment term groups (NC3 and NC4). The MOS within each of the four job groups, the sample sizes for each, the number and percentage who experienced attrition, and the number and percentage who were censored observations are given in Tables 2 through 5.

- - - - Insert Tables 2-5 About Here - - - -

Measures

Attrition. For this research, attrition is defined as a premature separation from first term service for reasons that might be viewed negatively from the military perspective. There are three critical components of this definition that require clarification: (1) what is meant by premature, (2) which types of separation would be viewed negatively by the military, and (3) how to establish the time window of the first tour.

First, "premature" is defined as any length of service that is less than the tour to which a recruit obligated him/herself at enlistment. Second, we adopted for this study the Compensatory Screening Model's (CSM)[2] grouping of separation types into "pejorative" and "non-pejorative" categories. Separations that the CSM identified as "pejorative" correspond to Knapp's (1993) Army separation behavior categories four and five.

Third, defining the first term window of time is easy for soldiers who did not reenlist and for those who reenlisted once their initial term of obligation was completed: it is the time between accession and (first) separation from the Army. Of the soldiers in the present dataset who reenlisted, however, 84.2 percent did so before, rather than after, the first term was completed. For this reason, identifying the length of the first tour for these soldiers is less clear.

[2] *The CSM is a selection procedure for identifying those non-high school diploma graduates who are more likely to complete at least two years of obligated service (cf. McBride, 1993).*

The following rule was developed for these immediate reenlistments: if the time between the basic active service date and separation from the reenlistment tour (or September 30, 1992, the final observation date available in the data base) was at least as long as the initial enlistment term, then the first-term window of time was set to the enlistment term. Of the 10,342 soldiers who reenlisted during their first term, 10,248 (99.1%) had their time window set to their enlistment term -- that is, their total time in the military exceeded their initial obligation. For the remaining 94 soldiers (0.9%) -- those whose time from accession to reenlistment separation was less than the initial enlistment term -- the first-term window was set to the time between accession and the reenlistment date. This is because we did not wish to include second-term (i.e., reenlistment) time as first-term time if the soldier exited prior to the contracted enlistment term. On the other hand, we wished to credit a soldier for completing his or her contracted enlistment, even if it was accomplished as part of an immediate reenlistment.

High School Diploma Graduate Status (HSDG). A dummy variable was constructed indicating whether the individual was a high school diploma graduate (HSDG=1) or not (HSDG=0).

Armed Services Vocational Aptitude Battery (ASVAB). The ASVAB is a written test of general cognitive ability administered to recruits prior to their entrance into the military. The ASVAB comprises ten subtests: Arithmetic Reasoning, Mathematical

Knowledge, Paragraph Comprehension, Word Knowledge, General Science, Numerical Operations, Coding Speed, Auto Shop Information, Mechanical Comprehension, and Electronics Information. The ten subtests were combined into four composite scores: Quantitative, Speed, Technical, and Verbal (cf. Campbell, 1986; Waters, Barnes, Foley, Steinhaus, & Brown, 1988). These four composites were used in the present analyses. The subtests comprising these composite scores are presented in Figure 1.

- - - - Insert Figure 1 About Here - - - -

Assessment of Background and Life Experiences (ABLE). The ABLE is a 199-item temperament and biodata inventory that was designed to predict Army-relevant criteria, including attrition (Hough, Barge, & Kamp, 1987). Three response options are available for each item. The ABLE contains 11 substantive (i.e., content) scales and four response validity scales. The current analyses included the 11 substantive scales and the response validity scale measuring the Social Desirability of the soldier's responses. The 11 substantive scales are given in Table 6.

- - - - Insert Table 6 About Here - - - -

Army Vocational Interest Career Examination (AVOICE). The AVOICE is an interest inventory that is based on the Air Force's Vocational Interest Career Examination (Peterson et al., 1990). The AVOICE contains four sections comprising lists of 37 jobs, 110 work tasks, 24 spare time activities, and 11 subject areas relevant to the Army. Respondents are asked to indicate whether they would like the jobs, work tasks, spare time activities, and subject areas. Five response options, ranging from "like very much" to "dislike very much," are available for each item. Scores on 22 AVOICE scales are computed on the basis of responses to those items. Eight AVOICE composites, made up of unit-weighted standard AVOICE scale scores, were used in this study. These composites, which tap broad clusters of interests, were developed during the LV phase of the Career Force Project (Campbell & Zook, 1990b). The eight AVOICE composites are presented in Table 7, along with the scales that constitute them.

- - - - Insert Table 7 About Here - - - -

Job Orientation Blank (JOB). The JOB is a 31-item inventory developed to measure job outcome preferences. This inventory contains a list of job features. Respondents are asked to indicate whether or not they would like each feature in their ideal jobs. Five response options, again ranging from "like very much" to "dislike very much," are available for each item. The JOB contains six scales: Job Autonomy, Job Routine, Ambition, Job Pride, Job Security/Comfort, and Serving Others. The first two scales constitute composites by themselves, whereas the standard scores of the latter four scales are summed to form a composite labelled High Expectations.

Thus, first-term attrition was modeled using 26 pre-enlistment predictors, comprising five variables available to the Army presently and 21 non-cognitive variables derived from measures developed during Project A/Career Force. Descriptive statistics for all 26 predictors and the coefficient alpha reliability estimates for the 21 non-cognitive predictors are available in an Appendix available from the first author.

Analysis

Testing the proportionality assumption. As described in equation 1, Cox's model allows the baseline hazard function, $h_0(t)$, to take any form, with the ratio of the hazards for any two individuals or groups assumed to be a constant value. Before estimating the proportional hazards regression equations, the tenability of this assumption was tested.[3]

Specifically, an empirical test of the proportionality assumption was conducted for each MOS within each of the four job groups by examining the significance of the parameter for a single MOS dummy variable (D_{MOS}) interacting with time. That is, the following models were calculated:

$$\begin{aligned} \ln[h(t)] &= \ln[h_0(t)] + \beta_1 D_{MOS} \\ \ln[h(t)] &= \ln[h_0(t)] + \beta_1 D_{MOS} + \beta_2 X \end{aligned} \qquad (2)$$

where $h(t)$ is the hazard rate, $h_0(t)$ is the baseline hazard for the jobs not modeled by D_{MOS}, and X is the interaction between D_{MOS} and the log of the event times. If β_2 is significant, then the ratio of the hazard plots is not constant, indicating that the hazard function for the MOS modeled by D_{MOS} is not proportional to

[3] *Opinions about the importance of testing the proportionality assumption vary greatly, ranging from its virtual indispensability (Singer & Willett, 1991) to its relative inconsequence (Allison, 1984).*

the aggregate hazard for the several other MOS in the job group. In all instances, the β_2 parameter was significant at $p < .001$. The baseline survivor and hazard functions for one MOS from each of the four job groups are given in Figures 2 through 9.[4]

- - - - Insert Figures 2 Through 9 About Here - - - -

Fitting the proportional hazards models. Because the hazards proved not to be proportional, a stratified analysis was conducted where "MOS" was the stratifying variable. In a stratified analysis, the baseline hazards are allowed to differ for each group, but the regression parameters are assumed to be the same across groups. That is,

$$\begin{aligned} &Group\ 1: \ \ln[h(t)] = \ln[h_{01}(t)] + \beta_1 x_1 + \cdots + \beta_k x_k \\ &Group\ 2: \ \ln[h(t)] = \ln[h_{02}(t)] + \beta_1 x_1 + \cdots + \beta_k x_k \end{aligned} \quad (3)$$

where $h_{01}(t)$ and $h_{02}(t)$ are group-specific hazards that are not proportional to each other. This is somewhat analogous to estimating regression equations that allow group intercepts to differ while constraining the slopes to be equal across groups.

Whether the hazards are proportional for all groups or only within stratified groups, the effect of the independent variables

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[4] *The survivor and hazard functions are related. The survivor function can be written*

$$S(t; x_n) = [S_0(t)]^{\exp(\mathbf{x}_n'\beta)}$$

where X_n is the vector of predictor variables for the n^{th} person, and $S_0(t)$ is the baseline survivor function,

$$S_0(t) = \exp(-\int_0^t h_0(u)\,du) \quad .$$

on the hazard is to shift the baseline hazard up or down, depending on the values of the variables. More formally, the effects of the independent variables are multiplicative on the hazard rate. This may be seen by taking the antilog of equation 1:

$$h(t) = h_0(t)\, e^{\beta x} \quad . \tag{4}$$

In a stratified model, an individual's hazard is shifted up or down relative to the baseline hazard for their group, whence equation 4 becomes

$$h(t) = h_{0i}(t)\, e^{\beta x} \tag{5}$$

with i being one of g groups (i = 1, . . ., g). The <u>magnitude</u> the hazard is shifted is the same for all individuals having identical X vectors, regardless of group membership. The <u>shape</u> of the hazard that is shifted, however, varies across strata.

Two types of proportional hazard analyses were conducted for each of the four job groups. The first set of analyses involved predictor blocks that were entered hierarchically. The first block contained the four ASVAB composites and the dummy variable HSDG denoting high-school diploma graduate status (HSDG=1 if a diploma graduate, zero otherwise). Block one comprises the "base" variables -- the pre-enlistment variables currently available to the Army, against which incremental prediction was assessed. As such, block one was included in all models. Blocks two through four contained the ABLE, AVOICE, and JOB scores, respectively.

The incremental fit afforded by each block was assessed relative to block one. Finally, a model was estimated containing all four blocks of predictors.

The second type of analysis used a best subset selection algorithm in the SAS procedure PHREG (SAS Institute, 1992), in which the best j equations containing k specified predictors is given. The model considered to be best for a given number of predictors is the one yielding the highest global score chi-squared statistic. Here, the best j = 3 equations containing k = 1, . . . , 26 predictors were obtained. Nested equations were then selected from the best equations and re-evaluated in PHREG to obtain the value of -2 Log L for each model. Likelihood ratio tests were calculated to evaluate the point at which additional predictors failed to significantly increase the fit of the model. Stringent p-values were selected, due to the large samples and the dependence of χ^2 on sample size. The effect of each variable, conditional on all other variables in the model, was also taken into account when deriving the "best" equation for each of the four groups.

Results

Predictor-Block Models

The results for the five models involving predictor blocks for each of the four job groups are given in Table 8. (The parameters for each of the models are given in the Appendix available from the first author.) The top half of the table reports the values of -2 Log L for the five models. (For stratified analyses, the likelihood, L, maximized for a job group is the product of each MOS-specific likelihood.) The bottom half of the table contains likelihood ratio test results (based upon the values in the top half of the table) for specific model comparisons.

- - - - Insert Table 8 About Here - - - -

Consider job group C3 as an example. The value of -2 Log L for Model 1 (the base variables) is 434.02 with 5 degrees of freedom ($p < .0001$). Clearly, the base variables provide significant prediction of first-term attrition for soldiers with three-year terms of enlistment in Combat jobs. Model 2 adds the 12 ABLE measures to the base variables. The value of -2 Log L increases to 653.08 (again, $p < .0001$). To examine whether this represents a statistically significant increase in the fit of the model to the data, we calculate the difference between -2 Log L for the two models. Hence,

$$653.08 - 434.02 = 219.06$$

with (17 - 5) = 12 degrees of freedom. The critical value for χ^2 at $p < .001$ is 32.91, indicating that the ABLE provides a significant increase in model fit. The other values in the bottom half of Table 8 were calculated similarly.

The results in Table 8 indicate the following:

- The base variables are significantly related to first-term attrition;

- The ABLE provides significant incremental fit to the base model for all four job groups;
- The AVOICE significantly increases the fit of the base model for three-year enlistments but not four-year enlistments; although the sample sizes differ by a factor of nearly two to one ($N_{.3}$ = 20,252 and $N_{.4}$ = 10,780), this is probably not a power issue, given the absolute size of each group;
- Except for NC3, the JOB does not provide a statistically significant increase in fit over the base model;
- Addition of the AVOICE and JOB to the ABLE model increases the fit of the model to the data for job groups C3 and NC3 (Model 2 vs. Model 5); again, this is unlikely a power issue.

Thus, the non-cognitive measures improve prediction of first-term attrition over and above current pre-enlistment information.

<u>Best Subset Selection</u>

The "variable traces" of the nested models for the best subset selection analyses are given in Tables 9 through 12, along with the associated -2 Log L values and differences between them. All likelihood ratio tests were evaluated as χ^2 with one degree of freedom. The tests for groups C3 and NC3 were evaluated relative to a critical value of 10.8 ($p < .001$); tests for groups C4 and NC4 were evaluated relative to a critical value of 7.9 ($p < .005$). The traces end at the point of the last significant increase in model fit. All models begin with k = 3 predictors.

- - - - Insert Tables 9-12 About Here - - - -

Tables 9-12 show that the number of significant predictors ranges from seven to eleven. No AVOICE or JOB scales appear in any of the equations. Although the equations are slightly different across the job groups, seven variables appear in each best model: high school diploma graduate status, the ASVAB Quantitative composite, and five ABLE scales (Nondelinquency, Dominance, Physical Condition, Self Esteem, and Social Desirability). Indeed, these seven variables constitute the best equation for both Combat groups.

The parameter estimates and p-values for each best equation are provided in Tables 13 through 16. To help determine the conditional impact of each variable on the hazard of first-term attrition, values of the risk ratio are also provided. The risk ratio is the exponentiated value of the regression coefficient (i.e., e^b). These values give some insight into the effect of the independent variables on the criterion, subject to the usual caveats applied when determining the effect of a predictor on a criterion in conventional multiple regression analyses based on the value of the regression coefficients (e.g., Darlington, 1972). A value less than one indicates a decrease in the hazard rate (the regression coefficient is negative); a value greater than one indicates an increase in the hazard rate.

- - - - Insert Tables 13-16 About Here - - - -

The parameters in Tables 13-16 were calculated in the raw metric of the predictors. Hence, they are analogous to raw coefficients. As with raw coefficients in conventional regression, the risk ratio indicates the effect on the hazard associated with a one unit increase in the predictor variable. For example, in the best equation for job group C3, the risk ratio for Social Desirability of 1.031 signifies that a one unit increase in the score on this ABLE scale increases the hazard rate for attrition by 3.1 percent. In the special case of dichotomous (i.e., dummy) variables, the risk ratio describes the difference in the hazard rates for the two groups. For example, the risk ratio for HSDG of .494 suggests that the hazard rate for high school graduates is 49.4 percent of that for non-graduates. Equivalently, the hazard rate for non-graduates is (1/0.494) = 2.024, or 102.4 percent that of high school graduates.

If one wishes to determine the impact on the hazard rate of an increase of x units (or decrease of -x units), one simply raises the risk ratio to the power of x (or -x). For example, to determine the increase on the hazard rate for a five-unit increase in the Social Desirability score, one computes $(1.031)^5 = 1.165$. Thus, a five-unit increase in the Social Desirability score increases the hazard of first-term attrition by 16.5 percent.

This same approach allows one to determine the effect of a one standard deviation (σ) increase in the measures, which is equivalent to obtaining standardized regression coefficients. The metrics of the predictors vary to a considerable degree, even within the same instrument. Hence, risk ratios based upon one unit increases could be of little interest. To facilitate metric-free comparisons, Tables 10 through 13 also contain the values of the risk ratios raised to the power of σ.

The results in Tables 10 through 13 indicate that the largest conditional effects are quite similar across the four job groups, with the largest effects provided by the ABLE scales Nondelinquency and Dominance. A higher Nondelinquency score translates into a decreased hazard for attrition, whereas the opposite is true for Dominance. For example, a one unit (standard deviation) increase in the Nondelinquency score for Combat soldiers with three-year enlistments decreases the hazard for attrition to 95.4 (76.9) percent of its current level. Equivalently (and perhaps easier to picture), a one unit (standard deviation) decrease in the Nondelinquency score yields risk ratios of 1/.954 = 1.048 (1/.769 = 1.300), signifying increases in the hazard of 4.8 (30.0) percent.[5]

[5] *The distribution of Nondelinquency is negatively skewed, with a mean for C3 of 47.5, a standard deviation of 5.6, and a maximum value of 60. Thus, full standard deviation increases in the Nondelinquency scale score might be difficult to attain for a large number of individuals.*

Discussion

The results of the event history analysis of first-term attrition indicate that high school diploma graduate status remains a very powerful predictor, with the hazard rate for non-graduates being approximately twice that for graduates. Nevertheless, information provided by non-cognitive measures (specifically, scales from the ABLE, a temperament/biodata inventory) provides significant incremental prediction to pre-enlistment information currently available to the Army. Information provided by an interest inventory (the AVOICE) and a job preference inventory the (JOB) contributed incremental prediction on occasion, but both were overshadowed when the ABLE was in the equation.

The results of the block analyses were reasonably consistent across the four job/enlistment term groups. The best subset analyses yielded remarkably similar results across the four groups, identifying six variables that appear in all four "best" equations and one (the Quantitative composite from the ASVAB) that appears in three of the four. These seven variables could be combined to yield a single, highly predictive Army attrition equation.

Using biodata and temperament inventories as pre-enlistment selection measures raises questions of the possible effects of coaching and faking on applicant responses. Biodata items tend to be less susceptible to such effects to the extent that they are verifiable. Temperament inventories, however, have been shown to be easily faked (e.g., Hough, Eaton, Dunnette, Kamp, & McCloy, 1990). Hough et al. found, however, that such distortion does not have marked effects on the validity of the instrument. To the extent that this result is generalizable, the concerns about faking might be exaggerated. Note, however, that the respondents in the Hough et al. study were not coached.

The effects on the validity of the ABLE of coaching was investigated by Young, White, and Oppler (1992). Soldiers in this study were asked to complete the ABLE and were assigned to one of three response conditions: Honest, Ad-lib Faking (i.e., respondents were to answer the questions in a manner each believed would most impress the Army), and Coached. Soldiers who were coached were given the same instructions given to the Ad-lib Faking group, but the respondents were then given three practice items and instructed which responses were the most favorable and why. Young et al. examined the effect of the three conditions on the point-biserial correlations between the ABLE scales and a dichotomous criterion variable representing attrition during the first 18 months of service (scored as 1 if attrition occurred, 0 otherwise).

Young et al. (1992) found that the magnitude of the corrrelations across the three conditions were similar, with few significant differences being found between the Honest and Ad-lib Faking conditions. In this respect, the results are similar to those reported by Hough et al. (1990) with regard to performance criteria. Virtually all of the point-biserials were negative, indicating higher ABLE scale scores were associated with decreased attrition. The point-biserials for the Coached respondents, however, switched sign, all becoming positive, indicating higher ABLE scores were associated with increased attrition. Although Young et al. stated that the reasons for this phenomenon were uncertain, the study suggests that the impact of coaching on the validity of the ABLE in an operational setting to screen for first-term attrition could be severe, although the effects of coaching might be partially mediated by warnings about scales that can detect faking, score corrections for faking, and so on.

The use of regression typically raises the question of cross validity. Event history models do not produce a measure similar to the coefficient of determination, obviating the use of shrinkage formulae. Nevertheless, a procedure has been suggested for assessing the fit of a proportional hazards regression model in a second sample (McCloy, 1993). To the extent that the procedure is viable, questions of cross validity may be addressed.

The issue of cross validity, however, has limited applicability to first-term attrition. Attrition relies in part on organizational policy that in turn depends upon social, economic, and political demands. For example, the current downsizing of the military could result in the Army being a bit more strict in the enforcement of certain standards for soldiers (e.g., minimum performance standards and physical requirements) than at other times. Optimal equations for predicting attrition that are developed during the observance of a specific organizational policy might cross-validate well as long as the current policy remains the rule. Any change in policy, however, could result in the inapplicability of the equations. A new analysis would be required to develop equations for predicting attrition occurring under the new organizational policy.

The effects of two variables on the hazard of first-term attrition merit special consideration. First is the positive relationship between Dominance and the hazard, indicating that dominant soldiers are more likely to exit prematurely. This relationship might appear counterintuitive, given that dominance could be associated with leadership and a "take-charge" demeanor. Perhaps the finding supports the notion that highly dominant soldiers are recalcitrant and unresponsive to orders, attempting to take charge when they should follow.

Of similar interest is the appearance of the ASVAB Quantitative composite in three of the four best equations. This composite comprises the two mathematics subtests, Arithmetic Reasoning (AR) and Mathematical Knowledge (MK). These two subtests, in turn, appear with the two verbal subtests of Word Knowledge (WK) and Paragraph Comprehension (PC) in the Armed Forces Qualification Test, the military's primary selection measure. As such, soldiers have already been selected to some degree on the Quantitative score. The AFQT has been shown time and again to have very little relationship to attrition, but the verbal subtests are given twice the weight of the quantitative subtests when calculating the present AFQT score. By removing the Quantitative subtests from the AFQT and using them as a composite, a sizable relationship appears with first-term attrition, notwithstanding the attenuating effects of range restriction.

Indeed, the lack of relationship between the AFQT and first-term attrition could be due to the Quantitative and Verbal subtests working in opposite directions. Whereas higher Quantitative composite scores are associated with a decreased hazard of first-term attrition, the parameters for the Verbal composite from both the block analyses and the best subset analyses are positive. Hence, higher Verbal scores are associated with an <u>increased</u> rate of attrition, with the relationship being negligible for the Combat MOS but relatively strong for the Non-Combat jobs.

The current research strongly suggests that the Army can improve the prediction of first-term attrition by gathering biodata/temperament information prior to enlistment and by better using the information they currently possess (i.e., ASVAB Quantitative scores). Regarding future research, the hazard functions given in Figures 6-9 indicate that most of the attrition occurs in the first six months of service. The determinants of early-term attrition (e.g., during the first six months) may differ from the determinants of attrition occurring later in the term. Such a hypothesis can be tested using event history analysis. Future research will be directed at this question, as well as further investigation into the issue of cross validity.

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Table 1

Summary of the 21 Army MOS

MOS	Name of Job	MOS	Name of Job
11B	Infantryman	55B	Ammunition Specialist
12B	Combat Engineer	63B	Light-Wheel Vehicle Mechanic
13B	Cannon Crewman	67N	Utility Helicopter Repairer
16S	MANPADS Crewman	71L	Administrative Specialist
19E	M60 Armor Crewman	76Y	Unit Supply Specialist
19K[a]	M1 Armor Crewman	88M	Motor Transport Operator
27E	Tow/Dragon Repairer	91A	Medical Specialst
29E	Comm.-Electronics Radio Repairer	94B	Food Service Specialist
31C	Single Channel Radio Repairer	95B	Military Police
51B	Carpentry/Masonry Specialist	96B	Intelligence Analyst
54B	NBC Specialist		

[a] MOS 19E and 19K differ only in terms of equipment (i.e., type of tank).

Table 2

Sample sizes, number and percentage of attritions, and number and percentage of censored observations for Soldiers with Three-Year Enlistments in Combat Jobs (C3)

MOS	N	Events		Censored Observations	
		N	Percentage	N	Percentage
11B	4,875	1,354	27.8	3,521	72.2
12B	1,131	295	26.1	836	73.9
13B	2,416	729	30.2	1,687	69.8
16S	410	140	34.1	270	65.9
19E	287	91	31.7	196	68.3
19K	570	128	22.5	442	77.5
TOTAL	9,689	2,737	28.2	6,952	71.8

Table 3

Sample sizes, number and percentage of attritions, and number and percentage of censored observations for Soldiers with Four-Year Enlistments in Combat Jobs (C4)

MOS	N	Events		Censored Observations	
		N	Percentage	N	Percentage
11B	4,196	1,397	33.3	2,799	66.7
12B	247	73	29.6	174	70.4
13B	1,227	405	33.0	822	67.0
16S	81	16	19.7	65	80.3
19E	123	47	38.2	76	61.8
19K	566	186	32.9	380	67.1
TOTAL	6,440	2,124	33.0	4,316	67.0

Table 4

Sample sizes, number and percentage of attritions, and number and percentage of censored observations for Soldiers with Three-Year Enlistments in Non-Combat Jobs (NC3)

MOS	N	Events		Censored Observations	
		N	Percentage	N	Percentage
54E	566	149	26.3	417	73.7
55B	198	73	36.9	125	63.1
64C	769	247	32.1	522	67.9
71L	1,341	362	27.0	979	73.0
76Y	518	115	22.2	403	77.8
91A	2,685	649	24.2	2,036	75.8
94B	1,579	547	34.6	1,032	65.4
95B	2,907	619	21.3	2,288	78.7
TOTAL	10,563	2,761	26.1	6,952	73.9

Table 5

Sample sizes, number and percentage of attritions, and number and percentage of censored observations for Soldiers with Four-Year Enlistments in Non-Combat Jobs (NC4)

MOS	N	Events		Censored Observations	
		N	Percentage	N	Percentage
27E	104	28	26.9	76	73.1
29E	188	50	26.6	138	73.4
31C	390	143	36.7	247	63.3
51B	319	88	27.6	231	72.4
63B	1,353	419	31.0	934	69.0
67N	277	55	19.9	222	80.1
76Y	874	275	31.5	599	68.5
94B	429	179	41.7	250	58.3
95B	406	99	24.4	307	75.6
TOTAL	4,340	1,336	30.8	3,004	69.2

Table 6

The Eleven Substantive ABLE Scales

Emotional Stability
Self-Esteem
Cooperativeness
Conscientiousness
Nondelinquency
Traditional Values
Work Orientation
Internal Control
Energy Level
Dominance
Physical Condition

Table 7

The Six AVOICE Composites and Their Constituent Scales

AVOICE Composite	AVOICE Scales
Administrative	Clerical/Administrative
	Warehousing/Shipping
Audiovisual Arts	Aesthetics
	Audiographics
	Drafting
Food Service	Food Service (Employee)
	Food Service (Professional)
Interpersonal	Leadership/Guidance
	Medical Services
Protective Services	Fire Protection
	Law Enforcement
Rugged/Outdoors	Combat
	Firearms Enthusiast
	Rugged Individualism
Skilled/Technical	Computers
	Electronic Communications
	Mathematics
	Science/Chemical
Structural/Machines	Electronics
	Heavy Construction
	Mechanics
	Vehicle/Equipment Operator

Table 8

Results for the five models involving predictor blocks for each of the four job groups

Values of -2 Log L

Model	df	C3	C4	NC3	NC4
		Job Group			
(1) Base	5	434.02	188.48	329.72	102.30
(2) Base + ABLE	17	653.08	330.67	649.52	272.58
(3) Base + AVOICE	13	478.96	207.32	352.78	115.67
(4) Base + JOB	8	444.08	198.97	356.95	105.05
(5) Base + ALL	28	693.84	351.96	690.04	284.40

Values of -2 Log (L2 - L1)

Model Comparisons	df	C3	C4	NC3	NC4
		Job Group			
1 vs. 2	12	219.06	142.19	319.80	170.28
1 vs. 3	8	44.94	18.84^{ns}	23.06^{*}	13.37^{ns}
1 vs. 4	3	10.06^{ns}	10.49^{ns}	27.23	2.75^{ns}
1 vs. 5	23	259.82	163.48	360.32	182.10
2 vs. 5	11	40.76	21.29^{ns}	40.52	11.81^{ns}
3 vs. 5	15	214.88	144.64	337.26	168.73
4 vs. 5	20	249.76	152.99	333.09	179.35

All values significant at $p < .001$ except * $p < .01$ and ^{ns} non-significant.

Table 9

Variable traces and fit statistics of the nested models for the best subset selection analyses: Job Group C3 (n = 9,689)

Model	-2 Log L	χ^2 (df = 1)
HSDG, QUANT, Nond[a]	41,353.64	
+ Dominance	41,328.84	24.80
+ Physical Condition	41,310.58	18.26
+ Social Desirability	41,290.80	19.78
+ Self Esteem	41,277.66	13.14

Significant χ^2 Values, df = 1: $p < .001 = 10.83$

[a]ABLE scale Nondelinquency

Table 10

Variable traces and fit statistics of the nested models for the best subset selection analyses: C4 (n = 6,440)

Model	-2 Log L	χ^2 (df = 1)
HSDG, QUANT, Nond[a]	31,667.26	
+ Dominance	31,651.36	15.90
+ Self Esteem	31,631.08	20.28
+ Social Desirability	31,620.74	10.34
+ Physical Condition	31,610.32	10.42

Significant χ^2 Values, df = 1: $p < .005$ = 7.88

[a]ABLE scale Nondelinquency

Table 11

Variable traces and fit statistics of the nested models for the best subset selection analyses: Job Group NC3 (n = 10,563)

Model	-2 Log L	χ^2 (df = 1)
HSDG, QUANT, Cond[a]	39,482.91	
+ Nondelinquency	39,411.01	71.90
+ TECHNICAL	39,387.20	23.81
+ VERBAL	39,358.51	28.69
+ Social Desirability	39,325.83	32.68
+ Emotional Stability	39,302.77	23.06
+ Dominance	39,269.28	33.49
+ Energy Level	39,253.28	16.00
+ Self Esteem	39,236.97	16.31

Significant χ^2 Values, df = 1: $p < .001$ = 10.83

[a]ABLE scale Physical Condition

Table 12

Variable traces and fit statistics of the nested models for the best subset selection analyses: NC4 (n = 4,340)

Model	-2 Log L	χ^2 (df = 1)
HSDG, Nond, Cond[a]	16,564.75	
+ Dominance	16,534.93	29.82
+ TECHNICAL	16,518.38	16.55
+ VERBAL	16,506.40	11.98
+ Social Desirability	16,491.86	14.54
+ Self Esteem	16,482.54	9.32

Significant χ^2 Values, df = 1: $p < .005$ = 7.88

[a]ABLE scale Physical Condition

Table 13

Parameters and Risk Ratios for the Best Equation: Job Group C3 ($n = 9,689$)

Variable	b	$\sigma_{se(b)}$	p value	Risk Ratio	Risk Ratio$^{\sigma}$
HSDG	-.705	.045	.0001	.494	--
QUANT	-.013	.002	.0001	.987	.836
Phys. Cond.	-.023	.008	.0014	.976	.933
Dominance	.039	.006	.0001	1.040	1.194
Self Esteem	-.026	.007	.0003	.974	.903
Nondelinquency	-.047	.004	.0001	.954	.769
Social Desir.	.030	.007	.0001	1.031	1.113

	Without Covariates	With Covariates	χ^2 (df = 7)
-2 log L	41,907.32	41,277.66	629.66 (p=.0001)

Table 14

Parameters and Risk Ratios for the Best Equation: Job Group C4 (n = 9,689)

Variable	b	$\sigma_{se(b)}$	p value	Risk Ratio	Risk Ratio$^{\sigma}$
HSDG	-.566	.057	.0001	.568	--
QUANT	-.008	.002	.0001	.992	.902
Phys. Cond.	-.027	.008	.0012	.973	.923
Dominance	.039	.007	.0001	1.040	1.196
Self Esteem	-.029	.008	.0004	.971	.891
Nondelinquency	-.040	.005	.0001	.961	.303
Social Desir.	.026	.008	.0008	1.026	1.090

	Without Covariates	With Covariates	χ^2 (df = 7)
-2 log L	31,927.11	31,610.32	316.79 (p=.0001)

Table 15

Parameters and Risk Ratios for the Best Equation: Job Group NC3 (n = 10,563)

Variable	b	$\sigma_{se(b)}$	p value	Risk Ratio	Risk Ratio$^{\sigma}$
HSDG	-.712	.054	.0001	.491	--
QUANT	-.012	.002	.0001	.989	.858
TECH	-.010	.001	.0001	.990	.835
VERBAL	.014	.002	.0001	1.014	1.165
Phys. Cond.	-.066	.007	.0001	.936	.816
Dominance	.032	.006	.0001	1.032	1.157
Energy Level	.026	.005	.0001	1.027	1.169
Self Esteem	-.030	.008	.0001	.970	.887
Nondelinquency	-.039	.004	.0001	.962	.808
Emotional Stab.	.036	.007	.0001	1.037	.833
Social Desir.	-.033	.005	.0001	.968	1.128

	Without Covariates	With Covariates	χ^2 (df = 11)
-2 log L	39,877.43	39,236.97	640.46 (p=.0001)

Table 16

Parameters and Risk Ratios for the Best Equation: Job Group NC4 (n = 4,340)

Variable	b	$\sigma_{se(b)}$	p value	Risk Ratio	Risk Ratio$^{\sigma}$
HSDG	-.568	.084	.0001	.567	--
TECH	-.011	.002	.0001	.989	.824
VERBAL	.013	.003	.0001	1.013	1.163
Phys. Cond.	-.067	.010	.0001	.935	.816
Dominance	.046	.008	.0001	1.047	1.239
Self Esteem	-.031	.010	.0022	.970	.887
Nondelinquency	-.046	.006	.0001	.955	.779
Social Desir.	.038	.009	.0001	1.038	1.136

	Without Covariates	With Covariates	χ^2 (df = 8)
-2 log L	16,726.49	16,482.54	243.95 (p=.0001)

Figure Caption

Figure 1. Formation of the four ASVAB composite scores from the ASVAB subtests.

Figure 2. Baseline survivor function for MOS 11B.

Figure 3. Baseline survivor function for MOS 13B.

Figure 4. Baseline survivor function for MOS 63B.

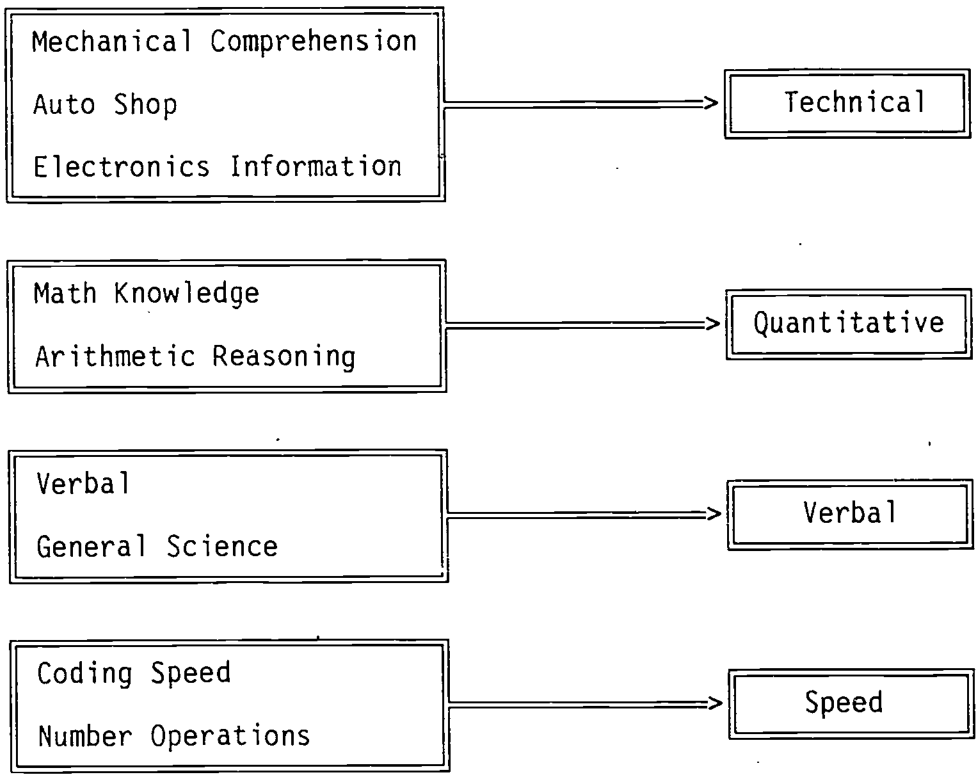
Figure 5. Baseline survivor function for MOS 95B.

Figure 6. Baseline hazard function for MOS 11B.

Figure 7. Baseline hazard function for MOS 13B.

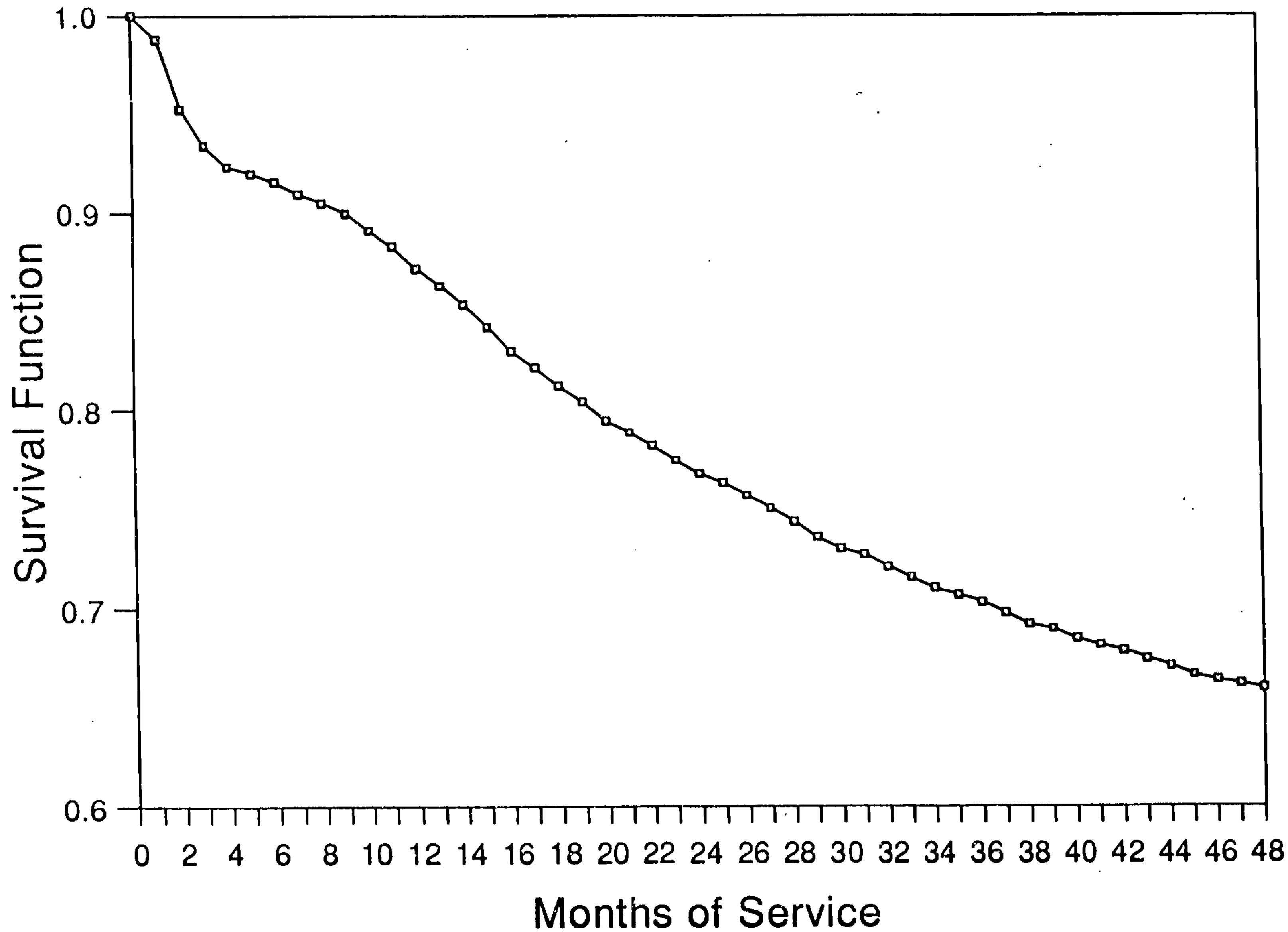
Figure 8. Baseline hazard function for MOS 63B.

Figure 9. Baseline survivor function for MOS 95B.

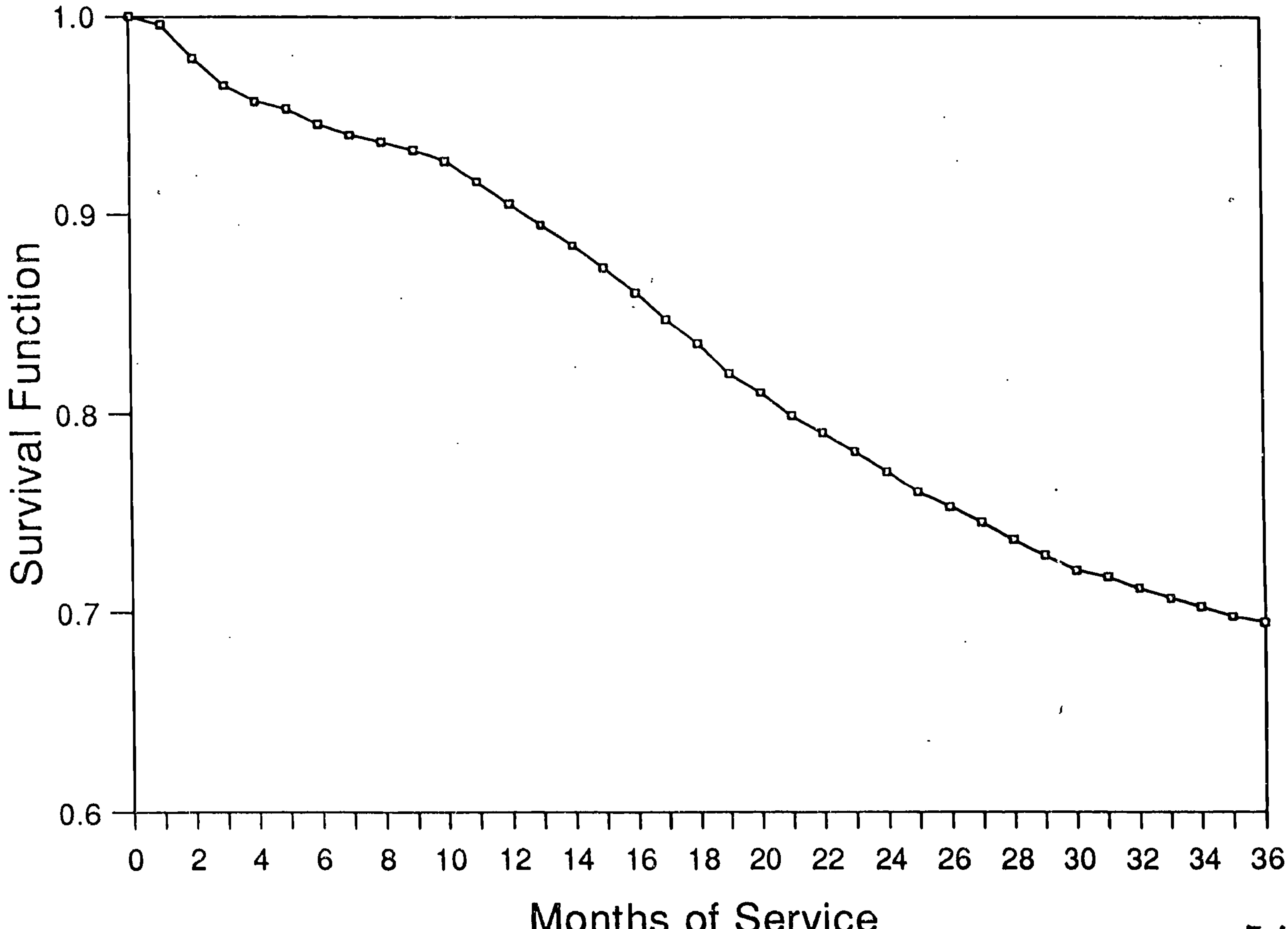


Note: From Campbell (1986), p. 4-16.

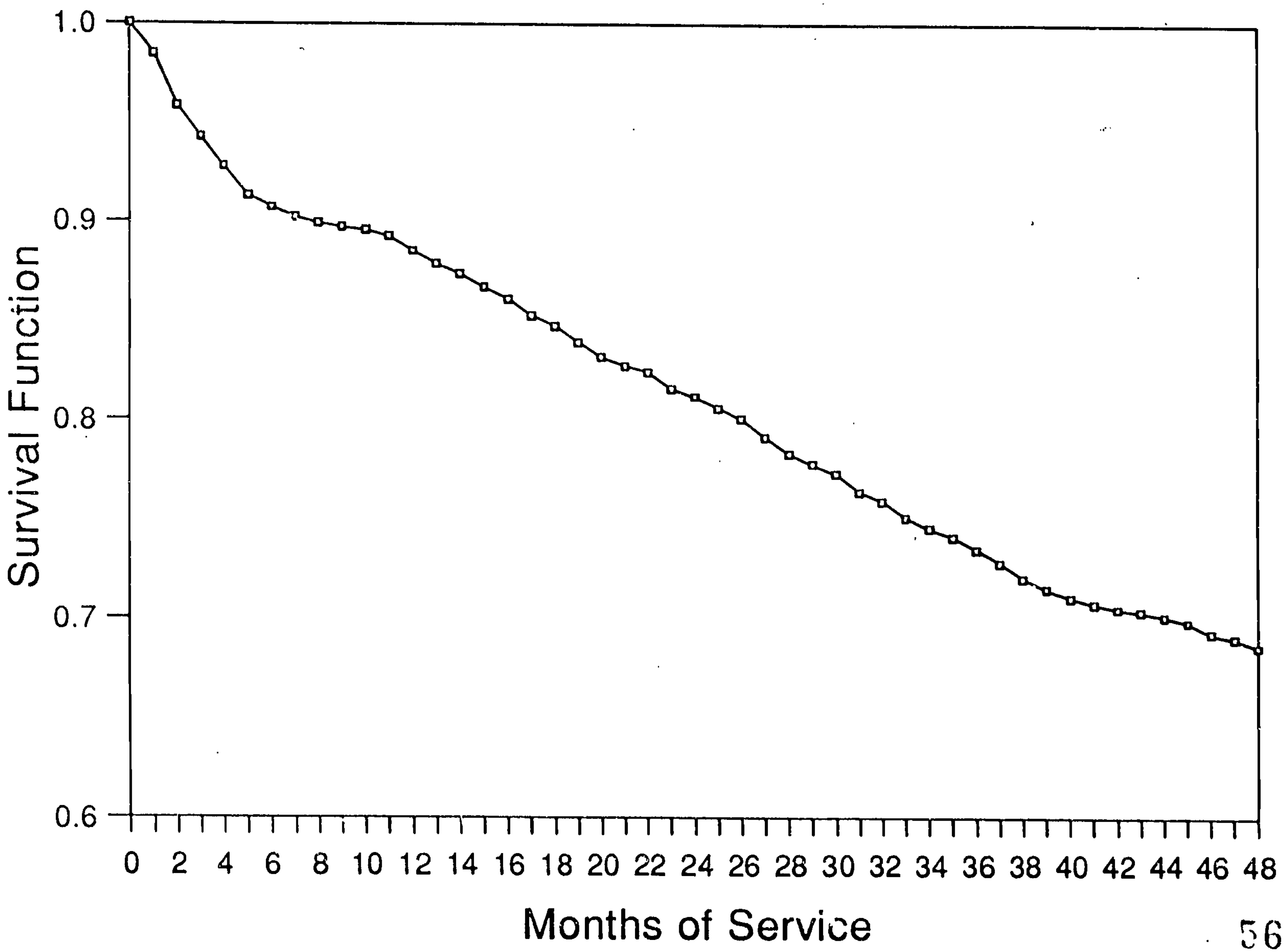
Baseline Survival Function for MOS 11B



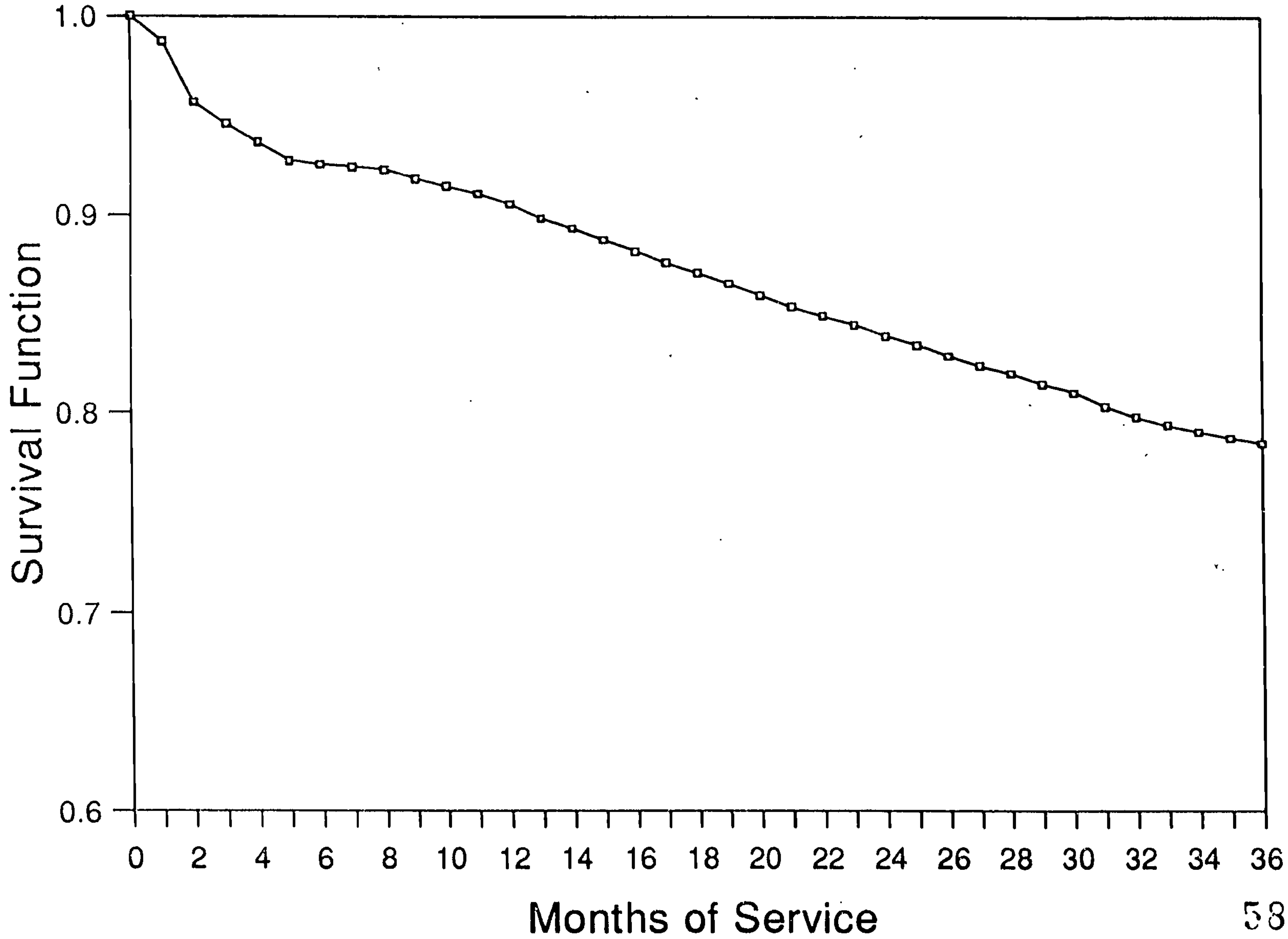
Baseline Survival Function for MOS 13B



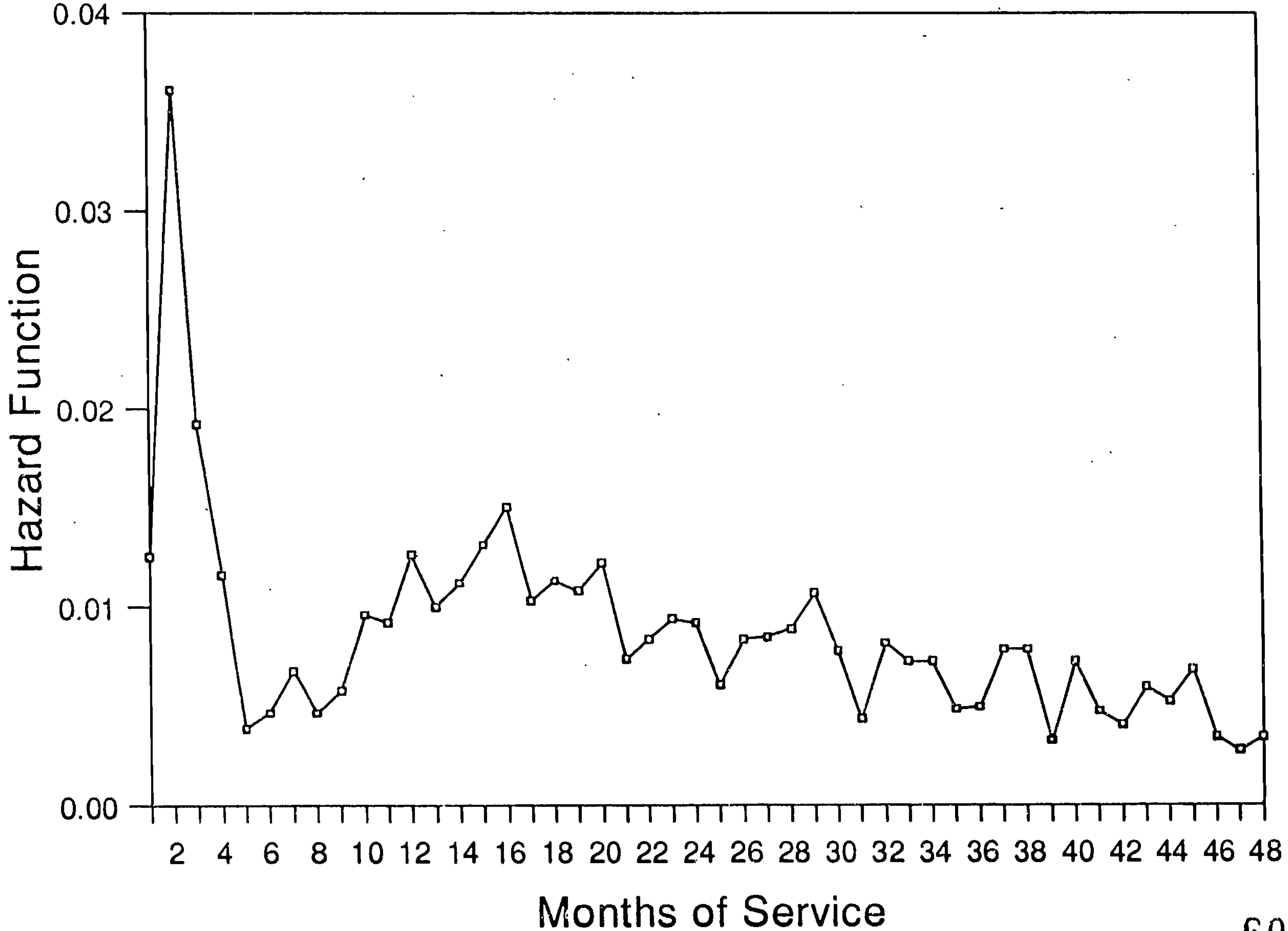
Baseline Survival Function for MOS 63B



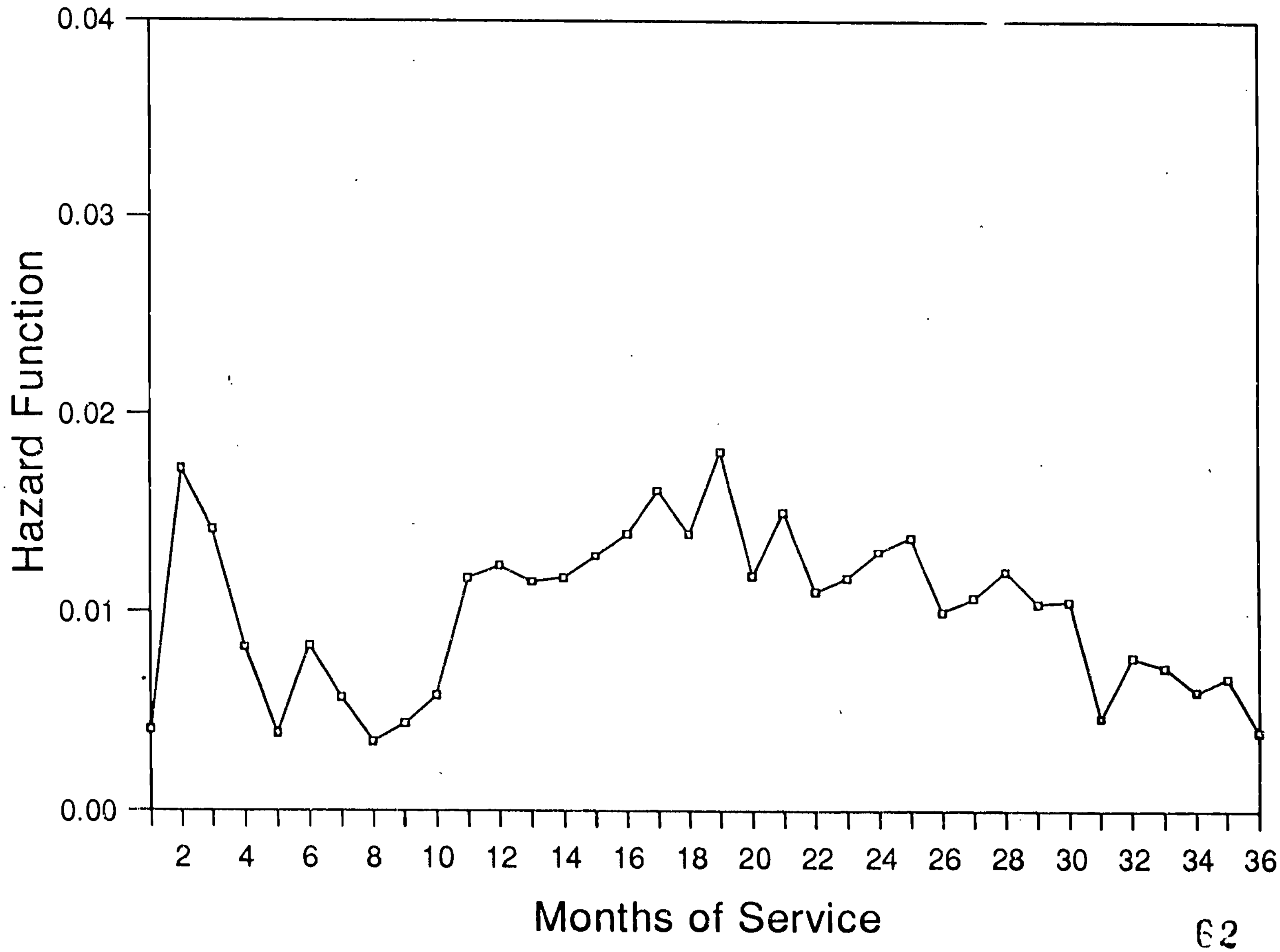
Baseline Survival Function for MOS 95B



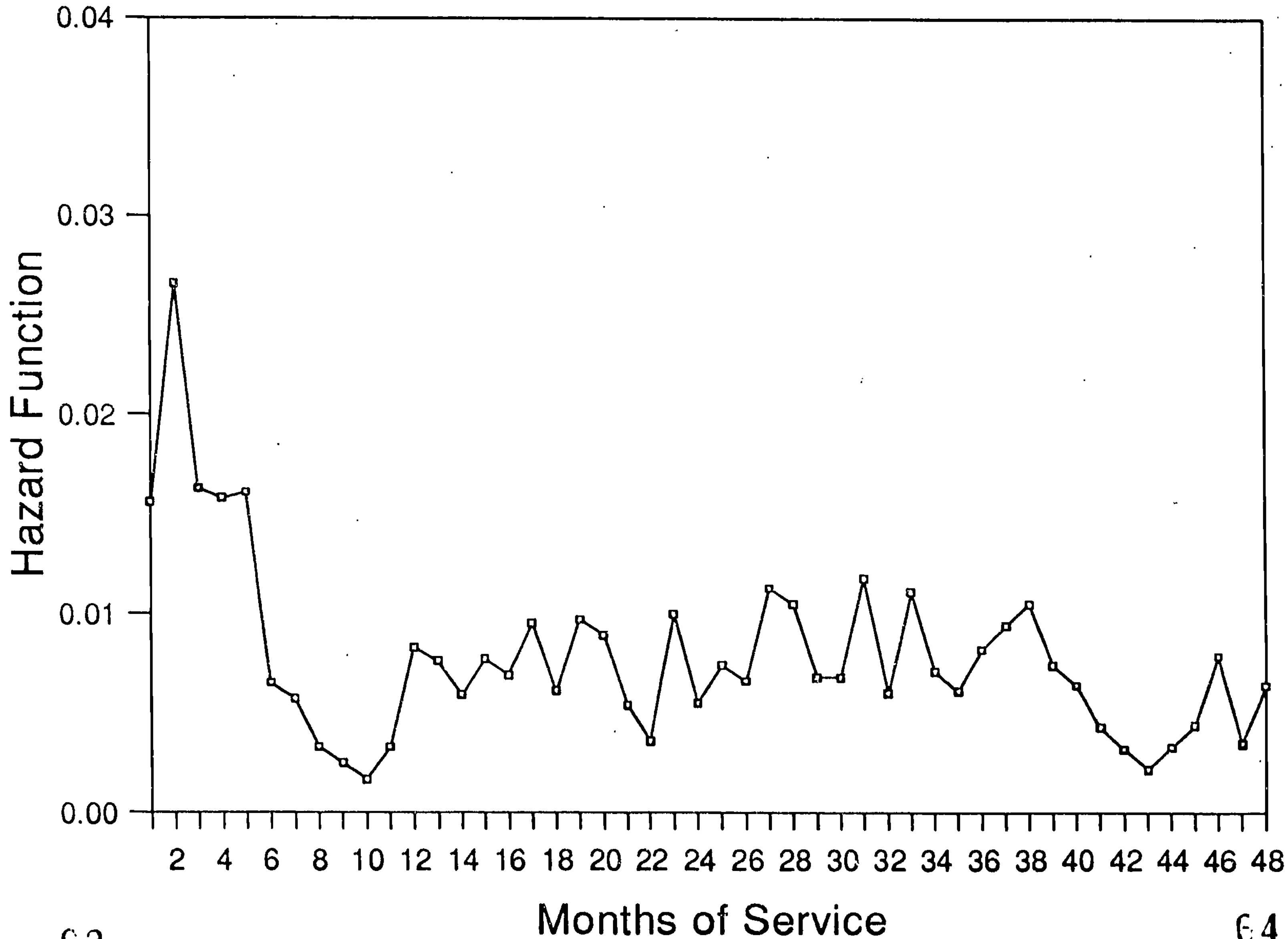
Baseline Hazard Function for MOS 11B



Baseline Hazard Function for MOS 13B



Baseline Hazard Function for MOS 63B



Baseline Hazard Function for MOS 95B