Detecting Meaningful Changes in Short-Term Military Attrition: Application of the Random Effect Model and Agreement Testing

Yuanzhang Li, Timothy Powers and Margot Krauss

Introduction

About one third of the first-term enlistees in each of the military services fail to complete their enlistment terms. The period of highest attrition occurs during the first six months of service. The cost of recruiting, processing and providing basic training to an individual is estimated to be as high as $30,000. Roughly 15% of the 120,000 recruits who begin basic training are discharged prior to completion, resulting in a replacement cost of over $500M per year. Accordingly, attrition reduction targets are frequently discussed as a sensible means of cost savings. These targets are often discussed in the context of short time spans, such as reducing monthly attrition by a specified amount.

When a specific attrition reduction goal is established, it is naturally desired that subsequent data be examined to determine whether the goal is being met. Similarly, it is always of interest to know if there is a short-term, unexpected upward spike in attrition, either overall or within a particular service or training site. Such deviations in attrition, when not in conjunction with a change in demographic features of the recruit population or other known covariates of attrition may be related to policy or other factors within the control of military managers. Knowing what these factors are can help to minimize attrition by eliminating unnecessary risk factors. Unfortunately, such a determination is generally difficult to make, as relatively large fluctuations in short-term attrition rates may be caused by seasonal patterns, time trends, and differences in the demographic profile of recruits over time, or simply random fluctuations.

The aim of this study is to develop attrition modeling that will account for these factors in order to better detect changes in core attrition rates at short-term intervals. We will use monthly accession and attrition data over 1995-1999 to develop short-term attrition prediction models. These models will then be used to predict monthly attrition for CY 2000, and these predictions will then be compared to actual monthly attrition for this period. Particular attention will be given to variance estimates of the predictions, as this will play an important role in determining whether an attrition rate is significantly different from that which was predicted.

Subjects and Methods

All first-time enlistees beginning active duty military service during January 1995 - December 2000 were included in the analyses. The enlistees were grouped according to the month and year of beginning military service (accession). Accession records on these individuals were linked with military personnel records to determine whether or not a subsequent early attrition occurred. For each month/year accession group, attrition percentages during the first 1, 2 and 3 months of service were then determined. In addition, a “demographic profile” was developed for each group, including the distribution of Armed Forces Qualification Test scores (AFQT), gender distribution, race distribution, etc. These factors have been found in previous studies to be strongly related to likelihood of attrition.[1]

Service-specific attrition rates by month/year group over the 60-month period 1995-1999 were first examined, and then adjusted for both seasonal and long-term trends by differencing. Remainder attrition after this differencing for the sequence of month/year groups was then examined for homogeneity. Finally, regression models were then developed to regress the remainder attrition rates against the demographic profiles. Both fixed and random effect models were used in the analysis.

A dynamic regression model was then used to predict attrition rates for the month-year groups of CY 2000. For example, in predicting attrition for enlistees beginning duty in January 2000, all 60 months of historical data from January, 1995 – December 1999 were used in the regression. Similarly, when predicting the attrition rate for enlistees beginning duty in February 2000, data from the previous 61 months (including January 2000) were used in the regression. A measure of the agreement between the predicted attrition rate and actual attrition rate a future month/year group will experience, proposed in the appendix, is used to detect significant differences in actual attrition from expected levels.

Results

First time enlistees were grouped by active duty month and year as well as by service, and raw attrition rates at 1, 2, and 3 months from beginning duty were computed. Figures 1-4 show the attrition rate within three months service for the Army, Navy, Marines, and Air Force from January 95 to June 2000. It can be seen that there is a common seasonal pattern to these attrition rates, with recruits beginning duty in the early part of the calendar year generally having somewhat higher attrition than those entering in the summer months.

[1] AMSARA Annual Report, 1999.

Figure 1. The Attrtion RateWithin 3 Months by AD Months of service in the Army

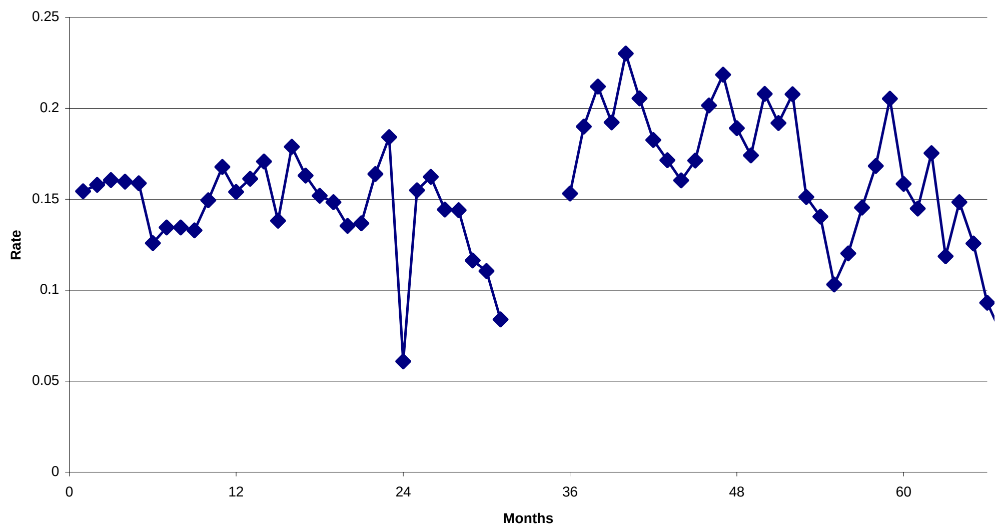


Figure 2. The Attrition Rate 3 Months by AD Months of service in the Navy

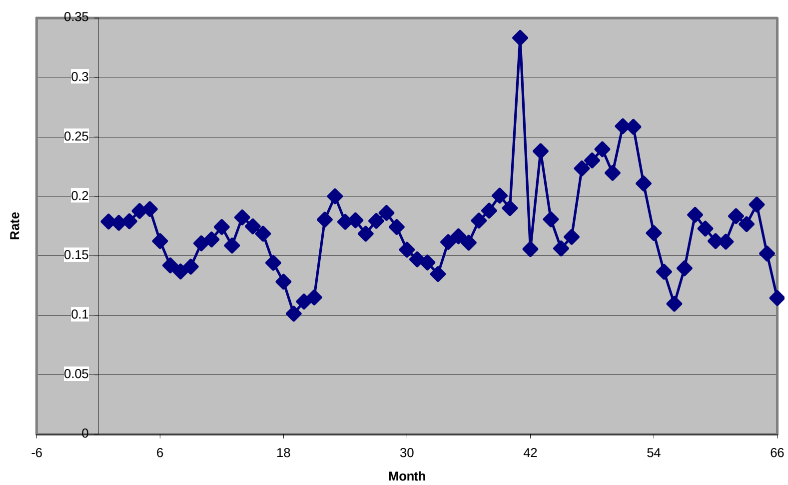


Figure 3. Attrition Rate within 3 months of service by AD months in the Marines

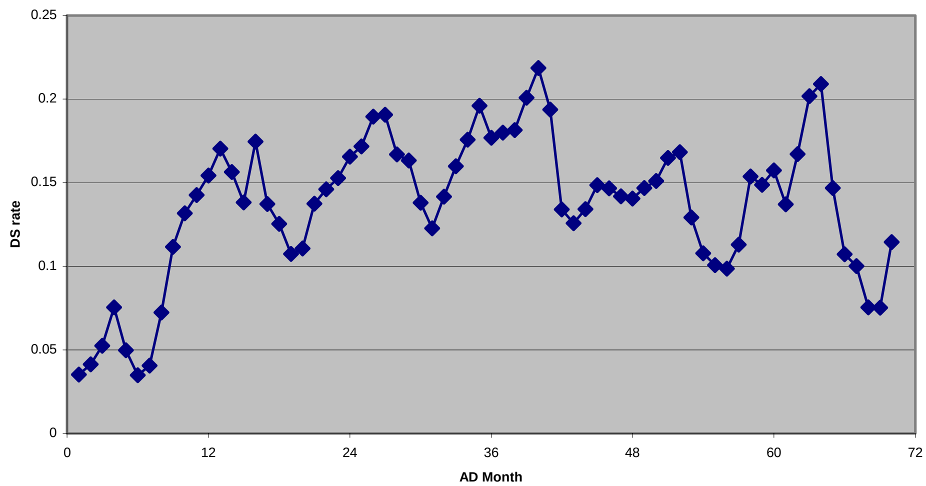
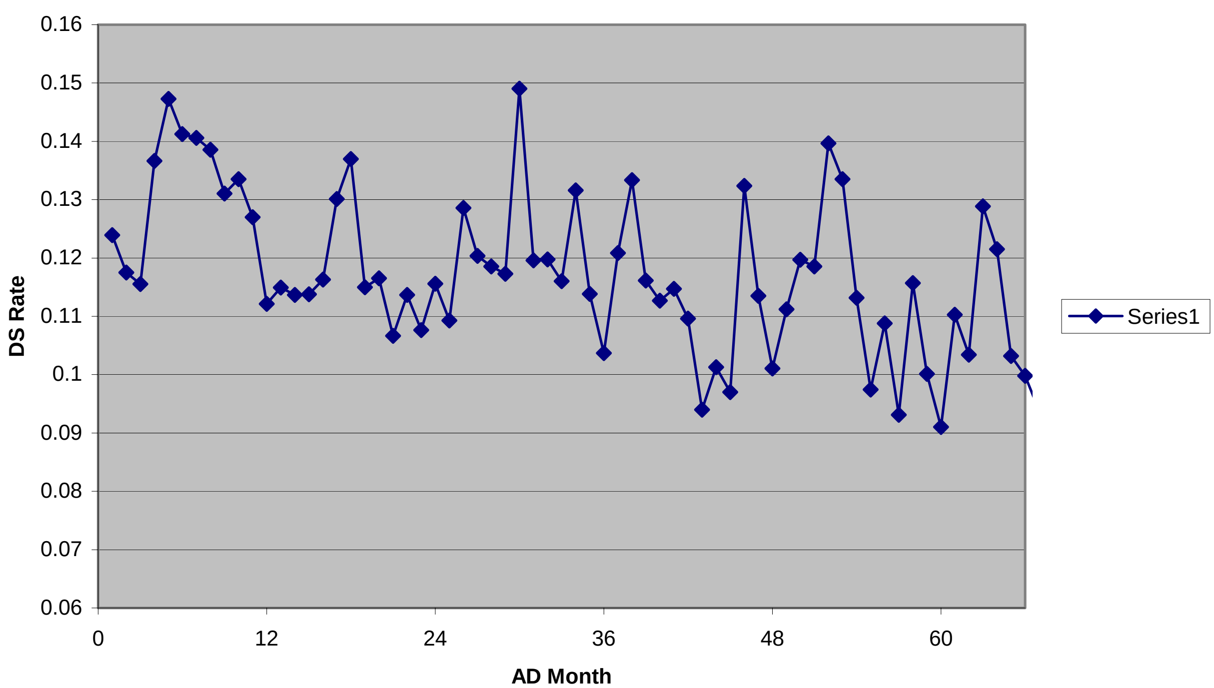


Figure 4. Attrition Rate within 3 months of service by AD Months in the Air Force



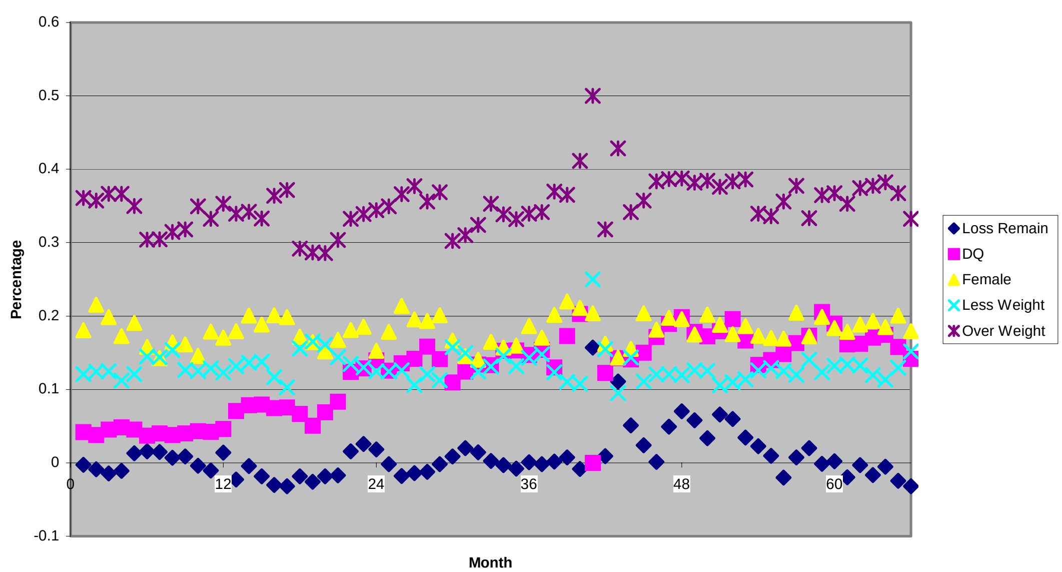
Anecdotal information and prior AMSARA analyses suggest that this phenomenon may be related to differences in the types of individuals beginning service at various times of the year. For example, those coming during the summer months have been shown to be a quite homogeneous group, consisting mostly of young applicants who have just recently graduated from high school. Those entering at other times of the year are somewhat more heterogeneous, consisting of some recent high school graduates and a mix of older individuals with various reasons for joining the military. Also by anecdotal information, the fitness level of this latter group is generally lower than that of recent high school graduates.

We account for this seasonal attrition pattern by subtracting from each monthly attrition rate the average level of attrition for that month over the time period studied (1995-2000). For example, to calculate the remainder attrition for January 1995, the average attrition rate for each January over 1995-2000 is subtracted from the raw rate in January 1995.

Figure 5 shows the remainder attrition rates after the seasonal differencing, along with demographic features of the month/year groups. It can be seen that the monthly remainder loss rates are still not pure random noise, but instead are related to the demographic factors which show non-random patterns over time. It can also be seen that the remainder attrition rates exhibit long-range changes over the time period examined. For example, the levels in 1995 and 1996 are considerably lower than those in 1999, and this relation is not linear.

We regress this remainder attrition against several demographic factors which were found in previous AMSARA studies to be strongly related to attrition, such as sex, race and age distributions, and body mass index (BMI). We will also consider variables of time and the square of time to account for long-term differences in attrition rates over the modeled time period.

Figure 5. The Monthly Remain Attrition Rate and Demographic Profiles



In order to avoid including too many variables in the model simultaneously, all candidate variables are examined in a forward stepwise manner in the order of their significance. The final model includes only significant variables ($p<0.10$).

We used both a random effect regression model and a fixed regression model to fit the historical data, with attrition rates after 1, 2 and 3 months of service as the outcome. It was found that the variance between months was virtually zero for each service except the Air Force. In other words, after controlling for the demographic factors, the residual attrition rates were subject to the same distribution and thus homogeneous, with the exception of those for the Air Force. The remaining analyses will therefore employ only a fixed effects model for the Army, Navy and Marines, while considering both a fixed and random effects model for the Air Force.

Comparison of Predicted to Actual Attrition

Table 1 shows predicted 3-month attrition rates and associated standard errors, by service, for an example month/year group (those beginning service in March 2000). Also shown are the corresponding actual rates and associated standard errors, and the measure of agreement between the predicted and actual for each group. It is seen that the actual 3-month attrition percentage in the Army was 7.8%, which is quite close to the predicted level of 7.7%. Accordingly, the z-score for this difference was not statistically significant (i.e. $|z|<1.96$), indicating that the 3-month attrition levels observed for the Army was in accordance with what would normally be expected after accounting for time trends, seasonal trends, and features of the recruits who began duty at this time.

For the Navy, the actual attrition was 14.9%, whereas the predicted level was 16.2%. This difference is larger than that seen between the actual and predicted levels for the Army, but not enough to achieve statistical significance. The z-score comparing actual to predicted attrition for the Navy was –1.90.

Conversely, the z-score for the Marines indicates a high level of significance. The actual 3-month attrition was 14.5%, whereas the predicted level was only 8.2%. Accordingly, the high z-score for this difference indicates that the observed attrition was much higher than was predicted from the modeling.

Finally, it is seen that the Air Force loss rate, when examined by the fixed effect model, is significantly higher than expected. However, when the random effects model is used to account for variability that was observed across months for the Air Force, the result is no longer statistically significant. It is this latter result that would be used in practice, as the random effects model was determined to be a better choice for the Air Force.

Table 1. Example of Actual versus Predicted Attrition and Agreement Testing: Subjects Beginning Active Duty in March, 2000

	Actual		**Predicted**			
Service (Model)	**Loss rate**	**Std Err**	**Loss Rate**	**Std Err**	**Param Err**	**Agreement Z-score**
Army (Fixed)	0.077	0.004	0.078	0.003	---	-0.28
Navy (Fixed)	0.149	0.007	0.162	0.002	---	-1.90
Marines (Fixed)	0.145	0.008	0.082	0.003	---	7.12
AF (Fixed)	0.097	0.006	0.082	0.001	---	2.43
AF (Random)	0.097	0.006	0.083	0.002	0.009	1.51

Table 2 summarizes the agreement results of modeled versus actual attrition at 1, 2 and 3 months of service for recruits beginning duty January – September 2000. It can be seen from the January results that attrition among recruits beginning duty in that month was significantly lower than expected in both the Army and Navy at all lengths of follow-up (1, 2 and 3 months). Army attrition was then lower than expected in June and July, whereas Navy was lower than expected in July. Attrition among Marines recruits was higher than expected at virtually all follow-up times over March – July.

Of the nine month/year groups examined, the Army had six months with at least one significant attrition deviation from the predicted level, the Navy had five, the Marines seven, and the Air Force four. These results indicate that attrition among recruits beginning military service during CY 2000 was not completely explainable on the basis of long-term trends, seasonal trends, and demographic makeup of the recruit populations.

It is difficult to say whether this large number of significant results is indicative of features of the particular recruit populations that were not included in the modeling, or of the ever-changing military training environment. The modeling results do not appear to have systematic bias, as the actual attrition is roughly evenly distributed above and below predicted levels.

Month (2000) Enter AD	Month Since AD	Army Fixed	Navy Fixed	Marines Fixed	Air Force Random Effect
January	1	-3.66	-4.29	0.12	-0.88
	2	-5.24	-4.18	-0.09	-0.92
	3	-4.73	-3.78	0.65	-0.42
February	1	-0.33	0.88	-0.93	-1.87
	2	0.36	0.16	1.90	-1.38
	3	0.70	-0.52	2.87	-0.82
March	1	1.88	-1.33	3.03	0.51
	2	0.44	-2.26	4.86	1.61
	3	-0.28	-1.90	7.12	1.51
April	1	0.44	-0.73	4.71	-0.53
	2	-1.97	-0.35	6.70	0.33
	3	-1.65	-0.27	7.12	0.98
May	1	1.22	-0.71	3.11	-3.40
	2	1.31	-3.69	4.33	-2.22
	3	2.00	-4.15	3.95	-2.31
June	1	4.11	-5.66	0.57	-2.22
	2	2.96	-7.53	2.14	-0.72
	3	3.73	-6.29	2.08	-1.01
July	1	4.42	-1.35	2.00	-0.72
	2	7.55	-0.80	3.15	0.14
	3	6.69	-0.66	2.17	0.15
August	1	4.28	-0.30	-1.15	-3.42
	2	-1.53	-1.23	0.47	-2.65
	3	-4.21	-1.53	0.72	-2.98
September	1	0.47	-4.40	-3.24	-4.47
	2	-0.78	-0.41	-0.45	-4.63
	3	-1.16	-1.11	0.57	-4.36

Discussion

Determining a reason (or set of reasons) for particular spikes in short-term recruit attrition for a particular service branch will require deeper focus on that branch, and perhaps on particular basic training sites within that branch. For example, this might include examining the two Marines basic training sites separately to see if the increase seen during March-June was a local phenomenon, or whether it was observed at both sites.

The coded reasons for Marines discharges during this period might also be compared to see if there was a spike in a certain category of discharges that might indicate group dynamics or other such effects. For example, there have been occasional episodes of “contagious” psychological problems within groups of recruits, such as an outbreak of suicide ideation episodes within a recruit class at one training site a few years ago.

Policy changes, traumatic or other unusual events, and contagious motivational or attitude problems are other possibilities that might be investigated. For example, the past few years have seen a considerable increase in the number of programs designed to keep recruits in basic training who would have been discharged in past years. For example, an injury rehabilitation program at the Army’s Fort Jackson is now a mandatory stop for recruits with injuries that previously would have led to a discharge. This program has recently been extended to the other four Army basic training sites. Even if such a program served only to delay attrition, this would result in a downward spike in short-term attrition rates.

Future study of these short-term attrition rates should therefore involve closer collaboration with the services, and the individual training sites. Accounting for local phenomena may be the key to fully and successfully modeling and monitoring short-term attrition rates.

Appendix: Measure of agreement between a pooled estimation and a new estimation

Let $r_1,\ldots,r_K$ be attrition rates of first K months, r_W be the weighted average of these, and r_{K+1} be the attrition rate for month K+1. The agreement between r_W and r_{K+1} is usually defined by $(r_{K+1} - r_W)/\text{sqrt}(V(r_{K+1})+ V(r_W))$. In general, $V(r_{K+1})= v_{K+1}$, where v_i is the sampling variance of the estimation of r_i, i=1,2, … K+1. However, if a random effects model is used, variance between months may exist, represented by τ^2. Moses (2002) suggests add the variance between months to variance of r_{K+1}, i.e. $V(r_{K+1})= v_{K+1}+\tau^2$. This suggestion is natural. The estimation in the K+1 month should be treated the same as those, which derived from the previous K months. We will follow his suggestions to measure the agreement between the prediction from the regression model and the observed attrition rate for the month K+1.

Measure of agreement between a predicted value and the observed value in the K+1 month:

Considering the attrition rate r_i in the month i, i=1,2, … K, which may depends on demographic profile by months and other factors, such as season, time trend etc. The fixed regression model

$F(r_i)=\boldsymbol{\beta}\mathbf{X}_i+\boldsymbol{\varepsilon}_i$,

$\mathbf{X}_i$ is the demographic profile by months, $\boldsymbol{\varepsilon}_i$, is the residual error term, which is from the regression. However, since $F(r_i)$ is a function of r_i, which is an estimation based on the monthly base, with the sampling error e_i, hence a random effect model should be used,

$F(r_i)=\boldsymbol{\beta}\mathbf{X}_i+\boldsymbol{\varepsilon}_i+ e_i$,

We assume the residuals are subject to a normal distribution with mean of zero and the variances are

$V(e_i)= \sigma^2_i$ (variance within month)

$V(\varepsilon_i)= \tau^2$ (variance between months)

then for random effect model: $V(F(r_i))= \sigma^2_i + \tau^2$

Using the above model, based on the demographic profile of the month K+j, j=1,2,…, the predictor of the attrition rate in the month K+j is $\acute{r}_{K+j}$. The agreement between the predictor and the observed attrition rate could defined by

$z_1=(F(\acute{r}_{K+j})-F(r_{K+j}))/\text{Sqart}(v(F(\acute{r}_{K+j}))+v_{K+j})$ or

$z_2=(F(\acute{r}_{K+j})-F(r_{K+j}))/\text{Sqart}(v(F(\acute{r}_{K+j}))+v_{K+j} +\tau^2)$

where z_1 is the classic measure for the agreement, z_2 is the new way to measure the agreement, which add the variance between months to the variance of the month K+j.

In the dynamic regression process, K is increasing when more data from the future months are available. The prediction is always for the month K+1.

References

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