Recurrent Event Model and Army Hospitalization

Yuanzhang Li, Timothy E. Powers

Introduction

In many fields of study, research questions involve life course events that can happen repeatedly over time, such as injuries, hospital admissions, risk events, etc. Researchers analyzing such data are often concerned with both the "if" and "when" of event occurrence. Traditional survival analysis methods, however, are most commonly applied to situations in which the outcome of interest that can occur only once for each subject under study. Different models, or at least adaptations of these traditional survival analysis techniques, are needed to examine data involving recurrent events.

One setting in which such models are needed is the study of hospitalizations among new enlistees in the United States Army. Early hospitalizations of enlistees are not only quite costly, but have been shown to be a strong risk factor for another costly problem -- early attrition. Hence, it is of interest to understand the risk factors for early hospitalizations, and multiple hospitalizations, among new enlistees.

A number of multivariate regression models have been proposed for use with recurrent events. [1-5] In this study, we will apply five different recurrent models that have been proposed in the scientific literature to Army enlistee hospitalization data, and to closely related data simulations. We will examine results for consistency across models, and for robustness of each model as alterations are made to event timing, percentage of subjects experiencing events, and sample size.

Methods

Five different recurrent models were compared by using SAS procedures: Poison Process, Counting Process, Conditional A, Conditional B, and Marginal. Each of these models will be used to estimate the influence of several three factors (hospitalization timing, proportion of subjects hospitalized, and sample size) on control variable effect estimates. The control variables include gender, race, age, Armed Forces Qualification Test (AFQT) percentile score, indicators of body weight (underweight or overweight), and an indicator of medical qualification status at the time of application for service (qualified, temporarily disqualified, permanently disqualified).

Details of the models to be used are given below.

The Poison process model

The Poison model is essentially event counting, with the assumption that each event is independent of other events. Under this model, a subject contributes to the risk set for an event as long as the subject is under observation. Further, it is assumed that all time periods of the same length have the same probability of an event occurring. In the current setting, it should be noted that some hospitalization causes (e.g. injuries which leave a subject at greater risk for subsequent injury) might not satisfy the above assumptions.

This model ignores the order of the events, leaving each subject to be at risk for any event as long as they are still under observation. The data structure for the Poison

model would consist only of the length of time at risk and the number of events experienced during that time.

The counting process model

The second model is the counting process. This model assumes that each event is independent. A subject contributes to the risk set for an event as long as the subject is under observation at the time the event occurs; the data for a subject with multiple events could be described as data for multiple subjects while each subject has different entry date and is followed until the next event occurs. For example, in the data set we see that the first subject will be at risk for any event occurring between 0 and 80 months and subject two for any events occurring between 0 and 71 months.

This model, thus, ignores the order of the events leaving each subject to be at risk for any event as long as they are still under observation at the time of the new event occurring. This implies that a subject could be at risk for a subsequent event without having experienced the prior events. Since this model ignore the event order, same as the Poison model, for some causes of hospitalization, it might not be fine. But for some causes of hospitalization, which can't be recovered well, such as asthma, mental disease, Schizophrenia, etc, it might be improper to use this model.

The conditional model A

The third model is a conditional model. Using such a model, it assumes that it is not possible for a subject to be at risk for event 2 without having experienced event 1. It means if a subject is at risk for a subsequent event, then it is already having experienced the previous event; In order to contract the data in such an order, a strata variable is designed to indicate the event number. In this model the time interval of a subsequent event starts at the end of the time interval for the previous event.

This model is useful for modeling the full time course of the recurrent event process. In the data set the time intervals are set up exactly the same as in the counting process model with each time interval starting at the time of the previous event occurring. But the difference between this model and the counting process model is that we are using the stratum variable to keep track of the event number; thus, ensuring that it is not possible to be at risk for subsequent events without having experienced the previous events.

The conditional model B

Next model is also a conditional model. This model only differs from the Conditional Model A in the way how the time intervals are structured. For the data, each time interval starts at zero and ends at the length of time until the next event occurs. The result is that the risk sets for each of these conditional models are completely different and the questions that these analysis answer are also very different. This model is very useful for modeling the time between each of the recurring events rather than the full time period of the recurrent event process. In the data set the first subject experiences four time intervals which each start at time zero but end at the length of time until the

next event. This model ignores the length of full time period. For the data including a lot of subjects without events, it might overestimate the significance of the factors we studied.

As in Conditional Model A we use the stratum variable to keep track of the event number; thus, ensuring that it is not possible to be at risks for subsequent events without having experienced the previous events.

The marginal model

In the marginal model each event is considered as a separate process. We assume that the time for each event starts at the beginning of follow up time and ends at the time of event occurring or to the end of the follow up time; Each subject is considered to be at risk for all events; The number of events at risks for all subjects are the same, which is the maximum number of events among all subjects. In other word, all subjects in the study contribute follow up times to all possible recurrent events. The marginal model considers each event separately and models all the available data for the specific event. By using the marginal model, the size of the data set is much bigger than that used by other models, especially, if there are a lot of subjects without experienced events.

Table 1 below shows the data structures necessary to implement each of the models described above. In this table, the "Time" variable shows the observation time (in months) used in the various models. The variable "Event" shows the number of events (in this case, hospitalizations) occurring in the given period. Finally the variable "Status" shows indicates the ordering of events (those with multiple events showing Status=1 indicate models that do not consider event order).

Table 1: Data Structure:

Table 1. Structure of Recurrent Event Data for Various Models

Model	Enlistee	Time(month)	Event	Status	Enlistee	Time	Event	Status
Poison Process	1	(0, 80)	4	1	2	(0,71)	2	1
Counting Process	1	(0, 5]	1	1	2	(0, 32]	1	1
		(5, 9]	1	1		(32, 62]	1	1
		(9, 56]	1	1		(62,71]	0	1
		(56, 80]	1	1				
Conditional A	1	(0, 5]	1	1	2	(0, 32]	1	1
		(5, 9]	1	2		(32, 62]	1	2
		(9, 56]	1	3		(62, 71]	0	3
		(56, 80]	1	4				
Conditional B	1	(0, 5]	1	1	2	(0, 32]	1	1
		(0, 4]	1	2		(0, 30]	1	2
		(0, 47]	1	3		(0, 9]	0	3
		(0, 24]	1	4				
Marginal	1	(0, 5]	1	1	2	(0, 32]	1	1
		(0, 9]	1	2		(0, 62]	1	2
		(0, 56]	1	3		(0, 71]	0	3
		(0, 80]	1	4		(0, 71]	0	4

For all models except the Poisson process, we use the proportional means regression model. For each observation

$$M(t) = M_0(t)\, e^{X'\beta}$$

where M(t) is the Mean Cumulative Function (MCF) for the number (or associated cost) of events of interest up to time t; X' is a vector of time invariant covariates; and $M_0(t)$ is a baseline MCF.

For the Poison regression, SAS/genmod procedure will be used. For all other models we will use SAS/PHREG.

Data

In this study we use both true data and simulated data. The true data consists of follow-up on all enlistees who began Army service from 1999 to 2002 for hospitalizations occurring during this same period. The life data is censored at Dec. 31 2002 or the date, when the enlistee left the service.

The simulated data are based on the true data, but three features of the data are altered to determine the influence of three factors (hospitalization timing, proportion of subjects hospitalized, and sample size) on control variable effect estimates.
Each of the generated data sets, described in detail below, was generated, 100 times each:

1. Hospitalization timing:

1.1. Early hospitalization

For each enlistee hospitalized k times, we set the date of first hospitalization at x days from the beginning of service, at 2x days for second hospitalization, …k*x days in the k^{th} time, where k=1, 2, 3. Eight datasets of this type were generated using x=5, 10, 15, 20, 30, 60, 70 and 80.

1.2 Late hospitalization

Similar to above, but the hospitalization date was start counting from the date, when they left the service, or the censor enduing date December 31, 2002. The total eight data sets were generated by selecting x=5, 10, 15, 20, 30, 60, 70 and 80.

2. Proportion of subjects hospitalized

In the true data, about 6% of subjects were hospitalized. Simulated data with different hospitalization proportions were created using a stratified sampling technique to select subsets of hospitalized and non-hospitalized subjects from the true data. The ratios of hospitalized to non-hospitalized subjects selected were set to be 1:19, 1:9, 1:7,1:4 and 1:3 respectively. Thus, the hospitalization rates were about 5%, 10%, 12.5%, 20% and 25% in the 5 generated data sets.

3. Sample size

Fixing the percentage of hospitalized subjects at 20%, we use stratified sampling to select samples of sizes 2000, 4000, 8000 and 10000 from the true data.

Fixing the percentage of hospitalized subjects at 20%, we use stratified sampling to select samples of sizes 2000, 4000, 8000 and 10000 from the true data.

Results

True Data

Table 2 shows the estimated control variable effects from each of the five different recurrent events models considered. It is seen that estimates were quite similar across the different models. The marginal model and Poison model have slightly higher significance levels than the others; while the two conditional models have slightly lower significance.

Assessing the factors themselves as hospitalization predictors, hospitalization rates were significant different by age, gender and AFQT. It is interesting that the presence of an initially disqualifying medical condition (presumably surmounted with an accession medical waiver) did not have a significant effect on likelihood of hospitalization. However, those with a temporarily disqualifying medical condition at the time of application had significant higher hospitalization rates than those who did not have any initial disqualification.

Table 2: Control Factors Related to Hospitalization Likelihood: Influence of Model Selection on Estimated Effects

Parameter	Model	Estimates	Standard Error	P_value
AFQT	Poisson	-0.0030	0.001	0.000
	Counting	-0.0030	0.001	0.000
	Conditional A	-0.0027	0.001	0.001
	Conditional B	-0.0026	0.001	0.002
	Marginal	-0.0037	0.001	<.0001
age	Poisson	0.0210	0.005	<.0001
	Counting	0.0201	0.005	<.0001
	Conditional A	0.0160	0.005	0.001
	Conditional B	0.0186	0.005	0.000
	Marginal	0.0243	0.005	<.0001
Female	Poisson	0.7751	0.032	<.0001
	Counting	0.7769	0.032	<.0001
	Conditional A	0.7213	0.032	<.0001
	Conditional B	0.6865	0.032	<.0001
	Marginal	0.7763	0.032	<.0001
Perm DQ	Poisson	0.0734	0.063	0.245
	Counting	0.0660	0.063	0.296
	Conditional A	0.0640	0.063	0.312
	Conditional B	0.0618	0.063	0.328
	Marginal	0.0890	0.063	0.159
Temp DQ	Poisson	0.1289	0.045	0.005
	Counting	0.1261	0.045	0.006
	Conditional A	0.1049	0.045	0.021
	Conditional B	0.1106	0.045	0.015
	Marginal	0.1485	0.045	0.001
Over Weight	Poisson	0.0241	0.033	0.457
	Counting	0.0242	0.033	0.456
	Conditional A	0.0165	0.033	0.612
	Conditional B	0.0171	0.032	0.599
	Marginal	0.0183	0.033	0.574
Less Weight	Poisson	0.0943	0.045	0.035
	Counting	0.0942	0.045	0.036
	Conditional A	0.0893	0.045	0.046
	Conditional B	0.0847	0.045	0.059
	Marginal	0.0897	0.045	0.045

Simulated Data

Table 3 shows the average z-scores of effect estimates from the various data simulation scenarios allowing for variation in the timing of hospitalizations. (Recall that 100 datasets were created under each scenario -- the results below are the averages of results from these.) These results help to examine the stability of model estimates as the timing of hospitalization events among subjects varies. Results from the Poison model are not shown since they depend only on the number of events that occur, and thus do not change according to the timing of events.

It is seen that, in general, the model estimates remain fairly stable as the timing of events is altered. For example, looking at the Conditional A model, the average z-score for the effect of being female when hospitalizations were set to occur an average of every 5 days, was 7.13. As the average time interval between hospitalizations increased, this coefficient did not change much, stabilizing at 7.30 as the average time between hospitalizations grew to 60 days or more. The estimated effects of the other factors were similarly stable within this model, and indeed within all of the models examined. Not surprisingly, then, the actual coefficient estimates also showed little variation (data not shown).

Perhaps the largest impact of timing on effect estimation is seen in the Conditional A model when comparing the effect of hospitalizations occurring early in service to those occurring late in service. For example, the z-scores for the "Temporary disqualification" variable when the hospitalizations occurred early in service ranged from 0.83-0.98, all far from statistical significance. However, when the hospitalizations occurred late in service, the z-scores ranged from 1.87-1.91, a range considered in some settings to indicate borderline statistical significance. A similar pattern was seen for the age variable under this model as the hospitalizations moved from early in service to late in service.

Finally, there were no dramatic differences in results from the different models. The Conditional A model and the Counting Process model yielded results very similar to one another, and the results from the Conditional B and Marginal models were quite similar to one another. This was true not only of the z-scores, but also of the effect coefficients (data not shown).

Table 3: Average Z-scores of Effect Estimates Relating Predictive Factors to Likelihood of Hospitalization: Applying Several Models to Simulated Data

Model	Hospitalization intervals		Average z-scores of effects						
	Zero Point	Days	Female	age	AFQT	Over DQ	Less Weight	Perm DQ	Temp DQ
Conditional A	Start of service	5	7.13	0.38	-0.10	0.32	1.48	1.80	0.83
		10	7.17	0.42	-0.14	0.31	1.52	1.82	0.88
		15	7.23	0.46	-0.15	0.30	1.53	1.87	0.90
		20	7.24	0.50	-0.16	0.28	1.56	1.90	0.96
		30	7.28	0.55	-0.14	0.29	1.60	1.93	0.98
		60	7.30	0.53	-0.14	0.28	1.59	1.92	0.98
		70	7.30	0.53	-0.14	0.28	1.61	1.91	0.96
		80	7.30	0.54	-0.15	0.27	1.61	1.91	0.96
	End of service	80	8.34	1.76	-1.15	-0.05	1.54	2.51	1.90
		70	8.34	1.76	-1.18	-0.06	1.54	2.50	1.88
		60	8.33	1.74	-1.21	-0.04	1.55	2.50	1.87
		30	8.42	1.78	-1.18	-0.10	1.57	2.50	1.91
		20	8.42	1.78	-1.21	-0.12	1.46	2.54	1.89
		15	8.42	1.74	-1.18	-0.11	1.49	2.53	1.90
		10	8.44	1.78	-1.22	-0.10	1.52	2.58	1.90
		5	8.50	1.75	-1.21	-0.03	1.54	2.59	1.91
Conditional B	Start of service	5	6.71	1.50	-0.83	-0.10	1.47	2.55	1.58
		10	6.69	1.50	-0.82	-0.12	1.48	2.54	1.60
		15	6.74	1.49	-0.80	-0.13	1.49	2.57	1.60
		20	6.76	1.48	-0.80	-0.13	1.48	2.56	1.64
		30	6.83	1.47	-0.79	-0.10	1.50	2.59	1.65
		60	6.86	1.45	-0.80	-0.10	1.48	2.59	1.64
		70	6.85	1.45	-0.80	-0.10	1.50	2.58	1.63
		80	6.86	1.46	-0.81	-0.11	1.50	2.58	1.63
	End of service	80	8.17	1.26	-0.49	0.08	1.51	2.02	1.41
		70	8.17	1.28	-0.50	0.07	1.52	2.03	1.38
		60	8.15	1.26	-0.54	0.07	1.53	2.03	1.37
		30	8.22	1.26	-0.53	0.10	1.52	2.02	1.37
		20	8.20	1.15	-0.55	0.12	1.50	2.00	1.33
		15	8.19	1.06	-0.49	0.15	1.52	1.97	1.34
		10	8.16	1.02	-0.45	0.21	1.54	1.93	1.28
		5	8.14	0.97	-0.38	0.24	1.56	1.89	1.26
Counting Process	Start of service	5	7.33	0.44	-0.09	0.29	1.44	1.78	0.86
		10	7.38	0.51	-0.14	0.26	1.45	1.81	0.92
		15	7.45	0.54	-0.16	0.25	1.47	1.86	0.94
		20	7.48	0.60	-0.17	0.22	1.48	1.90	1.00
		30	7.53	0.66	-0.16	0.21	1.51	1.97	1.01
		60	7.54	0.65	-0.16	0.20	1.50	1.97	1.00
		70	7.53	0.66	-0.16	0.20	1.52	1.96	0.99
		80	7.54	0.67	-0.17	0.20	1.52	1.96	0.98

	End of service	80	8.37	1.81	-1.14	-0.09	1.50	2.51	1.91
		70	8.36	1.83	-1.15	-0.10	1.52	2.52	1.88
		60	8.34	1.82	-1.18	-0.09	1.52	2.52	1.87
		30	8.41	1.83	-1.16	-0.07	1.51	2.50	1.87
		20	8.40	1.81	-1.17	-0.08	1.48	2.52	1.87
		15	8.39	1.78	-1.15	-0.07	1.50	2.51	1.87
		10	8.38	1.78	-1.15	-0.06	1.49	2.52	1.87
		5	8.36	1.78	-1.16	-0.04	1.50	2.53	1.88
Marginal	Start of service	5	7.02	1.53	-0.99	-0.10	1.41	2.58	1.74
		10	7.04	1.53	-0.99	-0.10	1.41	2.59	1.74
		15	7.05	1.53	-1.00	-0.10	1.42	2.59	1.74
		20	7.06	1.53	-1.00	-0.10	1.42	2.59	1.75
		30	7.07	1.53	-1.01	-0.09	1.42	2.60	1.75
		60	7.07	1.53	-1.01	-0.09	1.42	2.60	1.75
		70	7.07	1.53	-1.01	-0.09	1.42	2.60	1.75
		80	7.07	1.53	-1.01	-0.09	1.42	2.60	1.75
	End of service	80	7.85	1.98	-1.26	-0.05	1.37	2.36	1.74
		70	7.85	1.98	-1.26	-0.05	1.37	2.36	1.74
		60	7.85	1.98	-1.26	-0.05	1.37	2.36	1.74
		30	7.84	1.96	-1.25	-0.04	1.37	2.36	1.73
		20	7.81	1.93	-1.22	-0.01	1.40	2.35	1.74
		15	7.81	1.93	-1.22	-0.02	1.40	2.35	1.73
		10	7.80	1.93	-1.23	-0.02	1.40	2.36	1.74
		5	7.80	1.93	-1.23	-0.01	1.40	2.36	1.74

The Hospitalization Rate Effect

Tables 4 and 5 show the average effects and z-scores of effect estimates from the various data simulation scenarios allowing for variation in the percentage of subjects experiencing hospitalization. (Recall again that 100 datasets were created under each scenario -- the results below are the averages of results from these.)

Table 4. Average Effect Estimates for Predictive Factors: Applying Several Models to Simulated Data with Different Percentage of Hospitalization.

Model	Percent of subjects hospitalized	Sex	Age	AFQT	Overwt	Underwt	Perm DQ	Temp DQ
Poisson	0.05	0.726	0.019	-0.003	0.023	0.130	0.235	0.170
	0.10	0.698	0.015	-0.003	0.030	0.099	0.141	0.157
	0.15	0.652	0.017	-0.003	0.026	0.112	0.129	0.137
	0.20	0.618	0.017	-0.002	0.022	0.088	0.106	0.118
Conditional A	0.05	0.700	0.015	-0.003	0.014	0.140	0.187	0.148
	0.10	0.671	0.013	-0.003	0.013	0.104	0.124	0.130
	0.15	0.644	0.014	-0.002	0.016	0.101	0.127	0.123
	0.20	0.608	0.015	-0.002	0.019	0.089	0.089	0.104
Conditional B	0.05	0.664	0.017	-0.003	0.014	0.136	0.188	0.154
	0.10	0.638	0.015	-0.002	0.014	0.100	0.119	0.136
	0.15	0.610	0.015	-0.002	0.016	0.097	0.124	0.126
	0.20	0.574	0.016	-0.002	0.020	0.085	0.084	0.108
Counting	0.05	0.739	0.018	-0.003	0.021	0.147	0.211	0.176
	0.10	0.701	0.016	-0.003	0.021	0.106	0.130	0.151
	0.15	0.662	0.016	-0.002	0.021	0.103	0.133	0.137
	0.20	0.616	0.017	-0.002	0.026	0.089	0.091	0.115
Marginal	0.05	0.750	0.020	-0.004	0.014	0.148	0.243	0.205
	0.10	0.719	0.018	-0.003	0.016	0.103	0.158	0.181
	0.15	0.687	0.019	-0.003	0.015	0.099	0.164	0.167
	0.20	0.647	0.020	-0.003	0.021	0.083	0.119	0.145

It is seen that the average effect coefficients and z-scores for the various control factors are quite similar regardless of the percentages of subjects hospitalized. This is true both within and across the models considered. Sex is highly statistically significant in all models and across all percentages of hospitalization, while age, AFQT score, and the two medical qualification status variables are near statistical significance in all models and hospitalization percentages.

It is worth noting that the selected hospitalized and non-hospitalized samples have the same distribution by the control factors (sex, age, etc.) as the true data. Accordingly, the estimated effects of these factors should be similar to those from the modeling of the true data. This was, indeed, generally the case (data not shown).

Table 5: Average Z-scores of Effect Estimates Relating Predictive Factors to Likelihood of Hospitalization: Applying Several Models to Simulated Data with Different Percentage of Hospitalization.

Model	Percent of subjects hospitalized	Sex	Age	AFQT	Overwt	Underwt	Perm DQ	Temp DQ
Poisson	0.05	11.88	2.08	-2.02	0.37	1.54	2.14	2.00
	0.10	13.23	1.85	-1.96	0.55	1.35	1.43	2.14
	0.15	13.87	2.43	-2.04	0.53	1.71	1.47	2.09
	0.20	14.48	2.59	-2.07	0.51	1.46	1.32	1.96
Conditional A	0.05	11.73	1.62	-1.87	0.21	1.68	1.72	1.76
	0.10	13.07	1.65	-1.79	0.25	1.42	1.27	1.78
	0.15	14.12	1.95	-1.91	0.33	1.56	1.47	1.88
	0.20	14.72	2.28	-2.16	0.44	1.51	1.12	1.75
Conditional B	0.05	11.11	1.82	-1.85	0.22	1.68	1.78	1.85
	0.10	12.43	1.84	-1.73	0.25	1.39	1.26	1.87
	0.15	13.40	2.17	-1.84	0.32	1.52	1.48	1.94
	0.20	13.94	2.48	-2.06	0.46	1.47	1.09	1.82
Counting	0.05	11.13	1.75	-1.83	0.29	1.60	1.70	1.82
	0.10	12.46	1.78	-1.71	0.34	1.33	1.21	1.82
	0.15	13.46	2.09	-1.80	0.40	1.47	1.42	1.90
	0.20	14.06	2.38	-2.04	0.54	1.43	1.06	1.78
Marginal	0.05	10.74	1.87	-2.15	0.19	1.53	1.88	2.01
	0.10	11.95	1.92	-2.08	0.24	1.22	1.38	2.05
	0.15	12.84	2.28	-2.24	0.27	1.33	1.62	2.13
	0.20	13.34	2.58	-2.53	0.41	1.22	1.28	2.03

Table 6 shows the standard deviations of the estimated demographic effects in simulations with different percentages of subjects being hospitalized. In general, we would like to use the method with less standard deviation of estimates, if the estimates are unbiased. Overall, the standard deviations from both conditional models are similar to one another, and they are smaller than those from the counting process and marginal models.

Table 6: Standard Errors of Effect Estimates: Applying Several Models to Simulated Data with Different Percentage of Hospitalization

Model	Percent of subjects hospitalized	Sex	Age	AFQT	Overwt	Underwt	Perm DQ	Temp DQ
Poisson	0.05	0.046	0.010	0.002	0.058	0.065	0.089	0.072
	0.10	0.035	0.006	0.001	0.034	0.041	0.051	0.056
	0.15	0.028	0.005	0.001	0.028	0.040	0.042	0.045
	0.20	0.022	0.004	0.001	0.026	0.030	0.030	0.029
Conditional A	0.05	0.048	0.008	0.001	0.046	0.059	0.073	0.063
	0.10	0.032	0.007	0.001	0.035	0.043	0.061	0.045
	0.15	0.028	0.006	0.001	0.028	0.034	0.047	0.040
	0.20	0.023	0.004	0.001	0.020	0.029	0.043	0.033
Conditional B	0.05	0.047	0.008	0.001	0.044	0.058	0.069	0.061
	0.10	0.032	0.007	0.001	0.034	0.042	0.057	0.045
	0.15	0.028	0.006	0.001	0.027	0.034	0.043	0.039
	0.20	0.022	0.004	0.001	0.020	0.028	0.042	0.033
Counting	0.05	0.054	0.009	0.001	0.050	0.067	0.081	0.072
	0.10	0.035	0.007	0.001	0.039	0.048	0.065	0.050
	0.15	0.031	0.006	0.001	0.031	0.037	0.051	0.043
	0.20	0.025	0.005	0.001	0.022	0.031	0.047	0.037
Marginal	0.05	0.056	0.009	0.001	0.051	0.070	0.085	0.074
	0.10	0.038	0.008	0.001	0.040	0.050	0.066	0.053
	0.15	0.033	0.006	0.001	0.032	0.041	0.052	0.046
	0.20	0.027	0.005	0.001	0.024	0.033	0.049	0.040

Comparing Tables 4 and 6, it can be seen that for the sex variable, the standard errors are much less than their respective mean estimated coefficients for all five models and all 4 different hospitalization rates. This means the estimation of this effect is robust across the models, and shows that gender is a significant predictor of hospitalization.

For the other demographic factors, the mean coefficients are comparable in size to their respective standard errors. This means that the estimated coefficient may not be so reliable, and we should not draw conclusions based on only one selected model.

The standard errors of effect estimates are decreasing as the hospitalization rate is increasing, as would be expected. In particular, when the hospitalization rate is about 20%, the effects estimates for age and AFQT are quite reliable across models. When the hospitalization rate is about 5%, the standard errors are quite large compared to the mean estimated coefficients. Model selection and interpretation should be done more carefully at such lower levels of hospitalization percentages.

Sample Size Effect

The results in Table 7 show effect estimates from simulated data of various sample sizes. The selected numbers of hospitalized individuals were 500, 1000, 1500 and 2000 respectively, and four times as many controls were selected for each of these cases. Hence the hospitalization ratio was 20% overall for each data. As in the previous analyses, the distributions of hospitalized and non-hospitalized subjects by the control variables (sex, age, etc.) in this simulation were the same as in the true Army hospitalization data.

The results indicate that sample size has little effect on the effect estimates regardless of which model is used. As expected, however, larger sample size results in reduced standard error and thus greater statistical significance (data not shown).

Table 7: The demographic factor effect s by sample size

Model	Sample Size	Sex	Age	AFQT	Overwt	Underwt	Perm DQ	Temp DQ
Poisson	2,000	0.546	0.017	-0.003	0.022	0.170	0.293	0.203
	4,000	0.569	0.013	-0.002	0.015	0.122	0.125	0.156
	8,000	0.604	0.020	-0.002	0.020	0.108	0.123	0.115
	10,000	0.618	0.016	-0.002	0.032	0.100	0.110	0.125
Conditional A	2,000	0.559	0.014	-0.003	0.017	0.174	0.266	0.190
	4,000	0.566	0.011	-0.002	0.008	0.121	0.120	0.147
	8,000	0.601	0.018	-0.002	0.016	0.104	0.120	0.112
	10,000	0.611	0.014	-0.002	0.026	0.097	0.103	0.113
Conditional B	2,000	0.523	0.016	-0.003	0.016	0.164	0.270	0.190
	4,000	0.536	0.012	-0.002	0.009	0.118	0.113	0.150
	8,000	0.568	0.019	-0.002	0.015	0.103	0.114	0.109
	10,000	0.579	0.015	-0.002	0.027	0.093	0.101	0.116
Counting	2,000	0.548	0.016	-0.003	0.021	0.170	0.283	0.202
	4,000	0.572	0.012	-0.002	0.015	0.122	0.118	0.155
	8,000	0.607	0.020	-0.002	0.020	0.107	0.118	0.115
	10,000	0.620	0.016	-0.002	0.032	0.100	0.104	0.123
Marginal	2,000	0.580	0.021	-0.004	0.014	0.167	0.348	0.245
	4,000	0.599	0.016	-0.003	0.013	0.121	0.142	0.192
	8,000	0.640	0.023	-0.003	0.016	0.106	0.152	0.135
	10,000	0.651	0.018	-0.003	0.030	0.094	0.142	0.157

Conclusions

Five different model types were used to estimate the effects of several demographic factors on likelihood of hospitalization among new Army enlistees. When applying these models to actual data over a three-year period, the results from these models were quite similar. This result is somewhat comforting in that the major conclusions to be drawn from such modeling would therefore not be dependent on which model was used.

Results from simulated data, generated by making judicious changes to the true data, indicated that these models, and their similarity in results to one another, were fairly robust. In particular, it was found that changes in the timing of hospitalizations, the percentage of subjects hospitalized, and the sample size did not appreciably alter the harmony of findings within or across models.

Nonetheless, some observations were of note from the data simulations:

- After the Poisson (which does not depend the timing of events) the marginal model was the most robust with respect to hospitalization event timing.
- The Conditional A model was more sensitive to events occurring later in service than those occurring earlier.
- There was considerable similarity in results between the Conditional A and counting process models, and between the Conditional B and Marginal process models.

- Estimation of demographic effects was relatively stable as the percentage of subjects hospitalized increased.
- The Conditional models showed generally less variation in results, and lower significance levels of demographic effects, than the other models.
- The estimated effects of several demographic factors on hospitalization likelihood were not so reliable when the percentage of subjects hospitalized was low. In such a case, results from several models should be considered, and conclusions must be drawn carefully.

Modeling of recurrent events while accounting for the timing of those events requires extension of traditional survival analysis techniques. The results of this study indicate that any of the five models presented in this paper are adequate choices for the modeling of hospitalization data among new Army enlistees, and perhaps in other settings as well.

David W., Jr. Hosmer, Stanley Lemeshow, Applied survival analysis: Regression modeling of time to event data, 1999, Wiley-Interscience;
Fleming, T. R. and Harrington, D. P. (1991) Counting Processes and survival analysis, New York Willey

Lawless, J. F. and Nadeau, C. (1995), Some simple robust methods for the analysis of recurrent events, Technometrics, 37

Lin, D. Y., Wei, L. J., Yang, I., and Ying, Z. (2000), Semiparametric regression for the mean and rate functions of recurrent events, J. R. Statisc. Soc. B., 62,

Gordon Johnston andYing So, Analysis of data from recurrent events, SUGI 28, SAS Institute Inc. Cary, North Carolina.