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Theory and Methodology

The attrition of volunteers

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Abstract

We apply a flexible hazard-rate model to analyze the attrition rate of volunteers with the Belgian Red Cross. Our modeling framework handles right-censored and left-filtered observations, incorporates covariates, makes an adjustment for unobserved heterogeneity and estimates the baseline hazard non-parametrically. Two of our findings are of serious concern to the Red Cross administrators. First, the expected length of stay becomes smaller for the more recent entrants. Second, the conditional quitting probability does not decrease, but rather increases, with the volunteer's length of service. © 1997 Elsevier Science B.V.

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1. Introduction

Voluntarism is an important backbone of modern society which contributes significantly to the quality of life. Even though this quality improvement is most visible for the service recipients, several benefits for the service providers such as having a good feeling after an altruistic act, the acquisition of skills useful when (re)entering the labor market and the possibility to reduce social isolation have also been identified (Unger, 1991; Frish and Gerrard, 1981). According to a recent estimate in Newsweek, 80 million United States adults average 4.7 hours of volunteer work per week (Newsweek, 1989), while 10 to 20% of Europeans volunteer annually for not-for-profit organizations (Commission of the European Communities, 1986). Many charitable organizations (e.g. hospitals, blood-donation stations, personal-care facilities, crisis-counseling centers, hot lines) rely on this "free" (in terms of wages) labor source to provide their services. An increased dependence on volunteer services may even be expected in the near future since federal policies in the United States and Western Europe have lead to social-spending cutbacks (Morrow-Howell and Mui, 1989).

The act and extent of voluntarism have received growing attention in economics (Brown and Lankford, 1992), sociology (Gillespie and King, 1985), psychology (Frish and Gerrard, 1981; Unger, 1991) and marketing (Schram and Dunsing, 1981). Many studies have considered the incidence of voluntarism, with an emphasis on the demographic and motivational profile of new entrants (see e.g. Cnaan and Goldberg-Glen, 1991; Gillespie and King, 1985;

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Sundeen, 1992). Much less attention has been devoted to a volunteer's length of stay after entry. Yet, the variables that most strongly predict joining a charitable organization may not be the ones that best explain the longevity of participation (Rubin and Thorelli, 1984). Moreover, a high turn-over rate may be costly since replacements have to be recruited and trained, may be harmful to the recipients of the service (e.g. the discontinuation of a Big-Brother relationship) and may even disrupt the normal operation of the organization. If administrators become dissatisfied with the attrition rate of their volunteers, they should be able to assess the relative effectiveness of different strategies to increase the overall retention rate.

The scarcity of empirical research on the factors that affect a volunteer's length of stay may be due to a lack of adequate data, but can also be caused by the difficulties often encountered when modeling duration phenomena. First, unless the organization has kept good records of all starting and quitting dates, researchers must collect data at several points in time to separate "stayers" from "movers" (see e.g. Gidron, 1985), or must conduct retrospective interviews with both currently active and past volunteers (see e.g. Lammers, 1991). In addition, for those volunteers who are still an active member of the organization, the actual length of stay will only be known in the future. This makes the computation and comparison of sample means *impossible* and the application of standard regression procedures *inappropriate* (Heckman and Singer, 1984a, b; Tuma and Hannan, 1984). Our model takes these data characteristics into account, and offers managerially useful insights into the underlying causes and dynamics of an observed aggregate turnover rate.

Lafer (1991) suggests the following strategies to reduce the turnover of volunteers: 1) better selection processes, 2) improved training, and 3) better supervision and support. Some organizations accept every applicant, assuming implicitly that only highly-motivated and qualified people will apply. Such a policy may result in a waste of time and resources if all applicants receive an initial training. Indeed, it may be more economical to develop rigorous screening procedures and to only accept those candidates into training with a low quitting probability. Another method to reduce the drop-out rate is to provide better and/or more frequent training sessions. Training programs are costly, however, and administrators should be able to assess their relative effectiveness. Finally, a high quitting rate may be due to unrealistic expectations when joining the organization, a lack of support and supervision, or a perceived lack of appreciation for the volunteers' efforts. In this respect, useful insights can be derived from the over-time evolution of a volunteer's quitting probability. If this probability increases significantly during the first months after entering into service, a better briefing of the applicants may be called for, since they seem to join the organization with inaccurate expectations. If the quitting probability continues to increase, there is evidence that the long-time volunteers do not (or no longer) experience a satisfactory fit between their task requirements and their capabilities, or that they feel they have already "paid their dues" to the organization or society. As such, a stronger emphasis on the importance of their continued contribution, a better "career planning", and/or a better supervision may be called for.

Even though each of the aforementioned strategies is intuitively appealing, they may not be equally effective in all organizations. For example, if all applicants have the same quitting probability, more intense screening procedures will not affect the overall turnover rate. If heterogeneity exists, the question arises what characteristics best describe the applicants' propensity to quit. (That is, what factors should be considered in the initial screening procedure?) Similarly, some training programs may not have a noticeable impact on the subsequent quitting rate, and an improved briefing may only be necessary when there is a substantial increase in the quitting probability shortly after joining the organization.

In this paper, we present a formal modeling procedure which allows administrators to address these issues, and illustrate the proposed framework using a data set describing the length of stay with the Belgian Red Cross for more than 6,000 volunteers. The remainder of the paper is organized as follows. Section 2 contains a detailed description of the data and our research hypotheses. Section 3 introduces the statistical model, which is applied to the Red Cross data in Section 4. Finally, Section 5 summarizes our main findings and indicates some areas for future research.

2. Data description and hypotheses

2.1. Data description

The sample consists of 6,346 volunteers of the Belgian Red Cross. The Red Cross is by far the largest not-for-profit, charitable organization in Belgium, with a staff to volunteer ratio of less than 10 percent. The volunteers considered in our study are called "Active Volunteers" by the Belgian Red Cross. Their responsibilities are to provide 1) first-aid medical service at large sports or cultural events, 2) an efficient ambulance service, and 3) first aid in case of natural disasters. The head office increasingly gets signals from its local divisions that it becomes more and more difficult both to attract new volunteers *and* to retain them for longer periods of time (Annual Report of the Flemish Division of the Belgian Red Cross, 1992).

The first data collection took place in September 1988. Each volunteer filled out a questionnaire on some demographic characteristics and the month and year of entering the Red Cross. The same questionnaire had to be filled out by everyone joining later on. For those volunteers leaving the organization, the month and year of departure has been systematically recorded. The end of the observation period for our study is January 1993. By that time, 5,267 volunteers had not yet left the service.

2.2. Hypotheses

The covariates considered in our study are:

- cohort,
- gender,
- age when joining as an Active Volunteer,
- education level when joining,
- seniority.

Over the years, the Red Cross has periodically organized training sessions for its Active Volunteers. Unfortunately, no accurate data are available on which volunteers attended these courses. As such, the effectiveness of these programs could not be assessed. However, as will be indicated in Section 3, our modeling approach can easily quantify the relative effectiveness of such training programs when course-attendance data become available in the future. These data are currently collected for the new entrants.

Table 1
Description of covariate levels

Variable	Level	Frequencies ($N = 6346$)
Cohort	< 1983 *	17.5%
	1983–1988	25.7%
	> 1988	56.7%
Gender	Male *	42.5%
	Female	57.5%
Age	≤ 17 *	32.6%
	18–24	32.0%
	25–34	19.2%
	35–44	10.3%
	≥ 45	5.9%
Education	Elementary *	10.8%
	Junior high	40.1%
	High school	36.6%
	College	12.5%
Proportion censored		83.0%

* Defines the base case in the hazard-rate analysis

In what follows, we give a brief motivation for each of the included covariates, and explain how they were coded for our analysis (see also Table 1).

2.2.1. Cohort

Based on the year of entrance, we distinguish three different cohorts and hypothesize an increased quitting rate for the later cohorts. Over time, the volunteer public has experienced a number of changes which may affect their availability and motivation. First, it has been argued that the changing value system in Western societies leads more individuals to look for an immediate gratification of their needs (see e.g. Sorce et al., 1985). As such, they will be inclined to leave when their needs are no longer met through their activities with the organization. Second, the growing number of single-parent and dual-career families causes many traditional volunteers to be more time pressured than ever before (Mergenhagen, 1991). Third, the increasing number of women re-entering the workforce could not only reduce the pool of volunteers, but also have a negative impact on their average length of stay. Strober and Weinberg (1980) found that a reduction of their volunteer activities was one of the strategies used by working women to cope with time pressures.

2.2.2. Gender

Gillespie and King (1985) and Lammers (1991) argue that the turnover among volunteers will increase in proportion to the number whose primary motivation for volunteering is gaining training and skills. In their study on American Red Cross Volunteers, both Gillespie and King (1985) and Sorce et al. (1985) found that women were emphasizing more intrinsic motivations for volunteering, while men were emphasizing more the acquisition of job-related skills. Consequently, one could hypothesize a longer mean duration for women. This difference may become smaller, however, as women increasingly pursue an active career path. We will therefore investigate not only the main effect of gender, but also the presence of an interaction effect between gender and cohort.

2.2.3. Age when joining the Red Cross

Younger volunteers may be more concerned with their employment and career advances than older volunteers. Indeed, middle-aged volunteers may have reached a stage in their career where the skills and job-training opportunities available through volunteering are of little value. This was confirmed in a study by Gillespie and King (1985), who found that respondents aged 38 or older had more altruistic motivations for volunteering than their younger counterparts. Similar results are reported by Frish and Gerrard (1981). As such, we hypothesize a negative relationship between the quitting probability and age when entering. To allow for non-linear effects, we have discretized the underlying continuous variable into four categories (see Table 1).

2.2.4. Education when entering

Following Schram and Dunsing (1981), one could hypothesize that more educated volunteers can better assess beforehand the relative costs and returns of volunteer work. As such, higher-educated people would have more realistic expectations, and therefore a longer expected stay with the organization. On the other hand, since time for volunteering is by definition non-work time, the opportunity cost of volunteering increases with the socio-economic status for which education is a main indicator (Unger, 1991). This would suggest a negative relationship between education and length of stay.

2.2.5. Seniority

To the best of our knowledge, no empirical research has formally addressed the relationship between a volunteer's quitting probability and his/her length of stay with the organization. Consequently, little is known as to whether long-time volunteers are more, less or equally likely to quit in the coming period than more recent entrants. Still, as explained below, previous (indirect) research allows one to postulate the following four patterns:

- the absence of any time dependence,
- a monotonically decreasing (conditional) probability of quitting,
- a monotonically increasing probability,
- a non-monotonic pattern.

Even though volunteer work has many similarities to paid work (e.g. both require certain skills and are performed within a specific organizational context), there are important differences as well. Voluntarism is an act of free will, and also its discontinuation can be done by volition. Factors such as economic security or lack of alternatives may prevent dissatisfied employees from quitting their job, but these factors do not apply to volunteer work (Gidron, 1985). Because of this flexibility to quit volunteering at any time, one could hypothesize that there is *no* relationship between the timing of this decision and the seniority of the volunteer.

One could also argue that the longer a volunteer has been with the organization, the more he/she may become emotionally attached to it and perceive a congruence between his/her own goals and those of the organization (Huselid and Day, 1991). Provided that organizational commitment increases with length of stay, one could postulate a *negative* relationship between quitting probability and seniority.

The findings of Sorce et al. (1985), on the other hand, would rather suggest a *positive* time dependence, i.e. long-time volunteers becoming more and more likely to quit. They find that new Red Cross volunteers have more altruistic motivations than their long-time colleagues. As indicated before, altruistic motivations are often associated with longer expected durations. The findings from Sorce et al. therefore suggest that the expected *additional* duration will become smaller as one has spent more time in a specific volunteer function. This translates into an increasing quitting probability with seniority.

Finally, the nature of the time dependence may also be *non-monotonic*. For example, people may join the organization with an incomplete knowledge of the working conditions, which could result in an initial increase in the quitting probabilities. However, if they "stick around" for some time, they may adjust themselves to the requirements of the job, learn how to react to crisis situations or increase their organizational commitment. As such, their quitting probabilities may eventually start to decline.

3. Model development

To facilitate the exposition, we first introduce an exponential model to describe the duration phenomenon of interest. This model, which will serve as a comparison base and building block for later model extensions, has the following properties: it reflects the absence of any time dependence (because of the memoryless property of the exponential distribution) and assumes a homogeneous population. As such, no observable covariates are included and no correction is made for unobserved heterogeneity. In Section 3.2, this simple model is extended to include (time-varying) explanatory variables, allowing volunteers with different demographic characteristics to have different quitting probabilities. To assess the impact of seniority on the volunteers' quitting propensity, i.e. to explicitly allow for time dependencies, we add time-varying dummy variables to the model in Section 3.3. Finally, even when including several demographic characteristics, there may still be other potentially important factors such as personality traits that have not yet been incorporated. In Section 3.4, we introduce a procedure to account for these omitted factors, which are often referred to as unobserved heterogeneity.

3.1. The base model

Let T denote the random duration of a volunteer with probability density function $f(t)$, cumulative distribution function $F(t)$ and hazard function $h(t)$. For the exponential model, these are given by

$$f(t;\lambda)=\lambda e^{-\lambda t}, \tag{1a}$$

$$F(t;\lambda)=1-e^{-\lambda t}, \tag{1b}$$

$$h(t;\lambda)=\frac{f(t;\lambda)}{1-F(t;\lambda)}=\lambda. \tag{1c}$$

In this case, the hazard (i.e. the conditional probability of quitting) does not depend on the time the volunteer has already been with the organization, reflecting the memoryless property of the exponential distribution. To account for the discrete nature of the data (we know during what months the volunteer joined and left, but do not know the timing of these events within a given month), we defined monthly grouping intervals $[t_{k-1},t_k)$, $k=1, 2, \ldots, m+1$, $t_0=0$ and $t_{m+1}=\infty$, and recorded quitting in duration interval $[t_{k-1}, t_k)$ as t_k.

Parameter estimates are obtained by maximizing the (log) likelihood function. When deriving an individual volunteer's contribution to the likelihood function, it is useful to consider four types of volunteers, which are determined on the basis of two criteria:

- the volunteer either is still with the organization at the end of the observation period or has left,
- the volunteer joined either before or after the first data-collection wave.

3.1.1. Right censoring

Volunteers who are still with the organization at the end of the observation period are called right censored. The presence of such observations makes it impossible to compute a sample mean duration (e.g. to compare the mean duration of men and women), since their true duration will only be known in the future. In our empirical example, 83% of all volunteers had not yet left by January 1993. Ignoring these volunteers would not only cause the omission of most of the data, but would also result in biased parameter estimates in a traditional regression with the duration t_i as dependent variable (Heckman and Singer, 1984a, b). This would also be the case when the observed durations are used as an approximation for the true but unknown durations. As a consequence, traditional modeling procedures could lead to misleading findings in the presence of right-censored data. Our modeling approach, on the other hand, takes all relevant information on right-censored volunteers into account, as explained in Appendix A.

3.1.2. Left-filtered data

As indicated before, the data were first collected in September 1988, and everyone who was a volunteer at that point in time filled out the questionnaire. Consequently, pre-1988 volunteers who quit before 1988 are not included in the data base. The included 1984 volunteers are therefore no longer representative of the group starting in 1984, but only of the 1984 volunteers who stayed at least four years (Schmittlein and Morrison, 1983; Schmittlein and Helsen, 1989). These volunteers are called *left-filtered* and our modelling procedure explicitly corrects for this phenomenon. Specifically, our model takes into account the extra piece of information that for an included 1984 volunteer, no departure could be recorded in his/her first four years of service. Again, we refer to Appendix A for a more detailed technical discussion.

3.1.3. The likelihood function

As shown in Appendix A, the likelihood contribution of any volunteer i can be written by the following unifying expression:

$$L_i(t_{i,1}, t_{i,2}) = \left[\frac{S(t_{i,1}-1) - S(t_{i,1})}{S(t_{i,2})}\right]^{1-d_i} \left[\frac{S(t_{i,1}-1)}{S(t_{i,2})}\right]^{d_i}, \tag{2}$$

where $t_{i,1}$ equals the total number of months with the Red Cross, i.e. until the end of the observation period (for the right-censored observations) or until he/she left (for the completed observations). $t_{i,2}$ is the number of months the volunteer has been with the Red Cross before September 1988 (for the left-filtered volunteers), and is zero for those volunteers who joined after September 1988. $S(t_{i,j}) = 1 - F(t_{i,j})$, $j = 1,2$, is the survival function, and gives the probability that volunteer i stays for at least $t_{i,j}$ periods. Finally, d_i is a censoring dummy which equals zero if the volunteer has left, and one if he/she is still an active member. When substituting the expression for the survival function of the exponential distribution, Eq. (2) becomes

$$L_i(t_{i,1}, t_{i,2}; \lambda) = \left[\frac{e^{-\lambda(t_{i,1}-1)} - e^{-\lambda t_{i,1}}}{e^{-\lambda t_{i,2}}}\right]^{1-d_i} \left[\frac{e^{-\lambda(t_{i,1}-1)}}{e^{-\lambda t_{i,2}}}\right]^{d_i}. \tag{3}$$

The log-likelihood for a set of N volunteers (who are all assumed to have the same mean quitting rate λ) is then equal to

$$\mathrm{LL} = \sum_{i=1}^{N} (1-d_i)\ln\left[\frac{e^{-\lambda(t_{i,1}-1)} - e^{-\lambda t_{i,1}}}{e^{-\lambda t_{i,2}}}\right] - d_i\lambda(t_{i,1}-1) + d_i\lambda t_{i,2}, \tag{4}$$

which is maximized to get an estimate of λ. This exponential model reflects the absence of any time dependence (remember that the hazard is given by the constant λ), implying that long-time volunteers are equally likely to quit as those who have just joined. However, as was indicated before, positive, negative and non-monotonic time dependencies cannot be excluded a priori. To have maximum flexibility, we introduce in Section 3.3 a non-parametric approach to measure the nature of the time dependence. This non-parametric approach will be derived as a straightforward extension of the exponential model discussed in Eqs. (2)–(4).

3.2. Incorporating observable characteristics

In Eq. (4), we assumed that all volunteers have the same quitting rate λ. In this Section, we relax that assumption and allow volunteers with different characteristics to have different quitting probabilities. Following Vanhuele et al. (1995), we write the quitting rate of volunteer i in period τ as

$$\lambda_i(\tau) = \lambda_0 e^{bX_i(\tau)}. \tag{5}$$

$X_i(\tau)$ is a vector of explanatory variables which may be time-varying (e.g. whether the volunteer is in training in a given month) or time-invariant (e.g. gender), and b is a vector of coefficients. λ_0 is the quitting rate of the base group which comprises those volunteers for which all covariates are zero (see Table 1 for a description of our base category). The interpretation of the b-coefficients is straightforward. Positive coefficients imply that an increase in the value of the covariate increases the conditional probability of quitting in the next period (and thus reduces the expected length of stay). Specifically, when the jth covariate changes by one unit, the hazard function changes by $100[\exp(b_j) - 1]$ percent (Jain and Vilcassim, 1991).

To derive the likelihood function, an expression for the survivor function associated with the hazard rate in Eq. (5) is needed. This expression is derived in Appendix B. After appropriate substitutions in Eq. (2), the corresponding log-likelihood contribution is obtained (cf. Eq. (13)).

3.3. Incorporating time dependence non-parametrically

In Eq. (5), time dependence is only incorporated when some of the covariates change over time, i.e. the conditional probability of quitting remains constant unless some of the explanatory variables take on a different value over time. To allow for a hazard rate that can increase/decrease as a function of the amount of time spent with the organization (i.e. the volunteer's seniority), we add a set of time-varying dummy variables $D_i(\tau)$ to the explanatory variables in Eq. (5), which becomes (see also Vanhuele et al., 1995)

$$\lambda_i(\tau) = \lambda_0 e^{bX_i(\tau)} e^{cD_i(\tau)}. \tag{6}$$

A separate dummy variable can be used for each period the volunteer has been with the organization. For example, the time-varying dummy variable associated with period 2 is always zero, except during the second period of service when it takes the value of one, and therefore becomes (0 1 0 ... 0). Similarly, the variable associated with period 3 takes on the values (0 0 1 0 ... 0). No dummy variable is included for the first period, because the estimation of both c_1 and λ_0 would result in identification problems. λ_0 should therefore be interpreted as the quitting rate of the base group in the first period. Positive (negative) c-coefficients for the other intervals indicate a higher (lower) quitting probability as compared to the first period. Specifically, the hazard rate of volunteer i in period 2 is given by $\lambda_i(2) = \lambda_0 \exp[bX_i(2)] \exp[c_2]$, whereby $X_i(2)$ gives the values in period 2 of the included covariates, and $\exp[c_2]$ gives the magnitude of the proportional shift in period 2 relative to period 1, ceteris paribus. If volunteer i has an observed length of stay of t_i months, the integrated hazard $\theta_i(t_i)$ in Eq. (11), which is used to derive the volunteer's survival probability, will be the sum of t_i such terms.

Depending on the pattern of the c_i parameters, one may capture a monotonically increasing, monotonically decreasing or a wide variety of non-monotonic relationships between a volunteer's conditional quitting probability and his/her seniority. Our approach can be interpreted as a piece-wise approximation to an underlying, possibly very complex, continuous time-dependence pattern. Since it does not make any distributional assumptions on the nature of the time dependence, we call this procedure non-parametric. The log-likelihood function associated with this model is still given by Eq. (13), but $B_i(t_i)$ is now given by $\sum_j^{t_i} \exp[bX_i(j) + cD_i(j)]$. It should be emphasized that the only assumption we make is that within certain time intervals, the hazard function remains constant. The main advantage of this non-parametric specification is that it allows a consistent estimation of the model parameters even when the true time dependence is not know. In contrast, an incorrect parametric specification (e.g. the Weibull distribution) would result in inconsistent parameter estimates (Meyer, 1986, 1990). A similar step-function approach to approximate the underlying baseline hazard can be found in Han and Hausman (1990), Meyer (1990), Sharma and Sinha (1991), Trussell and Richards (1985), and Vanhuele et al. (1995).

Because of the variability in the observed durations (ranging from less than one year to more than 40 years), and because of the need to have a sufficient number of events in every period to reliably estimate the associated c-parameter, we do not allow for a change in the hazard rate after every month. Instead, in our empirical application we allow for discrete jumps after every twelve months for the first 10 years, after 15 years, and after 20 years.

3.4. Accounting for unobserved heterogeneity

Some of the factors that influence a volunteer's quitting probability may not be available in the data set at hand (e.g. occupation), or may be difficult to quantify (e.g. personality traits). Not accounting for these omitted factors (which is often referred to as unobserved heterogeneity) may not only cause a spurious negative duration dependence, but may also cause the coefficients of the included covariates to be biased and inconsistent (Lancaster, 1990; Manton et al., 1992). A procedure to correct for unobserved heterogeneity in the mean quitting rates is outlined in Appendix C. The resulting model specification is used in Section 4 to quantify the impact of the covariates mentioned before.

4. Empirical results

In what follows, we first discuss the impact of the observable covariates, after which we assess the nature of the time dependence. All parameter estimates are derived from the model discussed in Section 3.4. and detailed in Appendix C (Eqs. (22) and (23)). This model allows for both observed and unobserved heterogeneity, corrects for the grouped nature of the data, estimates the baseline hazard non-parametrically, and accounts explicitly for the presence of right-censored and left-filtered data. The parameter estimates, along with the t-statistics, are given in Table 2. All estimates should be interpreted relative to the base group consisting of male volunteers who entered before 1983, being less than 18 years old and having an elementary-school education at the time of joining the Red Cross. In terms of the nature of the time dependence, the c-coefficients indicate a proportional shift in the conditional quitting probability relative to the first month of service. A number of interesting findings emerge from our analyses, such as:

- More recent entrants have a shorter expected duration. As such, the overall quitting rate is expected to further increase in the future.
- In terms of the demographic characteristics, male applicants between 35 and 44 are the most appealing segment with a significantly lower quitting probability.
- Long-time volunteers are more likely to quit, suggesting a growing discontent with their volunteer activities.

Table 2
Parameter estimates *

Parameter	Estimate	Parameter	Estimate
Cohort		Seniority	
1983–1988	0.90 (3.11)	c_2 (months 13–24)	0.99 (5.99)
> 1988	1.81 (4.71)	c_3 (months 25–36)	1.61 (9.11)
Female	0.13 (1.97)	c_4 (months 37–48)	1.86 (8.38)
Age		c_5 (months 49–60)	1.73 (6.35)
18–24	−0.03 (−0.37)	c_6 (months 61–72)	2.27 (7.72)
25–34	0.03 (0.33)	c_7 (months 73–84)	2.40 (7.54)
35–44	−0.38 (−2.92)	c_8 (months 85–96)	2.56 (7.01)
≥ 45	−0.19 (−1.29)	c_9 (months 97–108)	2.30 (5.46)
Education		c_{10} (months 109–120)	2.94 (6.36)
Junior high	0.15 (1.27)	c_{11} (years 11–14)	2.78 (5.73)
High school	−0.01 (−0.09)	c_{12} (years 15–19)	2.61 (5.05)
College	−0.09 (−0.63)	c_{13} (years 20–...)	3.20 (5.73)

* The values between parentheses are the asymptotic t-statistics. The estimated parameters of the gamma distribution are: $a = 25034.52$ and $r = 5.52$, giving a ratio $r/a = 0.0002204$. Parameter estimates are derived from the model described in Eqs. (22) and (23).

In the following paragraphs, we discuss these findings in more detail, provide some face validity for the observed patterns, and consider their managerial implications.

1. *Cohort.* Over the last decade, volunteers have become less committed to stay for long periods of time, as reflected in the positive and highly significant coefficients associated with the later cohort dummies. Compared to the base group (< 1983), the second cohort (1983–1988) has a 145.96 (that is, $100(\exp(0.90) - 1)$) percent higher quitting probability, and the most recent entrants (> 1988) have an even higher propensity to quit. Obviously, the proportion of these more recent entrants in the total volunteer base will increase. Consequently, the Red Cross can expect an increase in its overall quitting rate over the coming years. This underscores the growing importance to the Red Cross of fine-tuning its selection and retention procedures.

2. *Gender.* Women have a somewhat (13.77%) higher probability to quit than men. An opposite effect had been postulated, based on the findings of Gillespie and King (1985), that women have more altruistic motivations to volunteer. A potential explanation for our finding lies in the nature of the considered function: Active Volunteers are mostly used to provide first-aid medical service at major

sporting events such as soccer games and cycling races, or at cultural activities such as parades. These types of events may be more attractive to men than to women. No interaction effect was found between gender and cohort: a likelihood-ratio test of the model presented in Table 2 against a more extended model was not significant. As such, the growing participation of women in the labor market may not be the main driver of the observed cohort effects.

3. *Age when entering*. The age category 35–44 has a significantly lower quitting rate than the base group (≤ 17). All else equal, the conditional quitting probability of someone who is 38 when joining is 31.62 percent lower than for someone who is only 16 when joining. This supports our hypothesis that this age category is the most "stable." It should be emphasized that the observed effect for age is not linear. For example, no significant difference is observed between the age categories ≤ 17, 18–24 and 25–34. As such, one cannot simply conclude that young applicants are less committed to prolonged volunteer work.

4. *Education*. The education level when joining does not have a significant impact on the expected length of stay, and should therefore not be used in the initial screening procedure. This lack of impact may be due to the opposite effect of the two factors identified in Section 2, i.e. more educated volunteers may have more realistic expectations but may also have a higher opportunity cost of time.

5. *Seniority*. To investigate the over-time evolution of a volunteer's quitting propensity, we plot in Fig. 1 the base group's hazard rate. The hazard rate of the other categories is proportional to this graph, and can easily be obtained by multiplying the hazard for the base group with $\exp(b_j)$.

A striking feature of Fig. 1 is that the hazard rate does *not* decrease with seniority. On the contrary, someone who has been with the Red Cross for three years is more likely to quit in the coming year than someone with only one year of service. These results are in line with the results from Sorce et al. (1985), who found that long-time Red Cross volunteers have less altruistic motivations than new entrants, and therefore a smaller expected additional duration.

The Red-Cross administrators were concerned, but not totally surprised, by this pattern. According to their head of recruiting, the *initial* increase may be explained by the way in which many volunteers join the organization. The Red Cross organizes on a regular basis first-aid courses for the general public, where one of the sessions in the course is devoted to convincing attendants to become an Active Volunteer. Approximately 25 percent of the attendants sign up. However, many do so on the spur of the moment, perhaps because they feel a lot of organizational commitment with the Red Cross after such an intensive training period, or because they are eager to put their newly-acquired knowledge to good use. However, many drop out pretty soon after experienc-

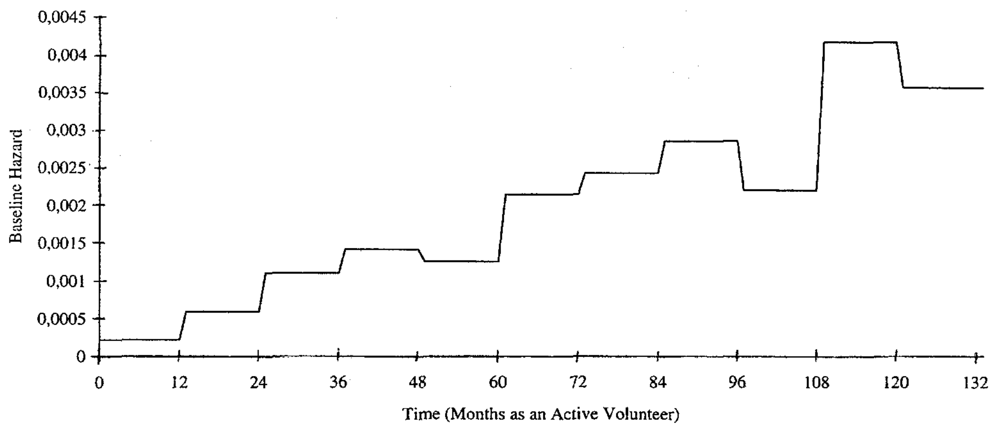

Fig. 1. The impact of seniority on a volunteer's quitting probability.

ing how time consuming and demanding it is to be an Active Volunteer (more than 60 percent of the Red Cross volunteers contribute more than 10 hours per week).

The *continued* increase may be explained in part by the heavy workload imposed by the Red Cross on its Active Volunteers. The Flemish Red Cross has a quasi-monopoly position with respect to the activities performed by its Active Volunteers, i.e. the provision of first-aid medical service at major events. In order to maintain this position, it accepts almost every request for its volunteers, often without a careful assessment of the scheduling difficulties involved. As a consequence, many of the Active Volunteers are called upon fairly often. As mentioned in a recent internal document: "The Red Cross keeps on asking more and more from its volunteers" (Verstraete, 1994). Our results suggest that some of them adopt a drastic strategy to reduce the time pressure imposed by their Red Cross activities: they quit.

5. Conclusion

A flexible method to study the attrition rate of volunteers has been presented which explicitly allows for the presence of right-censored and left-filtered data. The method allows to quantify the impact of both time-varying and time-invariant variables, and uses a non-parametric procedure to link a volunteer's quitting probability to his/her seniority. The latter is especially important since prior knowledge of the form of the underlying relationship is missing, and since a misspecified parametric form would result in inconsistent parameter estimates. We also provided a correction for unobserved heterogeneity. If not accounted for, unobserved heterogeneity would result in a downward bias on the estimated baseline hazard and inconsistent parameter estimates.

We illustrated the method on a large data set consisting of Red Cross volunteers. Two of our results should be of serious concern to the organization's administrators:

- the more recent cohorts have a significantly higher quitting rate. Since the volunteer base will gradually contain more of these recent and less steadfast volunteers, an increase in the aggregate quitting rate can be expected.
- long-time volunteers do not have a smaller quitting probability than more recent entrants. On the contrary, the quitting probability increases with their seniority.

To reverse the latter pattern, the Red Cross may first of all have to adjust its recruitment policies and provide a better briefing to potential applicants. Second, the workload may have to be adjusted in order to reduce the quitting probability of its more experienced volunteers. This may require a re-orientation of its overall strategy of accepting every request by other organizations to have Red-Cross volunteers present at their event (Verstraete, 1994). In case the Belgian Red Cross is reluctant to do so, procedures to increase the number of well-informed applicants as well as procedures to reduce the quitting propensity of its long-time volunteers will have to be developed, and further research is needed on the relative effectiveness of some of these strategies.

Several areas for future research remain wide open in this respect. First, the covariates used in our illustration were easy-to-collect demographic characteristics. However, previous research (Gidron, 1985; Lafer, 1991; Lammers, 1991; Sundeen, 1992) has emphasized the importance of other factors such as training and attitude towards volunteering. The Belgian Red Cross plans to centrally administer course attendance for its future cohorts, and will use our modeling approach to assess the effectiveness of these courses. Similarly, if applicants are asked to fill out a simple questionnaire to assess their attitude towards voluntarism, it will become possible to empirically test the importance of this factor on their average length of stay.

A first area for future research is therefore an empirical validation of the different factors that have been put forward as potentially important moderators of a volunteer's stay with the organization. Second, for those variables which were included in our study, further research is needed to determine whether the observed effects are organization/task specific, or whether they carry over to other functions and organizations.

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Appendix A. The contributions to the likelihood function

One can distinguish four basic types of volunteers depending on the arrival date (before or after September 1988) and departure date (before or after January 1993). For each type of volunteer, two durations can be computed: the observed number of months with the Red Cross (t_1), and the number of months before September 1988 (t_2). For those joining after September 1988, t_2 is set to zero. This is illustrated in Fig. 2.

An example of a completed, not left-filtered duration is the length of stay of volunteer A. His/her contribution to the likelihood function is given by $f(t_{A,1})$. When making an adjustment for the discrete nature of the data-gathering process, one replaces this density function by $S(t_{A,1}-1)-S(t_{A,1})$, where the survival function $S(t_{A,1})=1-F(t_{A,1})$ denotes the probability that the volunteer stays for at least $t_{A,1}$ time intervals. This adjustment is needed since not accounting for the discrete nature of the data has been shown to result in inconsistent parameter estimates, with increasing asymptotic bias as the grouping becomes more coarse (Kiefer, 1988; Sharma and Sinha, 1991).

For volunteer B with a total, completed duration of $t_{B,1}$ who joined $t_{B,2}$ months before September 1988, one should take into account that we could only observe B because this volunteer had not yet left in September 1988. As such, B's contribution to the likelihood function is the probability of observing a total duration of $t_{B,1}$ time periods, *given* a duration of at least $t_{B,2}$ time periods. Mathematically, the contribution becomes (Schmittlein and Morrison, 1983; Schmittlein and Helsen, 1989):

$$\frac{S(t_{B,1}-1)-S(t_{B,1})}{S(t_{B,2})}. \tag{7}$$

Volunteer C joined after September 1988 and is still an active member in January 1993. If the end of the observation period falls $t_{C,1}$ periods after his/her starting date, the contribution to the likelihood function of this volunteer is given by $S(t_{C,1}-1)$. Note that we assume the censoring to occur at the beginning of the time interval $[t_{C,1}-1, t_{C,1})$. Clearly,

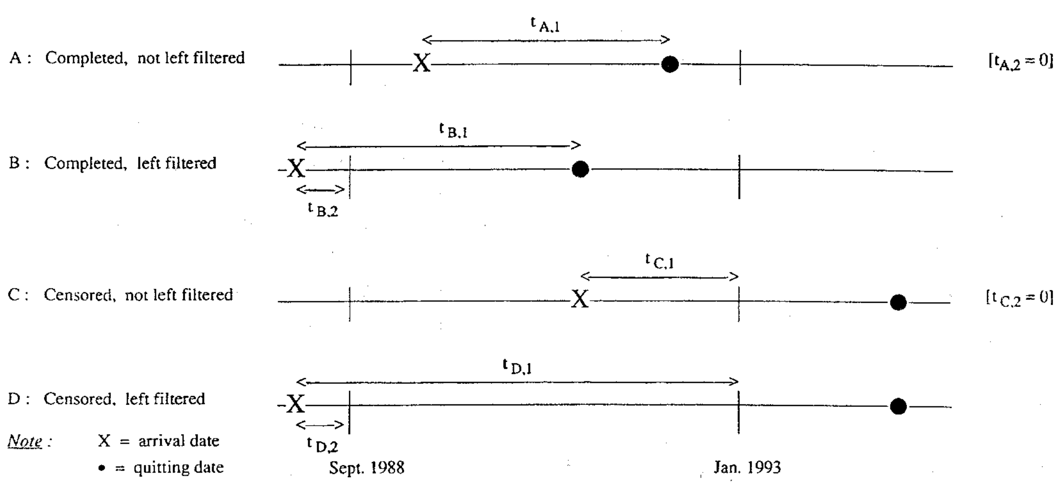

Fig. 2. Different types of volunteers.

some such assumption is needed given the discrete nature of the data. Specifically, someone who joined in December 1992 and was still a member in January 1993, is recorded with a duration of 2 months (even when the duration in days is 45 days), and the contribution to the likelihood function is given by $S(1)$. This reflects the information we have on this volunteer: he/she stayed for more than one month, while we do not know whether he/she will stay for more than two months.

Finally, volunteer D joined $t_{D,2}$ periods before September 1988 and is still an Active Volunteer after a total service of $t_{D,1}$ periods. D's likelihood contribution is

$$\frac{S(t_{D,1}-1)}{S(t_{D,2})}. \tag{8}$$

Given that $S(0)=1$, the different expressions can be combined, and the likelihood contribution of any volunteer i can be written as follows:

$$L_i(t_{i,1},t_{i,2}) = \left(\frac{S(t_{i,1}-1)-S(t_{i,1})}{S(t_{i,2})}\right)^{1-d_i}\left(\frac{S(t_{i,1}-1)}{S(t_{i,2})}\right)^{d_i}, \tag{9}$$

where d_i is a censoring dummy which equals zero if the volunteer has left before January 1993, and one if still an active member.

Appendix B. The likelihood contribution when allowing for covariates

A general relationship between a hazard function $\lambda_i(\cdot)$ and its associated survival function $S_i(\cdot)$ is (Gupta, 1991; Lancaster, 1990):

$$S_i(t_i) = e^{-\theta_i(t_i)}, \tag{10}$$

where $\theta_i(t_i)=\int_0^{t_i}\lambda_i(u)\mathrm{d}u$ is called the integrated hazard. If $\lambda_i(u)$ is given by Eq. (4), and if we assume that the covariates remain constant *within* each period but can change from period to period, Eq. (10) can be rewritten as

$$\begin{aligned}\theta_i(t_i) &= \int_0^1\lambda_i(1)\mathrm{d}u + \int_1^2\lambda_i(2)\mathrm{d}u + \cdots + \int_{t_i-1}^{t_i}\lambda_i(t_i)\mathrm{d}u\\ &= \lambda_i(1)+\lambda_i(2)+\cdots+\lambda_i(t_i)\\ &= \lambda_0 e^{bX_i(1)} + \lambda_0 e^{bX_i(2)} + \cdots + \lambda_0 e^{bX_i(t_i)}\\ &= \lambda_0 B_i(t_i),\end{aligned} \tag{11}$$

where $B_i(t_i)=\Sigma_{j=1}^{t_i} e^{bX_i(j)}$. Obviously, when all covariates are time-invariant (i.e. $X_i(j)=X_i$), $B_i(t_i)$ reduces to

$$B_i(t_i) = t_i e^{bX_i}. \tag{12}$$

After substituting Eq. (11) into Eq. (10) and Eq. (4), the log-likelihood contribution of volunteer i becomes:

$$\begin{aligned}&\mathrm{LL}(t_{i,1},t_{i,2};\lambda_0)\\ &\quad = (1-d_i)\ln\{e^{-\lambda_0 B_i(t_{i,1}-1)} - e^{-\lambda_0 B_i(t_{i,1})}\}\\ &\qquad - d_i\lambda_0 B_i(t_{i,1}-1) + \lambda_0 B_i(t_{i,2}).\end{aligned} \tag{13}$$

Appendix C. The log-likelihood function after correcting for unobserved heterogeneity

We account for unobserved heterogeneity in the mean quitting rate by allowing λ_0 to vary across the population according to a certain distribution. Thus, instead of assuming that every volunteer in the base group has the same quitting rate in period 1, we allow this value to vary. The likelihood contributions derived above (see e.g. Eq. (13)) are conditional in the sense that they depend on a specific value of λ_0. If this value is not the same for all volunteers, the unconditional likelihood contribution of the ith volunteer, which is the relevant one for data analysis under unobserved heterogeneity, is obtained by weighing the conditional likelihood by the relative occurrence of the respective λ_0-values:

$$L_i(t_{i,1},t_{i,2}) = \int_0^\infty L_i(t_{i,1},t_{i,2};\lambda_0)\, g(\lambda_0)\mathrm{d}\lambda_0, \tag{14}$$

where $g(\cdot)$ is called the (unobservable) mixing distribution. An often used mixing distribution is the gamma distribution (e.g. Han and Hausman, 1990;

Meyer, 1990; Schmittlein and Morrison, 1983; Vanhuele et al., 1995). Besides being quite flexible, it results in a closed form of the log-likelihood function. A limitation of the gamma distribution, though, is that it cannot take multi-modal forms (where e.g. one fraction of the population has a small λ_0-value and another fraction a large λ_0-value). Such a scenario could be captured by modeling the unobserved heterogeneity nonparametrically as in Jain and Vilcassim (1991) and Vilcassim and Jain (1991). This approach was justified by the findings of Flinn and Heckman (1982) and Heckman and Singer (1982, 1984a) that for a given parametric form of the baseline hazard, the results tend to be very sensitive to the form of the mixing distribution. However, recent research indicates that the specification of the unobserved heterogeneity component is not as crucial as a flexible specification of the baseline hazard (e.g. Han and Hausman, 1990; Manton et al., 1986; Ridder, 1986; Trussell and Richards, 1985). Based on these findings, we model the baseline hazard non-parametrically, and the unobserved heterogeneity component through a flexible parametric mixing distribution.

The conditional likelihood of volunteer i when both covariates and time-varying dummy variables are included is given by

$$L_i(t_{i,1}, t_{i,2}; \lambda_0) = \left(e^{-\lambda_0 B_i(t_{i,1}-1)} - e^{-\lambda_0 B_i(t_{i,1})}\right)^{1-d_i} \times \left(e^{-\lambda_0 B_i(t_{i,1}-1)}\right)^{d_i}\left(e^{-\lambda_0 B_i(t_{i,2})}\right)^{-1}, \tag{15}$$

in which $B_i(t_i)$ is defined as

$$B_i(t_i) = \sum_{j=1}^{t_i} e^{bX_i(j)+cD_i(j)}. \tag{16}$$

Noting that

$$B_i(t_{i,1}) = B_i(t_{i,1}-1) + e^{bX_i(t_{i,1})+cD_i(t_{i,1})}, \tag{17}$$

this conditional likelihood can also be written as

$$L_i(t_{i,1}, t_{i,2}; \lambda_0) = e^{-\lambda_0 B_i(t_{i,1}-1)}\left(1 - e^{-\lambda_0 e^{bX_i(t_{i,1})+cD_i(t_{i,1})}}\right)^{1-d_i} \times e^{+\lambda_0 B_i(t_{i,2})}. \tag{18}$$

The unconditional likelihood then becomes

$$L_i(t_{i,1}, t_{i,2}) = \int_0^\infty e^{-\lambda_0[B_i(t_{i,1}-1)-B_i(t_{i,2})]} \times \left(1 - e^{-\lambda_0 e^{bX_i(t_{i,1})+cD_i(t_{i,1})}}\right)^{1-d_i} g(\lambda_0)\,d\lambda_0. \tag{19}$$

Since

$$\left(1 - e^{-\lambda_0 e^{bX_i(t_{i,1})+cD_i(t_{i,1})}}\right)^{1-d_i} = (1+d_i) - \left(e^{-\lambda_0 e^{bX_i(t_{i,1})+cD_i(t_{i,1})}}\right)^{1-d_i}, \tag{20}$$

Eq. (19) can be written as

$$\int_0^\infty e^{-\lambda_0[B_i(t_{i,1}-1)-B_i(t_{i,2})]}(1+d_i)\,g(\lambda_0)\,d\lambda_0 - \int_0^\infty e^{-\lambda_0[B_i(t_{i,1}-1)-B_i(t_{i,2})]}\left(e^{-\lambda_0 e^{bX_i(t_{i,1})+cD_i(t_{i,1})}}\right)^{1-d_i} \times g(\lambda_0)\,d\lambda_0. \tag{21}$$

When the gamma distribution is used as $g(\lambda_0)$, the first part of Eq. (21) can be shown to equal

$$\begin{aligned} &= \int_0^\infty e^{-\lambda_0[B_i(t_{i,1}-1)-B_i(t_{i,2})]}(1+d_i)\frac{a^r}{\Gamma(r)} \times e^{-a\lambda_0}\lambda_0^{r-1}\,d\lambda_0 \\ &= (1+d_i)\frac{a^r}{\Gamma(r)}\int_0^\infty e^{-\lambda_0[B_i(t_{i,1}-1)-B_i(t_{i,2})+a]}\lambda_0^{r-1} \times \frac{(B_i(t_{i,1}-1)-B_i(t_{i,2})+a)^r}{(B_i(t_{i,1}-1)-B_i(t_{i,2})+a)^r}\,d\lambda_0 \\ &= (1+d_i)\frac{a^r\Gamma(r)}{\Gamma(r)(B_i(t_{i,1}-1)-B_i(t_{i,2})+a)^r}. \end{aligned} \tag{22}$$

Similarly, the second part of Eq. (21) becomes

$$\frac{a^r}{\left(B_i(t_{i,1}-1)-B_i(t_{i,2})+(1-d_i)e^{bX_i(t_{i,1})+cD_i(t_{i,1})}+a\right)^r}. \tag{23}$$

The log-likelihood function for our final and most general model is obtained after combining Eq. (22) and Eq. (23). The mean of the gamma distribution (r/a) then provides an estimate of the base group's quitting probability in the first period, and all coefficients are subsequently interpreted relative to that mean. It should be emphasized that even though, in our empirical application, we will only allow for a discrete jump after 12 months, r/a will still be the quitting rate for the first *month*. This same quitting rate then applies to months 2, 3, ..., 12.

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