EMERGENCY CARE USAGE AND LONGEVITY HAVE OPPOSITE EFFECTS ON HEALTH INSURANCE RATES

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Abstract

Purpose: To study the price of health insurance for individuals aged 65 years and over.
Methodology: A sample of private health policyholders in Spain is analysed. Joint models are estimated for men and women, separately. A log-linear model of the transformed cumulated number of claims associated with emergency room occupation, ambulance use and hospitalization is estimated, together with a proportional hazard survival model.
Findings: The association between the longitudinal process of severe medical care and the survival time process is positive and highly significant for both men and women. An increase in the price of health insurance due to the effect of a larger number of emergency care demand events is slightly offset by the decrease in expected longevity.
Practical implications: The effect of an increase in the number of claims is small compared to the reduction in survival, so age still plays a central role in rate making.
Originality: The proposed methodology allows dynamic rates to be designed, so that the price of health insurance can change as new usage information becomes available.
Keywords: Survival analysis, longitudinal data, log-linear models, pricing, risk.

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1. Introduction

The developed world has experienced a significant growth in its population aged 65 and over, which not only means that people are living longer but that they tend to face a greater number of years with a range of health problems. This demographic evolution has, in turn, led to a growth in demand for medical care and long-term care services, which extends longevity even further (see Dao et al., 2014).

Survival is quite clearly related to age, but it is also dependent on health conditions, habits, and cohort effects, as well as on subject-specific characteristics, such as early age migration (Solé-Auró et al., 2012) and environmental factors (Wu et al., 2015). Yet, when survival is threatened by disease or chronic pathology, medical care increases. As such, survival and medical care are in constant association, in what is an endogenous causal relationship.

The health insurance offered by insurance companies is greatly challenged by insured policyholders who reach an age when their annual number of emergency care demand events increases substantially. Here, we argue that companies can offset the risk of insuring such individuals (i.e., those insureds that make more claims, in particular, for such services as emergency room visits, ambulance use and hospitalization) with the simultaneous decrease in their survival probabilities, a relationship that has been previously reported by Bird et al. (2002). The effect, however, has yet to be examined because studies have traditionally only considered past events rather than the simultaneous analysis of claim counts and survival. For example, D'Amico et al. (2009) analysed a portfolio of insureds that were covered for disability and found that survival could not be separated from impairment conditions. Indeed, standard actuarial methods of health insurance (Ericson and Starc, 2015; Pitacco, 2014) ignore the longitudinal information about their policyholders that is being constantly gathered. And while count data models were analysed by Boucher and Guillen (2009), these authors did not analyse a time-to-event process.

Health insurance ratemaking is always based on the analysis of the historical records of the insurance company. The expected number of claims and the average cost per claim are the basis for calculating the expected cost of health care services for new customers. Risk factors such as age or general individual lifestyle indicators (for instance, smoking, exercising, dietary habits, …) can be used to produce personalized premiums. Gender can serve in the process of assessing risk but, in places like Europe, men and women must pay the same premium if all other characteristics are the same. The ban of gender as a risk factor is due to the existence of a directive aiming at preserving non-discrimination in services (Guillen, 2012).

Traditionally, insurers assume that all insureds are alive for the duration of the contract, which usually one year, except for multi-year products. Therefore no correction is introduced due to the fact that some insured could eventually die before the end of the contract. This is precisely the novelty of our analysis, because we introduce a model that considers both frequency of usage and survival. We argue that in portfolios of elderly individuals, the two effects can be contrary. Technical features of health insurance are discussed in Black and Skipper (2000). The impact of various risk factors (gender in particular) is addressed by a report from the Groupe Consultatif Actuariel Européen (2011) and by Riedel (2006).

The aim of this paper is to examine the use of joint models for predicting survival probabilities based on observed demand for emergency/hospital care. Here, we apply the model to individuals aged 65 and above, and we analyse emergency room treatment and hospitalization in a sample of private insurance policyholders. We conduct our analysis separately for men and women and we examine how rates are affected by the observation of claims and their corresponding survival probabilities.

2. Literature review

Health insurance refers to a type of coverage that is usually classified as non-life insurance. The reason is that this product does not consider survival explicitly and it mainly deals with claims aimed to receive a medical assistance whenever needed. Medical support can be provided in form of a service or as reimbursement of health care costs. Moreover, this product has different names around the world. For instance, the term "medical expense insurance" is used in the United States (see, for instance, Browne and Doerpinghaus, 1993), whereas the product is called "private medical insurance" in the United Kingdom (see, Foubister et al., 2006).

In addition to the references cited in the previous section, a textbook by Benjamin and Pollard (1993) provides a classical general introduction to concepts and statistical tools in the field of life and health insurance. Medical expense insurance and related actuarial aspects can be found in the paper by Orros and Webber (1988), where the authors overview the methods underlying the calculation of health insurance premiums and reserves.

There are many references related to sickness insurance, where the insured receives an economic compensation during his/her illness, but this is an extension of health insurance that we do not consider in our analysis. In sickness insurance, the duration of the process is crucial, because it impacts the overall cost of the claim (see more details in Pitacco, 2014). A contribution by Vercruysse et al. (2013) introduces an indexation mechanism in lifelong sickness insurance products, which aims at sharing the costs between insurer and policyholders. We emphasize this specific paper because it needs to consider the survival of policy holders because the coverage is for life.

Generalizations to the classical health insurance mechanisms include the contribution by Pitacco (1992), who introduces the a posteriori risk classification in ratemaking. Then, individual past experience on claims has an influence on the price paid by a policy holder. For instance, someone who has not claimed is likely to pay less at policy renewal, whereas insureds that claimed more than the expected frequency, are usually penalized and they pay more at renewal.

A case study on group health insurance has recently been presented by Hammad and Harby (2016). They discuss health insurance design for a group of individuals, they also show that ratemaking becomes more sophisticated for groups than for individuals due to the fact that, in the former case, methods need to accommodate to multilevel data, i.e. they need to adapt to information on the individual together with data on the group.

The cost of individual health insurance, if payed on a yearly basis, increases with age. This fact makes premiums unaffordable for many people after retirement. A satisfactory solution to this problem has not been found yet. Lifelong contracts are expensive because insurers need to establish reserves due to the uncertainty of duration. Level premiums, meaning that the price is flat and does not increase with age, require pre-funding, as so the price also expensive. Age patterns of individual health-related costs are analyzed in Yamamoto (2013) and an extensive review of possible health Insurance schemes is presented in Pitacco (2014).

3. A simple calculation of the price of health insurance

In health insurance, the price of a one-year insurance contract is equal to the product of the expected number of claims, the average cost of the event and the probability that the policyholder survives to the end of the period (see, for instance, Pitacco, 2014). Survival probabilities are usually overlooked as they are close to one. However, for people aged 65 years and over, the one-year survival probability diminishes gradually. Indeed, the survival probability for 65-year-old men and women is higher than 99%, while it is around 80% for those aged 95 (INE, 2016).

To ensure that the price of health insurance is stable for elderly policyholders, the increase in the expected number of claims needs to be compensated for by the decrease in survival probability. Otherwise, a fair premium would increase with age. If the impact on the total estimated cost of care attributable to the increase in the expected number of events is greater than the cost reduction attributable to the decrease in survival probability, then the price of insurance would rise. Using joint modeling techniques we can establish a relationship between these two effects. Thus, it can be concluded that the predicted premium is a function of the expected number of severe claims given the policyholder's age and sex and taking into consideration also the probability of survival at that age.

Additionally, the premium should account for the impact of the predicted number of claims on the one-year predicted survival probability. Once the size of the joint effects has been estimated, recommendations can be given.

4. Data and methods

We analyse a dataset provided by a Spanish health insurance company, which covers customers aged 65 and over. The data contain historical information on claims reported between 1 January 2006 and 1 February 2014 by 39,137 policyholders (aged 65+). The data also contain information about their survival. Only non-routine care was considered and, so, usage counts measure specifically episodes of hospitalization, emergency service visits and the use of ambulance services.

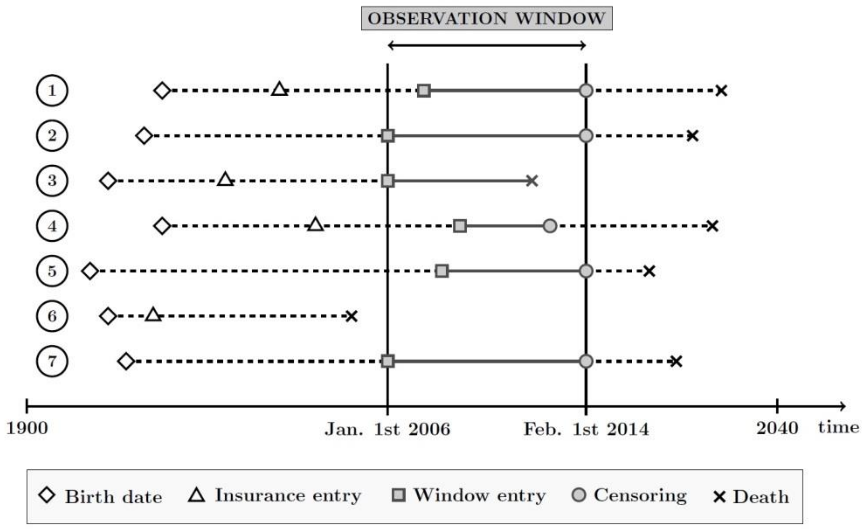

Figure 1. Data collection process for health insurance data, illustrating seven specific cases in the observation window.

Figure 1 presents the follow-up design employed, starting in 2006 and ending in 2014. Subjects are observed from age 65 onwards until they reach the end of the study (indicated with a circle) or until they either die (indicated with a cross) or leave the insurance company (also indicated with a circle). If they die, the exact event date is recorded. On 31 December each year, a measuring point records the number of times that the policyholder demanded a non-routine medical service during that year. For those subjects covered from 2006 to 2014, there are eight measuring points; however, for those that die or leave the company during this period, the number of measuring points is lower. Likewise, subjects who turned 65 after the beginning of the study are only monitored from that point onwards. Profile 5 in Figure 1 corresponds to a policyholder who was covered only from the age of 82, given that he did not take out a contract until that age. Profile 6 shows that policyholders who died before 2006 are not included in the study.

Table 1 presents the number of times the observed subjects requested services, i.e., specific types of medical care. Here, we consider the sum of the number of occasions that the subjects were admitted to hospital, plus the number of times they requested emergency room services plus the number of times they required an ambulance. Note that whenever a subject required all three services simultaneously, they are considered as separate requests, and so they count as three.

<< Table 1>>

It is clear that subjects insured for the longest periods of time and, hence, observed at more measuring points, account for a larger number of all three service requests than those observed on fewer occasions. Both the mean and standard deviation of the number of services per year are presented by gender and number of measuring points. The annual number of care usage units (also called claims) serves as the basis for the definition of the longitudinal process that is modelled together with the time-to-death. The means of the variables considered in Table 1 for those subjects observed over all eight years are smaller than those for subjects observed on fewer occasions. This is not surprising because the former correspond to the group of survivors that we expect to present good health.

As a main longitudinal outcome, we define $y_i(t) = \log(1 + c_i(t))$, where $c_i(t)$ is the number of claims in the previous 12 months for the i-th subject, $i = 1, \ldots, n$, at time point t. We only observe the number of emergency claims during the previous twelve months at a limited number of measuring points. A logarithmic scale was applied to allow for a log-linear specification.

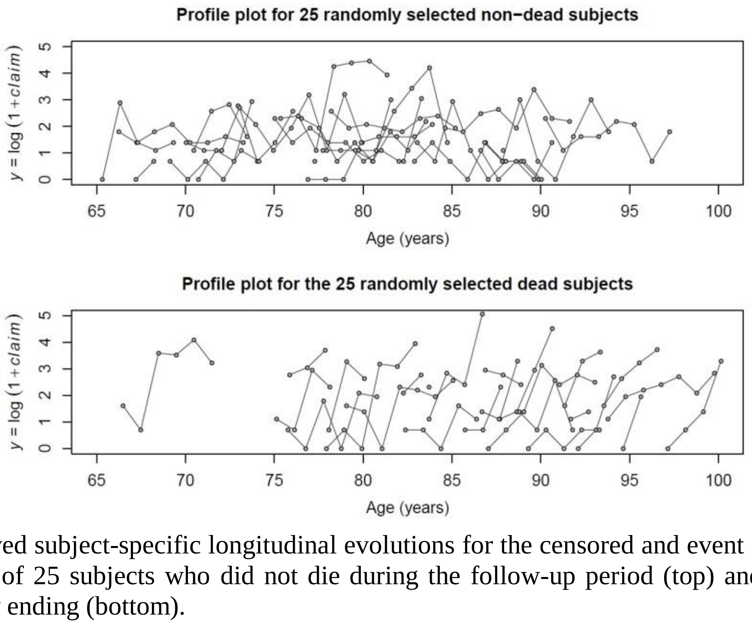

Figure 2. Observed subject-specific longitudinal evolutions for the censored and event groups. Randomly selected profiles of 25 subjects who did not die during the follow-up period (top) and 25 subjects who died before study ending (bottom).

The top panel in Figure 2 presents a gender-balanced, random sample of 25 subjects who were censored, while the bottom panel depicts 25 similarly selected subjects who died before the observation process was concluded. As expected, the latter typically correspond to older subjects, and so their requests for health care were also made at more advanced ages. Subjects who died during the study window generally present upward profiling trends, which is indicative of their worsened health status over the course of time. In contrast, censored profiles present more oscillating trends over a longer timescale. Consequently, the two panels show that higher usage levels tend to be associated with a shorter time to death-event.

When conducting longitudinal studies with health indicators, the current value of a given biomarker is not as relevant as its cumulative effects, although greater weight should be attached to measurements from the most recent past. In our analysis, the association between these cumulative effects and the risk of death is addressed in a single analysis employing a shared random effects structure with a bivariate Gaussian distribution. This means that dependence between the two components is assumed via an underlying latent process. In other words, two responses are conditionally independent given the associated random effect and the observed covariates. Joint models have been extensively used in this context (Andrinopoulou, et al, 2008) and also when modeling survival with cancer (Serrat et al., 2015).

We want to characterize time-varying effects by considering the so-called true and unknown demand process, $m_i(t)$, where $y_i(t) = m_i(t) + \varepsilon_i(t)$. The instantaneous measure $m_i(t)$ is not affected by measurement error. We specify a linear mixed effects model for $m_i(t)$, including a linear trend, which serves as the basis for defining the real and complete longitudinal history up to t (see Verbeke and Molenberghs, 2009). We denote by $F(m_i(t))$ a transformation of the instantaneous measure. In the basic joint model approach, it is assumed that $m_i(t)$ is not transformed when included in the survival model. However, we allow for this generalization so that we may take into account the fact that recent health care usage records are more relevant than past records. An exponential decay is assumed here, as in Piulachs et al. (2016) where several possibilities were tested.

Let T_i be the observed event time and the corresponding event indicator δ_i, which is equal to 1 if the death is registered within the study period and 0 otherwise. A standard proportional hazards model is assumed, which includes $F(m_i(t))$, so that time-varying effects exist.

The joint model is specified both as a longitudinal log-linear model and as a survival process simultaneously, where α is the parameter that captures the effect of the longitudinal component via the transformation of the instantaneous measure on the survival sub-model. Therefore, the joint model is defined as two submodels.

First, the longitudinal model:

$$y_i(t) = \beta_o + b_{i0} + (\beta_1 + b_{i1}) + \varepsilon_i(t) \qquad (1)$$

where vectors (β_o, β_1) and (b_{io}, b_{i1}) *i=1,...,n* are the components of the mixed effects in the longitudinal sub-model. The Gaussian assumption is considered for the error term and the individual random effects, which are assumed to have zero-mean and covariance matrix *D*, whereas the error term follows a Gaussian process with mean zero and variance σ^2. The per-observation noise terms are assumed to be not only mutually independent, but also independent with respect to the random effects.

Second, the survival component (Cox, 1972):

$$h_i(t \mid w_i, m_i(s), s \le t) = h_0(t)\exp\{\gamma^T w_i + \alpha F(m_i(t))\}, \qquad (2)$$

which includes a semi-parametric hazard regression model that embeds both the effect of a baseline covariate vector and subject-specific information (see also Kalbfleisch and Prentice, 2002). In our model, the only covariate is Age0, which is the age of entry in the study.

For the baseline hazard $h_0(t)$, a third degree B-spline approximation to the baseline risk function was implemented allowing nonlinear time-evolution (for more details, see Piulachs et al., 2016). The maximum likelihood estimation (Hsieh et al., 2006) was obtained with R software (see Rizopoulos, 2010, 2011 and 2012).

5. Results

The results for the joint model estimation in the insurance dataset are presented separately for men and women in Table 2. The association parameter α is positive and significantly different from zero for both genders, indicating that the larger the cumulative number of emergency services and hospitalizations the greater the risk of death. This result is consistent with expectations as an aggravated patient has a higher probability of death.

Our findings differ from those presented in Piulachs et al. (2015) for two reasons: (i) we only consider demand for certain specific types of medical care, which we believe to be more closely associated with emergency or severe conditions; and, (ii) we include a censoring mechanism because, clearly, some subjects are still alive at the end of the study period. A joint model for men and women, including a parameter for sex, is employed in Piulachs et al. (2016); however, the significance of this parameter suggests that a separate analysis is needed.

We note that the association between the longitudinal process and the survival outcome is slightly higher for men (1.4819) than it is for women (1.3624), but the difference is not statistically significant. These results point to an association between emergency care use and hospitalization, on the one hand, and survival, on the other, so that when a subject presents a greater demand for this type of care their probability of survival falls. The fact that we model the hazard rate explains why the sign is positive, indicating that death is more likely to occur.

The effect of age on survival can also be determined since the parameter for variable age0 is positive and significantly different from zero, but this is a well-known fact, as analysed by Vidiella-i-Anguera and Guillen (2005) among many others.

<< Table 2>>

The positive and significant coefficient for the age-at-entry covariate indicates that the older the subject was at the beginning of the study, the lower their probability of survival. In the log-linear model of the longitudinal process for claims, we find the expected result. A positive and significant population trend β_1 is found and, moreover, it is largely similar for men and women, albeit slightly lower for male insureds, while the mean intercept β_0 is higher for their female counterparts. This finding is also expected because women make a higher average number of medical claims. Note that the effect of each subject's age is included in the individual effects, which are not reported in Table 2.

<< Table 3>>

The results in Table 3 present the predicted survival probabilities at age 73 for an insured man and woman aged 65 at study entry. They both make a number of claims equal to 3, 1, 5 and 15 in the first four years. If we examine the case of the male insured, it can be seen that when at the age of 65 he claims for three emergency care events, he has an estimated probability of surviving to the age of 73 equal to 96.95%; however, when he turns 66 and he makes only one claim, the probability of his surviving to 73 increases to 97.07%. In contrast, if a man makes 15 claims at the age of 68, his probability of surviving to 73 falls to 94.63%, given the association between poor health and risk of death.

The example in Table 3 shows that when the number of claims rises from 5 to 15, between the ages of 67 and 68, there is a fall in the probability of survival of 0.0173 (0.9636-0.9463) for men and of 0.036 for women (0.9651-0.9515). A simple extrapolation from Table 3 implies that an increase in the number of claims leads to a reduction in the probability of survival of roughly 0.18% per claim in the case of men and of about 0.15% in the case of women. This result is obtained by dividing the reduction in survival probability by the initial survival estimate 0.0173/0.9636=1.80% and dividing by the difference in claims 10 (15-5).

Similar scenarios have been analysed for insureds aged 80 and 95 (the specific results for the latter being reported in Table 4). Here, the reduction in the probability of survival is about 0.99% per claim for men and 0.93% for women at the age of 80, compared to 3.61% per claim for men and 4.03% per claim for women at the age of 95.

<< Table 4>>

The analysis of the interplay between claims and survival reveals an association between the two, to the effect that an increase in the number of claims leads to a reduction in the probability of survival. However, this decrease in survival is small.

Let us consider that the cost of a claim equals C. In order to analyse the effect of this on the price of the premium, we would have the following result. Assume that for a given insured the expected number of claims is equal to E and the survival probability is p, then the pure premium price (note, we do not consider general additional expenses here) would be equal to $C \times E \times p$. When the number of expected claims increases by one, then we need to consider $(E+1)$, but the probability of survival at a later age decreases by r, so we have to substitute p by $(1-r)p$, so that the pure premium is $C \times (E+1) \times p(1-r)$. Thus, we obtain that the new premium is $C \times (E+1) \times p(1-r) = C \times E \times p - rC \times E \times p + C \times p(1-r)$. So, the premium would be equivalent to the initial premium if

$$C \times p(1-r) = r\, C \times E \times p.$$

Thus, the reduction in the probability of survival which compensates the cost of additional claims is exact if and only if

$$E = \frac{1-r}{r}.$$

This equality would imply perfect diversification of the two processes. For values of r ranging from 2.5% to 20% we have calculated the corresponding expected number of claims that would imply equilibrium in the premium. The results are presented in Table 5.

<< Table 5>>

6. Conclusions

We conclude that the reduction in survival should be much greater than that observed in our data in order to compensate for the increase in the demand for emergency care. This could be the case for very old age groups, but it does not seem to be feasible for adults around the age of 70.

Here, it should be noted that we do not consider dependence between the number of events and severity in terms of cost (Sarabia and Guillen, 2008). Further, a limitation of our study is that we only consider severe medical care events (namely, ambulance and emergency room use and hospitalization), while other medical treatments are not analysed and, as such, do not form part of the insurance policy under evaluation.

We have shown that the increase of frequency claim, even if we just consider severe assistance, is much larger than the reduction in survival, so the inclusion of a survival correction for elderly policyholders in the premium calculation, which would reduce insurance price, is not sufficient to force a substantial price decrease. The conclusion for practitioners is therefore that health insurance for the older group remains a matter of pooling the risk with younger customers or of increasing the price of the policy with age. However, we argue that joint modelling of frequency and survival is a method that must be considered when developing dynamic pricing techniques, which are aimed at policy durations shorter than one year. In that case, knowledge of the claiming experience should be combined with an update of the survival prediction.

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