Individual prediction of automobile bodily injury claims liabilities

Mercedes Ayuso, Montserrat Guillén and Miguel Santolino[*]

Dept. of Econometrics, RFA-IREA, University of Barcelona,
Avda. Diagonal 690, 08034 Barcelona, Spain

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Abstract

Many insurance companies estimate, and therefore reserve, automobile bodily injury compensation directly from initial medical reports. This practice may underestimate the final cost, because the severity is often assessed during the recovery period. In this paper we suggest two different statistical models to predict the *Reported But Not Settled* (RBNS) claims reserves. First we apply an ordered multiple choice model at different moments in the life of a claim reported to an insurance company. Using a real dataset, we show that the application of sequential ordered logit models leads to a significant improvement in the prediction of the BI severity level and, as a consequence, an adequate estimation of the insurer's reserves may be derived. Second we fit a log-linear model to estimate the RBNS claims reserves. Finally, a comparison of both methodologies is summarized.

JEL classification: C35, C53, G22

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[*] Corresponding author (e-mail: msantolino@ub.edu).

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1. Introduction

The high frequency of victims with BI damages involved in road accidents each year[1], and the unpredictability of awards in Courts for these kinds of damages have led to disproportionate costs to motor insurance companies. This worrying situation is a common problem among the European States. At the end of the financial year, the insurer must calculate the provision for the outstanding bodily injury claims. Unlike IBNR (Incurred But Not Reported), these outstanding claims are from events occurred and reported to the insurer, but the insurer doesn't know the final compensation payment yet. Usually, the insurer sets the provision for bodily injury compensation according to its own medical reports. Unfortunately, in many cases there exist huge differences between the injury severity awarded by the judge and the severity estimated by the medical expert, and therefore the corresponding provision of these claims will not match up with the final compensation payment.

The purpose of this paper is to estimate the insurer's loss reserves for reported but not settled (RBNS) claims. In the first place, we estimate the injury severity of the victim that the company must compensate and subsequently, a computation of loss reserves based on the prediction of the victim's severity is defined. Namely, we assume that the severity level of the injury is an ordered qualitative variable (we consider three categories[2]: only recovery days, non-severe injury and severe injury), and in this sense we apply an ordered logit model to estimate it. This estimation can be very useful to an insurance company because the level of injury is a "proxy" variable for the total compensation cost, and, therefore, an estimation of loss reserves may be derived. Moreover, the company may identify victims with a high probability of sustaining a serious injury, and then conduct a special follow-up of them during the recovery period. In the second part of the paper, we suggest to estimate directly the compensation cost of RBNS claims by means of a multiple linear regression model. Existence of positive autocorrelation and heteroscedasticity of the error term are possible. The former occurs when more than one claimant (BI victim) is involved in the judicial sentence; the latter is due to particular characteristics of medical valuations.

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[1] In Spain, more than 156000 people in 2003 (DGT, 2004).

[2] A low severity level includes claims where the injured person only needs to be compensated for some recovery days. A medium severity level is for non-severe injuries that require medical treatment, and complete recovery is

Both methodologies covered by this paper fall within the general class of statistical case estimation (SCE) that is applied to the prediction of characteristics of individual claims based on data related to individual claims (Taylor and Campbell, 2002; Brookes and Prevett, 2004; Taylor et al., 2003).When the claim occurs, it is classified on the basis of its severity level predicted by means of a qualitative scale, with the assumption that all claims of a given severity level correspond to the same expected claim size interval. However, individual information of the claim can be used to forecast the claim severity at different valuation dates. Alternatively, individual claim information may be used to predict directly the monetary compensation to the victim for personal damages.

In practice the estimations of the BI damages are made by the insurer at different moments: 1) after the claim is reported to the company, 2) after the first internal medical report, and 3) after the final internal medical report (full recovery of the victim). Consequently, we can consider different information levels of the claim, and gradually incorporate this information into the model. Comparisons between the reserves made by the insurer according the different internal reports, and the final BI compensation awarded by the judge could help us to extract conclusions concerning whether the reports are sufficient or not.

There exists a well-developed literature about ordered multiple choice models since the seminal paper by Mckelvey and Zavoyna (1975). Recent contributions to this literature are Adams et al. (2003) and Nayga et al. (2004) among many others. Adams et al. focuses on the determinants for the credit ratings awarded by the credit agencies to the insurance companies, while Nayga et al. discusses how to model the consumers' preferences by means of a probit model. In the vehicle accident field, O'Donell and Connor (1996), Abdel-Aty et al. (1998) and Kockelman et al. (2002) have used ordered multiple choice models to estimate the linkage between road user attributes and injury severity. Their studies point out that some attributes such as gender, age, kind of vehicle, alcohol or speed are highly related with the severity of the damages suffered by the individual. Toy and Hammit (2003) have analyzed the effect of different vehicle types' crash-worthiness (self-protection) on the risk to others in crashes, and Doerpinghaus et al. (2003) have focused on the assignment of fault to people involved in a car accident according to characteristics of the claim. However, no study has yet

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not achieved. A high severity level is used for individuals who suffered severe injuries and could not recover completely.

determined how the insurer can modify the BI assessment for an automobile victim on the claim life, and the influence of this process in reserving.

Regarding actuarial claim reserving techniques, there is scarce literature on the field of RBNS claims provisions. Most available statistical techniques were developed to compute IBNR claims reserves and they have been subsequently extended to the estimation of RBNS claims reserves. These techniques are normally based on run-off triangles and aggregated data (a deep review of IBNR reserving methods may be found in England and Verall, 2002). However, several techniques have been recently developed taking into account the specific characteristics of RBNS claims reserves (Haastrup and Arjas, 1996; Ntzoufras and Dellaportas, 2002; Stephens *et al*., 2004; Antonio *et al*., 2006). Although most of these techniques maintain within the framework of run-off triangles, some of them are based on individual data (Haastrup and Arjas, 1996; Antonio *et al*., 2006).

This paper is set out as follows. Section 2 refers to the econometric methodology used in the paper. A brief description of the ordered logit model is presented and we suggest a way to implement this multiple choice specification in the framework of automobile claims with bodily injuries. Section 3 describes the data used in our empirical work, which is taken from a Spanish insurance company (an overview of the process for bodily injury compensation within an insurance company is showed). In all claims there were BI damages and the total compensation was awarded by a judge. Therefore, we removed from the database those claims for which the insurer and the claimant reached an agreement on the compensation amount. The estimation results of the ordered logit model are presented in Section 4. The results include estimates of the parameters and the interpretation of the coefficients in terms of probabilities for different BI severity levels. Additionally, we analyze how these results can be used in the generation of loss reserves by the insurance company. Section 5 shows the estimation of RBNS claims reserves when a generalized linear regression model is fitted. Finally, in Section 6 we summarize our empirical results and present some concluding remarks, when both methodologies are compared.

2. Ordered logit model

The ordered logit model is based on a continuous latent variable specified as:

$$y_i^* = \beta' x_i + \varepsilon_i, \qquad -\infty < y_i^* < \infty \qquad [1]$$

where y_i^* measures the injury severity of the victim. Unfortunately, y_i^* is an unobserved variable. Let us assume that y_i is the observed discrete variable that reflects the different severity levels for individual *i*. The relationship between the latent variable and the discrete observed one will be obtained from the model according to:

$$\begin{array}{llll} y_i = 1 & if\ -\infty \le y_i^* < \mu_1 & i = 1,\ldots,n, & \\ y_i = 2 & if\ \ \mu_1 \le y_i^* < \mu_2 & i = 1,\ldots,n, & \\ y_i = 3 & if\ \ \mu_2 \le y_i^* < \mu_3 & i = 1,\ldots,n, & [2] \\ \ldots & \ldots & \ldots & \\ y_i = J & if\ \ \mu_{J-1} \le y_i^* < +\infty & i = 1,\ldots,n, & \end{array}$$

where *n* is the sample size.

The μ's are the thresholds where the discrete observed responses are defined and they must be estimated. In terms of the cumulative probability, this model estimates the probability that an individual *i* sustains a bodily injury of level *j* or lower (*j*-1,...,1). Note that in contrast with a multinomial logit model, the response categories in the ordered logit model reflect an ordered level among themselves. In our application, the dependent variable y_i has been coded according to three categories: only recovery days, non-severe injury, and severe injury.

The model specification is as follows:

$$\log\left[\frac{\gamma_j(x_i)}{1-\gamma_j(x_i)}\right] = \mu_j - \left[\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_K x_{Ki}\right], \quad j = 1,\ldots,J; \quad i = 1,\ldots,n, \qquad [3]$$

where γ_j is the cumulative probability, i.e. $\gamma_j(x_i) = \gamma(\mu_j - \beta' x_i) = P(y_i \le j \mid x_i)$. β is the column vector of parameters $(\beta_1, \beta_2, \ldots, \beta_K)$ and x_i is the column vector of covariates. Let us emphasize that μ_j depends only on the probability of the forecasting category but it doesn't depend on the explanatory variables. In the same way, the deterministic part $\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_K x_{Ki}$ is independent of the category. These two properties assure that the response categories are ordered and imply that the results are a set of parallel lines. Parameter estimates are obtained by maximum likelihood:

$$L(y \mid \beta; \mu_1, \mu_2, ..., \mu_{J-1}) = \prod_{i=1}^{n} \prod_{j=1}^{J} \left[\gamma\left(\mu_j - \beta' x_i\right) - \gamma\left(\mu_{j-1} - \beta' x_i\right) \right]^{z_{ij}} \qquad [4]$$

where z_{ij} is a binary variable that is equal to 1 if the observed category for the individual i is j, and 0 otherwise. A Newton-Raphson algorithm has been used in the maximization process (as implemented in SAS).

The interpretation of the coefficients is not direct. Note that when a predictor variable rises, the change in the probability depends on the value of this predictor and also on the rest of the variables. Since the change in probability is not constant, the interpretation of the coefficient is not straightforward. Consequently, we can only observe the direction for the probability variation (the coefficient sign), and only for the extreme categories (Liao, 1994). For example, a positive sign for the coefficient β_k means that if the predictor value rises Δx_k, the probability for the first category (y_i=1) will fall, whereas the probability for the last one (y_i=J) will increase, and *viceversa*. But we will not know the direction of change for the intermediate categories.

The marginal effect of a unit change in the predictor x_k over the probability for the category j is calculated according to:

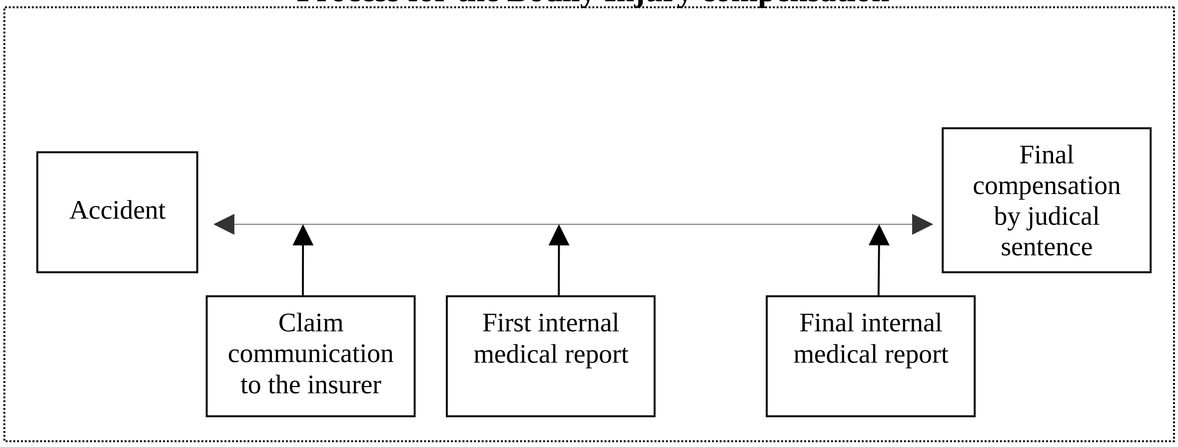
$$\frac{\partial P(y_i = j \mid x_i)}{\partial x_k} = \left[\frac{\partial \gamma(\mu_j - \beta' x_i)}{\partial x_k} - \frac{\partial \gamma(\mu_{j-1} - \beta' x_i)}{\partial x_k} \right] = \left[\lambda(\mu_{j-1} - \beta' x_i) - \lambda(\mu_j - \beta' x_i) \right] \beta_k \qquad [5]$$

where $\lambda_j(x_i) = \partial \gamma_j(x_i) / \partial x_k$; $\mu_0 = -\infty$ and $\mu_J = \infty$. Since the marginal effect depends on the values of all explanatory variables, we must decide which values to use when estimating it. Usually, the marginal effect is computed at the mean values of all variables.

3. Application to the Spanish automobile insurance market

In this section we briefly discuss the process from the moment in which the bodily injury file is opened by the insurance company (Figure1). We identify different phases in function of the information level concerning the claim. The first stage takes place when the company is first informed of the claim. At this moment the insurer obtains basic information about some characteristics of the accident (number of vehicles involved, types of vehicles, faulty party,…) and some attributes of the victims (age, gender,...).

FIGURE 1
Process for the Bodily Injury compensation



Since 1995, there exists in Spain a legislative scale regarding the assessment of damages for automobile bodily injuries. This scale provides a compensation system for three general categories: death, temporary disability and permanent disability. The disability level is assessed by a scoring system which describes different possible sequelae[3], and sets maximum-minimum bounds for each of them. The judge determines the final score for the sequelae according to severity. The final compensation depends on the overall scoring (in positive proportion) and the age of the victim (in inverse proportion). In short, in the Spanish legal system, as in other European countries, the rating scale sets what must be assessed and for how much money.

Except for some doubtful cases, the insurer learns quite quickly the identity of the victims to whom he must pay compensation. In order to make the corresponding provision, the insurer needs to estimate the total compensation for bodily injuries. Usually, the insurer has medical experts who carry out follow-up visits to the victims during the recovery period. During each visit, the medical expert writes up a report where he estimates the expected severity for the victims according to a normal recovery. Usually, they match their medical assessment with the corresponding items in the legislative scale. In order to estimate the corresponding provision, the insurer allocates a monetary value for each item in the medical report, which is normally the value stipulated by law.

[3] Sequela means the definitive reduction of physical and/or mental potential of a person (in the case of our study, resulting from an automobile accident) which can be identified or explained medically. Some examples are cervical spine pain with permanent functional impairment requiring caution in all movements, memory or communication disorders, paralysis of an arm, and so on.

When the lawsuit follows the Penal Procedure, a forensic doctor must also examine the victim and present a report to the judge. Sequelae considered by the forensic doctor must agree with those defined in the legislative scale. However, forensic doctor is not forced to assess the severity of these sequelae. The severity assessment is a judge's duty. In the Civil Procedure the forensic report is not required. At the end, the judge brings in a verdict according to all medical reports. In the verdict the judge must set the BI severity and the corresponding compensation. The judge must mention both the sequelae and their score.

3.1 The database

In our database we have information for the different medical reports in a sample of automobile claims. We also have information about the judicial verdict for each of them. In this sense, we can estimate the deviations between preliminary and final BI compensation amount.

Our database has 197 automobile BI claim records from an important Spanish insurance company. The common characteristic of all of these claim records is that the compensation amount was determined by judicial verdict. Notice that this kind of claim is not very frequent within the Spanish insurance companies because it is quite normal to reach an agreement between the parties. The insurer paid the compensation amount between the second semester of 2001 and the first semester of 2003.

We collected the information for each record taking into account four observations in the life of the claim:

I. General claim information. We obtained information regarding the accident year, the kind of vehicle, the location of the victim (inside the insured or the opposing vehicle), some of the victim's attributes (such as age and gender) and so on. All of this data is known by the insurer in a short period of time.

II. First Medical report. From this report we obtain information for the kind and severity of the bodily injury damages suffered by the victim, according to the first estimations of the insurance company medical expert. The number of sequelae, their assessment, the number of recovery days or the exact injured limb is included in this information.

III. Final medical report. We collected the same information as in the previous phase, but now the victim was fully recovered.

IV. Verdict/Appeal. Finally, we obtained information about the severity and the monetary compensation awarded by the judge at the end of the judicial process. This reflected the final compensation amount paid by the insurer.

With this structure we expect to reflect the full process for the BI compensation as it is shown in Figure 1. We have three categories for the ordinal dependent variable according to the victim BI severity level awarded by the judge: y_i=1 if casualty *i* has no sequelae after the recovery period (we named this category *Recovery days*); y_i=2 if casualty *i* has less than 15 points for sequelae according to the Spanish disability scoring system (*Non-severe injury)*, and y_i=3 if casualty *i* has equal or more than 15 points for sequelae (*Severe injury*). Victims coded as only *Recovery days* (y_i=1) represent a 36.0% of the sample, victims with *Non-severe injury* (y_i=2) represent 55.3%, and finally 8.6% suffer *Severe injury* (y_i=3). Table 1 shows a huge variation in the BI mean compensation amount between victims with 14 points or less, and victims with 15 points or more.

TABLE 1
Distribution of the BI mean compensation *versus* the sequelae assessment (Judicial sentence)

Sequelae assessment	Mean compensation (€)
<8	<10000
9	12511.07
10	13784.73
11	10078.36
12	18378.11
13	18005.33
14	16915.44
15	25556.92
18	23177.15
19	34550.90
20	18000.34
21	30192.10
22	29130.83
>22	>30000

Source: database

Explanatory variables included in the model are presented in Table 2. We also show some descriptive measures for the global sample.

TABLE 2
Variables in the data set and descriptive statistics

		Mean	Stand.Dev.
Before any medical report			
x_1	Accident year (1=1994; 2=1995;...; 10=2003)	6.975	1.430
x_{2a}	1 if the victim's vehicle is a motorbike; 0=otherwise	0.223	0.418
x_{2b}	1 if the victim's vehicle is a van; 0=otherwise	0.020	0.141
x_{2c}	1 if the victim is a pedestrian or cyclist; 0=otherwise	0.107	0.309
x_{2d}	1 if the victim's vehicle is a car; 0=otherwise	0.650	0.478
x_3	Victim age (in tens)	3.930	1.606
x_4	1 if male; 0=otherwise	0.497	0.501
x_5	1 if the victim is an occupant of the insured vehicle; 0=otherwise	0.091	0.289
First medical report			
x_6	Number of sequelae	1.092	1.340
x_7	Sequelae assessment (in points)	3.992	6.545
x_8	Number of recovery days with disability for working	53.563	53.971
x_9	Number of recovery days without disability for working	29.109	45.472
x_{10a}	1 if injury affects the head or trunk; 0=otherwise	0.361	0.482
x_{10b}	1 if injury affects extremities; 0=otherwise	0.185	0.390
x_{10c}	1 if injury affects more than one limb; 0=otherwise	0.025	0.157
x_{10d}	1 if no injury to any limb; 0=otherwise	0.429	0.497
x_{11}	1 if the victim suffers aesthetic damage; 0=otherwise	0.143	0.351
Last medical report			
x_{12}	1 if it is the same medical report as the first one; 0=otherwise	0.316	0.467
x_{13}	Number of sequelae	1.114	1.655
x_{13a}	Sequelae number variation across reports	0.009	0.917
x_{14}	Sequelae assessment (in points)	4.096	6.837
x_{14a}	1 if the sequelae assessment in the first medical report is larger than in the last one; 0=otherwise	0.193	0.396
x_{15}	Number of recovery days with disability for working	53.132	63.027
x_{15a}	Variation in the number of recovery days disabled for working across reports	2.079	37.601
x_{16}	Number of recovery days without disability for working	37.596	59.699
x_{16a}	Variation in the number of recovery days not disabled for working across reports	7.211	32.456
x_{17a}	1 if injury affects the head or trunk; 0=otherwise	0.281	0.451
x_{17b}	1 if injury affects extremities; 0=otherwise	0.158	0.366
x_{17c}	1 if injury affects more than one limb; 0=otherwise	0.044	0.206
x_{17d}	1 if no injury to any limb; 0=otherwise	0.518	0.502
x_{18}	1 if the victim suffers aesthetic damage; 0= otherwise	0.158	0.366
Forensic report			
x_{19a}	1 if forensic doctor assesses sequelae; 0=otherwise	0.210	0.409
x_{19b}	1 if forensic doctor defines sequelae, but he doesn't assess them; 0=otherwise	0.342	0.477
x_{19c}	1 if forensic doctor doesn't award sequelae; 0=otherwise	0.342	0.477
x_{19d}	1 if there was not forensic report; 0=otherwise	0.105	0.308

4. Estimation results of the ordered logit model

Let us assume that casualties have an underlying severity, although this severity is still unknown by the company. This assumption means that there are no variations in the level of severity during the recovery period. In this sense we do not consider in our study the category *death* because in our database all the victims that lose their life died when the accident took place.

In the following paragraphs we estimate the probability of suffering different BI severity levels, according to the information for different moments in the life of the claim (Figure 1). We compare the results at the different stages with the final classification as determined by the judges.

4.1 Before any medical report

When the claim arrives at the company the insurer obtains general information on the accident (victim's attributes, position in the vehicle,…). We can look for a causal relationship between the final BI classification awarded by the judge and some characteristics of the victim, without considering at this moment the BI damages suffered by the person. The dependent variable is the severity level taking into account the judicial verdict (three different levels) and an ordered logit model is assumed.

The estimation of the parameters was obtained using maximum likelihood according to the methodology presented in Section 2. The parameter estimates are shown in Table 3. The chi-squared statistic is significant, consequently the model gives better predictions than if our forecast is only based on the marginal probabilities of the outcome categories. Another interesting result is obtained for the test of parallel lines. This test considers whether it is reasonable to apply an ordered logit model or whether it is preferable to fit a classical logit model (Greene, 1999). According to our results, the parallel lines test statistic is not significant, and thus the null hypothesis cannot be rejected.

TABLE 3
Estimation of the parameters
(Before any medical report)

		Coefficient	P-value
μ_1	Threshold	-1.258	0.146
μ_2	Threshold	2.030	0.021*
x_1	Accident year (1=1994; 2=1995;...; 10=2003)	-0.201	0.061**
x_{2a}	1 if the victim's vehicle is a motorbike; 0=otherwise	1.611	0.000*
x_{2b}	1 if the victim's vehicle is a van; 0=otherwise	1.670	0.112
x_{2c}	1 if the victim is a pedestrian or cyclist; 0=otherwise	1.261	0.021*
x_3	Victim age (in tens)	0.177	0.099**
x_4	1 if male; 0=otherwise	-0.927	0.003*
x_5	1 if the victim is occupant of the insured vehicle; 0=otherwise	0.591	0.268

Number of observations: 197; *pseudo*-R^2: 0.170; chi-squared: 30.165 (0.000); parallel lines test: 5.661 (0.580); * indicates 5% significance level; ** indicates 10% significance level

Three coefficients are significant at the 5% level, and two at the 10% level. All estimates have the expected sign. The probability of suffering severe BI damages increases with the number of years that the claim record has been open within the company (negative coefficient for the variable a*ccident year*[4]) and when the victim's vehicle was not a car. Females face a higher risk of suffering severe injury than males, and also the probability for severe injury damages is positively related to the victim's age. Whether victims are occupants of the insured vehicle or not does not significantly influence the severity level.

Table 4 presents the predicted and observed frequencies for each severity level. Notice that the estimated model achieves 63.4% of total correct classifications. Consequently the insurance company would be able to make reasonable predictions of the victim's severity with very little information on the claim. Nevertheless, this initial forecast still has important constraints, basically, the estimated model does not adequately capture the most severe injury cases. Therefore, this result confirms that there is room for improving the prediction if we estimate models with larger amounts of information on the BI damages.

[4] We have information about dates when the insurer paid the total compensation amount (between the second semester of 2001 and the first semester of 2003), that we could identify as the closure dates, and we have information about the accident year. The primary objective was to include the difference between the two dates as an indicator of the time the claim was open. But this parameter was not statistically significant (parameter value: 0.166, significance level: 0.122). Therefore, we included the *accident year* as a proxy that is statistically significant, at least in the first model (before any medical assessment was received).

TABLE 4
Confusion matrix
(Before any medical report)

Predicted	Actual (according judicial sentence) Recovery Days	Non-severe injury	Severe injury	Total
Recovery days	35	19	1	55
Non-severe injury	36	90	16	142
Total	71	109	17	197

4.2 After the first medical report

In this section we estimate a new ordered logit model including the information from the first medical report. Parameter estimates are reported in Table 5. The chi-squared statistic is significant.

TABLE 5
Estimation of the parameters
(after the first medical report)

		Coefficient	P-value
μ_1	Threshold	2.100	0.138
μ_2	Threshold	7.432	0.000*
x_1	Accident year (1=1994; 2=1995;...; 10=2003)	0.017	0.924
x_{2a}	1 if the victim's vehicle is a motorbike; 0=otherwise	0.962	0.150
x_{2b}	1 if the victim's vehicle is a van; 0=otherwise	1.149	0.487
x_{2c}	1 if the victim is a pedestrian or cyclist; 0=otherwise	1.071	0.253
x_3	Victim age (in tens)	0.300	0.077**
x_4	1 if male; 0=otherwise	-1.587	0.002*
x_5	1 if victim is occupant of the insured vehicle; 0=otherwise	1.001	0.167
x_6	Number of sequelae	0.845	0.033*
x_7	Sequelae assessment (in points)	-0.014	0.855
x_8	Number of recovery days with disability for working	0.024	0.000*
x_9	Number of recovery days without disability for working	0.014	0.021*
x_{10b}	1 if injury affects extremities; 0=otherwise	-1.456	0.090**
x_{10c}	1 if injury affects more than one limb; 0=otherwise	-0.465	0.786
x_{11}	1 if the victim suffers aesthetic damage; 0= otherwise	1.359	0.122

Number of observations: 119; *pseudo*-R^2: 0.597; chi-squared: 83.018 (0.000); * indicates 5% significance level; ** indicates 10% significance level

In a comparison over models, the accident year and the type of vehicle lose explanatory capacity and their coefficients are no longer significant. However, age and gender continue being significant predictors of the severity level.

As regards the incoming variables, let us emphasize that the parameter for the predictor *Assessment of sequelae* is not significant. This variable reports the score allocated by the medical expert to the entire sequelae according to the Spanish scoring system. As we know, the response categories for the dependent variable are based on the final assessment of sequelae awarded by the judge. Therefore, the lack of significance of this parameter means that the medical expert does not set the final assessment for sequelae accurately and thus the victim's severity is not established with precision. As a consequence of this non-accurate estimation, there are misclassifications between the categories *Not severe injury* (y_i=2) and *Severe injury* (y_i=3) in the medical report. Obviously, these misclassifications can be relevant in the reserving process.

On the other hand, the coefficient for the variable *Number of sequelae* is positive and significant. Note that this variable has a lot of zeros (victims without sequelae), thus the medical expert in this first medical report differentiates correctly between victims with and without sequelae, but he doesn't estimate accurately their severity level. If the victim suffers BI damages it is more probable those will be severe when his/her head or trunk is affected rather than extremities.

Finally, the scoring system differentiates between the recovery period during which the victim is not able to work, and the time that the victim is able to work but is not yet fully recovered. In the model, the variables *Number of recovery days disabled for working* and *Number of recovery days not disabled for working* have positive coefficients, and both are variables that are positively related to the final injury severity level.

In Table 6 we compare both the results for the estimated ordered logit model and the observed medical expert classification with the final judicial verdict categories. The estimated model correctly forecasts 74.8% of the cases, whereas the medical expert only sets an accurate classification in 62.2% of cases. The interval of time from when the claim record is opened to the first medical report is on average 38 days in our sample. If the model presented in this section is implemented in practice the insurance company would be able to correctly estimate almost 75% of the victims' severity level in just over a month from when the claim is reported.

TABLE 6
Confusion matrix
(after the first medical report)

Medical expert classification	Actual (according judicial sentence) Recovery days	Non-severe injury	Severe injury	Total
No bodily injury†	3	1	0	4
Recovery days	24	18	0	42
Non-severe injury	13	45	7	65
Severe injury	0	3	5	8
Total	40	67	12	119

† Medical expert awarded neither recovery days nor sequelae to the victim.

Predicted	Actual (according judicial sentence) Recovery days	Non-severe injury	Severe injury	Total
Recovery days	27	11	0	38
Non-severe injury	13	54	4	71
Severe injury	0	2	8	10
Total	40	67	12	119

Marginal effects have been also calculated. In this sense, when the variable *Age* increases by one unit[5] the probability for the category *Recovery days* (y=1) decreases by 5.1% whereas the probability for the category *Non-severe injury* (y=2) increases by 4.6%, and the probability of *Severe injury damages* (y=3) increases by 0.05%. Regarding the gender of the victim, if she is a woman, *ceteris paribus*, the estimated probability for the category *Non-severe injury* and *Severe injury* rise by 23.9% and 2.9%, respectively. On the contrary, the probability of suffering only *Recovery days* decreases by 26.8%.

4.3 After the last medical report

Finally, in this section we estimate the ordered logit model with the information available after the last medical report, i.e. when the victim is completely recovered from his/her injury, or when no more medical treatment can be applied. Our aim is to combine the new information from the last medical report with the previous information. The incoming variables for this last model are identical to that of the previous model. However, in order to avoid collinearity with the explanatory variables from the first medical report, we include as a predictor the observed variation across reports for some of the characteristics analysed.

[5] We take the mean of each predictor as its representative value to calculate the marginal effects.

The chi-square statistic continues being statistically significant, and the pseudo-R^2 now performs better as a consequence of including more explanatory information.

The properties of the explanatory variables for the last medical report are quite similar to those of the first report (Table 7). Namely, the *Number of sequelae*, the *Number of recovery days disabled for working*, and the *Number of recovery days not disabled for working* perform as in the previous model and again have significant and positive coefficients. On the contrary, the parameter for the variable *Assessment of sequelae* is still not significant. This variable now provides information when the victim is fully recovered, thus it should be very similar to the severity level awarded in the judicial verdict. The non-significance of this parameter tightens the idea of possible variations between the victim's final severity level observed by the insurance company and the severity awarded by the judge.

TABLE 7
Estimation of the parameters
(after the last medical report)

		Coefficient	P-value
μ_1	Threshold	1.921	0.276
μ_2	Threshold	8.441	0.000*
x_1	Accident year (1=1994; 2=1995;...; 10=2003)	0.116	0.586
x_{2a}	1 if the victim's vehicle is a motorbike; 0=otherwise	1.303	0.095**
x_{2b}	1 if the victim's vehicle is a van; 0=otherwise	1.486	0.353
x_{2c}	1 if the victim is a pedestrian or cyclist; 0=otherwise	1.430	0.197
x_3	Victim age (in tens)	0.386	0.040*
x_4	1 if male; 0=otherwise	-2.589	0.000*
x_5	1 if victim is occupant of the insured vehicle; 0=otherwise	0.864	0.297
x_{12}	1 if it is the same medical report as the first one; 0=otherwise	-1.723	0.012*
x_{13}	Number of sequelae	1.017	0.054**
x_{13a}	Sequelae number variation across reports (last minus first)	-1.560	0.004*
x_{14}	Sequelae assessment (in points)	0.034	0.748
x_{14a}	1 if the sequelae assessment in the first medical report is larger than in the last one; 0=otherwise	-3.092	0.002*
x_{15}	Number of recovery days with disability for working	0.025	0.002*
x_{15a}	Variation in the number of recovery days disabled for working across reports (last minus first)	-0.037	0.000*
x_{16}	Number of recovery days without disability for working	0.020	0.010*
x_{16a}	Variation in the number of recovery days not disabled for working across reports (last minus first)	-0.011	0.365
x_{17b}	1 if injury affects extremities; 0=otherwise	-2.482	0.024*
x_{17c}	1 if injury affects more than one limb; 0=otherwise	-3.603	0.034*
x_{18}	1 if the victim suffers aesthetic damage; 0= otherwise	2.164	0.078**

Number of observations: 114; *pseudo*-R^2: 0.710; chi-squared: 103.72 (0.000); *indicates 5% significance level; ** indicates 10% significance level

Finally, in relation to the exact injured limb, in this model both *Injuries to extremities* and *Injuries to more than one limb* have significant and negative coefficients. Consequently, victims with head/trunk injuries are more likely to suffer severe BI. Moreover, the coefficient for the dummy variable *Aesthetic damage* is significant and positively related to a high severity level.

It is interesting to observe that most of the variables from the first medical report are relevant in this last estimated model. Namely, the variation in the number of sequelae, the variation in the number of recovery days disabled for working, and the dummy variable that reflects an assessment of sequelae in the first medical report larger than in the last one have significant parameters. In the same way, the dummy variable that indicates the same conclusions for the first and the last medical report has a significant and negative coefficient. Reasonably, victims who need to be examined only once would be severe with less probability.

The last medical report has the same constraints as the first one, and it does not accurately classify non-severe and severe injured victims. In relation to the "time-related" variables, we observed a positive correlation between the severity of injuries and the time interval between medical reports (in particular, if the last medical report was made after 100 days from the first report). This result seems reasonable, since severely injured victims need more time for complete recovery. However, we decided not to include this variable in the model to avoid collineality with other regressors (as the *Number of recovery days with disability for working* or the *Number of recovery days without disability for working*).

The categories predicted by the last estimated model are reported in Table 8. As in the previous section, we compare the predicted severity level and the severity as indicated by the medical expert with the final severity level awarded by the judge. Note that the percentage of cases accurately classified by the estimated model improves notably (78.1%). On the contrary, the cases that are correctly classified by the medical expert in the last report turn out to decrease in relation to the first medical report (61.4%).

TABLE 8
Confusion matrix
(after the last medical report)

Medical expert classification	Actual (according judicial sentence) Recovery days	Non-severe injury	Severe injury	Total
No bodily injury†	3	1	0	4
Recovery days	29	21	0	50
Non-severe injury	8	36	6	50
Severe injury	0	5	5	10
Total	40	63	11	114

† Medical expert didn't awarded neither recovery days nor sequelae to the victim.

Predicted	Actual (according judicial sentence) Recovery days	Non-severe injury	Severe injury	Total
Recovery days	26	9	0	35
Non-severe injury	14	54	2	70
Severe injury	0	0	9	9
Total	40	63	11	114

To conclude we are interested in analyzing how the reserving process can be improved by taking into account individual predictions for the BI severity levels. Individual estimations of provisions have become more and more important lately (Taylor et al., 2002, 2003; Antonio et al., 2006) and they were suggested in some other works as well (England and Verrall, 2002). Let us suppose that the insurer allocates the mean cost of the corresponding category to each observation in order to make the provision. Mean costs for each category are presented in Table 9.

TABLE 9
Mean compensation by category
(in euros)

	Mean compensation
Recovery days	1784.42
Non-severe injury	7330.77
Severe injury	31201.30

Source: database

In Table 10 we compare the global BI compensation for our sample according to the judicial verdict, and the provisions derived from both the insurance company medical expert (last report), and the ordered logit model classification. As can be seen, our model underestimates the final payment by approximately 7%, whereas underestimation is 17% when the medical expert classification is used.

TABLE 10
Reserving process

	Total amount (€)	Provision/ Total amount (%)
Total BI compensation according the judicial sentence	925011.95	—
Provision according to the medical expert classification (last report)	767772.50	83.00%
Provision according to the estimated severity by the model	856420.30	92.58%

5. Estimation results of the log-linear regression model

In this section, we consider that the insurance company already has all medical reports, including the forensic report (if it exists). Our goal is to estimate the individual monetary compensation awarded in judicial sentence by means of a log-linear model. Heteroscedasticity and autocorrelation are considered in the variance-covariance matrix structure of the error term. The first one is related to the forensic doctor performance. Correlation among observations occurs when more than one claimant (BI victim) is involved in the judicial sentence. The parameters estimates are shown in Table 11.

TABLE 11
Estimation results of the log-linear regression model

		Coefficient	p-value
β_0	*Constant*	8,402	0,000*
x_{2d}	1 if the victim's vehicle is a car; 0=otherwise	-0,218	0,107
x_4	1 if male; 0=otherwise	-0,764	0,004*
x_3	Victim age (in tens)	0,052	0,209
x_{12}	1 if it is the same medical report as the first one; 0=otherwise	-0,872	0,001*
x_{13}	Number of sequelae	0,218	0,001*
x_{13a}	Sequelae number variation across reports	-0,259	0,013*
x_{15}	Number of recovery days without disability for working	0,009	0,000*
x_{15a}	Variation in the number of recovery days disabled for working across reports	-0,005	0,015*
x_{16}	Number of recovery days without disability for working	0,005	0,001*
x_{19c}	1 if forensic doctor doesn't award sequelae; 0 otherwise	-0,714	0,000*
inter	1 if x_4=0 and x_{12}=0; 0 otherwise	-0,657	0,021*
σ^2_{ε}	Variance error (more than one claimant is compensated in the same sentence)	0,015	0,450
$\sigma^2_{\varepsilon,1}$	Variance error if x_{19a}=1	0,761	0,001*
$\sigma^2_{\varepsilon,2}$	Variance error if x_{19b}=1	0,185	0,086**
$\sigma^2_{\varepsilon,3}$	Variance error if x_{19c}=1	0,481	0,001*
$\sigma^2_{\varepsilon,4}$	Variance error if x_{19d}=1	0,661	0,020*

Number of observations: 114; *indicates 5% significance level; ** indicates 10% significance level

Regarding the statistical analysis, the conclusions are very similar to those obtained with the estimated sequential ordered logit model (in terms of coefficient signs and significance level). This confirms that there exists a close relationship between the injury severity and the final compensation amount. An exception is the lack of significance of the victim's age coefficient in the estimated log-linear model. In the first part, we demonstrated that the victim's age is positively correlated with the injury severity. On the other hand, the monetary value stipulated in the legislative scale for the injury assessment is inversely related to the victim's age. We propose that the lack of explanatory capacity of the victim's age may be due to the fact that the aforementioned effects counteract each other.

Finally, the application to claim reserving is presented in Table 12. In particular, we allocate to RBNS claims reserves the predicted compensation cost of each outstanding BI claim. Note that the estimated aggregated provision covers almost the 100% of the total claims cost. This percentage is notably higher than the percentage showed in the Table 10. This increase may be due to the influence of the forensic valuation on the final compensation.

TABLE 12
Reserving process

	Total amount (€)	Provision / Total amount (%)
Total BI compensation according to the judicial sentence	925011.95	—
Provision according to the estimated compensation cost by the model	907100.07	98.06%

6. Conclusions

When a new bodily injury claim is reported, the insurance company needs to make a prediction about the injury severity level, which can then be used as an indicator of the total compensation cost. Unfortunately, the company will not know the true severity until the judge gives a verdict, i.e. the insurer must pay the compensation amount according to this verdict. Certain attributes may help to estimate the victim's severity level by means of an ordered logit model, but normally the company doesn't know all of these attributes at the moment when the claim is reported. In fact, the company obtains the information in steps, when the claim is reported, after the internal medical reports, and finally when the trial takes place.

The parameters for the variables *Gender* and *Age* are always significant and with the same sign in all of the estimated logit models. Therefore, according to our data set, the riskiest group for suffering severe injury damages is old women. Regarding the remainder information when a new claim file is opened, the accident year, and the kind of vehicle seem to be related with the injury severity, but their parameters lose explanatory capacity when the insurance company has a professional assessment of the damages (medical reports).

The insurer has initial medical information which will be expanded in successive medical reports. Unfortunately, medical reports may pursue different aims which are not necessarily compatible. On one hand, the estimated compensation for the victim is based on the medical assessment. On the other hand, medical reports are used by the company as a negotiation tool or, as a last resort, as evidence at the trial, i.e. when the insurer admits a sequelae, he is implicitly accepting the payment and thus increasing the compensation cost. It is in this context that we should interpret that information obtained from the first medical report, which has a high explanatory capacity of the final injury severity (even when the company already has the last medical report), or when the medical expert classifies correctly with almost the same percentage of cases in both reports. One possible interpretation would be that the first medical report is closer to the first objective (enough provision) and the last medical report to the second objective (evidence at trial).

Variables related to the number of sequelae, or the number of recovery days would reflect the underlying severity better than direct assessment of the sequelae. These variables collect more objective data because when the medical expert assesses the sequelae, he is measuring the intensity of the injury, which is a subjective task. Finally, we have shown, by means of example, how improving the bodily injury severity classification using ordered logit models may help the insurer to make better provisions.

Alternatively, we have applied a log-linear model to estimate the RBNS claims provision. We have demonstrated that the resulting estimated provision for outstanding BI claims is adequate as well.

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