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Micro-level VS macro-level reserving in non-life insurance: why and when?

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Abstract

In non-life insurance, business sustainability requires accurate and robust predictions of reserves related to unpaid claims. To this aim, two different approaches have historically been developed: aggregated loss triangles and individual claim reserving. The former has reached operational great success in the past decades, whereas the use of the latter still remains very limited. Through two illustrative examples and introducing a new tree-based algorithm, we show, not surprisingly, that individual claim reserving is really promising in the context of long-term risks.

Keywords : reserving, long-tail, censoring, regression tree, P&C insurance.

1 Introduction

Given their greater complexity, is it worth using individual claims reserving techniques in non-life insurance? In this paper, we try to answer this question by illustrating in which situations a real contribution of individual claim reserving techniques seems to appear.

Despite some recent advances¹, insurance companies still seem to be reluctant to use micro-level reserving as compared to very standard techniques using aggregated data, like Chain Ladder and its extensions (Mack [1993], Bornhuetter and Ferguson [1972], Quarg

¹See the report on non-life reserving practices by ASTIN Working Party (June 2016) at http://www.actuaries.org/ASTIN/Documents/ASTIN_WP_NL_Reserving_Report1.0_2016-06-15.pdf

and Mack [2008]). In such traditional methods, individual claims are summed and stored into claim development triangles according to a two-dimensional scheme based on origin and development periods. Of course, the success of these models lies in that they are easily understandable, simple to use, and have worked very well in many circumstances in the past. However, practitioners are clearly aware of their limitations² and know that they can lead to poor estimates, especially concerning the reserves for the latest development periods. This mainly originates from the fact that these methods *do not capture the pattern of claim development*, which is of primary importance in some cases.

Simultaneously, spectacular improvements to collect historical information and individual characteristics on claims have been made in the insurance industry for more than fifteen years, and companies have now access to very comprehensive datasets. Using these data and regression models, actuaries can use sophisticated statistical procedures to estimate Incurred But Not yet Reported (IBNyR) and Reported But Not Settled (RBNS) claims. RBNS claims correspond to situations where the insurer knows about the existence of the claim, has possibly started to pay for it, but does not know how much the final charge will be. In such a context, taking into account individual features about claims offers many advantages to approximate the reserve. First, it enables to cope with heterogeneity issues that can arise when using aggregated data. Indeed, storing all claims into aggregate run-off triangles makes it impossible to consider changes related to claims management, reinsurance programs, legal context and product mix. It also prevents from integrating key claim characteristics and thus crucial risk factors explaining the final amount to pay. Second, it allows to separate RBNS and IBNyR claims to perform an advanced risk assessment and monitoring. Moreover, the specific development pattern of claims can be considered, which means that the full information about the history of the claim (occurrence, reporting, payments, and closure) are now inputs of the model. And last but not least, these techniques provide individual claims reserves which could be very useful from both a risk management and a claims management perspective (for instance in order to improve claims management policies).

One could then wonder why such techniques have not been widely applied yet. Except that it is harder to implement, the reason seems quite obvious: past contributions on individual claim reserving were mainly focused on parametric models and likelihood max-

²Several well-known issues concern propagation of errors through the development factors, instability in ultimate claims for recent arrival periods, necessary previous treatment of outliers, need to integrate tail factors (see for instance Halliwell [2007]). Assumptions underlying such models are also often discussed, as well as corresponding statistical tests (see Harnau [2017]).

imisation (Antonio and Plat [2014], Pigeon et al. [2013], Zhao et al. [2009], Larsen [2007], Haastруп and Arjas [1993]). Due to RBNS claims, deriving the likelihood associated with observed claims is not straightforward, because of truncation and censoring phenomena. Besides, the parametric relationship existing between claim amounts and risk factors under study can be tricky to specify. As a result, these approaches did not reveal neither convincing nor very effective in practice. Moreover, according to most of actuaries and under regulatory constraints (stating that ultimate reserve estimates should be regularly updated, say each quarter), parametric individual claim reserving models have not really been considered useful so far for one simple reason: quarterly gains/losses indicators (the so-called *boni-mali*) were not improved, which means that the overall quality of prediction of such models was not better than the Chain Ladder's one (at least on the short-term, showing that Chain Ladder remains somewhat effective in most of situations). Since the main threat for the top management concerns potential urgent need for capital injections, this statement diminishes the attractiveness of such techniques. Besides, *mali* can have impacts on the Solvency Capital Requirement, as well as on future premiums. To the best of our knowledge, this paper proposes a new way to anticipate, as soon as possible, the ultimate global reserve by aggregating individual reserve predictions for RBNS claims. We do not claim that our model is better than others, but simply show to which extent individual claim reserving by nonparametric approaches could be beneficial to approximate future payments. Although our application focuses here on claim reserving, it is also important to be aware that many other actuarial applications could use the technique presented in the sequel. Let us mention for instance the opportunity to decrease costs related to experts involved in claim estimations, as well as improving the targeting of specific claims causing atypical claim amounts.

The paper is organized as follows: Section 2 introduces our new method to estimate individual reserves, with tools similar to Wüthrich [2018]. However, ultimate individual reserves for RBNS claims are here estimated thanks to an adaptation of the CART algorithm to censored data. Then, two applications are conducted in Section 3 to answer the initial question. Results are compared to the Chain Ladder method, knowing that its usual stochastic extensions (Mack [1993], England and Verrall [2002]) all provide the same expected ultimate global reserve (the only difference lies in assessing its variance).

2 Proposed individual claim reserving technique

Up to now, very few references exist on individual claims reserving with nonparametric techniques (Wüthrich [2018], Baudry and Robert [2017]). In the case where the insurer can access individual information about the claims, our approach consists in using an extension of the CART algorithm to incomplete observations (Lopez et al. [2016]). This piecewise tree-based estimator allows for nonlinearities in the dependence structure between claim amounts and explanatory risk factors (Olbricht [2012]). The aim is to estimate the ultimate amounts of RBNS claims for individual policies, knowing that one has both closed and still open claims in the dataset.

2.1 Idea of the Weighted CART for duration analysis

The time development of a claim is crucial to predict its severity. Roughly speaking, a claim which requires a lot of time to be settled is more likely to be associated with a large amount. Therefore, if M denotes the claim amount, one must provide a model that takes the impact on this variable of the time before settlement.

We are thus interested in a random vector (M, T, \mathbf{X}) , where $\mathbf{X} \in \mathcal{X} \subset \mathbb{R}^d$ denotes a set of random covariates that may have an impact on T and/or M , and $(M, T) \in \mathbb{R}^{+2}$. In the following, T represents the time before a claim is fully settled, and M the total corresponding amount (only known at the end of the claim settlement process). As we are dealing with a duration T , this variable is subject to censoring, which is a classical issue in survival analysis. This means that, in the database that we use to calibrate the distribution of (M, T, \mathbf{X}) (and hence to predict M), all of the claims are not fully settled. To describe this phenomenon, let us introduce a censoring variable $C \in \mathbb{R}^+$, which represents the time between the opening of the claim and the end of observation for any other cause than its settlement. For example, retrocession of a claim leads to a loss of information after some point of time. The observed variables are thus not directly T and M , but $Y = \inf(T, C)$, $\delta = \mathbf{1}_{T \leq C}$, and $N = \delta M$. The covariates \mathbf{X} are considered as always fully observed. The data is made up of i.i.d. replications $(N_i, Y_i, \delta_i, \mathbf{X}_i)_{1 \leq i \leq n}$. We also assume that C is independent of (M, T, X) . This assumption implies that the amounts M should be free from inflation, see the discussion in Lopez [2018].

It is important to notice that one should not calibrate a model for M only on the closed claims, that is with $\delta = 1$. Although the closed claims bring a complete information on the variable, this information is biased: indeed, among closed claims, there is an excess

of claims with small time of settlement. Since these claims are more likely to be of small amount, this would lead to an underestimation of the typical values taken by M . The alternative is to correct the bias caused by censoring using an appropriate weighting scheme. For a comprehensive description of the algorithm used hereafter and related properties, the reader is referred to Lopez et al. [2016]. This algorithm is inspired from the well-known CART algorithm, where the problem of incomplete observations forces to introduce the Kaplan-Meier (KM) weights. Those weights are defined by

$$\omega_i = \frac{\delta_i}{n(1 - \hat{G}(Y_{i-}))},$$

with \hat{G} the Kaplan-Meier estimator for the cdf of the censoring variable C . Thanks to their nice properties, KM weights ensure that the conditional expectation of interest, i.e. $\mathbb{E}[M | T, \mathbf{X}]$, is consistently estimated in the presence of censoring. Concretely, the KM weight equals 0 when the observation is censored ; otherwise, the greater the fully observed lifetime the higher the weight. This enables to compensate for the fact that very few individuals with high durations are fully observed.

2.2 Our algorithm to estimate reserves in practice

We detail here the steps to implement our weighted CART algorithm in the context of individual claim reserving. For the sake of simplicity but without loss of generality, consider that the insurer has to pay 1 US\$ each day the claim remains open, which corresponds to the case $M = T$. Consider an open claim, that is $\delta = 0$, and the claim is opened since $Y = k$. We thus aim to estimate RBNS claims by the quantity $\mathbb{E}[T | \delta = 0, Y = k, \mathbf{X}] = \mathbb{E}[T | T \geq k, \mathbf{X}]$. In this context, there is a direct link between duration of the claim and final claim amount. For each reached lifetime k ,

1. Select claims (potentially censored) with higher lifetime than k ;
2. Estimate the Kaplan-Meier weights *from the whole data* ;
3. Build the regression tree $(T - k) | \mathbf{X}, T > k$; based on weighted observations ;
4. Prune appropriately the obtained tree (see Lopez et al. [2016]);
5. Estimate the residual lifetime : $E[T - k | T > k, \mathbf{X}]$;
6. Increase k and go back to step 1.

Let us note that the weight are computed from the whole data. Once the regression tree is built, the final claim amount can be estimated for each open claim. The behavior of the

method is expected to be poorer for the claims with the largest settlement times, which is essentially due to two facts: the lack of claims such that $T > k$; and the erratic behavior of the weights when T becomes too large, which is a classical issue when dealing with the Kaplan-Meier estimator. Nevertheless, the question of extreme claims would require a particular attention, which is not covered by regression trees.

3 Application

The goal of this section is to see whether individual claim reserving using our nonparametric approach leads to improve significantly the initial assessment of the global reserve corresponding to RBNS claims, as compared to Chain Ladder. In this view, we make comparisons based on a very simple indicator: the *boni-mali* (see Section 1). *Boni-mali* is useful to backtest the quality of predictions made for the expected global reserve.

In practice, real-life claims are stored in a database where each record corresponds to one unique claim, with all corresponding characteristics (in particular the dates of claim occurrence and closure, if available). Then, reserves are regularly estimated using Chain Ladder or the weighted CART algorithm, and thus updated at given dates, say each quarter for instance. This process enables to compute the *boni-mali* between each period. Implementing the Chain Ladder method requires to appropriately aggregate the data (see Section 3.2), whereas we need to define a grid of durations to be studied in the second case (see the parameter k in the algorithm of Section 2.2). This grid obviously depends on the data, and further details are provided in Section 3.3.

3.1 Data description

When looking at aggregated loss triangles, practitioners usually consider that long-term risks are characterized by more than ten developments periods. Here, liabilities (or guarantees) can last much longer. Indeed, short-term and long-term disability insurance exist to protect the policyholders against the loss of some revenue, due to some accident or disease that prevent them from working. Those type of contracts, mostly sold in collective insurance, can sometimes be assimilated into life annuities.

We focus here on short-term disability, meaning that the greatest potential duration of payments equals 1095 days (insurance coverage is based upon French Social Security guarantees). To simplify, say that each day corresponds to a payment of 1 US\$. The real-life database we consider reports the claims of income protection guarantees over six

years, from 12/31/2005 to 12/31/2011. It consists of 65 670 claims, with the following information for each claim: a policyholder ID, cause (57 131 sicknesses, and 8 539 accidents), gender (14 455 males, 51 215 females), socio-professional category (SPC: 2 406 managers, 62 799 employees and 465 miscellaneous), age at the claim date, duration in the disability state (perhaps right-censored), commercial network (three kinds of brokers: 28 662 “*Net-A*”, 4 890 “*Net-B*” and 32 118 “*Net-C*”). All insurance contracts considered have a common deductible of 30 days, and the overall censoring rate equals 7.2% at 12/31/2011. The mean observed duration in the disability state is about 100 days (beyond the deductible of 30 days), with a median of 42 days. There is strong dispersion among the observed durations, the standard deviation being 162 days. Our goal is to predict the global capital to reserve, either by Chain Ladder or by our algorithm. In the latter case, it consists in predicting the residual lifetime in the disability state for each policyholder (given the individual features), knowing that this duration fully explains the claim amount here, like in most of countries for this type of insurance contracts in Europe.

3.2 Building the database, and implementing

Reserves are periodically estimated, say each quarter between 12/31/2009 and 12/31/2010. Therefore, for every date, we look at the status of the claim (open, closed, new) since policyholders’ health is likely to deteriorate, remain stable, or improve between two consecutive quarters. This process allows to regularly update the characteristics of claims, in particular report the newly declared claims, those that become settled, and the remaining ones (RBNS) requiring an updated computation of the corresponding reserve for coming periods. Figure 1 illustrates, for three policyholders, how data are built through the historical pattern of claims. Estimation of the global reserve is made within our two frameworks, namely the Chain Ladder model and our weighted algorithm. Building the data this way, it is straightforward to get classical loss triangles so as to implement Chain Ladder technique given origin periods (quarters). Concerning individual claim reserving, it consists of using the algorithm described in Section 2.2 at the following dates: 12/31/2009, 03/31/2010, 06/30/2010, 09/30/2010, and 12/31/2010.

Let us now comment the different examples given in Figure 1. The first employee is a woman that suffered from sickness on 01/18/2008. Payments started on 02/17/2008. The insured’s absence lasted 57 days, terminating on 04/14/2008. When looking at the situation on 12/31/2009, this observation is thus not censored (this can be seen from the boolean *2009-12-31.NonCensure*, set to ‘true’). In this case, there is nothing to reserve

Sex	SurvDate	Cause	ComNet	BegIndDateW	EndIndDateW	BegAgeW	EndAncIndW	NonCensure	SPC
F	2008-01-18	Sickness	Net_A	2008-02-17	2008-04-14	51.96441	57	TRUE	Employee
F	2009-05-06	Sickness	Net_C	2009-06-05	2010-07-29	42.68583	419	TRUE	Employee
F	2009-03-16	Sickness	Net_C	2009-04-15	2011-12-31	50.09993	990	FALSE	Employee
2009-12-31.NonCensure				2009-12-31.EndObsW	2009-12-31.PredictCART	2010-03-31.NonCensure		2010-03-31.EndObsW	
	TRUE			57		NA		TRUE	57
	FALSE			209		239.7403		FALSE	299
	FALSE			260		234.5195		FALSE	350
2010-03-31.PredictCART				2010-06-30.NonCensure	2010-06-30.EndObsW	2010-06-30.PredictCART		2010-09-30.NonCensure	
	NA			TRUE		57		NA	TRUE
	226.4615			FALSE		390		234.7112	TRUE
	232.1991			FALSE		441		225.1316	FALSE
2010-09-30.EndObsW				2010-09-30.PredictCART	2010-12-31.NonCensure	2010-12-31.EndObsW		2010-12-31.PredictCART	
	57			NA		TRUE		57	NA
	419			NA		TRUE		419	NA
	533			215.8923		FALSE		625	200.5426

Figure 1: Three claims with their pattern of payments, showing how we build the database.

since the claim was settled and all payments were made (57\$). That is why this observation is never censored and prediction from the weighting CART algorithm is useless, whatever the quarter under consideration.

The second policyholder, with a total sickness lifetime of 419 days, is an interesting example since it will typically enable us to backtest our future predictions. Indeed, the censorship indicator changes as time flies. The global censorship indicator indicates that this observation is fully observed in 12/31/2011 (the claim was settled on 07/29/2010). However, this is not the case when looking for instance on 12/31/2009. At that time, this employee is considered a censored observation: 209 days were already paid, but the claim is not closed. Backtesting shows that there are still 210\$ to pay for, whereas weighted CART algorithm predicts that nearly 240\$ should be reserved. One quarter later, i.e. on 03/30/2010, updates are made: actual payments were increased by 90\$ (three months), and CART prediction equals 226\$ for this individual reserve. Six months later (09/30/2010), the observation gets uncensored for the first time. There is thus no further prediction to provide, but this information is used by our algorithm (updating the KM weights given to other uncensored observations to perform the estimation).

Finally, the third example remains censored from the beginning to the end of the period where reserves are calculated (quarters from 12/31/2009 to 12/31/2010). Moreover, the claim is still open on 12/31/2011, and total payments exceed 950\$ (990\$ exactly). In this case, which seems to correspond to an extreme observation (recall the mean duration equals 100 days, and that the maximum equals 1095), notice that the weighted CART algorithm anticipates that there are still about 200\$ to reserve, knowing that 625\$ have already been paid. This statement reveals that our algorithm somewhat captured this extreme situation, which is all the more interesting that most expensive claims are often the longest ones in practice.

3.3 Results on Boni-Mali and discussion

How to compute individual reserves has been explained in Sections 2.2 and 3.2. The aggregation of such reserves leads to approximate the expectation of the total reserve over the whole portfolio, at some given dates. This prediction can be compared to the Chain Ladder one for RBNS claims, for our five dates of interest (12/31/2009, 03/31/2010, 06/30/2010, 09/30/2010, and 12/31/2010). Figures 2 and 3 show the evolution of the different estimations, and several interesting remarks can be formulated.

First, the estimation of the ultimate cost of claims over the entire portfolio looks consistent, whatever the technique used (compare each bar to the last one, named “Ultime”). This is not surprising since the censoring rate is not so high (recall that it roughly equals 7%), which limits the interest of our method. Indeed, given that we focus here on RBNS claims to estimate the corresponding reserve, Chain Ladder can access almost the full information. However, it seems that long-tailed risks associated to a higher censoring rate would significantly increase its bias, leading to poor estimates of the ultimate costs and thus the global reserve.

Second, how to reach the ultimate cost is very different, depending on the technique under consideration. When using Chain Ladder, the global reserve provided at 12/31/2009 is clearly underestimated as compared to the one given by the weighted CART algorithm (compare the orange hatched area for Chain Ladder versus the green dotted one

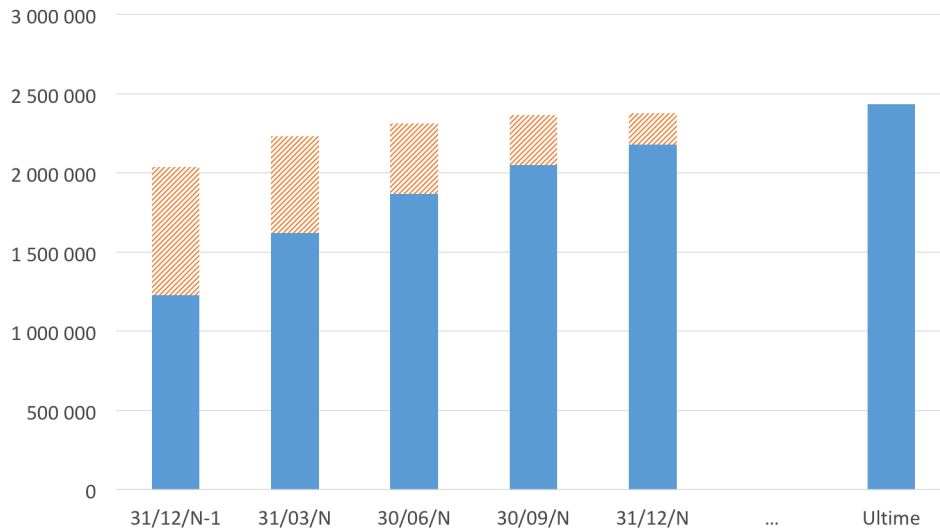


Figure 2: Barplot of the evolution of reserves estimated by Chain Ladder (‘N’ refers to the year 2010). For each bar, the filled area is the amount already paid, whereas the hatched one is the estimated reserve.

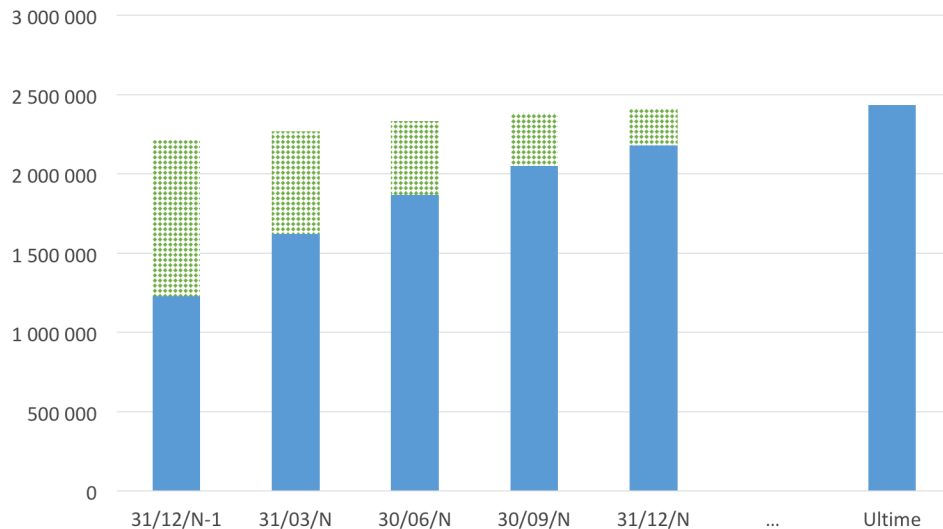


Figure 3: Evolution of reserves estimated by the weighted CART algorithm ($N=2010$). See the legend of Figure 2 for further details.

for weighted CART). People with high lifetimes were not overweighted with the standard Chain Ladder approach, since the pattern of individual claims is not taken into account. The global reserve is, by consequence, largely underestimated. On the contrary, weighted CART predictions lead to anticipate higher reserves from the beginning, which is interesting since potential future liquidity needs are then decreased. Looking at *boni-mali* indicators between each period confirms this, are summarized in Table 1. Clearly, the weighted CART algorithm is powerful on such a criterion, and capital injection needs would be impressively decreased (almost 150 000 US\$ would be saved in this case on an annual basis). Notice that this statement is not true for the last quarter under study, which was expected since the censored part of the lifetimes decreases little by little.

Another way to illustrate errors from both models is given in Figure 4. We compare prediction errors on both ultimate claims amount (solid line) and reserves (dotted line). Our method appears to be dominant, especially for the first estimations. This result is quite interesting since, beyond being able to predict individual reserves, their aggregation leads to better apprehend the overall need of reserves.

Boni (+) / Mali (-)	T1	T2	T3	T4	Annual
Chain-Ladder	-196 814	-80 173	-51 209	-14 394	-342 591
Weighted CART	-58 515	-65 743	-51 989	-21 801	-198 047

Table 1: Boni-mali indicators: *mali* require capital injections.



Figure 4: Errors (in %) of Chain Ladder method (lines with square marks) and weighted CART algorithm (lines with cross marks), at different dates of estimation. Solid lines correspond to the ultimate claim amounts, and dotted lines concerns the reserves.

4 Concluding remarks and on-going research

In this paper, we proposed a new simple algorithm based on nonparametric techniques to estimate RBNS claims in non-life insurance. Such techniques have a lot of advantages, the greatest one being that they allow to integrate the history of claims in the final estimation without specifying a parametric relationship. Our estimator is more responsive to any changes in the development patterns of claims, which makes it naturally adapted to long-tailed claim developments (e.g. in Third Party Liability insurance). Practically speaking, this is extremely important since experts know that the final claim amount is highly dependent on the final development time. However, using our algorithm requires a comprehensive database which is not always available in reserving departments, and has to be built by gathering information from different services. When working with very short-term and well-known risks, Chain Ladder and its extensions still seem to be a better trade-off to estimate the total reserve. Of course, our technique could be improved in several ways. We first think about the extension to the assessment of risk measures, and uncertainty of predictions.

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