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Cash flow generalisations of non-life insurance expert systems estimating outstanding liabilities

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A R T I C L E I N F O

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A B S T R A C T

For as long as anyone remembers non-life insurance companies have used the so called chain ladder method to reserve for outstanding liabilities. When historical payments of claims are used as observations then chain ladder can be understood as estimating a multiplicative model. In most non-life insurance companies a mixture of paid data and expert knowledge, incurred data, is used as observations instead of just payments. This paper considers recent statistical cash flow models for asset–liability hedging, capital allocation and other management decision tools, and develops two new such methods incorporating available incurred data expert knowledge into the outstanding liability cash flow model. These two new methods unbundle the incurred data to aggregates of estimates of the future cash flow. By a re-distribution to the right algorithm, the estimated future cash flow is incorporated in the overall estimation process and considered as data. A statistical validation technique is developed for these two new methods and they are compared to the other recent cash flow methods. The two methods show to have a very good performance on the real-life data set considered.

1. Introduction

The non-life insurance business is an important part of the economy for most developed countries with market revenues amounting to around five percent of GNP's. The best estimate of outstanding liabilities - often called the reserve - is perhaps the single most important number on the balance sheet of most non-life insurance companies. Insufficient reserves is one common reason for non-life insurance companies to go broke. A mismanaged reserving process can also lead to spurious and volatile yearly results leading to uninformed management decisions. Finally, a smoother and more transparent reserving process leads to significant cost savings in almost any non-life insurance company.

In this light it is perhaps surprising that statistical models for the most often used data set, the incurred run off triangle, are rarely considered in the literature. Incurred data is a mixture of historical payments of already settled claims and predicted severities of reported but not settled claims. The predicted severities are based on all available expert opinion in the company and are called case estimates. In that spirit, incurred data has added information about reported claims which are not available when only historical payments are considered. Actuaries often prefer working with chain ladder on the incurred triangle rather than on historical payments. But it is a bit unclear what this really means in terms of mathematical statistics. While incurred chain ladder probably makes good sense in a deterministic forecasting framework, the stochastic nature of the expert opinion in incurred data is not taken into account by this practice.

There is a little literature acknowledging the added value of incurred data: the probably most famous Munich chain ladder approach by Quarg and Mack (2004), regression approaches by Halliwell (1997), Halliwell (2009), Venter (2008), and a paid-incurred chain reserving method by Posthuma, Cator, Veerkamp, and van Zwet (2008), Merz and Wüthrich (2010), Happ, Merz, and Wüthrich (2012) and Happ and Wüthrich (2013). These eight papers combine payment data and incurred data into one statistical model resulting in one reserve estimate. However, none of those papers take the common micro-structure of payment data and incurred data into account. Payment data and incurred data are both constructed via manipulations on the same underlying data; incurred data with the extra element of expert knowledge on expected future cash flows.

To model this relationship one needs micro-structural assumptions about the underlying claim process. Pigeon, Antonio, and Denuit (2014) does exactly this. It is based on a recent trend to use so called granular data or micro data for reserving, see Antonio and Plat (2014) for one of the most interesting recent contributions in that area. See also Martínez-Miranda, Nielsen, Sperlich, and Verrall (2013a) for a continuous interpretation of the classical chain ladder

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methodology. While these approaches indeed seem to be favorable, they are not well established yet and rely on data and granular information that is most often not available at hand.

Double chain ladder, introduced in Martínez-Miranda, Nielsen, and Verrall (2012), builds on micro-structural assumptions but does not need granular data in the estimation procedure. It is based on the methods of Verrall, Nielsen, and Jessen (2010) and Martínez-Miranda, Nielsen, Nielsen, and Verrall (2011) where the objective was to only rely on data that is already available in most reserving departments. It uses additional information of claim counts which is another triangle most often available in the data portfolio of a reserving department. The result is a full statistical model based on historical payments and counts capable of incorporating the information of the incurred data in a natural way.

Agbeko, Hiabu, Martínez-Miranda, Nielsen, and Verrall (2014) recently introduced a model reproducing the deterministic results of the earlier mentioned chain ladder method on incurred data by incorporating the incurred data expert opinion into the well-defined full stochastic model of double chain ladder. One direct advantage of this approach is that the chain ladder model based on paid data can be validated against the chain ladder model based on incurred data. While the paid chain ladder and incurred chain ladder methods have been available for a long time as part of almost any non-life actuary's tool kit, it has never before been possible to compare them against each other when only the typical aggregated data were available.

Two other methods of incorporating expert knowledge of incurred data into these full cash flow models have been introduced in Martínez-Miranda, Nielsen, and Verrall (2013a) and Hiabu, Margraf, Martínez-Miranda, and Nielsen (2016). The first of these two methods is extracting the inflation of the cost of a single claim from the incurred data and then incorporates that information in the double chain ladder model of Martínez-Miranda et al. (2012). The second of these two methods suggests to incorporate a RBNS-preserving property. RBNS stands for Reported But Not yet Settled, and it can be estimated by the sum of all case estimates. This estimate is the best the claims department of an insurance company (with all the expert knowledge on the nature and severity of each claim available in such a department) is able to do. Hiabu et al. (2016) therefore produced a version of double chain ladder reproducing exactly the expert judgement of the RBNS reserves.

All those mentioned double chain ladder extensions take advantage of the underlying structure of the incurred data, extract the relevant information from it and plug it into the original double chain ladder method. The advantage of this approach is that the simplicity and intuition of the simple chain ladder method is preserved and that the full statistical interpretation and stochastic cash flow formulation is inherited from double chain ladder.

The two new stochastic cash flow methods developed in this paper build on the ideas and techniques of Hiabu et al. (2016). The first one treats the expert knowledge of the incurred data as real data and incorporates it into the model, the second builds a second RBNS preserving cash flow model on top of this method. The approach is first to unbundle the incurred data to get back to the original aggregated RBNS numbers. These aggregated numbers are re-distributed according to the estimated delay such that the resulting algorithm takes both historical data and expert data into account in the final estimation. We therefore let the estimated future cash flow be incorporated in the overall estimation process by considering it as data. Note that both of these two new methods are cash flow models of the same nature as the models considered in Agbeko et al. (2014), and they can therefore be validated and compared to the models considered there. In the applied data example, this validation indicates, that the two new methods seem to take better advantage of the incurred expert data than previous methods did.

Recent years have seen a growing interest in expert systems related to non-life insurance, see for example Belles-Sampera, Guillén, and Santolino (2014) and Abbasi and Guillén (2013), who consider ways of understanding risk in non-life insurance. Guelman and Guillén (2014) work with pricing of insurance claims and the customers sensitivity to that price; Guillén, Nielsen, Scheike, and Pérez-Marín (2012) and Kaishev, Nielsen, and Thuring (2013) transfer knowledge from one business line to another to optimize cross-selling. Human judgement is important in all these insurance applications. When prices are set, there is a business intelligence department evaluating how much weight to put on the model at hand and how much weight to put on market prices as such. When risk is evaluated, human judgement calibrates the entering parameters. And when RBNS claims reserves are set, then there is an element of human judgement in the settlement of every single claim. It is also a human judgement when it is decided to use model based claims reserves for some subset of the claims, for example the smaller ones.

We conclude this introduction by noting that Martínez-Miranda et al. (2012) has two versions of double chain ladder; one version where the delay is not adjusted and another where it is adjusted. In this paper only the unadjusted version of double chain ladder is considered. One reason for the adjustment of the delay in Martínez-Miranda et al. (2012) was to improve the performance of estimating the out-of-sample tail reserve. While this is a very important issue, it is beyond the scope of this paper to consider the out-of-sample tail reserve.

The rest of the paper is structured as follows. Section 2 describes the data and the expert knowledge, introduces the notation and defines the model assumptions. Section 3 discusses the outstanding loss liabilities point estimates. Section 4 describes four methods to estimate the parameters in the model: DCL, BDCL, PDCL, IDCL, EDCL and PEDCL. An application is considered in Section 5 and the validation of the six methods against each other is gone through in Section 6. Finally, Section 7 provides some concluding remarks.

2. Data and first moment assumptions

This chapter introduces the data used in maybe every insurance reserving department to calculate their outstanding liabilities. Also the methods described in this paper rely on these data sets. They are often shortly called run-off triangles. These run-off triangles are the aggregated incurred counts (data), aggregated payments (data) and aggregated incurred payments (mixture of data and expert knowledge). All of those three objects have the same structural form, i.e., they live on the upper triangle

$$\mathcal{I} = \{(i, j) : i = 1, \dots, m, j = 0, \dots, m-1;\ i + j \le m\}, \quad m > 0,$$

where m is the number of underwriting years observed. The parameter m also has another crucial role. If no tail-factors are considered, which will be assumed throughout this paper, then $m-1$ is the maximum delay, that is the time from the underwriting of the policy a claim is based on until its payment. This assumption is called being run-off, hence the name run-off triangles.

Let's first introduce the two data triangles.

Aggregated incremental incurred counts: $N_{\mathcal{I}} = \{N_{ik} : (i, k) \in \mathcal{I}\}$, with N_{ik} being the total number of claims of insurance incurred in year i which have been reported in year $i+k$, i.e. with k periods delay from year i.

Aggregated incremental payments: $X_{\mathcal{I}} = \{X_{ij} : (i, j) \in \mathcal{I}\}$, with X_{ij} being the total payments from claims incurred in year i and paid with j periods delay from year i.

A often confusing point is that the meaning of the second coordinate of the triangle $\mathcal{I}$ varies between the two different data. While in the counts triangle it represents the reporting delay, in the payments triangle it represents the development delay, that is reporting delay plus settlement delay.