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Individual claim reserving models

Adding value

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Individual claim reserving models are ready to complement aggregate triangle-based models, improving the reliability of reserve estimates and providing further insight into the drivers of claims and claim development

Loss reserving for general insurance is traditionally based on aggregate triangle-based models (ATBMs), which use a single runoff triangle as a simple representation of the activity of several cohorts of claims over their respective lifetimes. ATBMs may generate material errors in the reserve estimates when portfolio characteristics of claims cohorts inherent in the triangle data change over time in unanticipated ways. Individual claim models (ICMs) is an emerging area of research and practice that uses individual claim level data to estimate loss reserves.

Evolution in technology with respect to efficient data collection, storage and analysis has made ICMs more accessible. To date, there is convergence neither with respect to an ICM analysis framework nor to the universe of model parameter assessment and validation techniques. Further, the amount of expert judgement required in an ICM analysis can be substantial. Nevertheless, the use of valuable information embedded in individual claim data is a promising feature of the approach that should lead to more reliable loss reserve estimates. Highly reliable loss reserve estimates are accurate, reproducible and consistent over time.

Reliable estimates of loss reserves are essential for insurers to price their insurance products efficiently and to maintain adequate capital. Therefore, entities that are implementation leaders in the ICM space are likely to enjoy distinct market advantages relative to implementation laggards.

We discuss in this note a useful framework for ICMs, as presented at the 2018 International Congress of Actuaries in Berlin and the 2018 GIRO Conference in Birmingham.

It should be noted that there is still further research and development to be done in the field of ICMs and, at this stage, ICMs are not ready to supersede ATBMs. However, ICMs are ready to complement ATBMs, improving the reliability of reserve estimates generated using ATBMs and providing further insight into the drivers of claims and claim development.

Limitations of ATBMs

ATBMs work well in relatively stable contexts (i.e., the proportions of different claims types within a homogenous segment, such as bodily injury claims and property damage claims within a motor insurance segment, remain relatively stable) and for portfolios where the volume of claims ensures stability of development factors despite the inevitable larger claims experienced. However, for the vast majority of general insurance business analysed, such stability is rarely observed, which means an actuary’s confidence in the reserve estimates based on ATBMs can be low and the following limitations become important:

1. Loss of information when aggregating original claims data details for use in ATBMs.
2. ATBMs use a rigid structure of cumulative amounts with consistent cohorts of claims[1] that are evaluated at consistent intervals over time.
3. ATBMs are overly dependent on the average age within a cohort of claims, while alternative explanatory variables may possess significant signal.
4. ATBMs are poorly equipped to identify and account for changing levels of estimation bias.
5. ATBMs exhibit large estimation errors for the least mature cohort of claims.

There are techniques that have evolved in order to overcome some of these limitations. Underlying differences in actual versus expected development can be accounted for via segmentation decisions, subjective assessments of the perceived value of shorter-term as opposed to longer-term metrics, and use of credibility weighting with an a priori loss ratio (i.e., implementation of methods based on the Generalized Cape Cod or Bornhuetter-Ferguson approaches).

[1] Based on the period of a claim's occurrence for an accident year (AY) analysis, on the period of claims manifestation for a report year (RY) analysis (e.g., often used for claims-made coverage), or on a period associated with underlying exposures for an underwriting year (UY) or policy year (PY) analysis.

Potential benefits of ICMs

ICMs are most effective as a complement to existing models in a loss reserve analysis. They are already more effective than ATBMs in the context of deeper-dive analyses supporting the underwriting process. We are not proposing to discard ATBMs and immediately adopt ICMs, but there are some significant benefits that make immediate implementation worth considering.

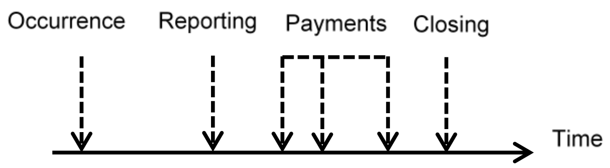
1. Use of information not used by ATBMs can lead to an increase in the reliability of loss reserve estimates.
2. Even if the indications from ICMs might seem suspect pending the development of concrete case studies, use of the ICM process can enhance the understanding of the drivers of development and of the associated uncertainty.
3. The enhanced understanding of development drivers adds value to the underwriting process and establishes more stable links between the pricing and reserving processes.
4. As no model or method is perfect, ICMs provide additional loss reserve indications that process the un-aggregated data and that are independent of the ATBMs currently in use, with the valuable side benefit that components of the ICM indications can be examined in order to understand differences.

Explaining complex ICMs to non-actuaries can be a challenge. The multiple levels of calibration required (i.e., decision points) during the modelling process can lead to a perception that ICMs offer a black-box solution. We can take steps to overcome this significant limitation by employing an understandable framework and documenting the multiple decision points (technique used, statistical significance, etc.).

A framework for modelling

In order to proceed, one needs a framework able to capture and use the characteristics of individual claims, and which can account for the observed activity in the life of an individual claim. Continuous time modelling provides the most precise description of the portfolio time pattern. The mathematical tools at the core of the model specification lie in the family of continuous-time stochastic processes, which model all types of activity related to an individual claim, including the time at which the claim occurs; its reporting delay; a series of case reserves assessments and payment amounts while the claim remains open; and its closing time (see Figure 1). Additional flexibility can be built into the framework in order to account for other specificities as needed, such as salvage and subrogation recoveries and reopening tendencies.

FIGURE 1: TYPICAL INDIVIDUAL CLAIMS PATHS



Grouping data

An early step in the process is to classify the entire individual claims data set into a finite number of subgroupings. This step can account for preconceived notions regarding different claims types (e.g., heads of damage for motor insurance), different policyholders (e.g., members of different professions for professional indemnity coverage), or any combination of explanatory variables. A number of techniques are available to support the evaluation and decision process. In particular, with respect to the integration of explanatory variables, cluster techniques in the field of machine learning can be leveraged to test and assess claims heterogeneity and support the identification of homogenous subgroups.

Not surprisingly, the individual claims in each subgroup should be similar and the subgroups should be different from one another. Credibility can be heightened by increasing the number of claims within each subgroup. A subgroup of claims should be large enough to be statistically reliable. Obtaining homogenous subgroupings requires refinement and partitioning of the data set. There is a point, however, at which further partitioning divides the data set into subgroups that are too small to provide credible model parameters. Considerations regarding the trade-off between homogeneity and credibility are also relevant for ATBMs, but granular grouping decisions are less limiting for ICMs as the number of observations (i.e., the number of claims) is orders of magnitude larger than the number of observations in ATBMs.

The exploratory data analysis used to determine the subgroups can unlock valuable insight regarding the behaviour of different types of claims in the data set and, in some cases, identify variables that impact the development. Such insight not only supports the reserving process (both ICMs and ATBMs) but also future underwriting decisions.

Although statistical techniques can guide grouping decisions, as always it is essential to assess the usefulness and rationality of the selected subgroups.

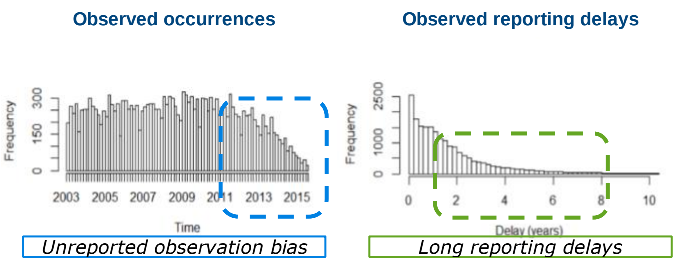
Estimation of parameters

The assessment of ICM parameters allows for detailed monitoring of key risk indicators, which are otherwise hidden in the aggregate development factors and related volatilities of ATBMs. Estimated parameters exhibit natural explanatory powers, and separate payment distribution specifications can provide information on the building blocks of the overall claims development path.

In order to estimate the parameters for each grouping of an ICM, a calibration procedure is performed, based on maximum likelihood. Deriving likelihoods for various claims activities associated with the observed claims data set is a challenging step due to sampling bias, as open claims only provide partial information and unreported claims provide no information with respect to claims activity. That said, the number of data points available enables advanced optimisation procedures, combined with goodness-of-fit analyses, which result in both increased confidence in the modelled output and precise identification of the drivers of uncertainty.

Occurrence intensity and reporting delay are jointly modelled, which leads to unbiased parameters, i.e., allowance for incurred but not yet reported (IBNyR) claims, therefore correcting for the sampling bias (see the blue dash line box in the left graph of Figure 2). Occurrence activity is modelled by a Poisson process with a given (time-varying) intensity, such that each claim is associated with a reporting delay assumed to follow specific distribution.

FIGURE 2: SAMPLING BIAS IN THE CLAIMS DATA SET



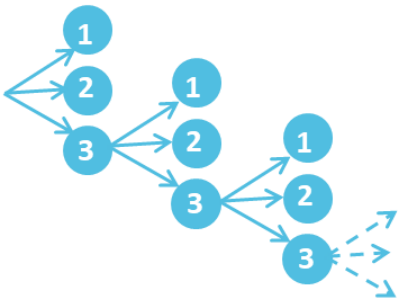
For payments and settlement, we can use the following convenient specification[2]. Model parameters allow the simulation of the stochastic future payment path, for both open claims and unreported claims, by defining three possible events at each future time unit (i.e., development period) in the life of a claim, namely:

1. Settlement without payment at settlement.
2. Settlement with payment at settlement.
3. Payment without settlement.

[2] As introduced in the paper 'Micro-level Stochastic Loss Reserving for General Insurance' by Antonio and Plat (2014).

Note that, according to this specification, only a claim modelled as event type 3 continues down the path to the next possible event (see Figure 3).

FIGURE 3: THREE POSSIBLE EVENTS AT EACH TIME UNIT



Each type of event (1, 2, or 3) for each subgrouping occurs according to its specific (time-varying) intensity parameter $h_1(v)$, $h_2(v)$, and $h_3(v)$, where v refers to the number of time units after reporting (in continuous time). Therefore, at each time unit, the proportion of each event type i is given by $h_i \,/\, (h_1 + h_2 + h_3)$. Conveniently, this approach also gives information on the modelled timing of events, as, for example, the time to wait between two intermediary payments (3) is $1 \,/\, h_3$ on average, and the time to wait between two events (of any type) is $1 \,/\, (h_1 + h_2 + h_3)$.

AN EXAMPLE

For a calibration with intensity parameters for a given time unit of h_1 = 0.5, h_2 = 3.5, and h_3 = 1.0:

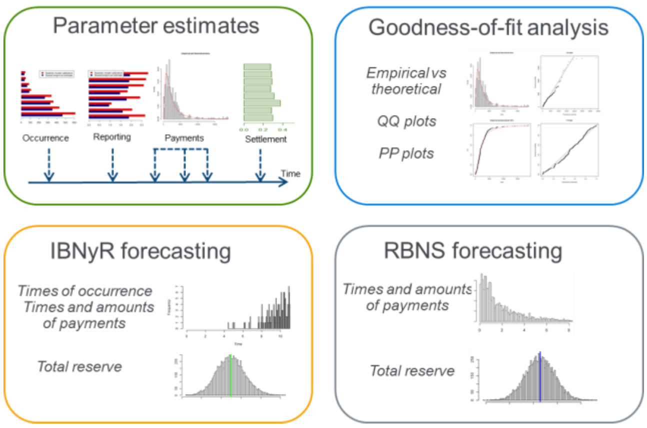
- 10% of the open claims experience a settlement without payment = 0.5 / (0.5 + 3.5 + 1.0).
- 70% of the open claims experience a settlement with payment = 3.5 / (0.5 + 3.5 + 1.0).
- 20% of the open claims experience a payment without settlement = 1.0 / (0.5 + 3.5 + 1.0).
- The number of time units between two payments without settlement is 1.0 = 1.0 / 1.0.
- The number of time units between any two events is 0.2 = 1.0 / (0.5 + 3.5 + 1.0).

Forecasting

Once parameters have been calibrated and goodness of fit tests completed, simulation procedures draw on stochastic paths of the future development of open and future reported claims. ICMs allow a practitioner to forecast future events in a very efficient way. The patterns in terms of claims reporting and time units between events can be set as general as possible.

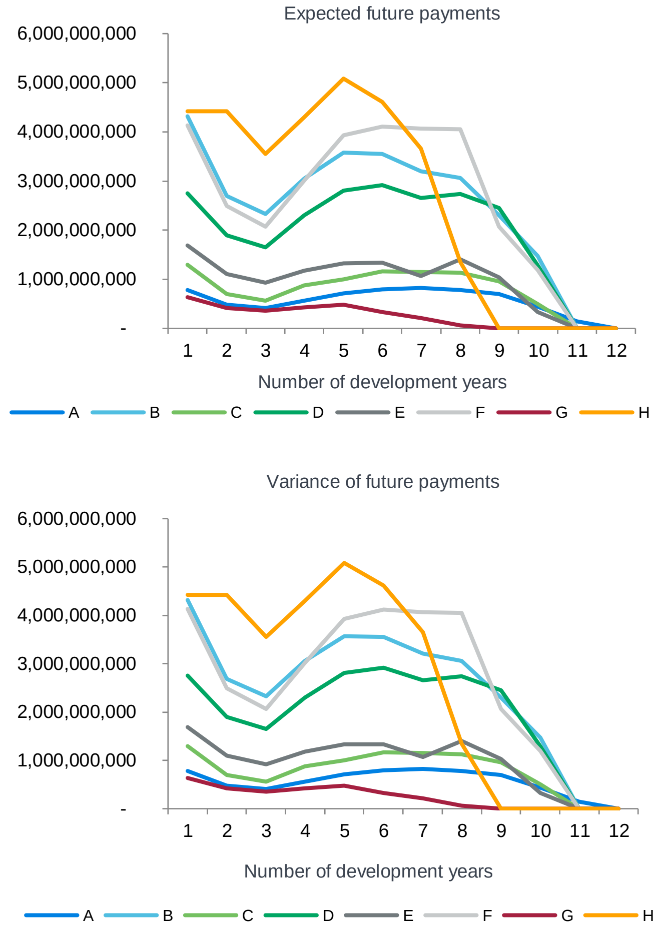
The methodology also allows for closed-form solutions that provide overall unpaid claim estimates and the associated confidence intervals in a straightforward way. The ICM methodology leading to the forecast for both incurred but not yet reported (IBNyR) and reported but not settled (RBNS) claims is depicted in Figure 4, which is a bifurcation of the reserve estimate associated with future reported claims and existing reported claims, respectively.

FIGURE 4: INDIVIDUAL RESERVING METHODOLOGY



The ICM forecast provides, for each subgroup and time unit, the expected payment (for events 2 or 3) and associated variance, which can be computed using either Monte Carlo simulations or closed form solutions (see example in Figure 5). Indeed, being able to compute such quantities in closed form is an appealing property of claims reserving models, which most ATBMs enjoy[3]. As such, ICM average prediction amounts and their corresponding risk indicators can be computed in a simple spreadsheet[4].

FIGURE 5: MODELLED EXPECTED FUTURE PAYMENT AMOUNTS AND RELATED PREDICTION VARIANCE, CONDITIONAL ON CLAIMS DEVELOPMENT YEARS FOR EIGHT (A THROUGH H) MEDICAL MALPRACTICE SUBGROUPS (ILLUSTRATIVE)



Once the frequency and severity, with their associated variances, have been combined, an assessment of the drivers of loss reserves can begin, including the relative importance of the number and amount of unreported claims for each modelled subgroup. Further, comparisons of the ICM indicated loss reserve with indications from ATBMs can take place, reconciling differences on a granular level.

[3] For example, see Mack's paper 'Distribution-free Calculation of the Standard Error of Chain-ladder Reserve Estimates' (1993).

[4] Further details can be found in 'Individual Claims Reserving: A Survey' by Boumezoued and Devineau (2017).

Assessing uncertainty

To date, comparisons of ICMs and ATBMs with respect to the assessment of uncertainty have provided a mixed message.

ICMs often exhibit a reduced estimation error (relative to ATBMs). ICMs take advantage of the detailed claims information in order to calibrate parameters according to a more natural specification, which avoids errors of parametrisation that can occur at the aggregated level. In several case studies, ICMs exhibit a substantial reduction in estimation error compared to ATBMs[5]. The process error, which relates to the pure randomness of the model, is also often reduced for the standard ICM. The specification of ICMs can also be enriched by choosing an alternative (i.e., more dispersed) stochastic framework, for example by switching from Poisson modelling to an over-dispersed counterpart (involving a stochastic intensity and/or other inter-arrival distributions). Such flexibility can be advantageous in situations where the original data volatility is not sufficiently reproduced by a Poisson framework. It can be particularly useful in the calibration and assessment of distributions of possible outcomes associated with a reserve estimate.

On the other hand, uncertainty indications from ICMs observed in many published case studies are uncomfortably low, in that the resulting coefficients of variation (CoVs) are significantly less than those produced by ATBMs. While the measurement of individual uncertainties for ICM parameters is sound, the aggregation of these uncertainties is a challenge that warrants further research. ICM modelling is completed on a more granular basis (i.e., for each subgroup and time unit), so the number of frequency and severity parameters (i.e., individual uncertainties) is large and the interrelationships, while measureable, are notwell understood. Recent research involving the back-testing of ATBMs using real data convincingly shows that ATBMs systemically underestimate actual reserve uncertainty. We are currently unaware of similar research, to back-test ICMs, having been successfully completed.

While the uncertainty indications from ICMs may be uncomfortably low, comparisons of relative uncertainty across the subgroups within an ICM still provide tremendous value to the underwriting process.

Step-by-step implementation of an ICM process

ICMs are a new way for actuaries to measure and manage risks efficiently, and are very promising as a complement to existing reserving models. To meet the associated challenges, Milliman has designed an integrated reserving process covering data needs, modelling and risk monitoring:

- **Data collection and preparation:** Organise a standardised collection strategy focusing only on the claims data used by the ICM, and perform the data transformation needed to feed the ICM.
- **Model specification and calibration:** Specify the model components to be addressed and the transformed data, according to the line of business (and sub-line groupings), and estimate the parameters of the ICM using advanced optimisation procedures combined with goodness-of-fit analysis.
- **Model simulation and validation:** Forecast unreported claims (i.e., IBNyR) and future development on open claims (i.e., RBNS) using efficient simulation algorithms, and perform a model validation process based on back-testing procedures and comparisons with ATBMs and benchmarks.
- **Reserve risk dashboard:** Claims path parameters are visualised through an automated dashboard in order to monitor periodically the key indicators and to leverage information in order to improve management actions.

This integrated reserving process allows users to assess why things happened—that is, to identify the underlying drivers that caused changes in aggregate payments. This can also lead to a reassessment of ATBM forecasts and their associated uncertainty. ICMs can add value to an insurer's reserving process as well as enable reserving actuaries to contribute more confidently to conversations regarding the portfolio performance at a granular level.

There are two key components to a successful implementation of ICMs:

1. Strong modelling expertise.
2. An optimised and rigorous data collection process.

Even if the integration of ICM techniques within the landscape of reserving is neither immediate nor obvious, there is no doubt that these models will become a strong paradigm in which to evolve in the near future.

[5] Boumezoued and Devineau (2017), ibid.

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