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A New Method to Derive PBA Prudent Estimate Assumptions from Company Experience

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With the introduction of a principle-based approach (PBA) to valuation, actuaries in a financial reporting role have inadvertently also become risk managers. PBA valuation is based on the premise that reserves have to reflect the riskiness of the business. What might appear to be a scary proposition also bears within it the potential to open up a whole new and exciting field of work and the ability to integrate the tools used in finance, risk management and even product development into a holistic view of life insurance business. The level of detail which NAIC's Valuation Manual 20 prescribes in the derivation of PBA "prudent estimate assumptions" may not be suggestive of such an innovative view, but if we take a small step back and ask a couple of fundamental questions, a wide field of potential innovations opens itself up to us.

PBA VALUATION REQUIREMENTS

Let's take a look at Valuation Manual 5. According to the NAIC's Model Standard Valuation Law (Section 12 A), a principle-based valuation must be probabilistic, must be "consistent with a company's overall risk assessment process," must "be established using a company's own available experience" where possible and must include explicit "margins for uncertainty, including adverse deviation and estimation error." So, we have a blueprint for building a PBA prudent estimate assumption right there, assuming we can figure out how to quantify estimation error and stochastic uncertainty. This blueprint was exactly the starting point for the case study, "Optimizing Risk Retention,"[1] which Werner Lennartz and I carried out for the SOA's Financial Reporting and Reinsurance Sections. The goal was to develop a method for deriving best-estimate assumptions which allows us to explicitly quantify margins for uncertainty. Knowing these margins accurately would then allow us to study the impact of reinsurance on reserves and capital. The method in question is a statistical tool called Survival Models. For decades this technique has been applied successfully by engineers and statisticians. Currently, it is widely used in the United Kingdom by actuaries working on large longevity risk transfer deals and within pension valuation. Importing this method to the life insurance practice area, we were interested in finding out how useful it would be for life insurance valuation and capital management.

SURVIVAL MODELS

We started off with the mortality experience of one company's term life business and built a survival model for the mortality behavior within this portfolio from seriatim claims experience data as follows.

1. Pick a parametric mortality law[2] in continuous time which matches the general shape of the mortality experience in aggregate;
2. Estimate the parameters of the mortality law by maximum likelihood method; and
3. Use the baseline survival model to identify different risk factors and quantify their impact.

MULTI-DECREMENT ANALYSIS

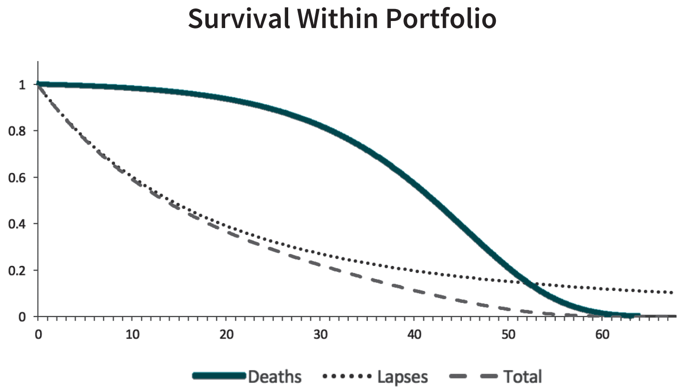
Early on, we realized that if we wanted to calculate life reserves on a realistic basis, we would have to model lapse hazard rates at the same time as mortality, because lapse has an important impact on the overall present value of claims. Luckily, survival models lend themselves naturally to multi-decrement analysis. You can model any decrement which might affect survival (or better: remaining time within the portfolio) and also combine the models for multiple decrements by simply adding their hazard rates. This is the beauty of continuous time models: you don't have to worry about when someone dies or lapses, or which happened first, because you are modeling both simultaneously moment by moment. At any given moment, the policyholder might (randomly) decide to lapse or surrender the policy, or the life insured might die. So, we completed the first three steps above for lapse[3] as well as mortality. Figure 1 (see page 9) illustrates the results for one individual.

IDENTIFYING RISK FACTORS

Note that for both the force of mortality and the lapse hazard model, we have to include a number of different risk factors which influence the mortality or lapse outcomes. One obvious candidate is sex, as we know that females typically have lower mortality rates than males. It is important that we include as many statistically significant risk factors as possible to ensure that we do not underestimate estimation error. Keeping within our simple example, fitting a model for aggregate unisex mortality likely gives a seemingly more accurate fit and smaller estimation error than if we fit curves for males and females separately. The apparently better fit in aggregate, however, is useless because it introduces distribution risk. While the unisex table might work for the exact business mix of policies within the experience data, the sex distribution may shift due to different new business sales or simply because the men lapse and die at higher rates than the insured women. The same problem arises with any set of risk factors which have a significant impact on mortality. For our case study, we found that we had to differentiate between gender, duration, smoking status, underwriting class, product type (10-year term, 20-year term, etc.), face amount band, and whether a policy was rated at issue or was accepted as standard.

The ability to identify different risk factors and quantify their impact is why survival models are so popular for clinical studies. This aspect of our multi-decrement survival model is especially important for PBA valuation, because mapping the different risk groups gives us a grasp on the business mix and how variable the claims for the portfolio will be. The most important source of variability is the fact that different insureds have different financial impacts due to their different policy face amounts.

Figure 1: Remaining time within portfolio for multiple decrements.



Source: Kaufhold and Lennartz (2016). Sample survival curves for a male non-smoker aged 52. Median remaining lifetime 42 years, median remaining time until lapse 15.5 years. End of level term period 10 years.

MEASURING UNCERTAINTY

We capture the variability of results by applying a stochastic Monte-Carlo simulation in two steps. First, we take the parametric model which describes the best-estimate mortality and lapse behavior of the portfolio and give the parameters a little "jolt." In other words, we randomly perturb the parameter set in a way which is consistent with the experience data. The perturbed parameters then describe mortality and lapse behavior which is a little different from the best-estimate, but which also could have materialized. So, we have created an alternative scenario consistent with the experience data.

Within this perturbed scenario, we know the survival curves as well. We can then use these to go through the list of in-force lives and stochastically determine whether they survived until the end of the level term period, whether they died or whether their policy lapsed. To do so, we simply draw a random number between 0 and 1, and then use the survival curve to check which remaining life-time this randomly drawn probability corresponds to. Since it's a two-decrement model, we need two random probabilities and the corresponding times until death and until lapse. If both are longer than the remaining time until the end of the level term period, we have a survivor. Otherwise, we count the event as a lapse or a death, whichever happened first. By going through the entire list of lives, and letting them randomly survive, lapse or die, we can add up what the total present value of claims would have been in our first perturbed scenario.

These two steps are then repeated many times to get a probabilistic distribution of total claims which reflects both the estimation error, which is covered by the perturbations, plus random deviations via the life-time simulations.

Ultimately, we have achieved what PBA valuation requires of us: we have a set of best-estimate assumptions to calculate best-estimate liabilities, and we can quantify exactly by how much we have to increase reserves to allow for uncertainty for any given level of confidence required. If you want to express the margin for uncertainty as padded prudent estimate assumptions, you can also back-solve for the margin by which you have to increase mortality and decrease lapses to get the prudent reserve.

OVERALL RESULTS

Applying the method described above to our term life portfolio in the case study, we found out a number of interesting things:

1. The margin required for reserves at a certain confidence level depended on the business mix. It was different for the different products, with 10-year term requiring the greatest mark-up and longer-term products requiring a lower mark-up.

2. Different portfolio sizes required different levels of prudential provisions with smaller blocks needing a greater reserve buffer. This is totally unsurprising, but a good check that the method makes sense.

3. What did surprise us at first was that reserve margins were hardly affected by reinsurance. We expected to see that reinsuring large policies and thereby reducing the risk would change the risk profile of the business so much that the reserve margin percentage on the retained portion would be a lot lower than on the portion without reinsurance. As it turns out, excess reinsurance has a very strong impact on the level of volatility of annual earnings, and therefore affects solvency capital requirements. However, benefit re-

serves which reflect the present value of claims and premiums over an extended period of time are a lot less sensitive to the life insurer's level of retention, because volatile annual results are smoothed over time. This result also very much depends on business mix. With a greater portion of short-term business, the reserve margins will be greater and will be more sensitive to reinsurance, too.

CONCLUSION

The original intention of the research project was to investigate the impact of reinsurance under modern reserving and solvency capital regimes. In this respect, the key result was that reinsurance has a greater influence on capital levels than on reserve levels, and that reinsurance can actually be used to optimize the return on economic capital which properly reflects the riskiness of the business. An important byproduct of this project is that we had to develop a method for setting reserves which truly reflects the uncertainty associated with setting the mortality and lapse assumptions (estimation error), and the volatility of the business itself (adverse deviation). Our results showed that reserve levels will vary depending on the business mix of the company, and that it is therefore important for life insurers to carry out their own analysis to derive company-specific mortality and lapse assumptions and quantify explicit margins for uncertainty. The method is applicable for small- to medium-sized life companies, just as it is to large life insurers, and can be applied to any kind of insurance risk.

To find out more, please check out the report. If you have any questions or comments, please feel free to contact me. I would be delighted to discuss them with you, because challenge will only make our method better. ■

ENDNOTE

1 https://www.soa.org/Files/Research/Projects/research-2016-quantitative-retention.pdf.

2 The method is called Survival Model, because we estimate the parameters of the mortality law by maximizing the likelihood of future lifetimes ${}_{t_i}p_{x_i}\,(\mu_{x_i+t_i})^{d_i}$ for each individual i, where ${}_{t_i}p_{x_i}$ is the probability of an individual aged x_i surviving t_i years, μ_{x_i} is the individual's force of mortality (a.k.a. mortality hazard rate) and d_i is a status variable which equals 1 if the individual has experienced death (or whichever decrement is being analyzed) and 0 otherwise.

3 For this study, we excluded post level-term experience in order to focus on the regular impact of mortality and lapse. Post level-term lapses and mortality will be the subject of another case study.

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