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Dynamic Assumption-Setting for Variable and Non-Variable Annuities—Part 2

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This article is the second of a three-part discussion that proposes an approach to develop dynamic assumptions for living benefits using a combination of available experience data and predictive modeling techniques.[1] In this article, we will provide an update of the modeling work with respect to full surrenders for variable annuities with guaranteed lifetime withdrawal benefits (VAs with GLWBs) since the publication of Part 1. We will then propose a methodology for applying these results to similar product types with more limited historical data, such as fixed indexed annuities with guaranteed lifetime income benefits (FIAs with GLIBs).

In a future Part 3 article, we plan to use the approaches developed in Parts 1 and 2 to examine FIA with GLIB data and apply the methods to determine a full surrender function for FIAs with GLIBs. We will also discuss possible applications to living benefit utilization assumptions for VAs with GLWBs and FIAs with GLIBs.

PART 1 MODELING ANALYSIS UPDATE

In Part 1, we defined three contract benefit utilization statuses for VAs with GLWBs as shown in Table 1 (below).

In that article, we demonstrated that each of these three contract statuses has full surrender experience significantly different from the other two statuses, as well as being distinct from the full surrender experience for VAs without GLWBs.

In the Part 1 article, a process developing a logistic regression dynamic surrender function was suggested for Statuses A and B. For Status A, using industry data, the resulting logistic regression dynamic surrender function had a "Concordance Statistic" (c statistic) of 0.77, while for Status B, the corresponding value was 0.75. The c statistic represents the percentage of the time the dynamic surrender function correctly predicted a surrender/non-surrender event allowing for an understanding of trade-off between model specificity and sensitivity.

Due to the overall low rates of surrender and minor variation by policy year for Status C, a model was deemed unnecessary at that point.

One goal in developing dynamic surrender functions in Part 1 was simplicity. Here we would also like to present the results of additional modeling that primarily emphasizes improving prediction accuracy with simplicity as a secondary consideration.

As background for the discussion, about 25 years ago researchers discovered that combining results from different predictive algorithms by employing averaging, "voting," and other techniques (now collectively referred to as ensemble modeling) produced significantly better results than any of the individual algorithms independently.[2]

Table 1
VAs with GLWBs Defined Contract Statuses

Benefit Utilization Category	Description	2013 Study Exposure	Comments
Status A	The contract holder has taken no withdrawals to date.	72%	
Status B	The contract holder has taken withdrawals, but the GLWB has not yet been utilized.	11%	This status includes withdrawals taken outside of 90% to 110% of the contractual maximum GLWB with no apparent pattern associated with GLWB utilization.
Status C	The contract holder is utilizing the GLWB benefit.	17%	Both Ruark Consulting and LIMRA consider that a contract is utilizing its GLWB benefit if the contract holder is taking regular withdrawals in the range of 90% to 110% of the contractual maximum GLWB and on a systematic basis.

For our purposes, an ensemble random forest model with 100 decision tree sub-models was built for Status A. Combining the sub-model results using a voting procedure developed a c statistic of 0.91. For Status B, a similar ensemble random forest model, in this case consisting of 1000 decision tree sub-models and a voting procedure, was built resulting in a c statistic of 0.81. While the simpler models are more intuitive, easier to explain, and have faster computer processing time, an ensemble model that incorporates several sub-models may provide the best results when accuracy is at a premium.

Table 2 (below) compares the c statistic and model validation results for the different models.

As mentioned above, although the full surrender rates for Status C were generally near 1 percent or less by policy year with little variation when measured from the contract issue date, we continue to measure experience by different factors as more historical data becomes available. Below we present an examination for contract status C that considers full surrender rates measured from the point of benefit election rather than from the contract issue date. As more data on Contract Status C policies becomes available we believe we should explore the potential advantages of using a modeling approach for this group.

Table 3 (below, right) shows the results measured from the duration of GLWB election based on LIMRA data for 2007 issues during calendar years 2007 through 2013 using the definition of utilization in Table 1.

ADJUSTING VA WITH GLWB RESULTS FOR FIAs WITH GLIBs

In Part 1, we proposed a three-step methodology for developing surrender assumptions for VAs with GLWBs: (1) Develop a set of base surrender assumptions, including unraveling the experience into three contract statuses (A, B and C, as defined above), and identify candidates for key predictors; (2) Construct a predictive model to estimate the impact of changes to base surrenders due to changes in these key predictors; and (3) Build dynamic surrender functions for contracts in each benefit utilization status.

An ensemble model that incorporates several sub-models may provide the best results when accuracy is at a premium.

In this section, we propose a methodology for using the more limited available experience for FIAs with GLIBs, plus other considerations, to adjust the VA with GLWB surrender experience in setting full surrender assumptions for FIAs with GLIBs.

First, we narrow the analysis by assuming that the surrender experience for Status C contracts following VA GLWB/FIA GLIB benefit utilization would be similar. We also assume that FIA with GLIB contracts in Status B are not material, due to the low expected percentage of these contracts in the VA with GLWB experience. The lower growth potential in the account value for an FIA contract with GLIB rider than in a VA contract with GLWB also may make it less likely that policyholders would make withdrawals prior to exercising the GLIB. Therefore, we will focus our analysis on contracts in Status A for this discussion, those contracts that have not begun to utilize the GLWB/GLIB benefit.

Table 2
Model Statistics: Ensemble Model versus Logistic Regression

	Status A		Status B	
	Logistic Regression*	Ensemble Model	Logistic Regression*	Ensemble Model
c statistic**	0.77	0.91	0.75	0.81
% observations predicted correctly	74%	83%	72%	78%

*Logistic regression cut off value = .6
**c statistic measures the concordance coefficient/statistic

Table 3
VAs with GLWBs Contract Status C (Utilizing Benefit)
Issue Year 2007

Duration from Benefit Election	Surrender Rate	% Exposure
1	0.20%	10%
2	0.30%	12%
3	0.50%	15%
4	0.80%	16%
5	0.92%	7%
6	1.10%	18%
7	1.50%	22%
Total	**.72%**	**100%**

Step 1—Develop base surrender assumptions for FIAs with and without GLIBs for Status A. Using predictive modeling tools, determine key predictors for Status A FIA with GLIB full surrenders. Compare these key predictors and base surrender assumptions with the corresponding results for VAs with GLWBs. These comparisons may assist in applying professional judgment in Step 8 below.

Step 2—Use cluster analysis to identify customer clusters with respect to Status A full surrenders in the VA with GLWB data and in the FIA with GLIB data. Cluster analysis includes algorithms and methods for finding structure in data by creating groups or "clusters" that maximize the associations among members of the group while minimizing the association with other data points.[3]

Step 3—Compare the customer clusters between the VA with GLWB and FIA with GLIB data. For each of the customer clusters that are similar between the two sets of data, stratify the full surrender experience by customer cluster for both the VA with GLWB and FIA with GLIB Status A blocks of business. For any clusters that are unique to the FIA with GLIB Status A data, develop base surrender experience for those clusters as well.

Step 4—For similar Status A customer clusters between VAs with GLWBs and FIAs with GLIBs, test hypotheses about the relative level of Status A full surrenders by customer cluster.

Step 5—If the level of full surrenders is significantly different for similar clusters, develop measures of benefit prominence and consider to what extent these measures account for the differences. With account values of FIAs with GLIBs being flatter than account values of FIAs alone due to the extra charges for the GLIBs, the annual reporting of the account value roll-forward provides a regular reminder of this benefit to the annuity owner. The larger the extra charges, the more prominent the GLIB will be for the FIA with GLIB owner. In contrast, the account value of a VA with GLWB has more potential volatility and more different types of charges which could reduce the prominence of the GLWB and thereby reduce the efficiency of the owner's use of the benefit. Such measures of benefit prominence might include:

a. The number of other riders on the VA or FIA contract.
b. The rider charge for the GLWB/GLIB as a percent of total contract charges.
c. The ratio of the current account value to the sum of the premiums paid less withdrawals.
d. The max withdrawal percentage for the given age and gender for the policy relative to newer policies offered in the marketplace post product de-risking.

Step 6—For similar Status A customer clusters between VAs with GLWBs and FIAs with GLIBs, combine the experience data for all those clusters and develop dynamic full surrender functions using the identified key predictors. Add new predictors for customer cluster ID, product type, and measures of benefit prominence where applicable.

Step 7—Calibrate the dynamic functions of Status A full surrenders against the experience for each product type and customer cluster. Optimize the model fit for each product type and customer cluster by testing different predictive model types, including ensemble models.

Step 8—For dissimilar FIAs with GLIBs customer clusters, use the stratified base surrender experience for FIAs with GLIBs. Include other factors derived from the other cluster analyses to apply judgment in setting the dynamic functions of Status A full surrenders, including a margin for greater uncertainty if appropriate to the purpose of the analysis.

FINAL THOUGHTS

While the methods proposed are intended to be used to develop anticipated experience (current or best estimate) assumptions, including margins may be appropriate in some cases.

For example, Actuarial Guideline 43 (AG 43) requires additional margins for uncertainty. Prudent Estimate Assumptions are to be set at the conservative end of the actuary's confidence interval based on the availability of relevant experience and its degree of credibility, as defined in Section 3.B.8 of AG 43. A margin for uncertainty is to be applied to the anticipated experience (without margins) that provides for both estimation error and a margin for adverse deviation. The larger the uncertainty, the larger the margin should be.

Appendix 9 of AG 43 applies these principles to contract holder behavior specifically. In the absence of relevant and fully credible experience, the actuary should define a plausible spectrum for each contract holder behavior assumption and set the Prudent Estimate Assumption at the conservative end of the plausible spectrum. The plausible spectrum need not be constrained by outcomes of historical experience. Appendix 9 includes additional guidance that should be referenced as well in setting assumptions and margins.

The use of targeted sensitivity testing and evaluation of trends should be considered in the actuary's analysis underlying assumption-setting. Several Actuarial Standards of Practice (ASOPs) refer to these methods in different contexts, such as ASOPs 2, 7, 10, 15, 18, 19, 24, 37, 40, 42 and 48. Targeted sensitivity testing should be undertaken to identify the degree of risk associated with possible variations in the surrender assumptions. The richer the guaranteed benefits, the more likely the benefits are to be lapse-supported, with higher sensitivities in profit projections and reserve and capital calculations. Though they're based on historical experience, the assumptions developed are estimates of future experience. Recognition of trends in the historical data of the assumptions may be particularly important for assumptions that are material to the results.

While AG 43 may have been the first implementation of principle-based reserves, the 2017 effective date of the Valuation Manual places a premium on setting assumptions as accurately as possible in the calculation of reserves. In the past, simply listing the assumptions used may have been deemed sufficient, but in the near future greater disclosure of the sources and analyses underlying particular assumptions will be expected. More focused experience studies are needed, as illustrated in this article in looking at contracts in Statuses A, B and C. Additional insights in looking at experience from benefit utilization date and not just issue date may be useful. Including distribution channel, product design features, and customer clusters as predictors may be important to more fully understand past experience. Studying the interactions of key factors using predictive models may be vital to measuring the risks of more complex products. With the development of new benefits, new methodologies are needed to develop assumptions where credible historical experience does not yet exist. In Part 3, we will apply the methods described in this article to develop FIA with GLIB Status A full surrender assumptions, test the relative computer run times of ensemble models versus single method models, and examine GLWB/GLIB utilization experience for both VAs and FIAs. ■

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ENDNOTES

1 Part 1 appeared in the September, 2015 issue of *The Financial Reporter*

2 "Ensemble Methods in Data Mining: Improving Accuracy by Combining Predictions" by Giovanni Seni and John F. Elder, *Synthesis Lectures on Data Mining and Knowledge Discovery* published by Morgan & Claypool Publishers, 2010, Chapter 1.

3 *Electronic Statistics Textbook* provided by Dell Statistica at *www.statsoft.com/textbook/cluster-analysis*. See also "Cluster Analysis" by Marianne Purushotham, *The Actuary*, June/July 2016 issue, Society of Actuaries.