Life insurance portfolio aggregation

Is it optimal to group policyholders by age, gender, and seniority for BEL computations based on model points?

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Solvency II

- EU directive that codifies and harmonizes the EU prudential framework
 - $\,\hookrightarrow\,$ Amount of capital to reduce the risk of insolvency
- ▶ Enforcement on the 1st of January, 2016

Best Estimate Liability computations via stochastic ALM Cash-Flows Projection Model

- Capture the strong interaction between asset and liability
- Take into account the time value of options and guarantees

The Running Time issue

- Monte-Carlo simulations + Policy-by-policy approach
- AXA France participating contracts portfolio \Rightarrow 3 millions
 - $\,\hookrightarrow\,$ Cumbersome volume of computations

Executive Summary

What is a model point?



A two-step procedure

- Clustering algorithms used in the field data analysis group policies to yield the clustered portofolio
- An aggreation procedure build a representative contract for each group and yield the aggregated portfolio
- Aggregated portfolio of 4000 model points associated to relative error on the BEL of 0.05%
- Official AXA France Model Point building process since the closing of 2013

The Present Surrender Value of a participating contract

- {
 r_a(t)}_{t≥0} and {
 r_d(t)}_{t≥0} are stochastic processes governed by a
 probability measure ℙ_f that model respectively the accumulation
 and discounting rate
- Let **F** be a financial scenario drawn from \mathbb{P}_f

The Surrender Value

$$SV^{\mathsf{F}}(t) = SV(0) \times exp\left(\int_{0}^{t} r_{\mathsf{a}}(s) \mathrm{d}s\right),$$

The Present Surrender Value

$$\mathsf{PSV}^{\mathsf{F}}(t) = \mathsf{SV}^{\mathsf{F}}(t) \times \exp\left(-\int_{0}^{t} r_{d}(s) ds\right),$$

Let $\tau | \mathbf{F}$ be a continuous random variable that models the time of early surrender due to

- Death \Rightarrow Age and Gender of the policyholder
- \blacktriangleright Lapse \Rightarrow Seniority of the contract and financial scenario F

Let T be the term of the contract or end of the horizon of projection.

▶ The actual surrender time is $\tau | \mathbf{F} \land T = \min(\tau | \mathbf{F}, T)$ with probability measure

$$\mathrm{d}\mathbb{P}_{\tau|\mathbf{F}\wedge T}(t) = f_{\tau|\mathbf{F}}(t)\mathrm{d}\lambda(t) + \overline{F_{\tau}}(T)\delta_{T}(t)$$

Mean of the present value of the future exiting Cash-Flows weighted by their probability of occurence

Given a Financial Scenario F

$$BEL^{\mathbf{F}}(0, T) = \mathbb{E}\left[PSV\left(\tau | \mathbf{F} \wedge T\right)\right]$$
$$= \int_{0}^{T} SV(0) \times \exp\left[\int_{0}^{t} (r_{a}(s) - r_{d}(s)) ds\right] d\mathbb{P}_{\tau | \mathbf{F} \wedge T}(t)$$

Over a set of Financial Scenarios $(\mathbf{F}_1, \ldots, \mathbf{F}_N)$

$$BEL(0,T) = \frac{1}{N} \sum_{i=1}^{N} BEL^{\mathbf{F}_i}(0,T)$$

Approximation through a discretization of time

$$BEL^{\mathbf{F}}(0,T) \approx \left[\sum_{t=0}^{T-1} p(t,t+1) \prod_{k=0}^{t} \frac{1+r_a(k,k+1)}{1+r_d(k,k+1)}\right] SV(0) + \left[p(T) \prod_{k=0}^{T-1} \frac{1+r_a(k,k+1)}{1+r_d(k,k+1)}\right] SV(0),$$

where

- Time step equal to one year
- Horizon of projection equal to 30 years
- p(t, t + 1) is the probability of surrender between year t and t + 1
- p(T) is the probability to reach the end of projection year
- ► r_a(k, k + 1) and r_d(k, k + 1) denote the accumulation and discounting forward rate

BEL Computation of a portfolio (C_1, C_2)

Let C₁ and C₂ have identical probabilities of surrender over the years
 SV_{MP}(0) = SV_{C1}(0) + SV_{C2}(0)

Then

$$BEL_{MP}^{\mathbf{F}}(0,T) = \sum_{i=1}^{2} BEL_{C_i}^{\mathbf{F}}(0,T).$$

• Exact valuation of the BEL of the portfolio (C_1, C_2)

Getting as close as possible to this additivity property sounds like a good idea...

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First Aggregation

Aggregation of contracts having

- Identical probabilities of surrender
- Identical ALM Group defined by features such as
 - Product Line
 - Benefit sharing features
 - Technical rate
 - ▶

Initial Portfolio				Portfolio After First Aggregation		
Maille ALM	Probability of Surrender	Initial Surrender Value		Maille ALM	Probability of Surrender	Initial Surrender Value
Grp_ALM_1	Vector_1	100	o>0	Grp_ALM_1	Vector_1	100
Grp_ALM_1	Vector_2	200	0	Grp_ALM_1	Vector_2	3280
Grp_ALM_1	Vector_3	50		Grp_ALM_1	Vector_3	50
Grp_ALM_1	Vector_2	80	0 >	Grp_ALM_2	Vector_4	5200
Grp_ALM_1	Vector_2	3000	0 70	Grp_ALM_2	Vector_5	40000
Grp_ALM_2	Vector_4	5000	• •	Grp_ALM_3	Vector_6	10250
Grp_ALM_2	Vector_4	200	0			
Grp_ALM_2	Vector_5	40000	0			
Grp_ALM_3	Vector_6	100	•			
Grp_ALM_3	Vector_6	700	0			
Grp_ALM_3	Vector_6	9000	0			

The Clustering Problem

Let

$$\mathcal{P} = {\mathbf{C}_i}_{i \in 1, \dots, n}$$

be a portfolio of contracts that belong to the same ALM Group

$$\mathbf{C}_{i} = \left(p_{i}(0,1), p_{i}(1,2), ..., p_{i}(T-1,T), p_{i}(T)\right),$$

characterized by their trajectory of surrender probabilities

- Giving up the financial dependency hypothesis
- Euclidean distance as dissimilarity measure
- AHC and K-MEANS Algorithm
- Weighting procedure based on the initial surrender value

$$w_{\mathbf{C}} = \frac{SV_{\mathbf{C}}(0)}{\sum_{\mathbf{C}\in\mathcal{P}}^{n}SV_{\mathbf{C}}(0)},$$

Similar to longitudinal data

A Meli-Melo of trajectories



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Constraint on the number of Model Points

- Allocation of a number of model points to each ALM Group with respect to their mathematical reserves
- K-Means algorithm is better suited
 - \hookrightarrow The number of clusters is a parameter
- The random initialization is problematic
 - $\,\hookrightarrow\,$ AHC to determine the initial centroid
- Idea Number of model points \Rightarrow Compromise between heterogeneity and mathematical reserve of the ALM Group

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Combination of AHC and K-Means Then BOOM!



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The problem reduces itself to assign the best characteristics to the MP The Simple Way

Weighted mean of the policyholder characteristics within the group

A Trickier One

- Generate every possible probability trajectories
- Compute the barycenter in each group
- Assign to the model point the characteristics leading to the trajectory which is closest to the barycenter

Overview of the Aggregation Process



Backtesting: Criteria and Figures

- $\blacktriangleright \ \mathcal{PF}_1$ denotes the aggregated portfolio after first aggregation
- *PF*₂ denotes the final aggregated portfolio with the barycenter method
- The relative error on the BEL is defined as

$$\frac{\textit{BEL}\left(\mathcal{PF}_2\right)-\textit{BEL}\left(\mathcal{PF}_1\right)}{\textit{BEL}\left(\mathcal{PF}_1\right)}$$

The compression rate is defined as

$$\frac{\textit{Card} (\mathcal{PF}_2) - \textit{Card} (\mathcal{PF}_1)}{\textit{Card} (\mathcal{PF}_1)}$$

Portfolio	Number of Contracts	BEL (millions of euros)
\mathcal{PF}_1	72 000	72 336
\mathcal{PF}_2	3 753	72 371

- ▶ A relative error of 0.0485% equivalent to 35 millions of euros
- ► A compression rate of -95% VS \mathcal{PF}_1 and -99.9% VS policy-by-policy

Global Error over the years of projection



Compression Rate VS Relative Error Product-by-Product



Relative Error on the BEL by Product Lines



Conclusion

- The aggregation procedure for participating contracts portfolios is very efficient
 - \hookrightarrow Easy to implement
 - $\,\hookrightarrow\,$ Theoretically based and efficient in practice
- The aggregation procedure plays a key role within the valuation process of AXA France as
 - It enables to do a full ALM valuation
 - It meets the expectations of the regulators

There are Rooms for Further Improvements

- Try dissimilarity measures better suited to the problem than the euclidean distance
- Link the level of error to the number of Model Points
- Find a compromise between heterogeneity and mathematical reserve to allocate the number of model points

On the Optimal Number of Clusters



20/23

Clustering Philosophy



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K-Means Algorithm

- Step 1 Set the number of clusters
- Step 2 Random initialization of the centroids
- Step 3 Each individual is assigned to the closest centroid
- Step 4 Computations of new centroids
- Step 5 Repeat step 3 and 4 until convergence



Ascending Hierarchical Clustering Algorithm

- Step 1 Group the two policies that minimize the increase of the Within-Cluster Inertia and replace them with the barycenter
- Step 2 Repeat step 1 until only one group remains
- Step 3 Cut the tree

