Multivariate analyses for modelling lapse risk capital charge under Solvency II

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Multivariate analyses for modelling lapse risk capital charge under Solvency II
Agenda

• Introduction
  – Why investigating lapse risk capital charge
• Lapse Risk capital charge
  – Solvency II framework and its challenges
• Determining Lapse assumptions
  – Univariate
  – Multivariate – adopting a Generalised Modelling techniques
  – Multivariate dynamic – varying assumptions by simulation
• Case Study
  – Own Funds
  – Solvency Capital required
  – Key Observations
Introduction

Why investigating lapse risk?

• Capital charge for lapse risk is the biggest SCR in the life underwriting risk capital charge:
  – EU average life companies: 59%
  – EU average composite companies: 43%

• Own Funds are very sensitive to lapse assumptions, hence strong impact on solvency levels
  – Long dating evidence from MCEV analysis
Lapse risk capital charge
CP 26 and CEIOPS expectations

• High expectation from Solvency II legislation in terms of solidity of derivation and validation of best estimate and dynamic assumptions

• CP26:
  – Need to allow for uncertainty in best estimate assumptions, including policyholder behaviour and management responses
  – Assumptions should be validated and reviewed by insurance undertaking
Determining Lapse assumptions

• We will concentrate for the purposes of this presentation on work aimed at
  – Improvement of derivation of best estimate lapse assumptions using GLM techniques
  – Investigating the applicability of GLM techniques to investigate dynamic PH behaviour
  – Investigating impact on Own Funds and SCR
• We won’t deal
  – With the variability around best assumptions – which could be used to determine a distribution of irrational lapse behaviour and / or company specific lapse stress
  – With the improvement of aggregation methodologies for lapse risk
Determining Lapse assumptions

Case Study

- Case study based on an actual portfolio of a continental European bank insurance business
  - The products were participating life insurance savings policies, mostly (recurrent) single premium products, with guaranteed surrender values
- Policy data analysed
  - Observation from years 1991 – 2007
  - 6,129,000 exposure and 279,000 lapses
- Split of portfolio in product types, based on the interest rate guarantee level
  - High: 3% - 4% (35% of the reserves) (H)
  - Medium: 2.5% (42% of the reserves) (M)
  - Low: 0% (23% of the reserves) (L)
- The results presented here are to be understood ‘for illustration purposes’ only – are to be considered work in progress
Determining Lapse assumptions

Univariate lapse assumptions

Traditional approach

- For each product type (H, M, L) the average lapse frequency has been derived, distinguished by duration in force

Note:

- this is different from a 2-factor GLM model with the factors of guarantee and duration
Determining Lapse assumptions
Univariate lapse assumptions

<table>
<thead>
<tr>
<th>Duration</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
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<tbody>
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<td>1,9%</td>
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<tr>
<td>&gt;=11</td>
<td>1,4%</td>
<td>6,3%</td>
<td>1,4%</td>
</tr>
</tbody>
</table>
Determining Lapse assumptions

Multivariate lapse assumptions

- Multivariate assumption, based on the adoption of Generalised Linear Modelling (GLM) Techniques
- What are GLMs?
  - A method that can model
    - a number
    as a function of
    - some factors
  - For instance, a GLM can model
    - Motor claim frequency as a function of driver age, car type, bonus malus …
    - Policyholder lapse/surrender probability (L or NL)
    - Policyholder mortality (L)
  - Historically associated with non-life personal lines pricing
Determining Lapse assumptions

Case study: predictive factors

- The risk factors available for our analysis were:
  - Product classified by minimum guaranteed rate
  - Year of event
  - Duration
  - Age
  - Sex

- Key predictive factors
  - **Duration** – highly predictive, and the GLM shows this factor to have more effect in explaining lapse/surrender behaviour than would be apparent from a one-way analysis.
  - **Minimum guarantee** of the tariff
  - **Age** (although a relatively minor effect)
  - Interactions between some of these factors were significant
  - **Calendar year** of exposure is highly significant but using this in a predictive way is not straight-forward
  - **Difference** between the insurer’s *fund book yield* and *long-term government yields*

- Non-predictive factors
  - **Sex**

Note: see Cerchiara, Edwards, Gambini, AFIR 2008
Effect of policyholder age

Unsmoothed estimate

Approx 95% confidence interval

P value = 0.0%

Rank 1/3

Corporate

0-39

40-59

60-79

80+

P value = 0.0%

Rank 1/3

Effect of policyholder age

Log of multiplier

Coverage

Approx 95% confidence interval

Unsmoothed estimate

P value = 0.0%

Rank 1/3

Corporate

0-39

40-59

60-79

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Approx 95% confidence interval

Unsmoothed estimate

P value = 0.0%

Rank 1/3

Corporate

0-39

40-59

60-79

80+

P value = 0.0%

Rank 1/3
Sex – not significant

P value = 20.7%
Determining Lapse assumptions

Case study: predictive factors

- **Formula**
  - **Base** level = 6.3% exposure weighted average rate
  - **Factor** duration (1 – 11+)

<table>
<thead>
<tr>
<th>Factor Level</th>
<th>0</th>
<th>1</th>
<th>1.4</th>
<th>1.13</th>
<th>0.84</th>
<th>0.84</th>
<th>0.62</th>
<th>0.46</th>
<th>0.46</th>
<th>0.22</th>
<th>0.07</th>
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<td>1.4</td>
<td>1.13</td>
<td>0.84</td>
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<td>0.62</td>
<td>0.46</td>
<td>0.46</td>
<td>0.22</td>
<td>0.07</td>
</tr>
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</table>

- **Factor** guarantee (L (0% - 2.5%), M (3%), H (4%))

<table>
<thead>
<tr>
<th>Factor Guarantee</th>
<th>Level</th>
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<tbody>
<tr>
<td>H (4%)</td>
<td>1.7821</td>
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<tr>
<td>M (3%)</td>
<td>1.0000</td>
</tr>
<tr>
<td>L (0 – 2.5%)</td>
<td>1.0164</td>
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</table>

- **Factor** age (0-39, 40 – 59, 60*)

<table>
<thead>
<tr>
<th>Factor Age</th>
<th>Level</th>
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<tbody>
<tr>
<td>0 -39</td>
<td>1.064</td>
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<tr>
<td>40 – 59</td>
<td>0.986</td>
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<tr>
<td>60+</td>
<td>0.915</td>
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Determining Lapse assumptions
Results for High guarantee products

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<thead>
<tr>
<th>Guarantee</th>
<th>Duration</th>
<th>Under 40</th>
<th>Under 60</th>
<th>Over 60</th>
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<td>Multivariate</td>
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Determining Lapse Assumptions

Results for Medium guarantee products

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<th>MEDIUM Univariate</th>
<th>MEDIUM Multivariate</th>
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<tr>
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## Determining Lapse assumptions

### Results for Low guarantee products

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<th>Multivariante LOW</th>
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<td>Over 60</td>
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<tr>
<td>11 +</td>
<td>1,4%</td>
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</table>
Determining Lapse assumptions

Key Observations:

• One dataset analysed in different ways can give rise to very different lapse assumptions, both in the shape and the level
  – We observe here that multivariate assumptions seem on average higher (the average of univariate assumption is 3%, the average of multivariate is 4% for L and M, 7% for H)
  – The shape of the assumptions might be different as well, for example here the duration effect varies (where the maximum is, and how ‘high’ the maximum is)

• Some other points:
  – As expected younger policyholders tend to exhibit a higher propensity to lapse
  – High guarantees show an apparently higher propensity to lapse – this is not intuitive and hides a significant movement by calendar year
Lapse assumptions & Solvency II
Case study

• We have analysed the impact of multivariate lapse assumptions on the own fund level, SCR and Solvency Ratio of our case study

• Stochastic model:
  – very simple approach, only explanatory purposes
  – 1,000 risk-neutral simulations
  – Bonus driven by achieved book return on the WP fund
  – Constant asset allocation and new investment in cash
  – Yearly alignment of Book Values of Assets to local GAAP mathematical reserves
  – No Surplus assets in the model
  – Results produced with Watson Wyatt proprietary software

The results presented here are to be understood ‘for illustration purposes’ only – are to be considered work in progress
Lapse assumptions & Solvency II

Case study

• “Own funds”
  – Defined as excess MVA less Best Estimate Liabilities
  – Ignoring Risk Margins
  – Deferred taxes are part of the Best Estimate Liabilities

• SCR estimated according to a simplified version of QIS4 standard formula, in particular
  – Up and down stress applied on all simulations and not only those having a positive / negative surrender strain
  – Mass lapses have been ignored
  – … consequently potential underestimation of lapse capital charge

• Aggregation according to the correlation matrix used in the QIS4
Lapse assumptions & Solvency II
Case study

Mathematical Reserves by guarantee
Lapse assumptions & Solvency II
Case study

Markt Value asset

- Bond: 54%
- Cash: 34%
- Equity: 12%

UGL= 79

UGL= 156

URG approx. 2.5% of MVA
Lapse assumptions & Solvency II
Case study: Own Funds

**Univariate** Own Funds = 2.9% of MVA

- MVA = 10,000
- Own Funds = 290
- DTL = 380
- BEL = 9,411

**Multivariate** Own Funds = 0.56% of MVA

- MVA = 10,000
- Own Funds = 56
- DTL = 360
- BEL = 9,584
Lapse assumptions & Solvency II

Case study: SCR

<table>
<thead>
<tr>
<th></th>
<th>UNIVARIATE</th>
<th>MULTIVARIATE</th>
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<tbody>
<tr>
<td>SCR UNDIVERSIFIED</td>
<td>387,77</td>
<td>341,19</td>
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<tr>
<td>Interest rate risk</td>
<td>181,85</td>
<td>112,97</td>
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<tr>
<td>Equity risk</td>
<td>91,50</td>
<td>117,68</td>
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<tr>
<td>Lapse risk</td>
<td>114,42</td>
<td>110,54</td>
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<tr>
<td>SCR DIVERSIFIED</td>
<td>257,25</td>
<td>218,74</td>
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<tr>
<td>diversification effect</td>
<td>34%</td>
<td>36%</td>
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Lapse assumptions & Solvency II

Key Observations on moving from traditional basis to GLM assumptions

• Own Funds show a higher degree of sensitivity to the change to a multivariate lapse approach than the SCR
  – Own funds fall from 2.9% of MVA to 0.56% of MVA
  – SCR diversified falls from 2.57% to 2.19% of MVA

• The change to a multivariate lapse assumptions has a bigger impact on market SCR than on lapse SCR
  – Reduces overall SCR market capital charge
  – Increases weight of equity SCR from 24% to 35%
Lapse assumptions & Solvency II
Dynamic behaviour

• The ability to model interactions in particular can assist in understanding policyholder behaviour from the perspective of relationships with market movements
• We combine the concept of an interaction with the use of external data
• The first graph shows the dependence of the surrender frequency from the calendar year of exposure
• The second graph uses the product guarantee * calendar year of exposure interaction to show how the surrender rate seems to vary according to high or low guarantee levels
  – For low guarantees, market decreases lead to increased surrenders in a fairly linear manner
  – For high guarantees, market decreases seem to lead to decreased surrenders – perhaps because policyholders value their guarantees more
Determining Lapse assumptions

Dynamic lapses: Calendar Year of exposure

Determining Lapse assumptions

Dynamic lapses

• The ability to model interactions in particular can assist in understanding policyholder behaviour from the perspective of relationships with market movements
• We combine the concept of an interaction with the use of external data
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• The second graph uses the product guarantee * calendar year of exposure interaction to show how the surrender rate seems to vary according to high or low guarantee levels
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  – For high guarantees, market decreases seem to lead to decreased surrenders – perhaps because policyholders value their guarantees more
Determing Lapse assumptions

Dynamic lapses: Calendar Year of exposure x product
Determining Lapse assumptions

Dynamic lapses

Key observations:

• Clear evidence of dependence of lapse rate from calendar year and level of guarantees
  – Could suffer impact of contingent events, hence
  – …. difficult to extrapolate for the future

• Looking for an approach, which at the same time captures the path dependency of lapses, but is less contingent to specific calendar years, hence better suitable for predictive purposes
  – Investigate the risk factor “yield – guarantee”
  – Demonstrates close confidence intervals around estimation
Determining Lapse assumptions

Dynamic lapses: Factor based on \(\{\text{yield} - \text{guarantee}\}\)

<table>
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<tr>
<th>Yield minus guarantee</th>
<th>Log of multiplier</th>
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<td>&lt;= -0.64%</td>
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</tr>
<tr>
<td>-0.64% - 0.86%</td>
<td>0</td>
</tr>
<tr>
<td>0.86% - 1.28%</td>
<td>0</td>
</tr>
<tr>
<td>1.28% - 1.64%</td>
<td>0</td>
</tr>
<tr>
<td>1.64% - 1.86%</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
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<tr>
<td>&gt; 7.01%</td>
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Exposure (years)

- 0
- 100,000
- 200,000
- 300,000
- 400,000
- 500,000
- 600,000
- 700,000
- 800,000
- 900,000
- 1,000,000
- 1,100,000
- 1,200,000
- 1,300,000
- 1,400,000
- 1,500,000
- 1,600,000
- 1,700,000
- 1,800,000
- 1,900,000
- 2,000,000
- 2,100,000
- 2,200,000
- 2,300,000
- 2,400,000
- 2,500,000

Yield minus guarantee

Unsmoothed estimate

Approx 95% confidence interval

Oneway relativities

P value = 0.0%
Determining Lapse assumptions

Dynamic lapses

- Adding risk factor “yield – guarantee”, we obtain the following new factors, adjusting the GLM formula

<table>
<thead>
<tr>
<th>Factor yield – less guarantee</th>
<th>Multiplier</th>
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<tr>
<td>&lt; 0.25%</td>
<td>0.8835</td>
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<td>1.0346</td>
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<tr>
<td>1.25%-3.5%</td>
<td>1.1557</td>
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<tr>
<td>3.5% +</td>
<td>0.8263</td>
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</table>
Lapse assumptions & Solvency II
Case study: Dynamic behaviour & Own Funds

Univariate

- MVA = 10,000
- NAV = 290
- DTL = 380
- BEL = 9,411

Multivariate

- MVA = 10,000
- NAV = 56
- DTL = 360
- BEL = 9,584

Multivariate dynamic

- MVA = 10,000
- NAV = 64
- DTL = 363
- BEL = 9,573
Lapse assumptions & Solvency II
Case study: Dynamic behaviour & SCR

Univariate - SCR

- Interest rate risk: 30%
- Equity risk: 24%
- Lapse risk: 46%

Multivariate - SCR

- Interest rate risk: 32%
- Equity risk: 33%
- Lapse risk: 35%

Multivariate Dynamic - SCR

- Interest rate risk: 32%
- Equity risk: 34%
- Lapse risk: 34%
### Lapse assumptions & Solvency II

#### Case study: Dynamic behaviour & SCR

<table>
<thead>
<tr>
<th></th>
<th>UNIVARIATE</th>
<th>MULTIVARIATE</th>
<th>MULTIVARIATE DYNAMIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCR</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UNDIVERSIFIED</td>
<td>387,77</td>
<td>341,19</td>
<td>323,88</td>
</tr>
<tr>
<td>Interest rate risk</td>
<td>181,85</td>
<td>112,97</td>
<td>109,77</td>
</tr>
<tr>
<td>Equity risk</td>
<td>91,50</td>
<td>117,68</td>
<td>110,75</td>
</tr>
<tr>
<td>Lapse risk</td>
<td>114,42</td>
<td>110,54</td>
<td>103,35</td>
</tr>
<tr>
<td>SCR DIVERSIFIED</td>
<td>257,25</td>
<td>218,74</td>
<td>207,50</td>
</tr>
<tr>
<td>diversification effect</td>
<td>34%</td>
<td>36%</td>
<td>36%</td>
</tr>
</tbody>
</table>
Lapse assumptions & Solvency II
Key Observations

• Relatively small impact on lapse SCR, compared to the change from univariate to multivariate
• All relative movements are of a similar relative magnitude (own funds, scr div, scr lapse, scr market)
Problems and challenges with dynamic policyholder behaviour modelling

• Any dataset is based on a certain range of economic/investment conditions, how can we reasonably model movements outside that range?
• How to model irrational policyholder behaviour?
• Insights from other fields? (Retail banking market; non life work offers insight on some aspects of PH behaviour but not on investment aspect
• How should dynamic management decisions link in with dynamic policyholder behaviour?
Multivariate analyses for modelling lapse risk capital charge under Solvency II

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