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Multivariate analyses for modelling lapse risk capital charge under Solvency II

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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 bankinsurance 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

<i>Duration</i>	<i>Product guarantee</i>		
	<i>High</i>	<i>Medium</i>	<i>Low</i>
0	0,5%	0,2%	1,9%
1	0,5%	3,3%	6,0%
2	2,5%	3,7%	8,6%
3	3,2%	4,1%	7,7%
4	3,2%	4,4%	6,8%
5	6,7%	4,8%	5,8%
6	5,9%	5,2%	4,9%
7	5,2%	5,6%	4,0%
8	4,5%	6,0%	4,0%
9	3,8%	6,3%	3,1%
10	3,1%	6,3%	2,2%
>=11	1,4%	6,3%	1,4%

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 numberas 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

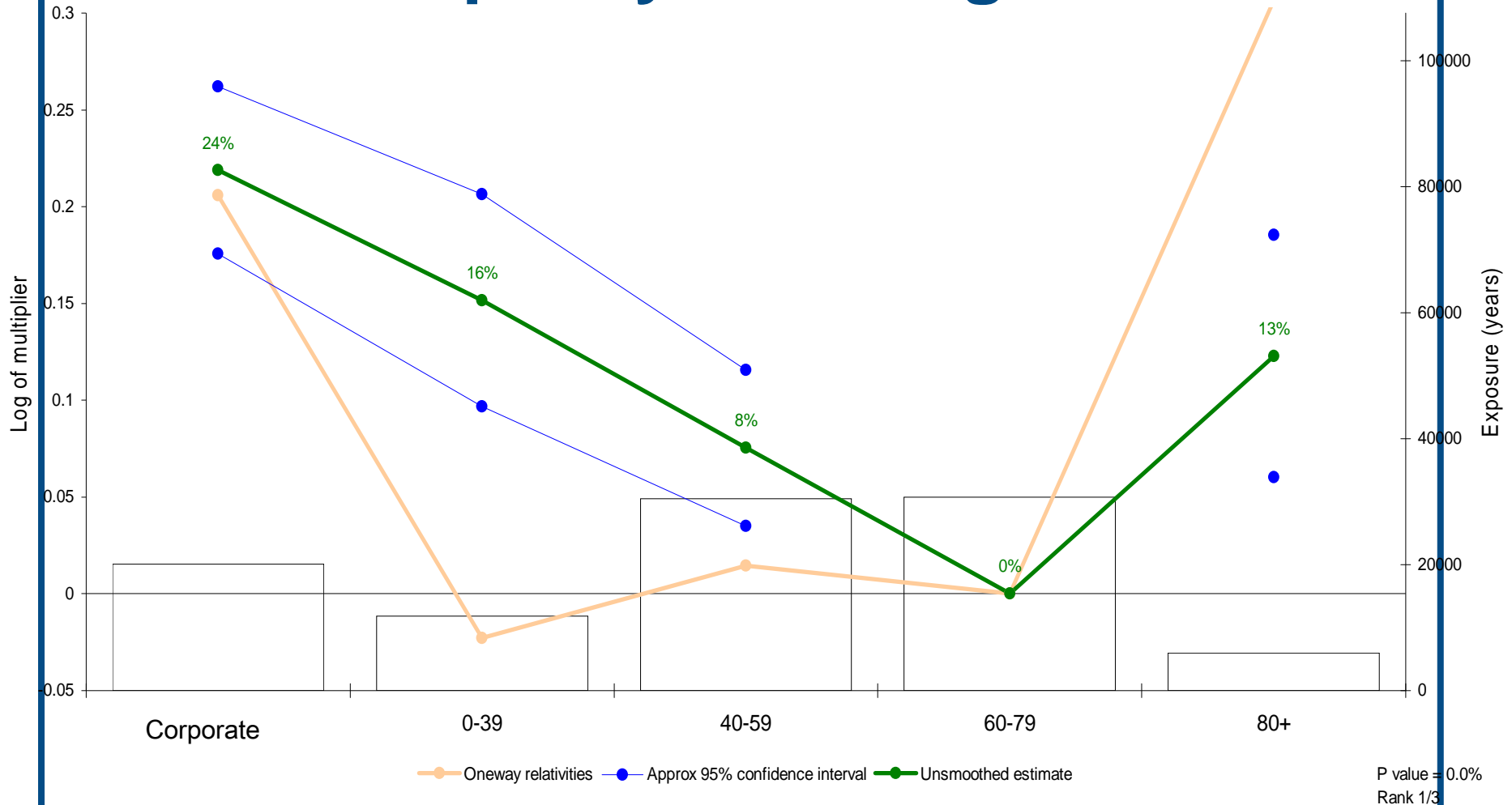
Determining Lapse assumptions

Case study: predictive factors

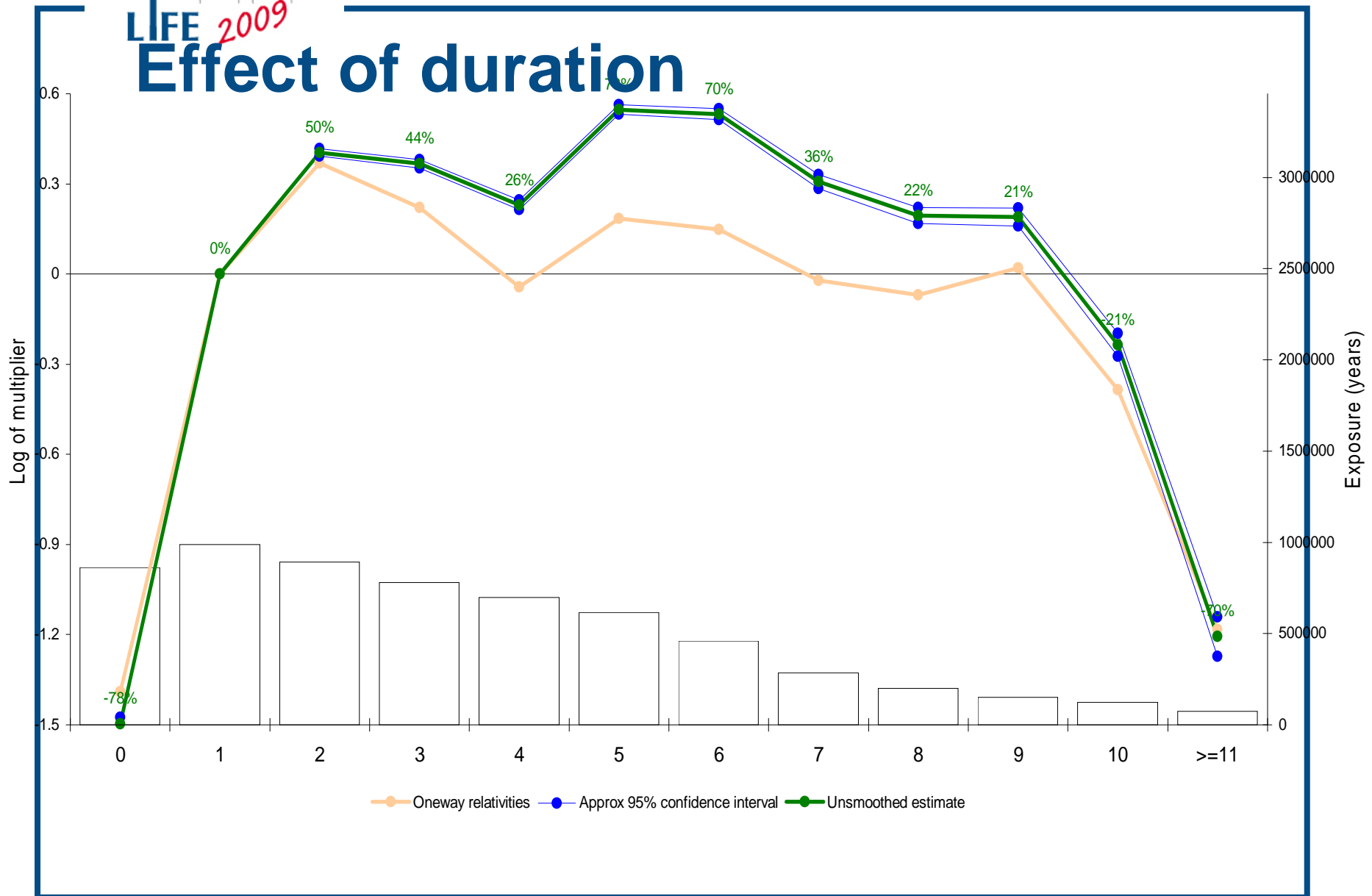
- The risk factors available for our analysis were:
 - Product classified by minimum guaranteed rate
 - Year of event
 - Duration
 - Age
 - Sex
- Key predictive factors
 - **Duration** – highly predictive, and the GLM shows this factor to have more effect in explaining lapse/surrender behaviour than 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

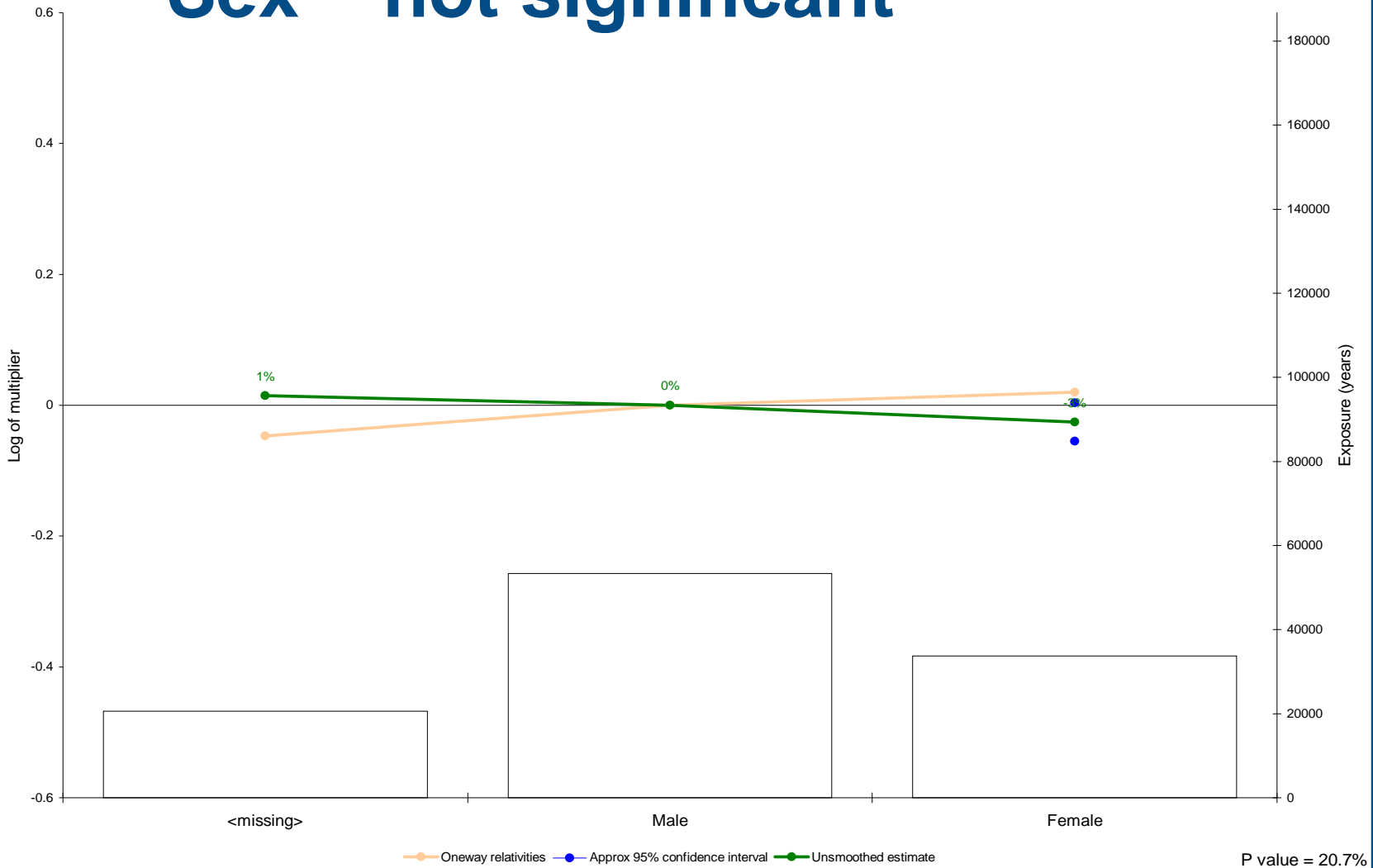
Effect of policyholder age



Effect of duration



Sex – not significant



Determining Lapse assumptions

Case study: predictive factors

- Formula

- **Base level** = 6,3% exposure weighted average rate
- Factor **duration** (1 – 11+)

Factor Level	0	1	2	3	4	5	6	7	8	9	10	11
Multiplier	0,30	1	1,4	1,13	0,84	0,84	0,62	0,46	0,46	0,46	0,22	0,07

- Factor **guarantee** (L (0% - 2,5%), M (3%), H (4%))

Factor Guarantee	Level
H (4%)	1,7821
M (3%)	1,0000
L (0 – 2,5%)	1,0164

- Factor **age** (0-39, 40 – 59, 60*)

Factor Age	Level
0 -39	1,064
40 – 59	0,986
60+	0,915

Determining Lapse assumptions

Results for High guarantee products

<i>Guarantee Duration</i>	<i>HIGH</i>			
	<i>Univariate</i>	<i>Multivariate</i>		
		<i>Under 40</i>	<i>Under 60</i>	<i>Over 60</i>
0	0,5%	3,6%	3,32%	3%
1	0,5%	11,9%	11%	10%
2	2,5%	16,7%	15%	14%
3	3,2%	13,5%	12%	12%
4	3,2%	10,0%	9%	9%
5	6,7%	10,0%	9%	9%
6	5,9%	7,4%	7%	6%
7	5,2%	5,5%	5%	5%
8	4,5%	5,5%	5%	5%
9	3,8%	5,5%	5%	5%
10	3,1%	2,7%	2%	2%
11 +	1,4%	0,8%	1%	1%

Determining Lapse assumptions

Results for Medium guarantee products

<i>Guarantee</i>	<i>MEDIUM</i>			
	<i>Univariate</i>	<i>Multivariate</i>		
		<i>Under 40</i>	<i>Under 60</i>	<i>Over 60</i>
0	0,5%	2%	1,89%	2%
1	0,5%	7%	6%	6%
2	2,5%	10%	9%	8%
3	3,2%	8%	7%	7%
4	3,2%	6%	5%	5%
5	6,7%	6%	5%	5%
6	5,9%	4%	4%	4%
7	5,2%	3%	3%	3%
8	4,5%	3%	3%	3%
9	3,8%	3%	3%	3%
10	3,1%	2%	1%	1%
11 +	1,4%	0%	0%	0%

Determining Lapse assumptions

Results for Low guarantee products

Guarantee Duration	LOW			
	Univariate	Multivariate		
		Under 40	Under 60	Over 60
0	0,5%	2%	1,86%	2%
1	0,5%	7%	6%	6%
2	2,5%	9%	9%	8%
3	3,2%	8%	7%	6%
4	3,2%	6%	5%	5%
5	6,7%	6%	5%	5%
6	5,9%	4%	4%	4%
7	5,2%	3%	3%	3%
8	4,5%	3%	3%	3%
9	3,8%	3%	3%	3%
10	3,1%	2%	1%	1%
11 +	1,4%	0%	0%	0%

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*

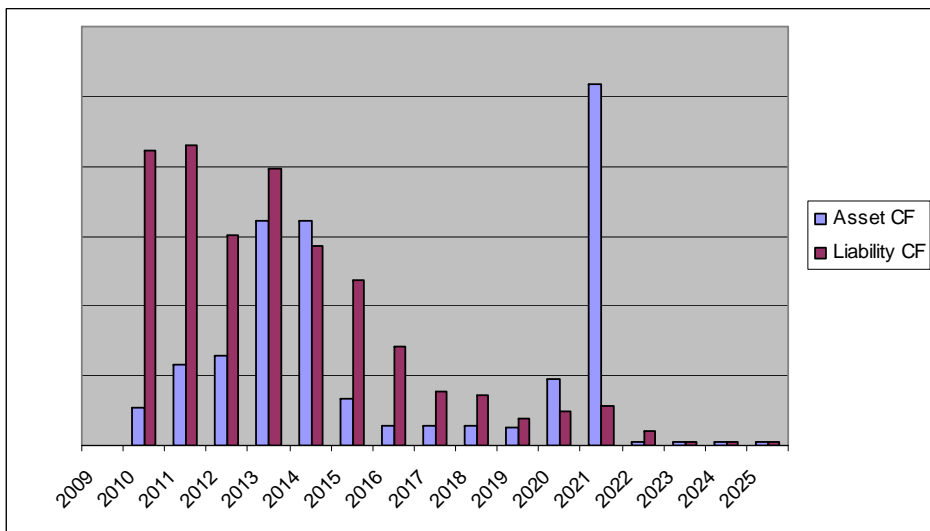
Lapse assumptions & Solvency II

Case study

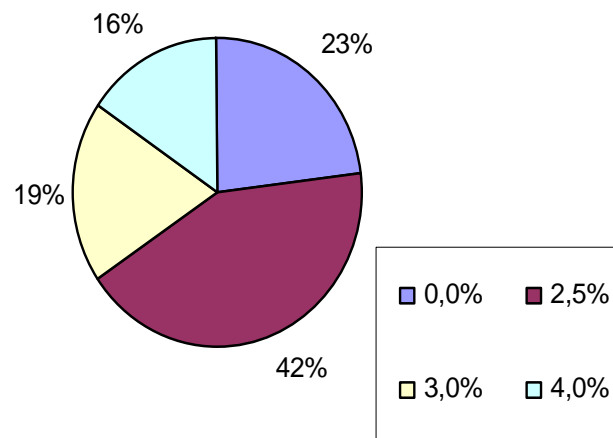
- “Own funds”
 - Defined as excess MVA less Best Estimate Liabilities
 - Ignoring Risk Margins
 - Deferred taxes are part of the Best Estimate Liabilities
- SCR estimated according to a simplified version of QIS4 standard formula, in particular
 - Up and down stress applied on all simulations and not 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

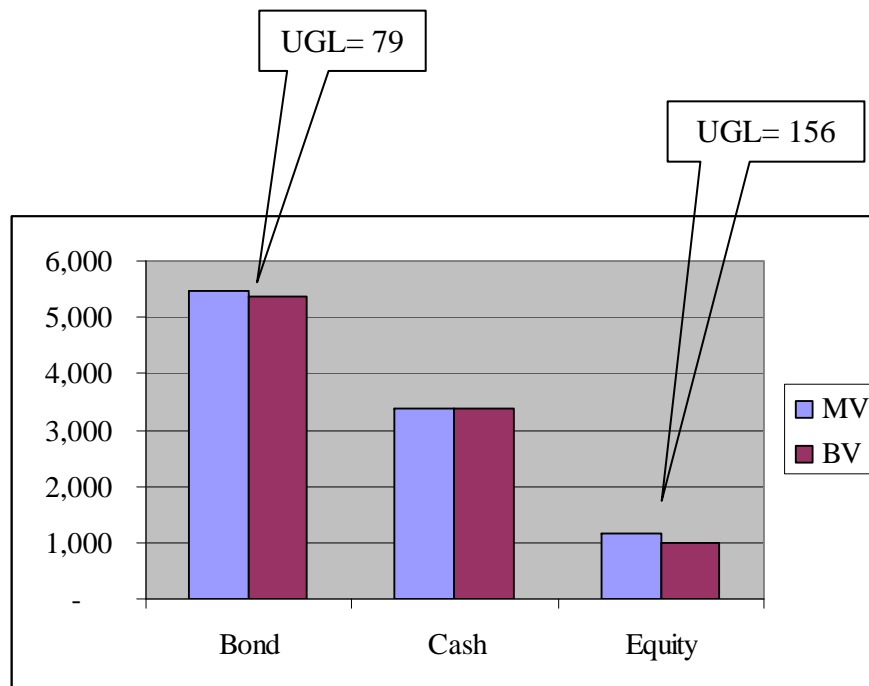
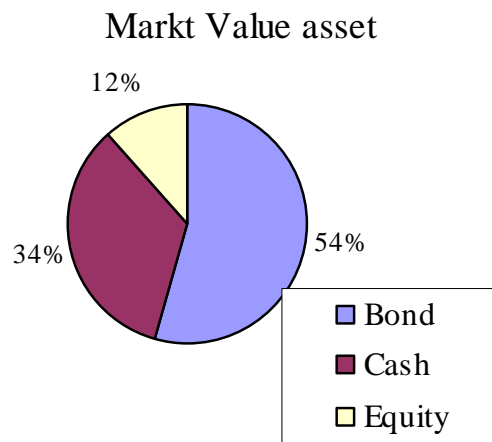


Mathematical Reserves by guarantee



Lapse assumptions & Solvency II

Case study

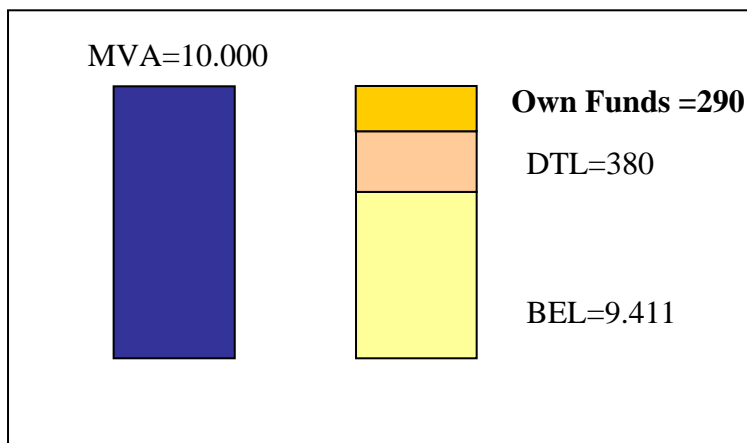


URG approx. 2,5% of MVA

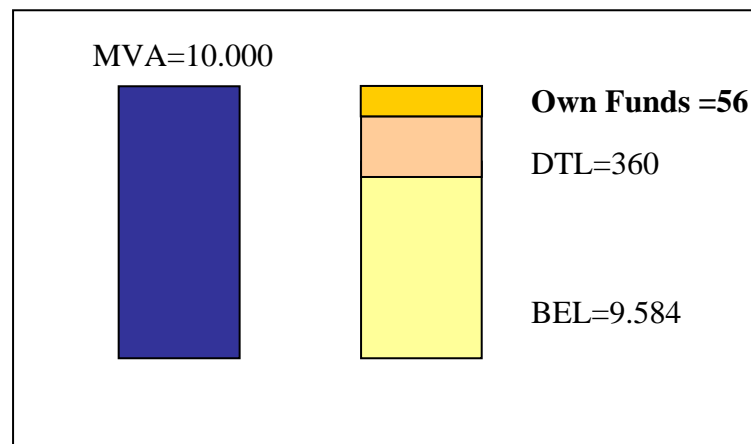
Lapse assumptions & Solvency II

Case study: Own Funds

Univariate Own Funds = 2,9% of MVA



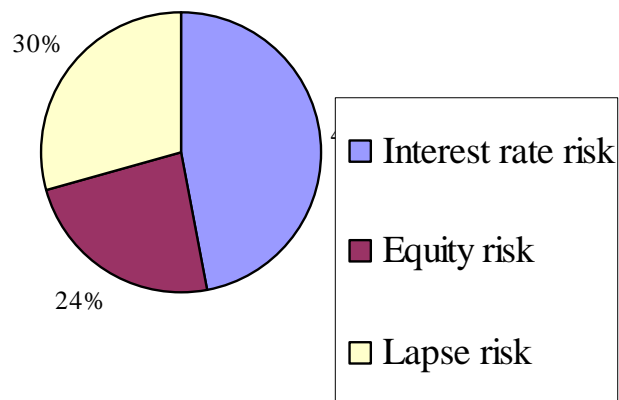
Multivariate Own Funds = 0,56% of MVA



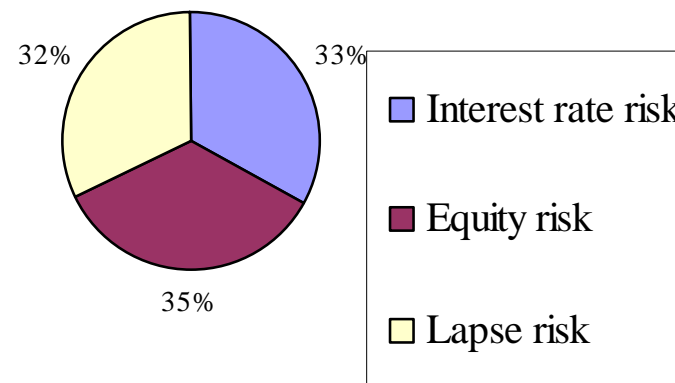
Lapse assumptions & Solvency II

Case study: SCR

Univariate - SCR



Multivariate -SCR



	<i>UNIVARIATE</i>	<i>MULTIVARIATE</i>
SCR UNDIVERSIFIED	387,77	341,19
Interest rate risk	181,85	112,97
Equity risk	91,50	117,68
Lapse risk	114,42	110,54
SCR DIVERSIFIED	257,25	218,74
diversification effect	34%	36%

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%

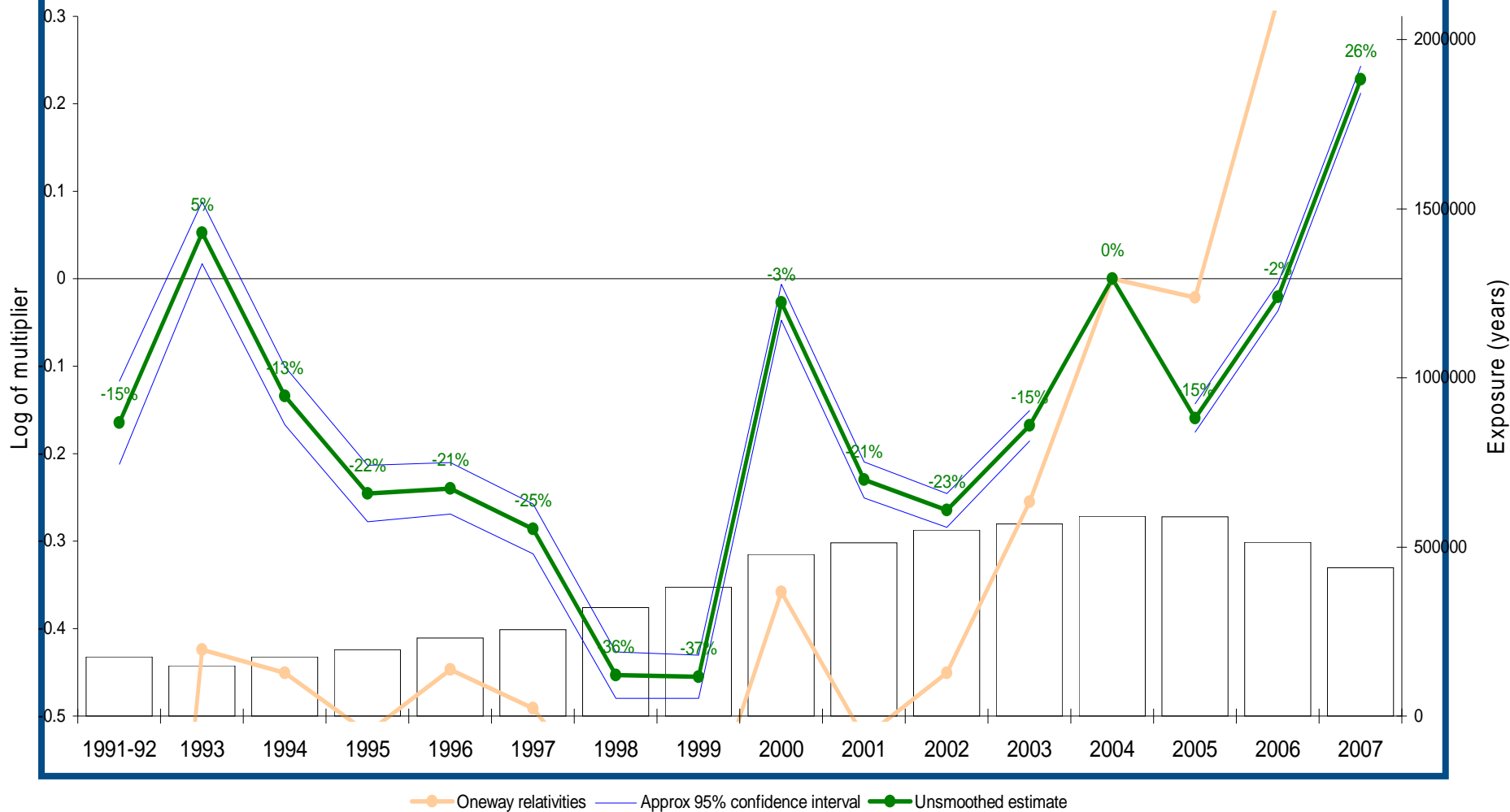
Lapse assumptions & Solvency II

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



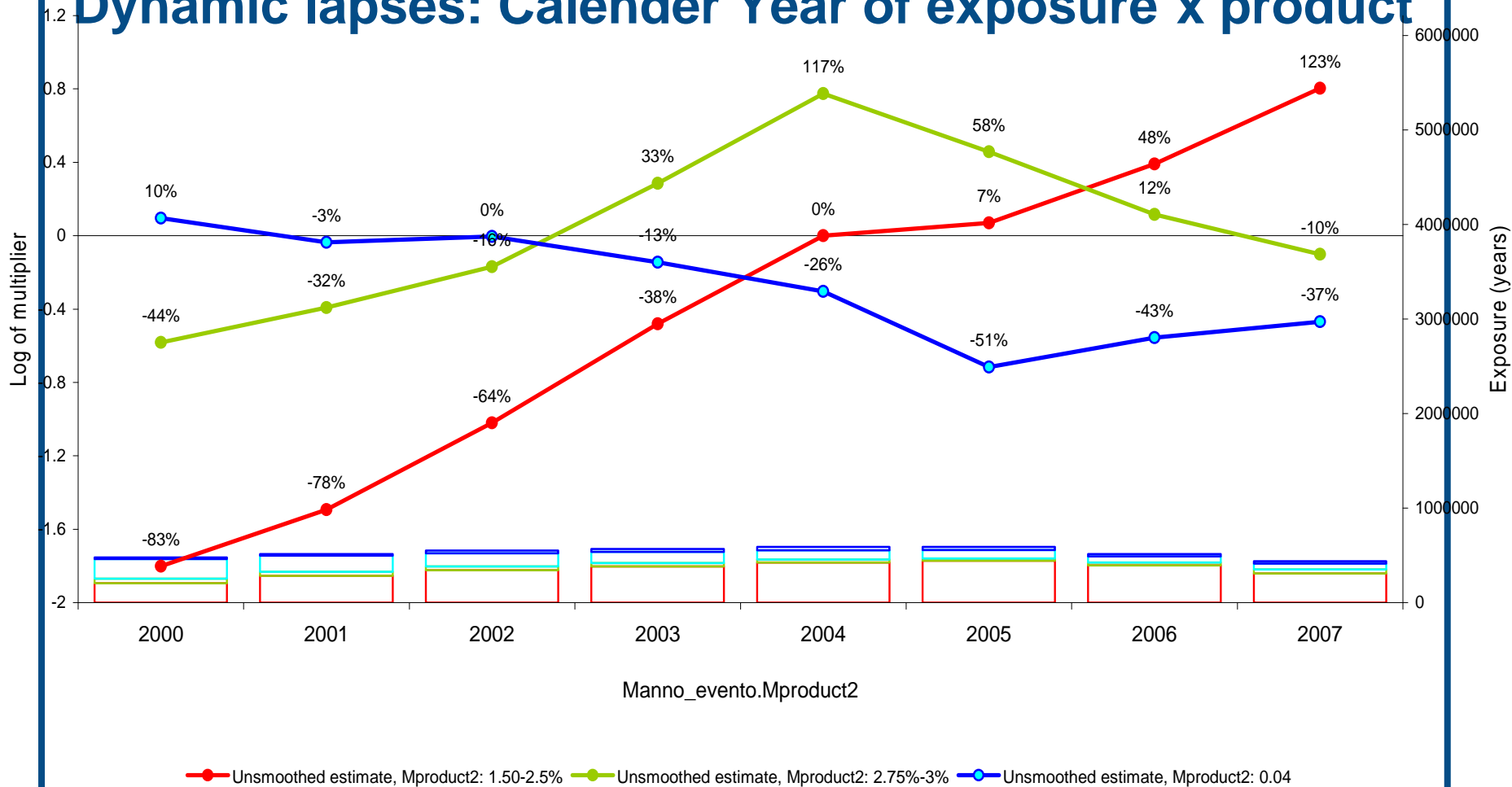
Determining Lapse assumptions

Dynamic lapses

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Determining Lapse assumptions

Dynamic lapses: Calendar Year of exposure x product



Determining Lapse assumptions

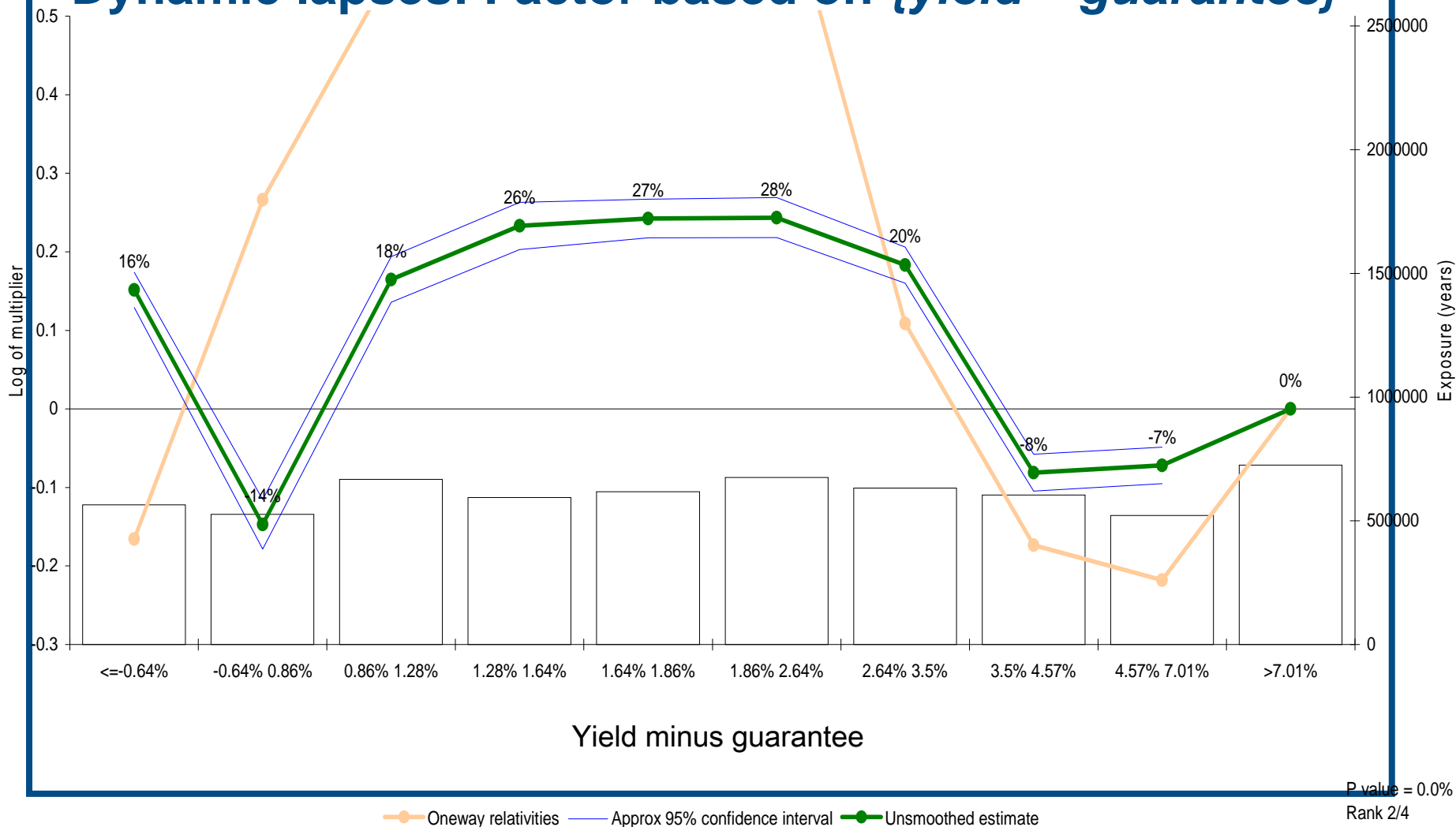
Dynamic lapses

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 $\{yield - guarantee\}$



Determining Lapse assumptions

Dynamic lapses

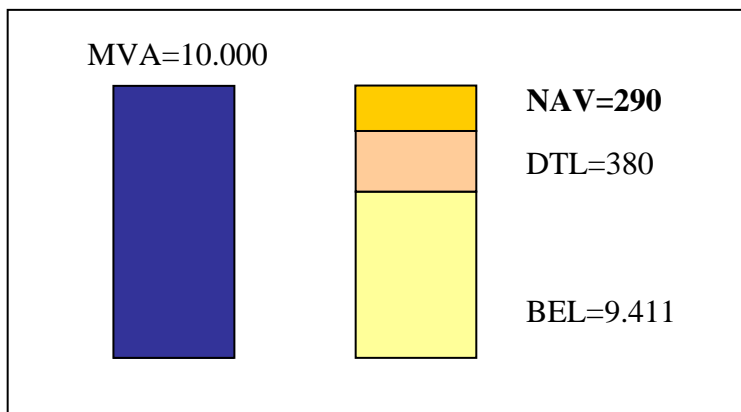
- Adding risk factor “yield – guarantee”, we obtain the following new factors, adjusting the GLM formula

<i>Factor yield – less guarantee</i>	<i>Multiplier</i>
< 0.25%	0,8835
0.25%-1.25%	1,0346
1.25%-3.5%	1,1557
3.5% +	0,8263

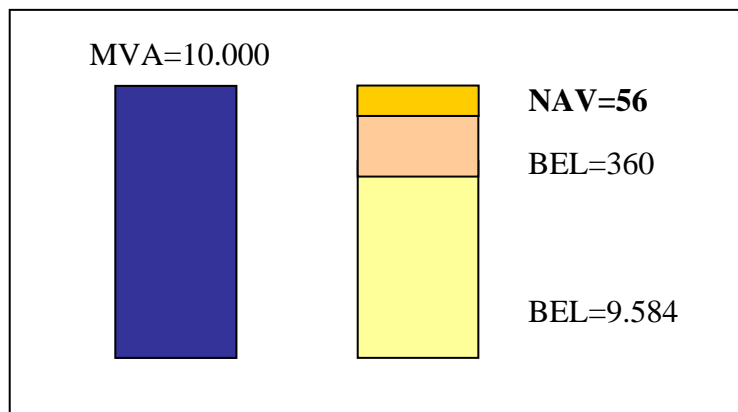
Lapse assumptions & Solvency II

Case study: Dynamic behaviour & Own Funds

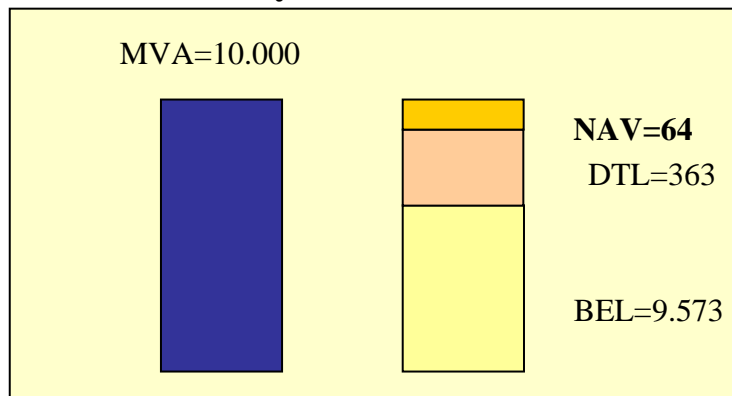
Univariate



Multivariate



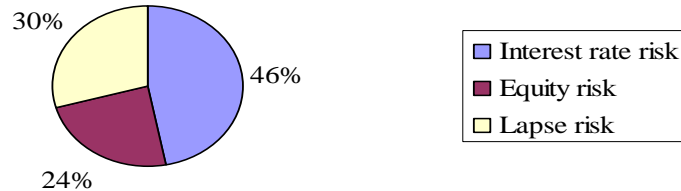
Multivariate dynamic



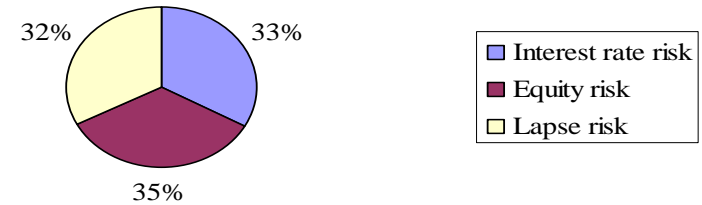
Lapse assumptions & Solvency II

Case study: Dynamic behaviour & SCR

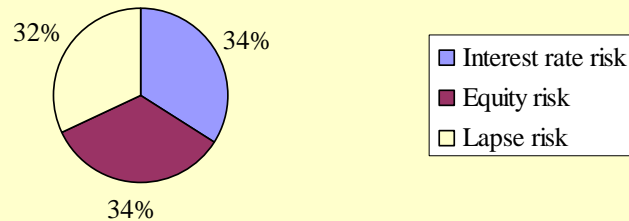
Univariate - SCR



Multivariate -SCR



Multivariate Dynamic - SCR



Lapse assumptions & Solvency II

Case study: Dynamic behaviour & SCR

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Interest rate risk	181,85	112,97	109,77
Equity risk	91,50	117,68	110,75
Lapse risk	114,42	110,54	103,35
SCR DIVERSIFIED	257,25	218,74	207,50
diversification effect	34%	36%	36%

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?



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