U.S. Post-Level Term Lapse and Mortality Predictive Modeling

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Executive Summary

The traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* published by the Society of Actuaries in May 2021 provided analysis of shock lapse at the end of term, lapse in PLT and mortality deterioration in PLT. The results were analyzed by many variables, and the statistical modeling technique of variable selection was used to identify the most important drivers of lapse and mortality behavior. As an extension to the traditional report analysis, predictive models were built to provide unique insights into the drivers of behaviors in PLT.

This report provides an educational background on the process of building predictive models, as well as a detailed presentation of the model results. Predictive models provide a method to capture variation by multiple variables and understand the relationship between these variables. This allows for a deeper understanding of key variables than is possible under a traditional approach.

<u>Predictive Modeling Approach</u>

The shock lapse in the last duration of the level term period was modeled through a logistic regression in a Generalized Linear Model (GLM) framework. The output of this model provides the predicted shock lapse which can be included as a variable for further PLT analysis. Predicted shock lapse is included together with the duration in PLT to model the relationship between the predicted shock lapse and mortality deterioration or lapse in PLT through non-parametric methods.

This approach was applied as a first step for lapse and mortality in PLT to produce shock lapse relationship models. Adjustments by other variables were then applied using GLM techniques to build the final models for mortality deterioration and lapse in PLT. Modeling in this two-step approach provides insight into the variation in PLT behavior that can be explained by the shock lapse relationship and highlights where other variables have an impact on PLT behavior.

<u>Key Takeaways</u>

The shock lapse at the end of term is the pivotal point and influences the lapse and mortality experience in PLT. Predictive modeling provides the capability to directly capture these relationships through modeling with shock lapse as a variable. In the traditional report analysis, the variables that impact the shock lapse at the end of term were observed to also impact the lapse and mortality in PLT. Predictive modeling helps to capture the PLT lapse and mortality patterns that can be explained by the shock lapse and identify the behavior in PLT that is driven by other variables.

The inclusion of other variables in modeling shock lapse is more important when the premium increase is lower. In the lower premium jump range 1.01x-3.00x, policyholder behavior is more sensitive to the premium increase but also to changes in other variables. This was observed for attained age, face amount, risk class and level term where the biggest differences in shock lapse by these variables were observed for lower premium jumps. Variation by billing type was also largest over the lower premium jumps, except when billing type changed at the end of term. This modeling of the different sensitivities to premium increase depending on billing type highlights that the size of the premium increase is less important when the billing type changes at the end of the level term period. There is an increasing pattern of shock lapse

with attained age, but the differences are less significant at higher ages. Furthermore, as the premium increases, the difference in the shock lapse variation by premium mode tends to decrease. The predicted model captured these relationships, and review of the model outputs highlight the deeper insights into shock lapse behavior at the end of term.

The model for Jump to ART shock lapse was built using T10 and T15 data only, but the model predictions provide a good fit for T20 shock lapse when compared to actual T20 data.

Lapses in each duration in PLT are higher when shock lapse is higher. Separate predictive models were built for Jump to ART and Graded to capture the different relationships. In the traditional report analysis, it was observed that lapse rates decrease by duration in PLT, but the decreasing pattern is less steep for Graded. For Jump to ART, the lapse rates in the first duration in PLT range from 18% to 55%, plateauing around 55% for the highest shock lapse range of 75-100%. There is still variation by shock lapse in later durations, but over a smaller range, with lapses in PLT falling between 5% and 20% for PLT duration 4 and later. For Graded, the fitted lapse rates rise sharply from 20% to 64% in the first duration in PLT, then gradually decrease by duration in PLT, but still range from 15% to 34% in PLT duration 4.

Shock lapse, as an explanatory variable, models the lapse rates by duration in PLT accurately at an overall level, but additional variables were required to fully explain lapse behavior in PLT. For Jump to ART, adjustments by risk class, face amount, initial premium jump and premium mode were applied in the final model. Policyholders with a Super Preferred **risk class** had higher lapses in PLT, and there was an increasing pattern of lapses by **face amount band** that was not explained by the shock lapse variable. There is a larger variation by risk class and face amount for lapses in PLT than for shock lapse. **Initial premium jump** was still an important variable with policyholders who had higher premium increases at the end of term showing higher lapses in PLT, even when shock lapse was the same. **Premium mode** was included as a variable and an interaction term with PLT duration improved the model fit. The pattern by premium mode varies by duration in PLT so the interaction term allowed the model to capture the higher lapse for Monthly premium mode compared to Annual mode in PLT duration 1 and then the lower lapses for Monthly premium mode in all later durations.

For Graded, the premium increases in subsequent years in PLT were highlighted as drivers of lapse in PLT not captured in the shock lapse variable. A more detailed model was not built for Graded, but analysis of the model fit highlighted variation by cumulative premium jump showing that subsequent duration premium increases impact lapse in PLT for Graded. The subsequent duration premium increases were not highlighted as significant for Jump to ART, and the model including only the initial premium jump was shown to fully explain the lapse behavior in PLT.

Mortality deterioration in PLT was higher when shock lapse was higher. For Jump to ART, the fitted mortality deterioration increased gradually from 120% - when shock lapse is less than 30% - to 400% when shock lapse ranges from 80-89%. For extremely high shock lapse rates, the mortality deterioration increased dramatically, hitting 2000% on average for predicted shock lapse probabilities in the 90-100% range. For Graded, the fitted mortality deterioration increased gradually from 110% to 300% on average for shock lapse ranges of 30% to 60%, and more steeply from 300% to 500% for the 60-79% range. For higher lapse rates, the mortality deterioration increased sharply, reaching 660% on average in the 80-89% range.

The pattern of mortality deterioration wear-off varies by shock lapse range. For Jump to ART in the higher shock lapse range, the high initial mortality deterioration wore off quickly, with the steepest wear-off pattern observed for the highest shock lapse group. For shock lapse probabilities lower than 50%, deterioration appeared to be relatively flat across later PLT durations. The predictive model highlights that the pattern by duration differs depending on the shock lapse range, capturing a pattern that was not clear in the traditional report analysis. Mortality deterioration for Graded was aggregated across all durations, and a model was built for aggregate mortality deterioration in PLT. No significant variations in mortality deterioration were observed when comparing actual mortality deterioration split into duration 1 and duration 2+ grouped to model predictions based on aggregate data. This confirms the findings from the traditional report that mortality deterioration is relatively flat across the durations available for Graded analysis. This is consistent with the pattern observed for Jump to ART over the lower shock lapse range.

Shock lapse, as an explanatory variable, models the mortality deterioration in PLT accurately at an overall level, but additional variables were required to fully explain anti-selective behavior. For Jump to ART, mortality adjustments by initial premium jump, risk class, billing type and premium mode were applied in the final model. Mortality deterioration was higher for Super Preferred and Preferred **risk classes** compared to Residual, irrespective of smoker status. Actual mortality deterioration was higher for Bill Sent and lower for Automatic payment than predicted by the shock lapse variable, suggesting that those who received a bill exhibited more anti-selective behavior. The difference between **billing types** was largest in the first duration in PLT but was maintained in later durations. The **premium mode** variation was overstated by the shock lapse relationship model as Annual mode business did not have as high of a mortality deterioration as predicted by the higher shock lapse. For premium jumps 8.00x and higher, the shock lapse relationship model underestimated the mortality deterioration in PLT. Mortality deterioration was higher when **premium jump** was higher even for a given shock lapse, suggesting there was more anti-selection at higher premium jumps.

The trends by study year are explained by changes in other variables over time. The model predicted shock lapses were compared to actual experience by study year. In the Jump to ART shock lapse data, there was an apparent increasing trend in shock lapse across study years since 2008. However, comparing to model predictions showed that the upward trend is not, in fact, a study year effect but can be explained by the changes in other variables over time. Similarly, the model-predicted mortality deterioration was compared to actual experience by study year which confirmed that apparent variation by study year was explained by the changes in other variables over time.

Section 1: Disclaimer

This study was published by the Society of Actuaries ("SOA") and contains information from a variety of sources. It may or may not reflect the experience of any individual company. The study is for informational purposes only and should not be construed as professional or financial advice. The SOA does not recommend or endorse any particular use of the information provided in this study. The SOA makes no warranty, express or implied, or representation whatsoever and assumes no liability in connection with the use or misuse of this study.

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The study results are based on data received from a variety of life insurance companies with unique product structures, target markets, underwriting philosophies and distribution methods. As such, these results should not be deemed directly applicable to any particular company or representative of the life insurance industry as a whole.

Section 2: Introduction

The Society of Actuaries ("SOA") engaged SCOR Global Life USA Reinsurance Company ("SCOR") to complete a research study on shock lapse, post-level term ("PLT") lapse and mortality experience for U.S. term life policies. The traditional report on the study findings, *U.S. Post-Level Term Lapse & Mortality Experience,* was published by the Society of Actuaries in May 2021. As a follow-up to the traditional report, this report presents techniques and results using predictive models for the shock lapse at the end of term, lapse in post-level term and post-level term mortality. In addition, an interactive tool based on these predictive models has also been developed.

2.1 SCOPE

The models include only fully underwritten U.S. level term life policies with a specific focus on post-level term ("PLT") experience for 10-year level term ("T10") and 15-year level term ("T15") plans. Data for 20-year level term ("T20") was too limited to support a predictive modeling exercise. The two main PLT premium structures that dominate the U.S. term life insurance market were modeled separately and are defined as follows:

1) Jump to ART: Premium increases at the end of the level term period follow an annual renewable term ("ART") scale in the PLT. This PLT premium structure is characterized by large increases in premiums at the end of the level term period, with initial premium jumps as high as 10, 20 or even 30 times the level period premium. After this large initial increase, premiums increase annually in smaller increments in line with typical age-related increases in mortality.
2) Graded: Premium increases at the end of the level term grade annually from the level premium until they reach an ART scale after a specified number of years. This PLT premium structure is characterized by generally lower initial premium jumps relative to the Jump to ART, usually no higher than five times the level term premium. A small amount of data with higher initial premium jumps is excluded from the study as it is not representative of this premium structure. After the initial premium increase, premiums continue to increase in subsequent years in significant step increases. This includes policies for which premiums were changed to Graded PLT premium structures and policies that had a Graded PLT premium structure from policy issue.

Predictive modeling analysis is carried out separately for Jump to ART and Graded, and separate models are built to capture the specific lapse and mortality results related to each of these PLT premium structures. Throughout the report, the Jump to ART model and Graded model are referred to separately. Similar methodologies were considered but different approaches were taken where justified by the data.

2.2 DATA

To support the creation of the models discussed in this paper, the same industry dataset used to create the SOA's 2021 U.S. post-level term experience study was used to build the predictive models. The data includes PLT experience for 25 companies and covers issue years 1990+ with a study period of 2000 to 2017. For a more in-depth understanding of the source data, please refer to the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* published by the Society of Actuaries in May 2021.

In the traditional report analysis, the results by each variable were considered independently, and different filters were applied as required to remove segments where data were not credible or points were dominated by one participant's data. For the predictive models, the same dataset was used for the whole analysis. Any restrictions required for one variable were applied to the overall dataset. For example, premium jump was a key variable. In the traditional report analysis, data where premium jump information was missing were excluded from views that included premium jump as a variable but were included for other views where premium jump was not analyzed. In the predictive models, the data missing premium jump information were excluded from the dataset. In addition, data missing premium mode or billing type were excluded. As a result, the predictive modeling was based on a reduced dataset.

In addition to policies missing information for any of the variables, undifferentiated smoker and non-smoker risk classes and substandard business were excluded from the dataset used to build the predictive models. These were excluded only from views by risk class in the traditional report analysis. The traditional report analysis included a small amount of data for 20-year term plans which was also excluded when building the predictive models. Data for substandard business and data for 20-year term plans were analyzed through comparisons to the predictive model expected values to identify how behavior compares for these segments.

2.3 LAPSE STUDY SPECIFICATIONS

Lapse Decrement Definition

The lapse decrement used in the predictive models included both lapse and conversion decrements. This is consistent with the traditional report. This approach was used because some contributors were not able to distinguish between these decrement types.

Description of Calculations

The lapse study, as outlined in the *U.S. Post-Level Term Lapse & Mortality Experience* report, was completed on a policy year basis where exposures start on the policy anniversary in the first calendar year that the policy contributed to the study and end on the policy anniversary in the last calendar year that the policy contributed to the study.

A policy year study is preferable for lapses which are not evenly distributed over the policy year. Lapses tend to be clustered around policy anniversaries or premium payment due dates, and this pattern is exaggerated in the post-level term period. As a result, looking at partial policy years could misstate the lapse rates due to including a disproportionate share of lapses relative to the proportionate partial year of exposures. A policy year study includes observations from policy anniversary to policy anniversary so that only complete policy years are included in the study.

A full policy year of exposure was assigned for policies when in-force, and a full policy year of exposure was assigned in the year of decrement for lapse or conversion. Other decrements, including deaths and maturities, contributed to the exposure up to the termination date.

2.4 MORTALITY STUDY SPECIFICATIONS

Description of Calculations

The exposure, as outlined in the *U.S. Post-Level Term Lapse & Mortality Experience* report, was calculated in the following manner for the calendar year study:

- Each policy received a full calendar year of exposure when in-force (except in the year of issue),
- The policy received the full calendar year of exposure in the year of death, and
- The exposure ended on the termination date in the year of a non-death termination.

The expected basis was calculated by first determining the appropriate mortality rate ("q_x") from the relevant industry table. This was then multiplied by the table rating (when applicable) and the flat extra amount (when applicable) was added to the resulting number. The exposure was then multiplied by this adjusted q_x, resulting in the expected mortality. The formula is as follows:

$$Expected = Exposure\ \times ((q_x\ \times table\ rating) + flat\ extra)$$

The mortality deterioration was calculated as the actual-to-expected ratio ("A/E") in the post-level term period divided by the A/E ratio in the level term period. The durations of the level period used in the mortality deterioration calculation varied by the level term period as follows:

- T10 – durations 6 to 10
- T15 – durations 6 to 15
- T20 – durations 11 to 20

Below is an example of the mortality deterioration calculation for duration 11, i.e., the first duration in the post-level term period for a 10-year level term plan:

$$Mortality\ Deterioration\ (Dur\ 11) = \frac{\frac{A}{E}\,15VBTCount(Dur\ 11)}{\frac{A}{E}\,15VBTCount(Dur\ 6-10)}$$

For other details regarding the mortality deterioration calculation, please refer to the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* published by the Society of Actuaries in May 2021.

Expected Mortality Basis

The mortality analysis in this report uses the 2015 Valuation Basic Table ("15VBT") to calculate the expected mortality. When "mortality deterioration" is referenced, it will be on a 15VBT count basis unless stated otherwise.

The 15VBT has a series of relative risk ("RR") tables that are intended to be used for different risk classes. These range from RR50 to RR175 for non-smokers and RR75 to RR150 for smokers. For reference, the base 15VBT is RR100 for both non-smokers and smokers. The expected mortality was calculated using the RR table associated with the individual policy risk class and used when studying the mortality deterioration by risk class. See Appendix B of the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience.*

The choice of expected basis is less impactful as PLT mortality is expressed as relative mortality deterioration compared to level term.

Confidence Intervals

The Poisson Distribution can be used to determine confidence intervals on an A/E ratio. Given that A deaths occurred where E would have been expected, the usual assumption as recalled by Liddell (1984) is that E is without error (because it is based on sufficiently large numbers) and that A is generated by a Poisson process. This report adopts the same assumptions.

The 95% confidence interval on A/E requires $1 - \alpha/2 = 0.975$ and $\alpha/2 = 0.025$. The quantile of order $1 - \alpha/2$ and $\alpha/2$ of the Poisson distribution can be obtained using some approximations, either by exact procedures as defined by Liddell (1984) and applied in a mortality context by Rhodes and Freitas (2004) or by standard statistical software. In this report, the 95% confidence interval on A/E is approximated using the software R, R Core Team (2021).

2.5 DISTRIBUTION OF DATA

The dataset used includes data for PLT premium structures Jump to ART and Graded and level term plans T10, T15 and T20. A breakdown of the lapse and claim data available is provided in tables 2.5-1 and 2.5-2 below for the traditional report post-level term analysis and predictive modeling, respectively. The dataset for predictive modeling excludes substandard policies, undifferentiated risk class and any policies missing premium jump, billing type or premium mode information.

Table 2.5-1

TRADITIONAL REPORT DECREMENTS BY TERM PLAN AND PLT STRUCTURE

PLT Structure	Term Plan	Lapse Count	Death Count
Jump to ART	10	716,328	3,861
	15	108,576	710
	20	18,017	59
Graded	10	101,081	432
	15	42,993	242
	20	16,815	82

Table 2.5-2

PREDICTIVE MODELING STUDY DECREMENTS BY TERM PLAN AND PLT STRUCTURE

PLT Structure	Term Plan	Lapse Count	Death Count
Jump to ART	10	226,029	2,162
	15	33,836	477
Graded	10	55,677	425
	15	20,878	163

Lapse counts shown include lapses occurring in the last duration of the level term when the shock lapse is observed (PLT duration 0), as well as lapses in the post-level term period (PLT durations 1+). Claim counts represent claims in the post-level term period only (PLT durations 1+).

Table 2.5-3 below shows the lapse counts by duration split by Jump to ART and Graded for analysis in the predictive modeling.

Table 2.5-3

LAPSE COUNTS BY PLT DURATION AND PLT STRUCTURE

PLT	PLT Premium Structure	
Duration	Jump to ART	Graded
0	195,011	61,622
1	36,634	10,752
2	8,937	2,867
3	5,530	1,055
4	4,138	259
5	3,077	NA
6	2,088	NA
7	1,409	NA
8	1,051	NA
9	713	NA
10	572	NA

Table 2.5-4 below shows the claim counts by duration split by Jump to ART and Graded for analysis in the predictive modeling.

Table 2.5-4

CLAIM COUNTS BY PLT DURATION AND PLT STRUCTURE

PLT Duration	PLT Premium Structure	
	Jump to ART	Graded
0	1,239	298
1	459	187
2	229	69
3	164	23
4	149	7
5	116	4
6	79	NA
7	59	NA
8	41	NA
9	42	NA
10	27	NA

2.6 MODELING APPROACH

Predictive modeling was carried out for:

1. shock lapse
2. lapse in PLT
3. mortality deterioration in PLT

Generalized Linear Model (GLM) Regression was applied to build a model for the shock lapse at the end of term. The GLM approach has been applied in previous research to model lapse risk and, in particular, shock lapse risk, see Kueker, et al. (2014) and Qian, et al. (2020) among others. The predictive model for shock lapse included all the variables and interactions between variables that are deemed significant using the likelihood-ratio test. Model building is an iterative process, and the criteria for determining a final model include review of statistical measures but also model fit analysis. The aim is to determine the simplest model that provides a good representation of the experience data. The approach to building a predictive model for shock lapse is described in section 3.

The predicted shock lapse output from the model was added as a new variable in the dataset for analysis of lapse and mortality in PLT.

Next, considering only this predicted shock lapse variable, a non-parametric model was built for lapse rates by duration in PLT to capture the relationship directly. This model for lapse in PLT is called the *shock lapse relationship model*. In a second step, this model was adjusted using GLM techniques to incorporate other variables to explain lapse rates in PLT, and this is referred to as the *final model*. The final model included, as a variable, the estimated lapse rates in PLT from the shock lapse relationship model and other variables deemed significant using the likelihood-ratio test. Details are outlined in section 4.

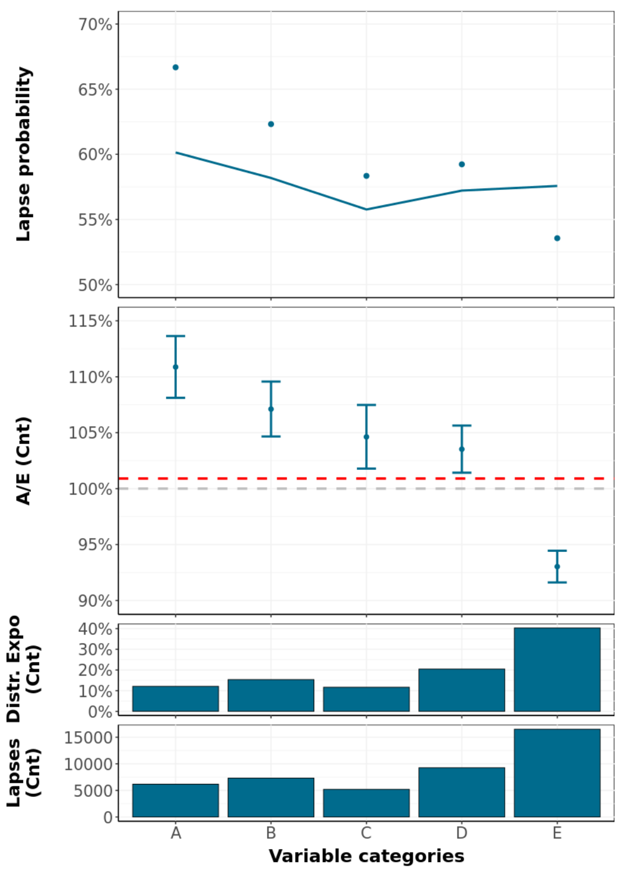
The mortality deterioration by duration in PLT was modeled in a similar two-step approach. A non-parametric model including only predicted shock lapse was built to directly capture the relationship between shock lapse at the end of term and mortality deterioration by duration in PLT. This model for mortality deterioration in PLT is called the *shock lapse relationship model*. The second step allows for modeling any significant deviations by other variables using a GLM regression approach to generate the *final model*. The modeling of mortality deterioration is described in section 5.

2.7 MODEL FIT ANALYSIS

Analysis of the model fit was carried out at each stage to determine how well the model predictions captured actual experience. This is an important tool in the model building process, as well as in the interpretation of results. This analysis is presented graphically with dots representing the actual experience and lines showing the model predictions. The first panel in Figure 2-1 shows an example for lapse rates. When the lines representing the model predicted lapse rates follow the dots representing actual experience lapse rates, the model is a good fit. This provides insights into the patterns predicted by the model and how these compare to the actual data. For a more accurate assessment, an A/E analysis is shown where the expected basis (E) is the model output prediction to compare to the actual experience (A). An example of these A/Es is shown in the second panel of Figure 2-1 with their associated 95% confidence intervals. The overall A/E is illustrated by the red dashed line, and the 100% A/E is illustrated by the grey dashed line. When the A/E is close to 100% for each category of the variable, the model fits the actual experience very well. Higher or lower A/Es represent underestimate and overestimation, respectively. When the 100% line is within the confidence interval, the model is a good fit. Confidence intervals are wider when less data are available. The third and fourth panels present the distribution of the exposure and the number of lapses, respectively.

Figure 2-1

MODEL FIT ANALYSIS SAMPLE CHART



The following approach was used to develop the models used in this report.

1. Decide on the variables to include in the model

The choice of variables was determined using statistical tests, but there was also an element of judgement. The A/E analysis helped to visualize the explanatory value added by an additional variable or interaction between variables by comparing a model including this effect to a model excluding this effect. In this way, model fit analysis was used to aid the decision in choosing the final combination of variables and interactions to include in the model.

2. Compare two models

Mortality deterioration is modeled in two steps, and A/E analysis was carried out to compare the model fit for the step one model (shock lapse relationship model) and the step two model (final model). This provides insight into how well the mortality deterioration by duration in PLT can be explained by including only the shock lapse variable compared to a final model including additional variables. The comparison was also used as a justification for including additional variables in the final model where the pattern was not captured by the shock lapse relationship model. A similar comparative analysis was carried out for lapse in PLT modeling, which also has a two-step approach.

3. Demonstrate how well the chosen model fits the experience

Once the final model was determined, analysis of the model fit was carried out using the final model predictions as the expected basis. Through A/E analysis, the model fit analysis can be reviewed for the variables that were included in the model and variables that were not included in the model. This analysis demonstrates the ability of the model to explain all deviations observed in the experience data.

4. Understand the relationship captured by the predictive model

Predictive modeling allows for the analysis of the impact of multiple variables on lapse and mortality experience, as well as the interaction of these variables. Reviewing the model fit by multiple variables helps to explain the relationship captured by the predictive model. An interactive tool is provided alongside this report that allows for review of the model fit by any two variables. The dynamic relationships captured by the model can be understood through this analysis.

5. Assess residual variation

Using the final model predictions as the expected basis, model fit analysis was used to assess variations by external variables not considered during the model building process. One example is study year. While study year is not a driver of behavior, it is interesting to understand whether experience varies year-over-year. A/E analysis allows for a more consistent comparison across study years as it adjusts for modeled variation. If the A/E is close to 100%, the apparent variation in actual experience is fully explained by the model and no residual variation is observed.

6. Test the model on other data

Data that were not used in the model building exercise can be assessed in model fit analysis by comparing actual experience to model predictions. For example, substandard data were excluded from the model build analysis, but an A/E analysis was carried out to compare the actual substandard experience to predictions based on the model built using standard data only.

Section 3: Shock Lapse Model

Policyholder premiums remain the same each year during the level term period. At the end of the level term period, policies are automatically renewed without additional underwriting but at annually increasing premium rates. The largest premium increases occur at the end of the level term period and many policyholders do not pay these high premiums, resulting in a shock lapse at the end of the last duration of the level term period. This section focuses on the shock lapse and covers the building of a predictive model to explain shock lapse variation.

The shock lapse in the last duration of the level term period was modeled through a logistic regression in a Generalized Linear Model (GLM) framework. With the GLM, the variation of the shock lapse was explained by the selected variables. The choice of variables was determined using statistical tests, but there was also an element of judgement. Model fit analysis (as described in section 2.6) is presented to compare the explanatory value added by an additional variable or interaction between variables by comparing a model including this effect to a model excluding it. Statistical analysis was also used to determine groupings for categorical variables where full granularity was not required, and this data preparation is described for face amount bands and initial premium jump groups. The modeling approach, data preparation and selection of variables is described in section 3.1.

Separate models were built for Jump to ART and Graded. Section 3.2 presents the model output for each in terms of the model predicted shock lapse for a given set of characteristics and provides discussion on the interpretation of the model results.

The model explains the connection between the shock lapses and the relevant drivers selected from the available variables based on their ability to predict the shock lapse rates. Section 3.3 illustrates the shock lapse rates by relevant variables by comparing the model predictions to actual experience. This analysis reviews the ability of the model to explain all deviations observed in the experience data. The charts presented also help to illustrate the relationship between variables that are captured by the predictive model. The dynamic relationships captured by the models are discussed to provide insights into shock lapse behavior.

In section 3.4, the shock lapse variation was assessed by external variables that were not included in model building. Using the model predictions as an expected basis, a more consistent comparison was achieved by adjusting for modeled variation. This approach was applied to investigate whether there were differences in shock lapse experience for T20 plans, substandard policies, study year and by company depending on communication with policyholders at the end of term.

3.1 DATA AND MODELING APPROACH

3.1.1 DATA

In the shock lapse data, eight variables were considered. Most are categorical variables with the exception of attained age which was modeled as a numerical variable. A categorical variable is a variable that only takes a finite number of distinct values. These values are called categories. A numerical variable is a variable that may take on any value within an interval. Table 3-1 describes the variables and the exposure distribution for each PLT premium structure.

Table 3-1
VARIABLES

Variable	Class	Description	Exposure in PLT (%)	
			Jump to ART	Graded
Level term plan	Categorical	10	88	74
		15	12	26
Gender	Categorical	Male	65	69
		Female	35	31
Attained age	Numerical	18-49	35	20
		50-59	32	36
		60-69	24	36
		70+	9	8
Risk class	Categorical	Residual SM	5	3
		Preferred SM	5	3
		Residual NS	34	35
		Preferred NS	34	26
		Super Preferred NS	22	33
Face amount	Categorical	$0-100K	31	18
		$101-250K	35	31
		$251-500K	22	29
		$501K+	12	22
Initial premium jump	Categorical	1.01x-1.50x	6	3
		1.51x-2.00x	14	6
		2.01x-2.50x	10	13
		2.51x-3.00x	5	24
		3.01x-3.50x	4	20
		3.51x-4.00x	3	17
		4.01x-4.50x	4	12
		4.51x-5.00x	4	5
		5.01x-5.50x	4	NA
		5.51x-6.00x	4	NA
		6.01x-7.00x	7	NA
		7.01x-8.00x	6	NA
		8.01x-10.00x	9	NA
		10.01x-14.00x	11	NA
		14.01x+	9	NA
Billing type	Categorical	Automatic payment	55	31
		Bill Sent	41	69
		Automatic payment changed to Bill Sent	4	NA
Premium mode	Categorical	Annual	29	49
		Semi-annual	6	7
		Quarterly	16	14
		Monthly	49	30

Attained age is included as a numerical variable so that shock lapse can be modeled at individual ages. It was decided to include Initial premium jump as a categorical variable to capture the nonlinear relationship with shock lapse probability and because less granular groupings adequately capture the relationship. While initial premium jump data was available at a more granular level split into 23 groups, this was reduced to 15 groups, as shown in Table 3-1, as determined based on statistical analysis (as described in section 3.1.3 below).

Similarly, face amount bands were available at a more granular level, but four groups were determined based on statistical analysis. The groupings differed for Jump to ART and Graded, as shown in section 3.1.3 below.

3.1.2 LOGISTIC REGRESSION IN A GLM FRAMEWORK

A logistic regression model was used to predict the shock lapses. This approach is practical and ensures that the fitted probabilities are bounded between 0 and 1. In addition, the GLM framework allows for statistical inference and hypothesis testing to determine the groupings of categories of variables, with the intention to improve model parsimony and select interactions between variables to enhance model performance. More technical details about Generalized Linear Models can be found in Appendix A.

The lapse count in the shock duration, i.e., the last duration of the level term period, was modeled with a binomial distribution where the exposure was included as weight and the expectation of the dependent variable linked to the linear predictor by the logit link function. The logit link ensures that the predictions of the lapse probabilities are in the interval |0,1].

Each cell is determined by a unique combination of variables,

$$C_I^{\mathrm{S}} \sim \text{Binomial}\left(\mathrm{E}_I^{\mathrm{S}}\, p_i^{\mathrm{S}}\right),$$

whereas

$$\operatorname{logit} p_i^{\mathrm{S}} = \ln\left(\frac{p_i^{\mathrm{S}}}{1 - p_i^{\mathrm{S}}}\right) = \beta_0 + \sum_{j=1}^{r} \beta_j x_{ij}$$

where

- C_I^{S} is the lapse count in the shock duration, the last duration of the level term period, for cell i.
- $\mathrm{E}_I^{\mathrm{S}}$ is the exposure in the last duration of the level term period for cell i.
- p_i^{S} is the probability of lapse in the last duration of the level term period for cell i.
- x_{ij} is the set of variables described in Table 3-1.

The logit of p_i^{S} is the log of the odds that a policyholder in cell i will lapse in the last duration of the level term period, i.e., $\ln\left(\frac{p_i^{\mathrm{S}}}{1-p_i^{\mathrm{S}}}\right)$. The corresponding probability of a policyholder in cell i to lapse in the last duration of the level term period is, therefore,:

$$p_i^{\mathrm{S}} = \frac{\exp\left(\beta_0 + \sum_{j=1}^{r} \beta_j x_{ij}\right)}{1 + \exp\left(\beta_0 + \sum_{j=1}^{r} \beta_j x_{ij}\right)}.$$

It is worth noting that the model predicts exactly the total actual number of lapses for each category of the variables by equating the partial derivative of the log-likelihood with respect to β_j,

$$\sum_{i|x_{ij}=1} C_i^S = \sum_{i|x_{ij}=1} \mathrm{E}_i^S\, p_i^S.$$

The ratio between the actual and expected number of lapses in the last duration of the level term period is 100%, not only at the overall level, but also for each category of the variables included in the model.

A logistic regression model is developed separately for Jump to ART and Graded. In the following section, the main steps for grouping the categories of variables and selecting the variables described in Table 3-1 and interactions are discussed.

3.1.3 GROUPINGS FOR CATEGORICAL VARIABLES

While granular data are available for many of the variables, modeling at the granular level may not be required to capture the shock lapse variation. The granular groupings for face amount and initial premium jump are reviewed in this section to identify whether categories of these variables have the same effect on the predicted shock lapses and whether further grouping could be applied. The approach is to determine groupings based on statistical analysis rather than traditional methods. Advantages of this approach include a simpler and more informative interpretation of the results and greater parsimony.

Face Amount Bands

Face amount band is considered at a granular level with 13 bands, and the estimated coefficients are reviewed to identify further groupings. When the estimated coefficients are similar between bands, this implies that the effect of these bands is the same on the predicted shock lapses. Table 3-2 illustrates the estimated coefficients, and the suggested groupings are highlighted using the same color for bands with similar coefficients.

Table 3-2
ESTIMATED FACE AMOUNT BAND COEFFICIENTS AND SUGGESTED GROUPINGS

Face Amount Band	Estimated Coefficients	
	Jump to ART	Graded
$0-49K	Reference	Reference
$50-99K	-0.382	0.941
$100K	-0.365	1.201
$101-249K	-0.184	1.418
$250K	-0.118	1.549
$251-499K	-0.070	1.586
$500K	-0.062	1.584
$501-749K	0.047	1.598
$750K-999K	0.046	1.633
$1M	-0.011	1.528
$1.1-4.9M	0.010	1.563
$5.0-9.9M	0.210	1.504
$10M+	0.319	1.789

Models were fitted separately on Jump to ART and Graded with face amount band $0-49K being the reference band. All coefficients were estimated with respect to the reference band.

The suggested groupings illustrated in Table 3-2 were then validated using the likelihood ratio test.

Regarding the model fitted to Jump to ART data, from Table 3-2, the estimated coefficient of face amount band $50-99K was similar to the $100K band. There was only a small amount of data in the $0-49K band, so it was decided to group all three bands -- $0-49K, $50-99K and $100K -- into a single face amount band of $0-100K. Similarly, the bands $101-249K and $250K were grouped into a band $101-250K, and the bands $251-499K and $500K were grouped into a band $251-500K. The estimated coefficients for the bands $501-749K, $750-999K, $1.0M and $1.1-4.9M were similar, and a grouping of $501K-4.9M was statistically justified. Finally, it was decided to include the highest face amount bands $5.0-9.9M and $10M+ together with the $501K-4.9M due to the small amount of data available.

Regarding the Graded model, from Table 3-2, the estimated coefficients for face amount band $250K+ did not seem to differ between bands. Therefore, the bands $250K+ were grouped together. The lower face amount bands had estimated coefficients that varied significantly, so grouping those bands was not statistically justified.

For informational purposes, the five band groupings -- $0-99K, $100-249K, $250-499K, $500-999K, and 1M+, as applied in the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience*, were also fitted to both premium structures. In addition, a model fitted on Graded data with the face amount bands as applied for Jump to ART was also compared. Table 3-3 summarizes the groupings compared in Figure 3-1.

Table 3-3

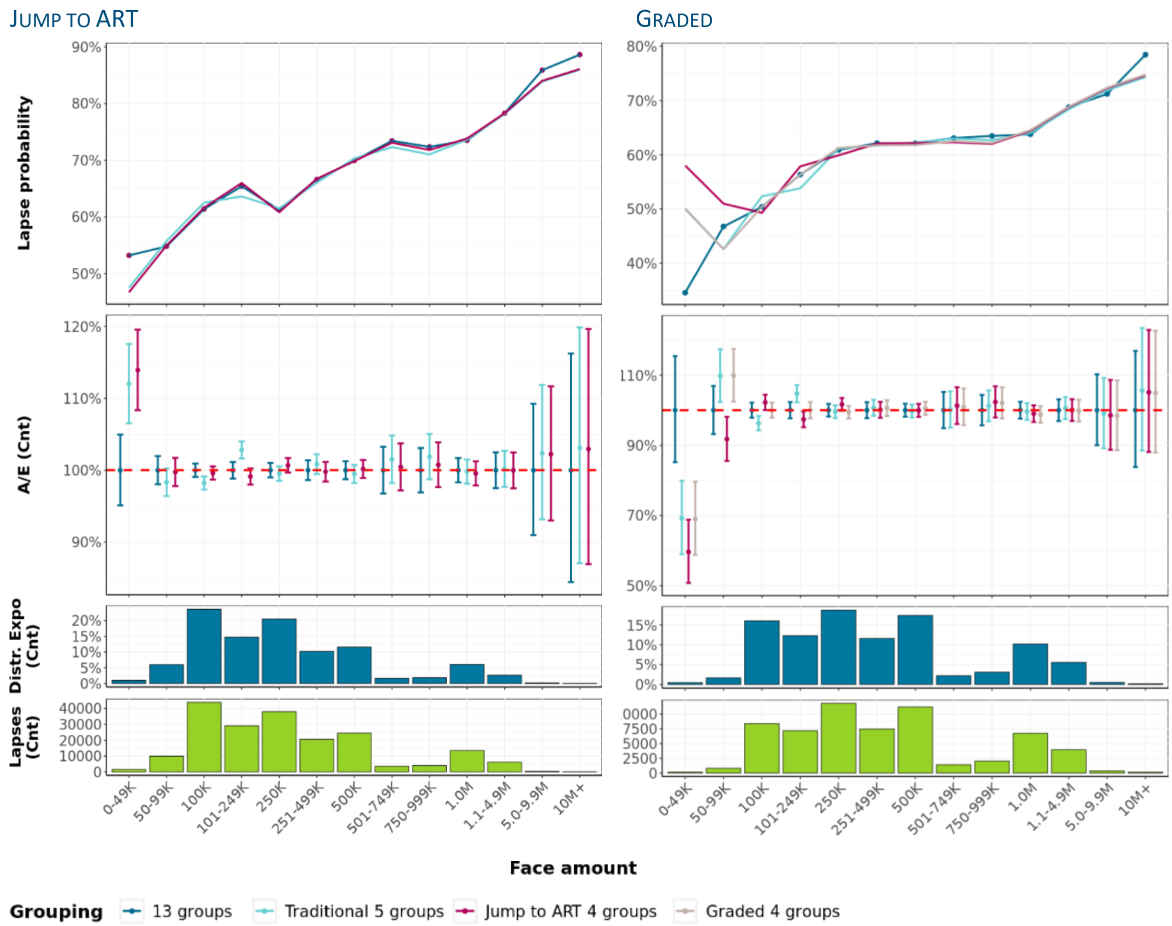
FACE AMOUNT BAND GROUPINGS

<table>
<tr><th>13 groups</th><th>$0-49K</th><th>$50-99K</th><th>$100K</th><th>$101-249K</th><th>$250K</th><th>$251-499K</th><th>$500K</th><th>$501-749K</th><th>$750K-999K</th><th>$1M</th><th>$1.1-4.9M</th><th>$5.0-9.9M</th><th>$10M+</th></tr>
<tr><td>Jump to ART
4 groups</td><td colspan="3">$0-100K</td><td colspan="2">$100-250K</td><td colspan="2">$251-500K</td><td colspan="6">$501K+</td></tr>
<tr><td>Graded
4 groups</td><td colspan="2">$0-99K</td><td>$100K</td><td>$101-249K</td><td colspan="9">$250K+</td></tr>
<tr><td>Traditional report
5 groups</td><td colspan="2">$0-99K</td><td colspan="2">$100-249K</td><td colspan="2">$250-499K</td><td colspan="3">$500-999K</td><td colspan="4">$1M+</td></tr>
</table>

The fit of the models for both premium structures is illustrated in Figure 3-1, first panel. The observations are denoted by dots, while the full lines represent the predictions. The second panel displays the corresponding actual over expected number of lapses as predicted by the models with their associated 95% confidence intervals, while the third and fourth panels present the distribution of the exposures and the number of lapses, respectively.

Figure 3-1

FACE AMOUNT BANDS GROUPING COMPARISON



For both premium structures, at the overall level, the model with the 13 face amount groups predicted exactly the observed number of lapses for each face amount band. This is the level of specificity of the GLMs used in section 3.1.2. As a result, the corresponding A/E are 100%.

Regarding the models fitted on Jump to ART data, the model having four groups captured the shock lapse variation by face amount appropriately with the exception of the lowest face amount band, $0-49K, where the model predicted lower lapses than observed. At the highest bands, the model with four bands continued to capture the shock lapse variation above $5M+. The A/E ratios are 102% and 103% for bands $5.0-9.9M+ and $10M+, respectively, and the 100% A/E is within the 95% confidence interval.

The model using the five bands as applied in the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* led to significant deviations from 100% A/E for face amount bands $50-99K, $100K and $101-249K. By applying the five-band groupings, the shock lapse variations were not modeled adequately. Significant overestimation of the number of lapses for face amount bands $50-99K and $100K and underestimation for face amount band $101-249K was seen.

Regarding the Graded premium structure, the model with four face amount bands fitted the shock lapse variation adequately. The 100% A/E falls within the 95% confidence interval for all premium jump bands with the exception of the lowest face amount band $0-49K. The model using the five bands as per the traditional report analysis led to significant overestimation of the number of lapses for face amount band $100K and underestimation for face amount bands $50-99K and $101-249K. For informational purposes, a model fitted with the face amount bands as applied on Jump to ART data was also compared in Figure 3-1. The model led to significant overestimation of the number of lapses for bands $50-99K and $101-249K.

For the remainder of this report, face amount bands were grouped into four bands: $0-100K, $101-250K, $251-500K, and $501K+ for the model fitted on Jump to ART data, and $0-99K, $100K, $101-249K, and $250K+ for the model fitted on the Graded premium structure.

Initial Premium Jump Bands

As with the face amount bands, the estimated coefficients for some initial premium jump bands were similar, and a grouping was suggested in the initial iterations of the model applied to Jump to ART. Starting with 23 initial premium jump bands, the final grouping included 15 bands after testing. Table 3-4 illustrates the groupings.

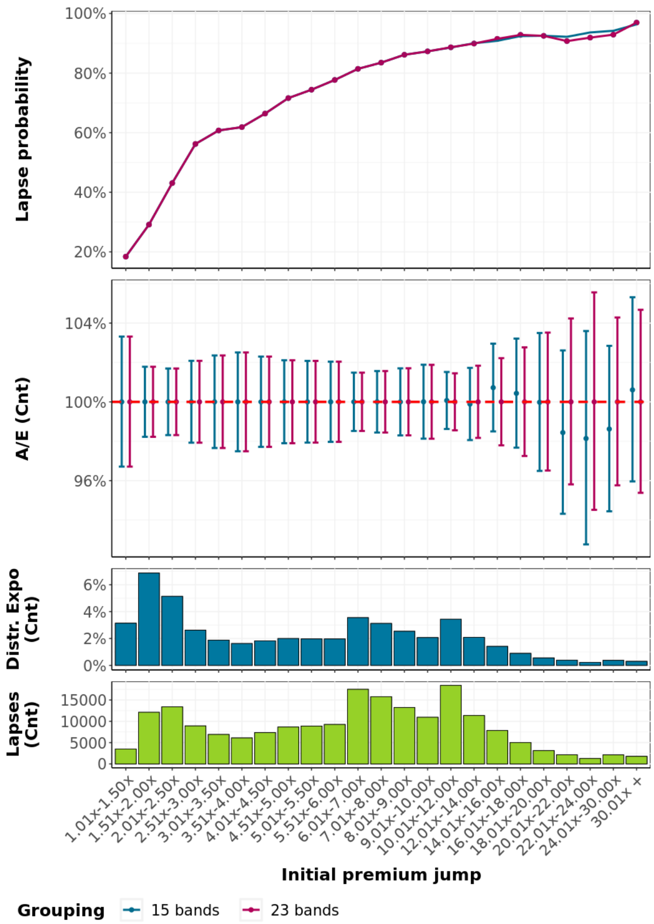
Table 3-4
INITIAL PREMIUM JUMP BAND GROUPINGS

<table>
<tr><th>Initial premium jump 23 bands</th><td>1.01x-1.50x</td><td>1.51x-2.00x</td><td>2.01x-2.50x</td><td>2.51x-3.00x</td><td>3.01x-3.50x</td><td>3.51x-4.00x</td><td>4.01x-4.50x</td><td>4.51x-5.00x</td><td>5.01x-5.50x</td><td>5.51x-6.00x</td><td>6.01x-7.00x</td><td>7.01x-8.00x</td><td>8.01x-9.00x</td><td>9.01x-10.00x</td><td>10.01x-12.00x</td><td>12.01x-14.00x</td><td>14.01x-16.00x</td><td>16.01x-18.00x</td><td>18.01x-20.00x</td><td>20.01x-22.00x</td><td>22.01x-24.00x</td><td>24.01x-30.00x</td><td>30.01x+</td></tr>
<tr><th>Jump to ART 15 groups</th><td>1.01x-1.50x</td><td>1.51x-2.00x</td><td>2.01x-2.50x</td><td>2.51x-3.00x</td><td>3.01x-3.50x</td><td>3.51x-4.00x</td><td>4.01x-4.50x</td><td>4.51x-5.00x</td><td>5.01x-5.50x</td><td>5.51x-6.00x</td><td>6.01x-7.00x</td><td>7.01x-8.00x</td><td colspan="2">8.01x-10.00x</td><td colspan="2">10.01x-14.00x</td><td colspan="7">14.01x+</td></tr>
</table>

The impact of the grouping is illustrated in Figure 3-2. For Graded, no grouping of the initial premium jump band was required. The top panel illustrates the fit of the models when including either 15 or 23 initial premium jump bands. The second panel displays the corresponding actual over expected number of lapses with the associated 95% confidence intervals, while the third and fourth panels present the distribution of the exposure to risk and the number of lapses, respectively.

Figure 3-2

INITIAL PREMIUM JUMP BAND GROUPINGS COMPARISON FOR JUMP TO ART



At the overall level, the model with the 23 bands predicted exactly the observed number of lapses for each initial premium band and the corresponding A/E was 100%. The fit of the model, including 15 initial premium jump bands, only differed where the grouping had been applied. This was specifically seen for bands 14.01x-16.00x and 20.00x+. Deviations from 100% A/E were, therefore, observed. However, the actual expected number of lapses was between 98% and 101%. In addition, the 100% A/E falls within the 95% confidence interval, illustrating that by grouping the largest initial premium jump bands together, i.e., 14.00x+, the model still adequately captured the shock lapse variations. In other words, shock lapse variations at the highest initial premium jump bands are not explained by the premium jump increases, but rather by a combination of other variables.

3.1.4 SELECTING VARIABLES

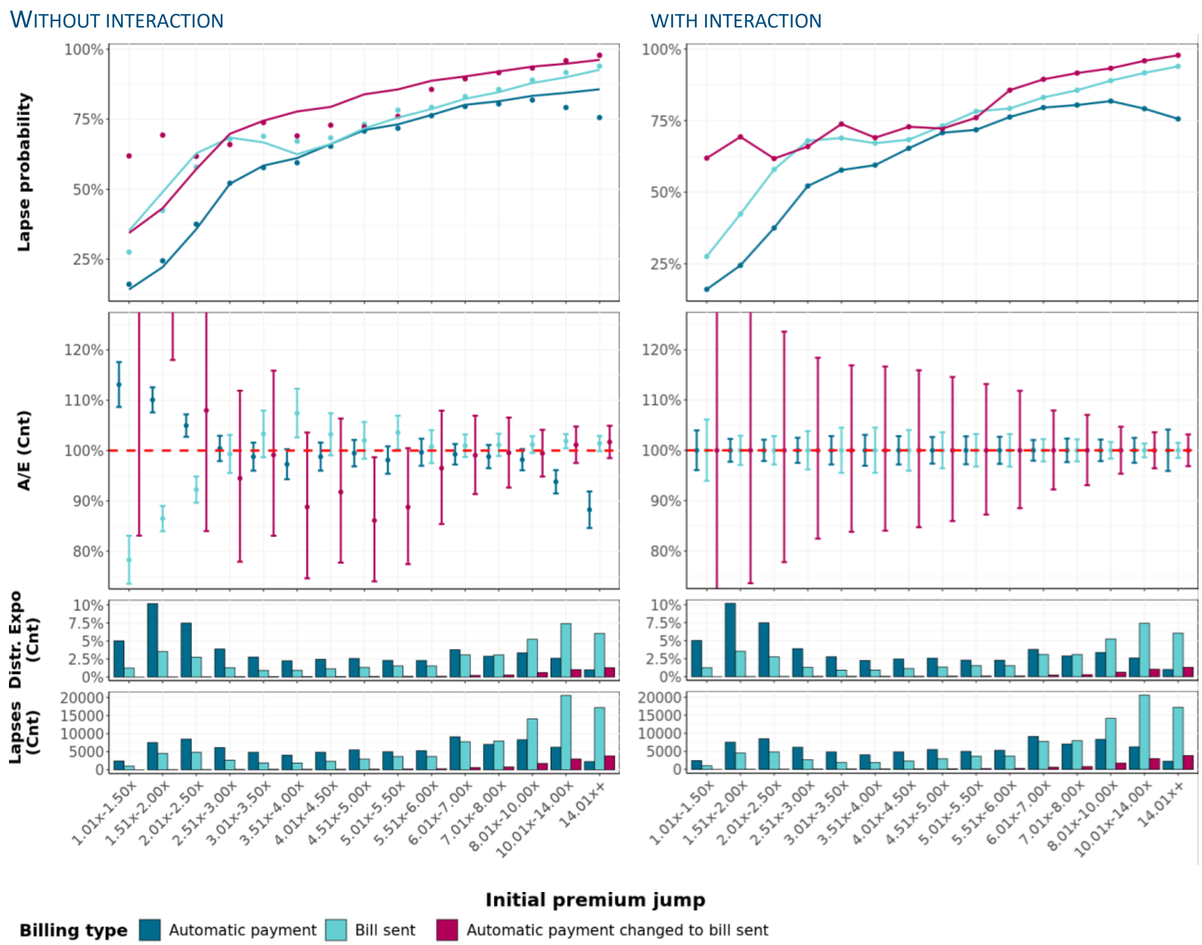
The main steps in selecting the variables described in Table 3-1 and the variable interactions are discussed in the following section.

A saturated model was set at the start including all main effects and interactions. The insignificant effects were excluded by comparing the models with and without the variables using the likelihood-ratio test.

- **Initial premium jump**, **attained age**, **premium payment mode**, **billing type**, **risk class and face amount**: The likelihood-ratio test comparing a model (applied separately on Jump to ART and Graded) without each of these variables to a model which includes the variable gives, for each of them, a *p*-value[1] lower than 0.1%. This indicates that for both Jump to ART and Graded, the model including each of these variables is statistically justified.
- **Level term plan:** The likelihood-ratio test comparing a model fitted on Jump to ART to a model without this variable gives a *p*-value lower than 0.1%, while the corresponding *p*-value is 3% for a model applied on Graded. This shows that, for both premium structures, the model including level term plan is statistically preferred, although, for Graded, the shock lapse variation by level term plan is smaller.
- **Gender**: Comparing the model with and without this variable leads to a *p*-value of the likelihood-ratio test of 7% and 11% for Jump to ART and Graded, respectively. This shows that gender is the least significant variable for Jump to ART. At a 95% significance level, the model without the gender effect is preferred. The shock lapse variation by gender is relatively small compared to the variations within each of the other variables.
- **Higher order term for attained age**: Lapse rates, for both Jump to ART and Graded, as a function of attained age have a quadratic shape that cannot be explained by a simple linear predictor. However, higher order terms explain the reduced effect on the lapse rate when attained age increases. The p-value of the corresponding likelihood ratio-test comparing the models with and without the quadratic attained age term is less than 0.1% for both PLT premium structure models. This suggests that the model with a quadratic attained age term is preferred.
- **Initial premium jump and billing type interaction:** A significant interaction is observed between the initial premium jump and billing type for the Jump to ART premium structure model. A model including this interaction term is compared to a model without it in Figure 3-3. Including the interaction by initial premium jump band and billing type allows the model to predict exactly the observed number of lapses. As a result, the A/E ratios are 100% (see the right panel). Without including this interaction, the shock lapse variations at the lowest initial premium jump range (1.01x-2.50x) for the three billing type categories are not captured adequately by the model. This is illustrated in the second left panel in Figure 3-3 where the A/E 100% did not fall within the confidence interval. In addition, the interaction term is capturing the pattern by premium increase for Automatic payment changed to Bill Sent, which is different from the other billing type categories (see the left panel of Figure 3-3). Policyholders who face a change in billing type at the end of term have a higher shock lapse probability irrespective of premium increase.

[1] The *p*-value is the probability that the model with less variables is preferred. Having a p-value lower than 5% means the model with the additional variable is statistically justified at a 95% significance level.

Figure 3-3
SHOCK LAPSE VARIATIONS BY INITIAL PREMIUM JUMP AND BILLING TYPE FOR JUMP TO ART



3.2 MODEL OUTPUT

The main effects and interactions included in the final models fitted separately to Jump to ART and Graded data are displayed in Tables B-1 and B-2 of Appendix B, respectively. From these estimated regression coefficients, the effect of selected variables can be derived.

A reference category is selected for each of the categorical variables that corresponds to the category where the largest exposure is observed. For these models, the reference categories are given in Table 3-5.

Table 3-5
REFERENCE CATEGORIES FOR CATEGORICAL VARIABLES

Categorical Variables	Jump to ART	Graded
Level term plan	T10	T10
Face amount band	$101-250K	$250K+
Risk class	Preferred NS	Residual NS
Initial premium jump band	4.51x-5.00x[1]	2.51x-3.00x[1]
Billing type	Automatic payment	Bill Sent
Premium payment mode	Monthly	Annual

[1]Average premium increase.

3.2.1 INTERPRETATION OF THE JUMP TO ART REGRESSION MODEL OUTPUT

The shock lapse probabilities with their associated 95% confidence intervals and corresponding relative risk with respect to a policyholder with characteristics corresponding to the reference categories are displayed in Tables 3-6 (main effects) and 3-7 (interaction effects) for Jump to ART.

Table 3-6

SHOCK LAPSE PROBABILITIES WITH THEIR ASSOCIATED 95% CONFIDENCE INTERVALS AND RELATIVE RISK FOR THE MAIN EFFECTS WITH RESPECT TO A POLICYHOLDER WITH CHARACTERISTICS CORRESPONDING TO THE REFERENCE CATEGORIES FOR JUMP TO ART

Variable – Main Effects	Lapse Probability with 95% CI	Relative Risk
Reference categories: *T10, face amount band $101-250K, Preferred NS risk class, initial premium jump band 4.51x-5.00x, billing type: Automatic payment and Monthly premium mode*	56% [55%,57%]	100%
Term 15	51% [49%,54%]	91%
Attained age: Policyholder aged 50 years old	49% [48%,50%]	
Policyholder aged 70 years old	72% [71%,74%]	147%
Risk class: Residual SM	69% [67% 71%]	123%
Risk class: Preferred SM	66% [63%,68%]	118%
Risk class: Residual NS	58% [56%,60%]	104%
Risk class: Super Preferred NS	59% [57%,61%]	105%
Face amount $0-100K	51% [49%,53%]	91%
Face amount $251-500K	58% [56%,60%]	104%
Face amount $501K+	60% [58%,62%]	107%
Premium mode: Quarterly	71% [69%,72%]	127%
Premium mode: Semi-annual	79% [78%,81%]	141%
Premium mode: Annual	82% [81%,83%]	146%
Billing type: Bill Sent	67% [64%,70%]	120%
Billing type: Automatic payment changed to Bill Sent	74% [67%,80%]	132%

From Table 3-6, the predicted lapse probability during the last duration of the level term period for the main effects of the model can be interpreted. Below, three examples of the computation of the estimated risk factors and interpretation of the corresponding predicted shock lapse probabilities are given. For example:

- Intercept / Reference categories: A policyholder with characteristics corresponding to the reference categories (i.e., T10, face amount band $101-250K, Residual NS risk class, initial premium jump band 4.51x-5.00x, billing type: Automatic payment, and Monthly premium payment mode) has a $\exp(\hat{\beta}_0)/(1+\exp(\hat{\beta}_0)) = \exp(0.239)/(1+\exp(0.239)) \approx 56\%$ probability of lapse during the last duration of the level term period. Additionally, based on the standard error, the corresponding 95% confidence interval is:

$$\begin{bmatrix} \exp\left(\hat{\beta}_0 - 1.96 \times s.e.(\hat{\beta}_0)\right)/\left(1+\exp\left(\hat{\beta}_0 - 1.96 \times s.e.(\hat{\beta}_0)\right)\right) \\ \exp\left(\hat{\beta}_0 + 1.96 \times s.e.(\hat{\beta}_0)\right)/\left(1+\exp\left(\hat{\beta}_0 + 1.96 \times s.e.(\hat{\beta}_0)\right)\right) \end{bmatrix} \approx [55\%, 57\%]$$

- **Level term plan**: The shock lapse probability of a policyholder with characteristics corresponding to the reference categories except with a T15 product is:

  $\exp(\hat{\beta}_0 + \hat{\beta}_1)/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_1)) = \exp(0.239 - 0.185)/(1 + \exp(0.239 - 0.185)) \approx 51\%$ (95% CI [49%, 54%]).

  An individual having a T15 policy has a relative risk of 91% of lapse compared to a T10 policy:

  $$\frac{\exp(\hat{\beta}_0+\hat{\beta}_1)/1+\exp(\hat{\beta}_0+\hat{\beta}_1)}{\exp(\hat{\beta}_0)/1+\exp(\hat{\beta}_0)} \approx \frac{51\%}{56\%} = 91\%.$$

- **Attained age**: The shock lapse probability of a 50 year-old policyholder with characteristics corresponding to the reference categories is:

  $\exp(\hat{\beta}_0 + \hat{\beta}_1 \times \mathrm{AgeSd}_{50} + \hat{\beta}_2 \times {\mathrm{AgeSd}_{50}}^2)/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 \times \mathrm{AgeSd}_{50} + \hat{\beta}_2 \times {\mathrm{AgeSd}_{50}}^2)) \approx 49\%$ (95% CI [48%, 50%]) where AgeSd_{50} refers to the attained age 50 standardized[2]. While a 70-year-old has a 72% (95% CI [71%, 74%]) probability of lapsing, a policyholder with characteristics corresponding to the reference categories aged 70 has 1.5 more chance of lapse compared to a 50-year-old policyholder. The corresponding relative risk is:

  $$\frac{\exp(\hat{\beta}_0+\hat{\beta}_1\times\mathrm{AgeSd}_{70}+\hat{\beta}_2\times{\mathrm{AgeSd}_{70}}^2)/(1+\exp(\hat{\beta}_0+\hat{\beta}_1\times\mathrm{AgeSd}_{70}+\hat{\beta}_2\times{\mathrm{AgeSd}_{70}}^2))}{\exp(\hat{\beta}_0+\hat{\beta}_1\times\mathrm{AgeSd}_{50}+\hat{\beta}_2\times{\mathrm{AgeSd}_{50}}^2)/(1+\exp(\hat{\beta}_0+\hat{\beta}_1\times\mathrm{AgeSd}_{50}+\hat{\beta}_2\times{\mathrm{AgeSd}_{50}}^2))} \approx \frac{72\%}{49\%} = 147\%.$$

[2] Attained age variable has been standardized to have a mean of 0 and a standard deviation of 1.

Table 3-7

SHOCK LAPSE PROBABILITIES WITH THEIR ASSOCIATED 95% CONFIDENCE INTERVALS AND RELATIVE RISK FOR THE INTERACTION EFFECTS WITH RESPECT TO A POLICYHOLDER WITH CHARACTERISTICS CORRESPONDING TO THE REFERENCE CATEGORIES FOR JUMP TO ART

Variable – Interaction Effects	Lapse Probability with 95% CI	Relative Risk
Initial premium jump 1.01x-1.50x × Billing type: Automatic payment	26% [23%,28%]	46%[1]
Initial premium jump 1.51x-2.00x × Billing type: Automatic payment	28% [25%,30%]	50%[1]
Initial premium jump 2.01x-2.50x × Billing type: Automatic payment	34% [31%,37%]	61%[1]
Initial premium jump 2.51x-3.00x × Billing type: Automatic payment	43% [40%,46%]	77%[1]
Initial premium jump 3.01x-3.50x × Billing type: Automatic payment	46% [43%,49%]	82%[1]
Initial premium jump 3.51x-4.00x × Billing type: Automatic payment	47% [43%,50%]	84%[1]
Initial premium jump 4.01x-4.50x × Billing type: Automatic payment	51% [47%,54%]	91%[1]
Initial premium jump 5.01x-5.50x × Billing type: Automatic payment	58% [54%,61%]	104%[1]
Initial premium jump 5.51x-6.00x × Billing type: Automatic payment	63% [60%,66%]	113%[1]
Initial premium jump 6.01x-7.00x × Billing type: Automatic payment	66% [63%,68%]	118%[1]
Initial premium jump 7.01x-8.00x × Billing type: Automatic payment	67% [64%,71%]	120%[1]
Initial premium jump 8.01x-10.00x × Billing type: Automatic payment	69% [66%,72%]	123%[1]
Initial premium jump 10.01x-14.00x × Billing type: Automatic payment	64% [61%,67%]	114%[1]
Initial premium jump 14.01x+ × Billing type: Automatic payment	57% [53%,61%]	102%[1]
Initial premium jump 1.01x-1.50x × Billing type: Bill Sent	20% [15%,27%]	30%[2]
Initial premium jump 1.51x-2.00x × Billing type: Bill Sent	24% [19%,30%]	36%[2]
Initial premium jump 2.01x-2.50x × Billing type: Bill Sent	32% [26%,40%]	48%[2]
Initial premium jump 2.51x-3.00x × Billing type: Bill Sent	49% [41%,57%]	73%[2]
Initial premium jump 3.01x-3.50x × Billing type: Bill Sent	58% [49%,66%]	87%[2]
Initial premium jump 3.51x-4.00x × Billing type: Bill Sent	63% [55%,71%]	94%[2]
Initial premium jump 4.01x-4.50x × Billing type: Bill Sent	64% [55%,71%]	96%[2]
Initial premium jump 5.01x-5.50x × Billing type: Bill Sent	72% [64%,78%]	107%[2]
Initial premium jump 5.51x-6.00x × Billing type: Bill Sent	72% [65%,79%]	107%[2]
Initial premium jump 6.01x-7.00x × Billing type: Bill Sent	76% [69%,81%]	113%[2]
Initial premium jump 7.01x-8.00x × Billing type: Bill Sent	77% [71%,83%]	115%[2]
Initial premium jump 8.01x-10.00x × Billing type: Bill Sent	80% [74%,85%]	119%[2]
Initial premium jump 10.01x-14.00x × Billing type: Bill Sent	82% [77%,87%]	122%[2]
Initial premium jump 14.01x+ × Billing type: Bill Sent	82% [76%,87%]	122%[2]
Initial premium jump 1.01x-1.50x × Billing type: Automatic payment changed to Bill Sent	80% [51%,94%]	108%[3]
Initial premium jump 1.51x-2.00x × Billing type: Automatic payment changed to Bill Sent	82% [63%,92%]	111%[3]
Initial premium jump 2.01x-2.50x × Billing type: Automatic payment changed to Bill Sent	71% [51%,86%]	96%[3]
Initial premium jump 2.51x-3.00x × Billing type: Automatic payment changed to Bill Sent	73% [53%,86%]	99%[3]
Initial premium jump 3.01x-3.50x × Billing type: Automatic payment changed to Bill Sent	79% [61%,90%]	107%[3]
Initial premium jump 3.51x-4.00x × Billing type: Automatic payment changed to Bill Sent	72% [53%,86%]	98%[3]
Initial premium jump 4.01x-4.50x × Billing type: Automatic payment changed to Bill Sent	77% [59%,88%]	104%[3]
Initial premium jump 5.01x-5.50x × Billing type: Automatic payment changed to Bill Sent	77% [60%,89%]	104%[3]
Initial premium jump 5.51x-6.00x × Billing type: Automatic payment changed to Bill Sent	85% [71%,93%]	115%[3]
Initial premium jump 6.01x-7.00x × Billing type: Automatic payment changed to Bill Sent	89% [79%,95%]	120%[3]
Initial premium jump 7.01x-8.00x × Billing type: Automatic payment changed to Bill Sent	90% [80%,95%]	122%[3]
Initial premium jump 8.01x-10.00x × Billing type: Automatic payment changed to Bill Sent	91% [83%,96%]	123%[3]
Initial premium jump 10.01x-14.00x × Billing type: Automatic payment changed to Bill Sent	94% [87%,97%]	127%[3]
Initial premium jump 14.01x+ × Billing type: Automatic payment changed to Bill Sent	95% [90%,98%]	128%[3]

[1]Relative risk with respect to Initial premium jump 4.51x-5.00x × Billing type: Automatic payment.
[2]Relative risk with respect to Initial premium jump 4.51x-5.00x × Billing type: Bill Sent.
[3]Relative risk with respect to Initial premium jump 4.51x-5.00x × Billing type: Automatic payment changed to Bill Sent.

From Table 3-7, the predicted lapse probability during the last duration of the level term period for the interaction effects can be interpreted:

- **Initial premium jump**: In the presence of an interaction of initial premium jump by billing type, the coefficients $\beta_{16}, \ldots \beta_{29}$ for initial premium jump are the effect of initial premium jump when billing type is Automatic payment. For example, the shock lapse probability of a policyholder experiencing a premium jump increase in the 8.01x-10.00x range is $\exp(\hat{\beta}_0 + \hat{\beta}_{27})/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_{27})) \approx 69\%$ (95% CI [66%, 72%]) when billing type is Automatic payment. This policyholder has 1.23 more chance of lapsing than a policyholder having a premium jump increase in the 4.51x-5.00x range, i.e., the relative risk is:

$$\frac{\exp(\hat{\beta}_0+\hat{\beta}_{22})/(1+\exp(\hat{\beta}_0+\hat{\beta}_{22}))}{\exp(\hat{\beta}_0)/(1+\exp(\hat{\beta}_0))} \approx \frac{69\%}{56\%} = 123\%.$$

  A policyholder having a Bill Sent billing type and experiencing the same initial premium jump increase has a shock lapse probability of $\exp(\hat{\beta}_0 + \hat{\beta}_{14} + \hat{\beta}_{27} + \hat{\beta}_{41})/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_{14} + \hat{\beta}_{27} + \hat{\beta}_{41})) \approx 80\%$ (95% CI [74%, 85%]), while the probability of lapsing becomes 91% (95% CI [83%, 96%]) if the policyholder changed their billing type from Automatic payment to Bill Sent in the post-level term period. The shock lapse probability of a policyholder with a premium jump increase in the 8.01x-10.00x range compared to a 4.51x-5.00x jump is 1.19 larger, the relative risk is:

$$\frac{\exp(\hat{\beta}_0+\hat{\beta}_{14}+\hat{\beta}_{27}+\hat{\beta}_{41})/(1+\exp(\hat{\beta}_0+\hat{\beta}_{14}+\hat{\beta}_{27}+\hat{\beta}_{41}))}{\exp(\hat{\beta}_0+\hat{\beta}_{27})/(1+\exp(\hat{\beta}_0+\hat{\beta}_{27}))} \approx \frac{80\%}{67\%} = 119\%.$$

  When the billing type is Bill Sent, a policyholder has 23% more chance of lapsing if their billing type changed from Automatic payment to Bill Sent in the post-level term period.

3.2.2 INTERPRETATION OF THE GRADED REGRESSION MODEL OUTPUT

The shock lapse probabilities with their associated 95% confidence intervals and corresponding relative risk with respect to a policyholder with characteristics corresponding to the reference categories are displayed in Table 3-8 for the main effects related to Graded.

Table 3-8

SHOCK LAPSE PROBABILITIES WITH THEIR ASSOCIATED 95% CONFIDENCE INTERVALS AND RELATIVE RISK WITH RESPECT TO A POLICYHOLDER WITH CHARACTERISTICS CORRESPONDING TO THE REFERENCE CATEGORIES FOR GRADED

Variable – Main Effects	Lapse Probability with 95% CI	Relative Risk
Reference categories: *T10, face amount band $250K+, Residual NS risk class, initial premium jump band 2.51x-3.00x, billing type: Bill Sent and Annual premium payment mode*	72% [71%,73%]	100%
Term 15	73% [71%,74%]	101%
Attained age: Policyholder aged 50 years old Policyholder aged 70 years old	66% [65%,67%] 80% [79%,81%]	 121%
Risk class: Residual SM	74% [71%,76%]	103%
Risk class: Preferred SM	76% [74%,78%]	106%
Risk class: Preferred NS	69% [68%,71%]	96%
Risk class: Super Preferred NS	68% [66%,70%]	94%
Face amount $0-99K	53% [49%,56%]	74%
Face amount $100K	64% [62%,66%]	89%
Face amount $101-249K	69% [67%,70%]	96%
Premium mode: Monthly	47% [45%,49%]	65%
Premium mode: Quarterly	63% [61%,65%]	88%
Premium mode: Semi-annual	69% [67%,71%]	96%
Billing type: Automatic payment	69% [67%,71%]	96%
Initial premium jump 1.01x-1.50x	53% [49%,57%]	74%
Initial premium jump 1.51x-2.00x	57% [54%,59%]	79%
Initial premium jump 2.01x-2.50x	64% [62%,66%]	89%
Initial premium jump 3.01x-3.50x	75% [74%,76%]	104%
Initial premium jump 3.51x-4.00x	79% [77%,80%]	110%
Initial premium jump 4.01x-4.50x	82% [81%,83%]	114%
Initial premium jump 4.51x-5.00x	85% [84%,87%]	118%

From Table 3-8, the predicted lapse probability during the last duration of the level term period can be interpreted. Four examples of the computation of the estimated risk factors and interpretation of the corresponding predicted shock lapse probability are given below. For example:

- Intercept / Reference categories: A policyholder with characteristics corresponding to the reference categories (i.e., T10, face amount band $250K+, Residual NS risk class, premium jump band 2.51x-3.00x, billing type: Bill Sent and Annual premium payment mode) and Graded premium structure has a 72% (95% CI [71%, 73%]) probability of lapse during the last duration of the level term period.
- Initial premium jump: The shock lapse probability of a policyholder facing a premium jump increase in the 4.51x-5.00x range is 85% (95% CI [84%, 87%]). The corresponding relative risk of lapse of a policyholder with characteristics corresponding to the reference categories and experiencing an initial premium increase in the 4.51x-5.00x range compared to an increase in the 2.51x-3.00x band is 118%.
- Billing type: The shock lapse probability of a policyholder with characteristics corresponding to the reference categories with billing type Automatic payment is 69% (95% CI [67%, 71%]). When the billing type is Automatic payment, a policyholder with characteristics corresponding to the reference categories has a 96% chance of lapsing compared to the Bill Sent category.

- **Premium payment mode**: The probability of lapsing for a policyholder in the reference categories is 47% (95% CI [45%, 49%]) for a Monthly premium mode, 63% (95% CI [61%, 65%]) for a Quarterly premium mode and 69% (95% CI [67%, 71%]) for a Semi-annual premium mode. The relative risk of a policyholder in the reference categories with a Monthly premium mode compared to an Annual premium mode is 65%. The relative risk for a policyholder with a Quarterly premium mode and a Semi-annual premium mode are 88% and 96%, respectively.

3.3 MODEL FIT ANALYSIS

In this section, the model output is reviewed by relevant variables. Similar figures are presented for each variable, each containing four panels with results shown side by side for the Jump to ART and Graded models. The first panel provides a visual indication of the quality of the fit and allows comparison of the fitted shock lapse variations within each relevant variable by initial premium jump. The dots represent the observed lapse probability in the last duration of the level term period, while the full lines illustrate the predicted lapse probability. The second panel displays the corresponding actual experience over expected number of lapses as predicted by the model, where actual over expected close to 100% represents a good fit of the model to the observations. The third and fourth panels present the distribution of the exposure and the number of lapses, respectively. In each sub-section, the shock lapse probability is reviewed with initial premium jump on the axis and one other variable. Using the Tableau dashboards[3], it is possible to review the model output by any two variables to view the model fit and understand the relationship captured by the model.

3.3.1 INITIAL PREMIUM JUMP

Premium increase at the end of the level term period was grouped into 15 bands for Jump to ART (see section 3.1.3.2), although results can be reviewed at a more granular level with 23 bands in the first panel in Figure 3-4. For the Graded structure, premium increase was grouped into eight bands with no further grouping being applied. The lapse probability in the last duration of the level term period increases with initial premium jump. However, this increase is not uniform across the initial premium jump bands. Changes in the slope can be seen for both PLT premium structures. These variations illustrate changes in the sensitivity to the premium increase. For example, for both premium structures, the slope is the steepest for initial premium jumps in the lowest range, 1.01x-3.00x. Policyholders in this range are more sensitive to the increase of the premium. Plateaus are observed around initial premium jump 3.01x-4.00x and at the highest range, 14.01x+, for Jump to ART.

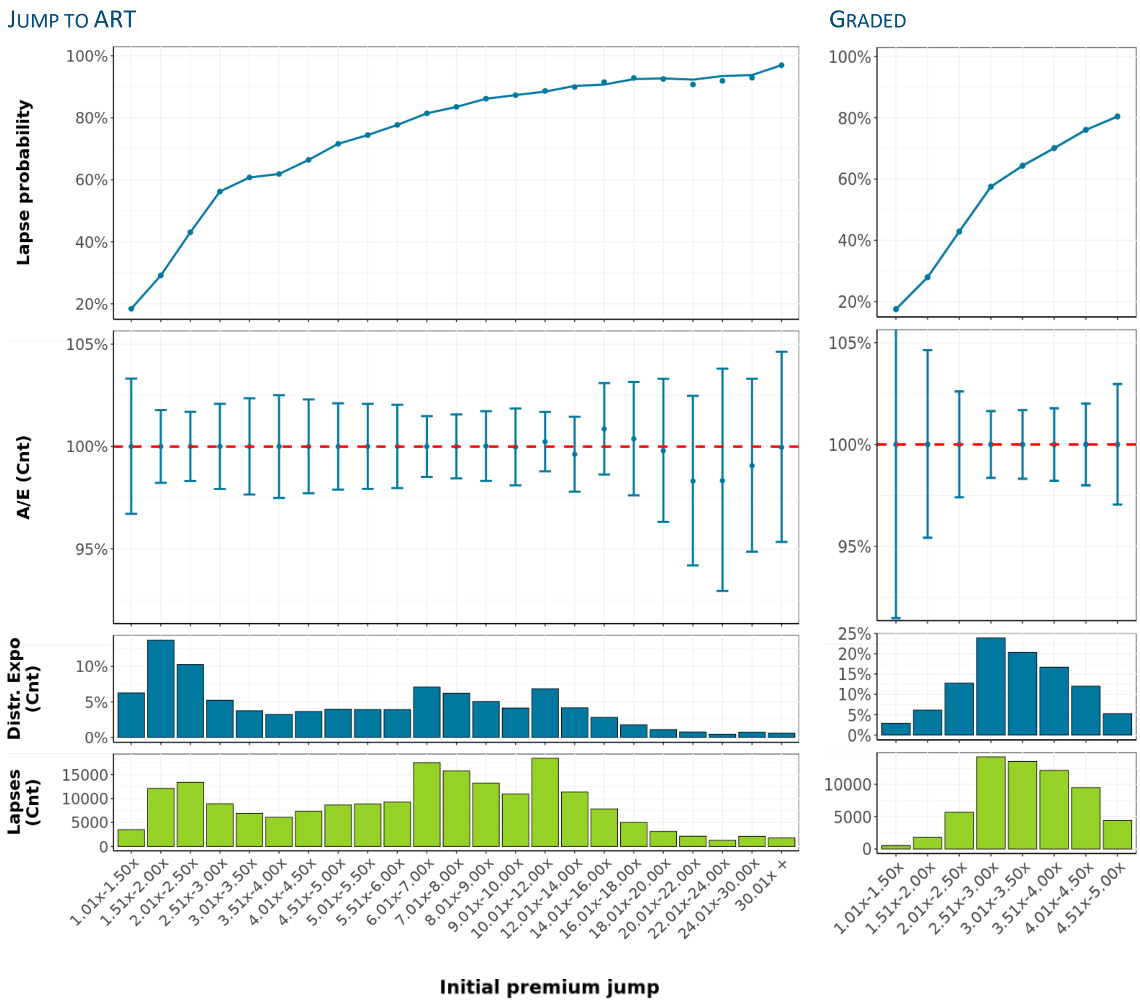
By including the variable initial premium jump in the modeling, the observed number of lapses by initial premium jump at the overall level, as well as for each initial premium jump band, is exactly predicted by the model. Therefore, the A/E ratio at the overall level (red dashed line, Figure 3-4, second panel) is 100% and the A/E ratio for each initial premium jump band included in the model is 100%, as seen for both Jump to ART and Graded (see the second panel of Figure 3-4). For Jump to ART, the A/E ratio for the model, including 15 premium jump bands, only differs from 100% where grouping has been applied. This is specifically seen for bands 14.01x-16.00x and 20.00x+. Although deviations from 100% A/E are observed, the actual over expected number of lapses is between 98% and 101%. In addition, the 100% A/E falls within the 95% confidence interval illustrating that, by grouping the largest initial premium jump bands together, i.e., 14.00x+, the model still adequately captures the shock lapse variations. In other words, shock lapse variations at the highest initial premium jump bands may not be explained by the initial premium jump increases but rather by a combination of other variables. This is an important insight from predictive modeling that cannot be easily observed in the traditional report analysis. While the increasing relationship between initial

[3] https://tableau.soa.org/t/soa-public/views/USPost-LevelTermPredictiveModelingInteractiveTool/1-ShockLapseOverview

premium jump and shock lapse has been established for some time, the changing sensitivity to premium increase at different levels offers further insight.

Figure 3-4

SHOCK LAPSE PROBABILITY BY INITIAL PREMIUM JUMP BAND



3.3.2 ATTAINED AGE

The lapse probability in the last duration of the level term period increases with initial premium jump and is higher for older attained ages for both premium structures, as illustrated in the first panel of Figure 3-5. Older policyholders are likely to experience higher initial premium increases at the end of the level term period leading to higher lapse.

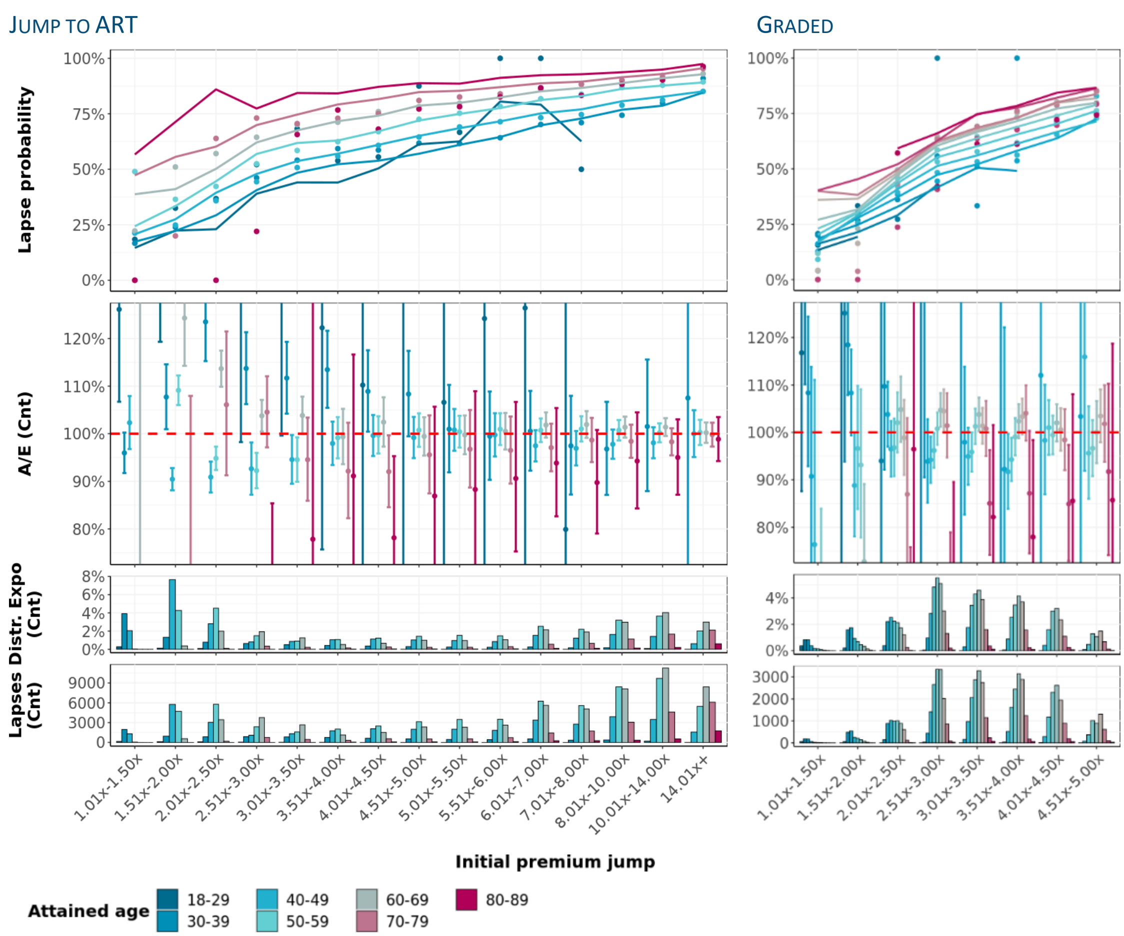
The change of the sensitivity to the initial premium increase below and above 3.00x is still visible, although it reduces as attained age increases for Jump to ART data.

The models applied on Jump to ART and Graded capture the shock lapse variations by attained age and initial premium jump adequately, with the exception of the lowest initial premium jump band where the 100% A/E at the youngest attained age falls outside the 95% confidence interval (see the second panel of Figure 3-5).

In Figure 3-5, the third and fourth panels present the distribution of exposure and the number of lapses. The proportion of the oldest attained age groups grows with the premium jump increase. This highlights that older policyholders tend to face higher initial premium jumps at the end of term. However, by considering both variables, it is clear that there is shock lapse variation by attained age even after accounting for variation explained by premium jump differences. This was also observed in the traditional report analysis when considering results by both variables jointly, but the relationship can be captured at a more detailed level through predictive modeling.

Figure 3-5

SHOCK LAPSE PROBABILITY BY ATTAINED AGE AND INITIAL PREMIUM JUMP BAND



3.3.3 BILLING TYPE

For Jump to ART, the lapse probability in the last duration of the level term period increases with initial premium jump and is higher for Automatic payment changed to Bill Sent, followed by the categories Bill Sent and Automatic payment as illustrated in the first panel of Figure 3-6. Policyholders in the Automatic payment changed to Bill Sent and Bill Sent categories need to take action to pay the bill to keep the policy leading to more policy lapses than when premium payment is Automatic. Regarding Graded, the shock lapse probability is similarly higher for Bill Sent than Automatic payment.

For both premium structures, policyholders in Bill Sent and Automatic payment are more sensitive to the premium increase in the lowest range (1.01x-3.50x for Jump to ART and 1.01x-3.00x for Graded) than higher ranges as illustrated by the steeper slopes. However, when billing type is changed from Automatic to Bill Sent, there is no difference in the sensitivity to the premium increase. Modeling the different relationships by billing type highlights that the size of the premium increase is less important when the billing type changes at the end of the level term period. This confirms the observation in the traditional report analysis that shock lapse is higher if billing type changes, with much less variation by premium jump.

By including the interaction term between the initial premium jump and billing type, the model fitted on Jump to ART data predicts exactly the observed number of lapses by initial premium jump and billing type. As a result, the A/E ratios by initial premium jump band and billing type category are 100% (see second panel of Figure 3-6). The model applied on Graded data captures the shock lapse variations by billing type and initial premium jump appropriately. The 100% A/E falls within the 95% confidence interval for all the initial premium jump bands with the exception of the premium jumps in the lowest range, i.e., 1.01x-2.00x.

Most of the data available for Automatic payment changed to Bill Sent were at the higher initial premium jumps as illustrated in the third and fourth panels of Figure 3-6. The low amount of data available by initial premium jump over the lowest range leads to higher uncertainty regarding the predictions, as highlighted by the wider confidence intervals in the second panel of Figure 3-6. Despite the data limitations, the reduced sensitivity to premium increase is observed consistently across the range of initial premium increases.

Figure 3-6
SHOCK LAPSE PROBABILITY BY BILLING TYPE AND INITIAL PREMIUM JUMP BAND

3.3.4 PREMIUM MODE

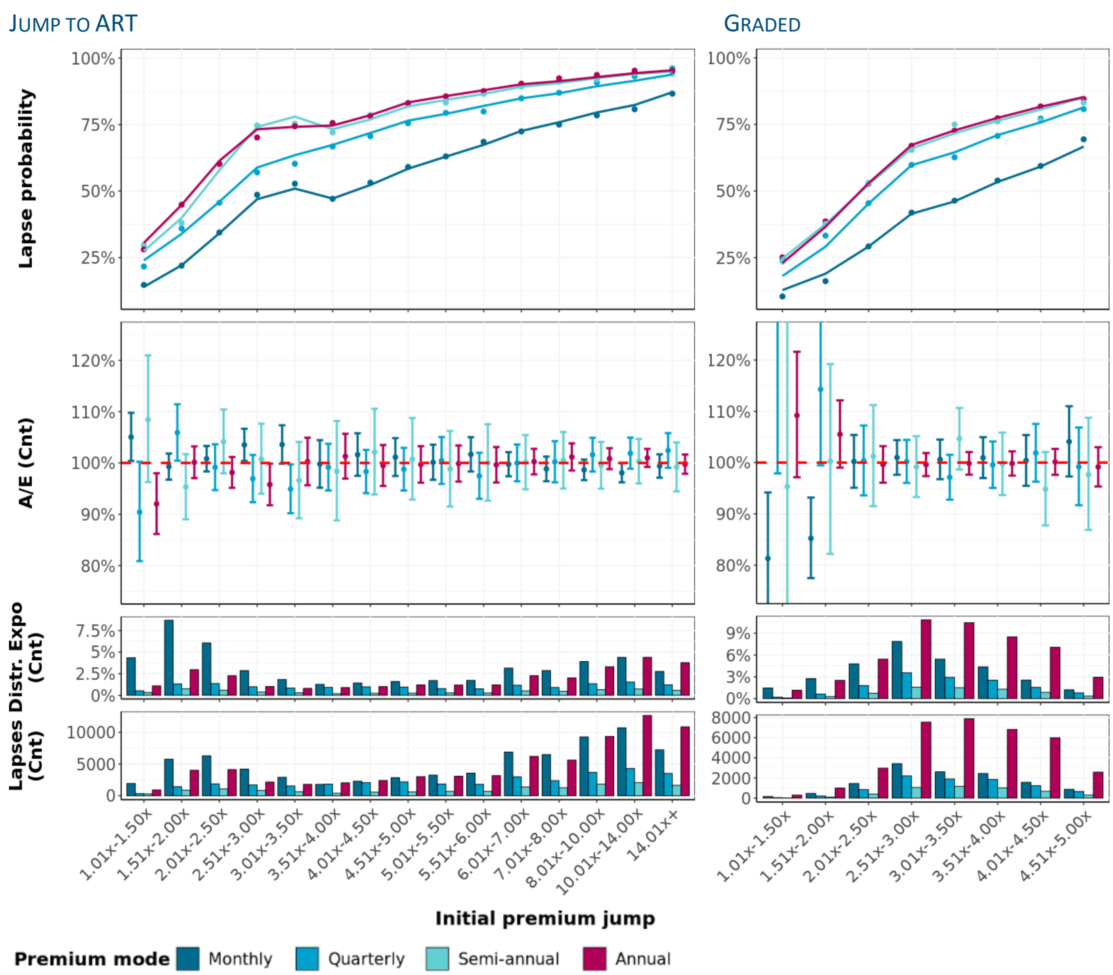
The shock lapse probability increases with initial premium jump in a similar pattern for all premium modes, but is the highest for premium mode Annual, followed in a decreasing order by modes Semi-annual, Quarterly and Monthly, for both Jump to ART and Graded as illustrated in the first panel of Figure 3-7. The explanation for this behavior as noted in the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* is that policyholders are less sensitive to the premium increases when their premiums are paid monthly because the dollar amount of increase does not appear as large compared to when paid annually. In addition, premium payment mode is related to the billing type and results are influenced by the combined interaction. For example, monthly payment is more likely to be linked to automatic payment type, which means these smaller dollar amounts are paid automatically without a specific action required by the policyholder.

Similar to the pattern observed by billing type and attained age, a change point is present in the shock lapse variation for each premium payment mode below and above initial premium jump 3.00x in both premium structures. In addition, for Jump to ART data, a plateau around initial premium jump 3.01x-4.00x is seen for each premium mode, with the exception of the Quarterly payment. The lapse probability by initial premium jump for premium mode Annual and Semi-annual is similar in both premium structures. Regarding Jump to ART data, as the premium increases, the difference in the shock lapse variation by premium mode tends to reduce. The lapse probability converges to 95% for premium mode Annual, Semi-annual and Quarterly for premium jump 14.01x+.

The models, fitted on Jump to ART and Graded separately, capture the shock lapse variations by premium mode and initial premium jump adequately. In the second panel of Figure 3-7, the 100% A/E falls within the 95% confidence interval for all the initial premium jump bands, with the exception of the lowest premium jump range 1.01x-2.00x. As premium mode is included in the model, the observed number of lapses by initial premium jump and premium mode at the overall level, as well as for each premium mode, is exactly predicted by the model.

Figure 3-7

SHOCK LAPSE PROBABILITY BY PREMIUM MODE AND INITIAL PREMIUM JUMP BAND



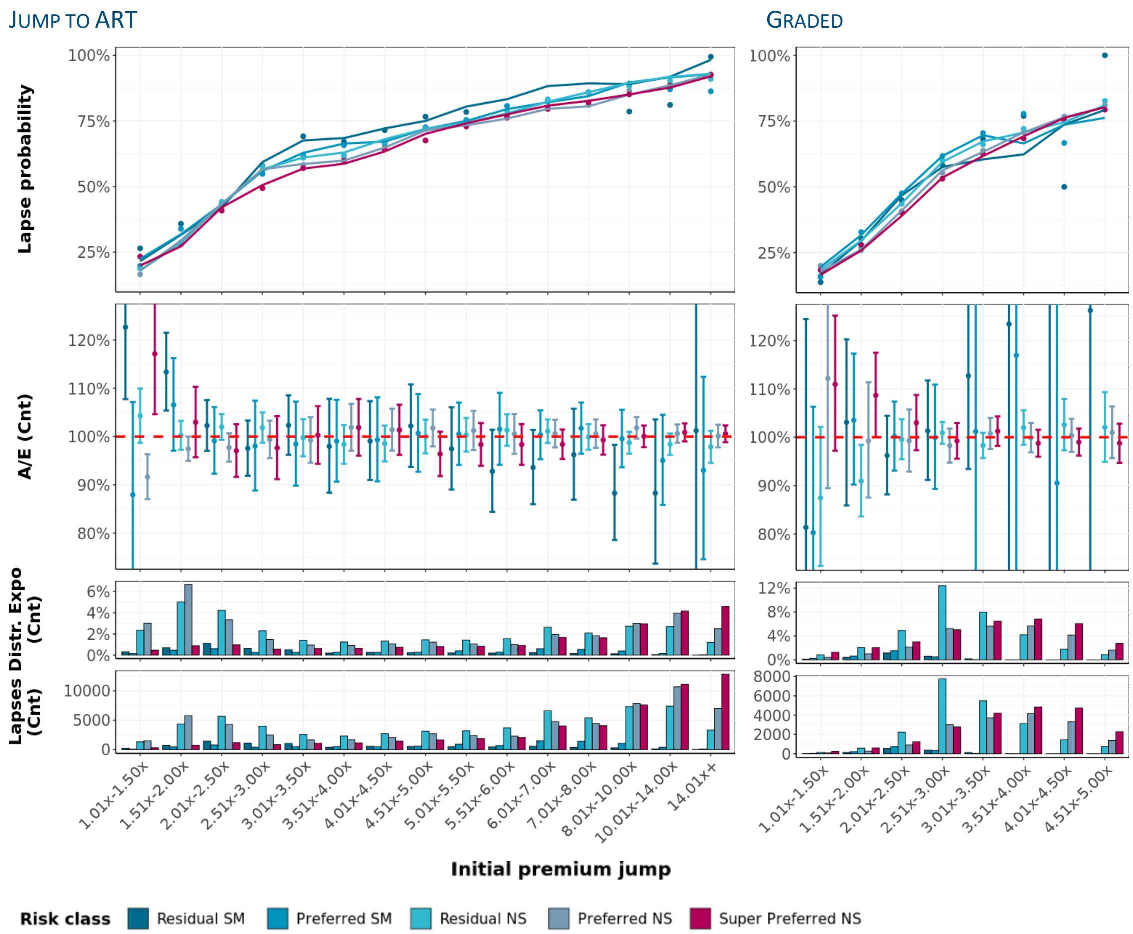
3.3.5 RISK CLASS

The plot of the fit in the first panel of Figure 3-8 illustrates that the lapse probability in the last duration of the level term period increases with initial premium jump and is larger for risk classes with less healthy policyholders (in decreasing order, Residual SM, Preferred SM, Residual NS, Preferred NS and Super Preferred NS). In addition, the shock lapse variation by premium increase within each risk class differs for initial premium jump below and above 3.50x (to a lesser extent for the class Super Preferred NS), as illustrated by the slope change at initial premium jump band 3.00x-3.50x. This is seen for both premium structures. This suggests a substantial difference in the sensitivity to the premium increase below and above 3.50x for risk classes Residual SM, Preferred SM, Residual NS and Preferred NS, while Super Preferred NS policyholders exhibit less difference in sensitivity to the premium increase.

The models, fitted on Jump to ART and Graded separately, capture the shock lapse variations by risk class and initial premium jump adequately. In the second panel of Figure 3-8, the 100% A/E falls within the 95% confidence interval for all the initial premium jump bands with the exception of the premium jumps in the lowest range, i.e., 1.01x-2.00x.

In terms of the distribution of exposure and number of lapses by risk class, the proportion of the healthiest policyholders, i.e., Super Preferred NS, grows with the premium jump increase to become the main risk class at the highest initial premium jump bands for both PLT premium structures (see the third and fourth panels of Figure 3-8). The fact that premium increase tends to be higher for Super Preferred NS was noted in the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* particularly for Jump to ART where PLT premiums generally only varied by smoker status and not by risk class. While the traditional report analysis showed that apparent variation by risk class was attributed mainly to initial premium jump differences, the predictive analysis here captures in more detail the relationship between these two variables. The variation by risk class observed in one-way analysis is largely explained by premium jump differences, but an increasing pattern of shock lapse for less healthy categories is observed, even within a given initial premium jump band.

Figure 3-8
SHOCK LAPSE PROBABILITY BY RISK CLASS AND INITIAL PREMIUM JUMP BAND



3.3.6 FACE AMOUNT

The lapse probability in the last duration of the level term period increases with initial premium jump for all face amount groups for both premium structures as illustrated in the first panel of Figure 3-9. For Jump to ART data, the shock lapse probability also increases with increasing face amount for initial premium jumps in the 1.01x-3.50x range. For premium jumps larger than 3.50x, the positive relationship between the lapse probability and face amount becomes less discernible. For a given premium increase, policyholders with a large face amount experience higher dollar amounts of premium increase than individuals with lower face amounts. Differences in face amount relationship by premium increase may indicate that the dollar amount of premium increase impacts the shock lapse probability when the initial premium jump is below 3.50x but has less impact over higher initial premium jumps. It may indicate that the tendency to lapse due to a higher dollar amount of initial premium increase is softened as the initial premium jump increases. For Graded data, the relationship between lapse probability and face amount is less apparent.

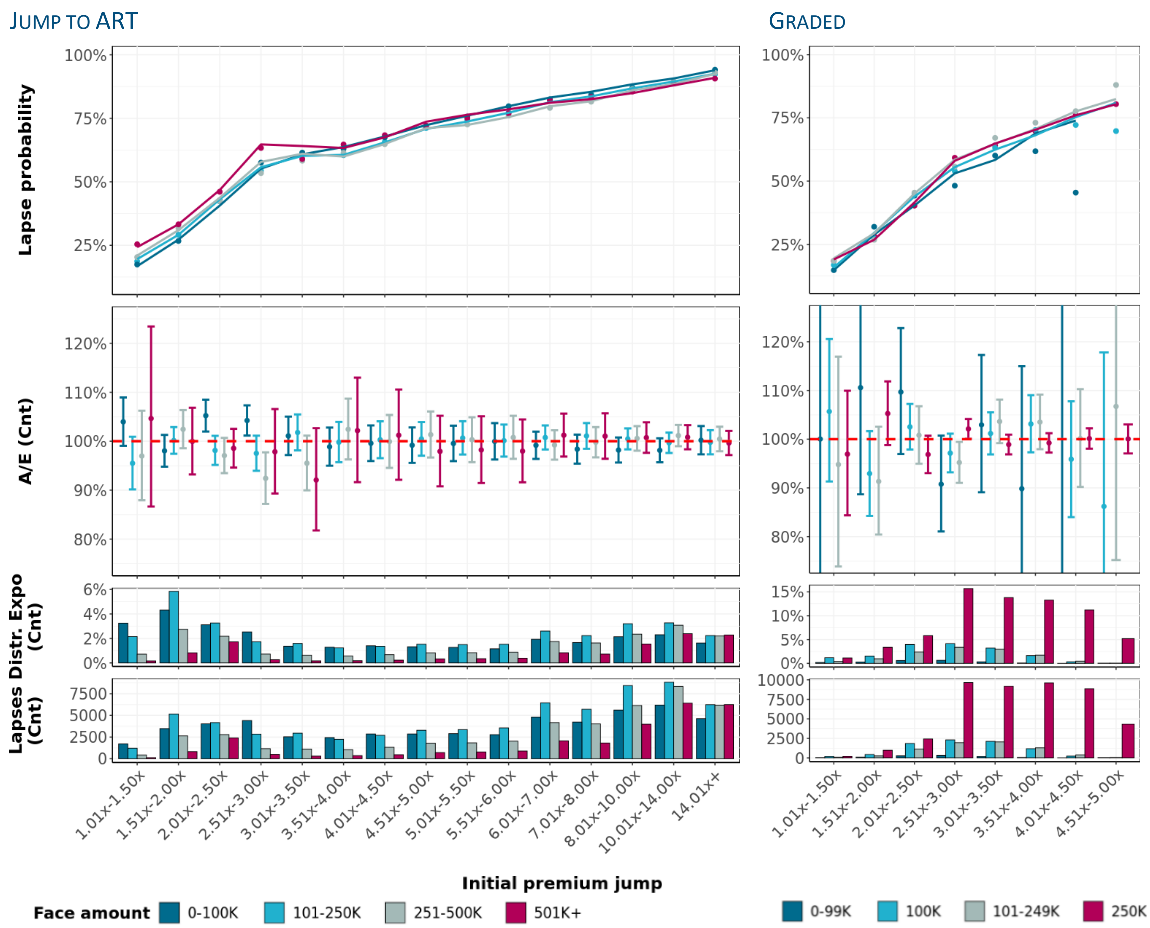
The change of the sensitivity to the premium increase below and above 3.50x is still visible for each face amount band in both premium structures, as well as the presence of a plateau for Jump to ART data around initial premium jump band 3.01x-4.00x. As the premium increases, the differences in the shock lapse variation by face amount band become indistinguishable.

The models, fitted on PLT premium structures separately, capture the shock lapse variations by face amount and premium jump adequately. In the second panel of Figure 3-9, the 100% A/E falls within the 95% confidence interval for all the premium jump bands.

In Figure 3-9, the third and fourth panels present the distribution of exposures and the number of lapses. The proportion of the highest face amount band, $501K+ for Jump to ART and $251K+ for Graded data, grows with the premium jump increase. This was also observed in the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* which discussed that the apparent variation by face amount can be explained by initial premium jump differences. While this observation holds over the higher initial premium jumps, predictive modeling provides an additional insight into face amount variation for premium jumps less than 3.50x for Jump to ART.

Figure 3-9

SHOCK LAPSE PROBABILITY BY FACE AMOUNT AND INITIAL PREMIUM JUMP BAND



3.3.7 LEVEL TERM PLAN

For Jump to ART data, the lapse probability in the last duration of the level term period increases with initial premium jump and is larger for T10 up to premium jump band 5.01x-5.50x as illustrated in the first panel of Figure 3-10. The change of the sensitivity to the premium increase below and above 3.50x is apparent for T10, as well as the presence of the plateau for initial premium jump band 3.01x-4.00x. For T15, the change of the sensitivity to the premium increase is less apparent as no change point below and above initial premium jump 3.50x can be detected.

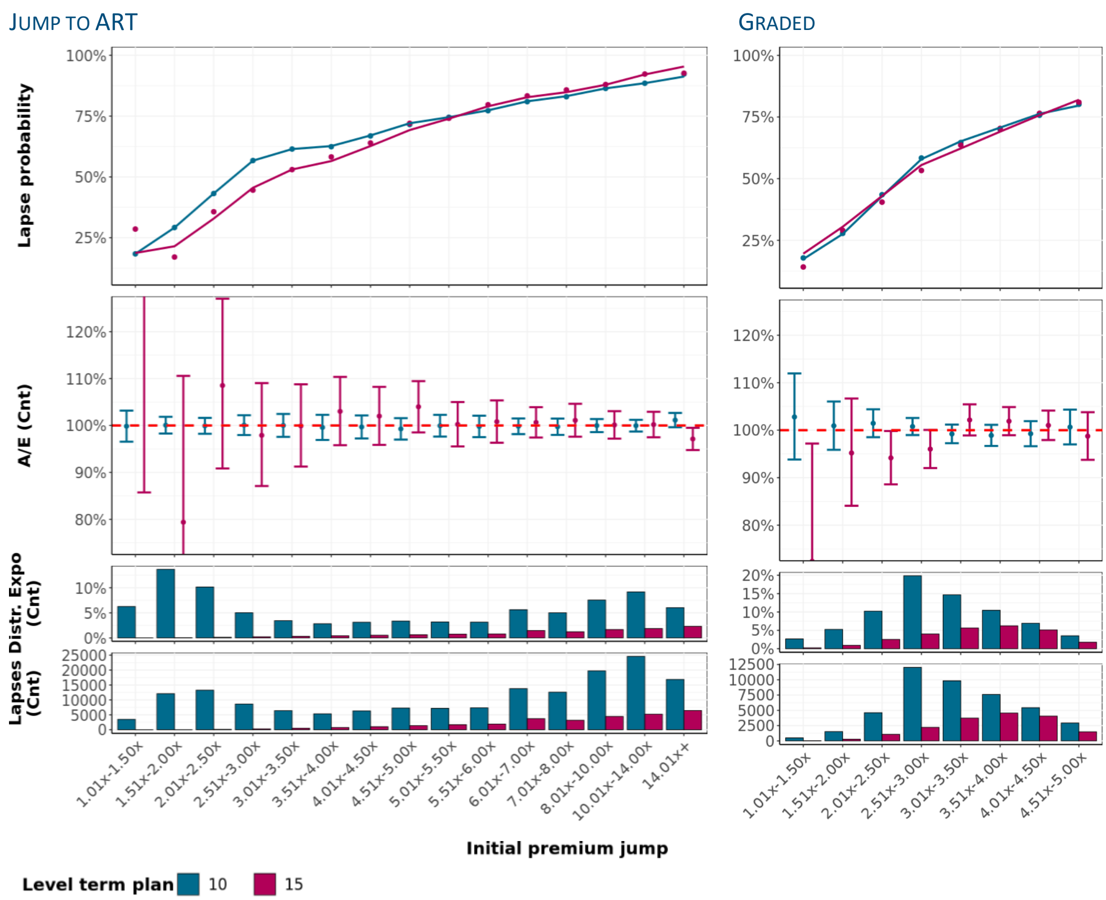
For Graded data, the relationship between the lapse probability and term plan is less discernible than for Jump to ART data.

The models, fitted on both premium structures separately, capture appropriately the shock lapse variations by level term plan and premium jump. In the second panel of Figure 3-10, the 100% A/E falls within the 95% confidence interval for all the premium jump bands, with the exception of the highest premium jump band for Jump to ART and lowest for Graded for T15.

The proportion of T15 in the exposure and number of lapses increases with the premium jump increase (see third and fourth panels of Figure 3-10). There was less data available for T15 over lower initial premium jump ranges. Longer term plans tend to have higher initial premium jumps at the end of the level term period due to the longer period since the level term premium was set at policy inception (15 years for T15 compared to ten years for T10). For a T15 policyholder, a 3.50x premium jump at the end of the level term period may represent good value for their current age. This may explain the differences in behavior between term plans over the lower initial premium increases.

Figure 3-10

SHOCK LAPSE PROBABILITY BY LEVEL TERM PLAN AND INITIAL PREMIUM JUMP BAND



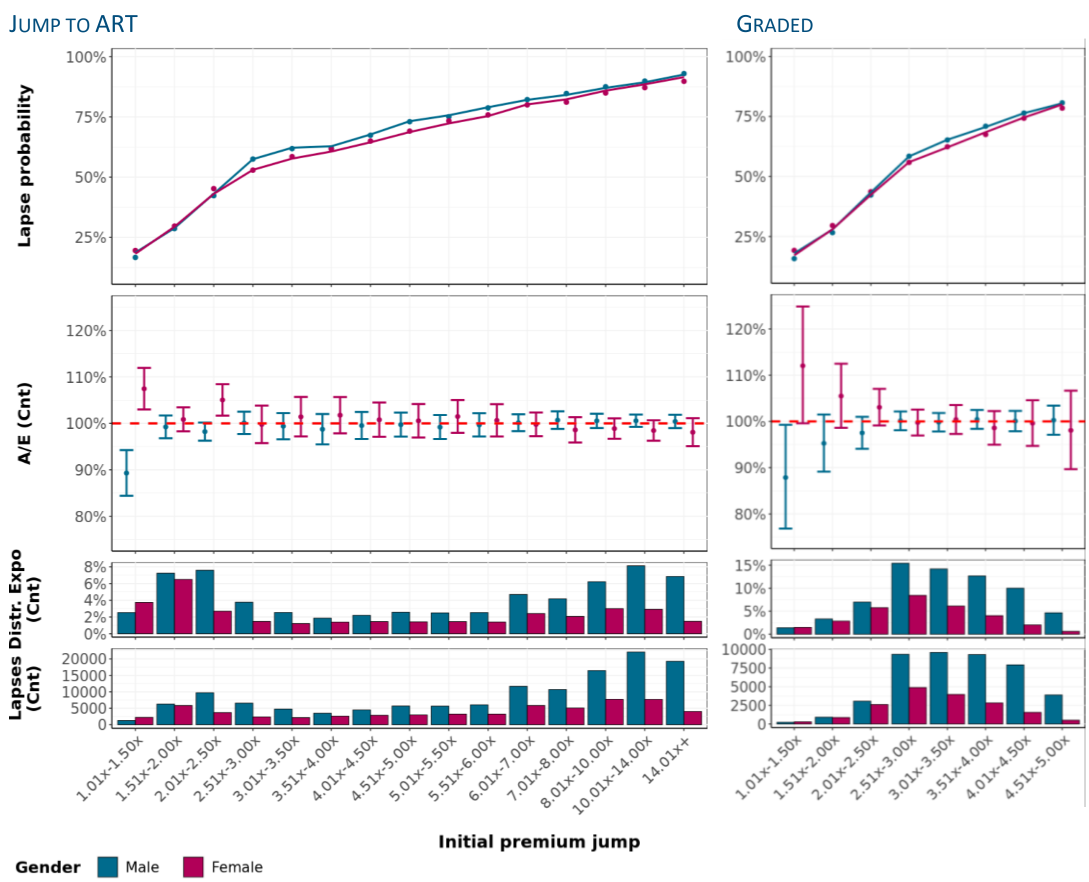
3.3.8 GENDER

Gender information was not included in the modeling for both PLT premium structures. Nevertheless, the models' ability to capture the shock lapse variations by gender can be studied.

The shock lapse probability increases with initial premium jump and is larger for Male than Female policyholders for premium increases in ranges 2.51x-10.00x and 2.51x-4.00x for Jump to ART and Graded, respectively (see the first panel of Figure 3-11). The lapse probability is similar for Male and Female policyholders for premium jumps in the lowest range 1.01x-2.50x (for both premium structures) and in the highest range 10.00x+ (for Jump to ART data). In addition, both Males and Females have a substantial difference in the sensitivity to the premium increase below and above 3.50x as illustrated by the change of steepness of the slopes.

Even though the gender effect was not included in modeling the shock lapse probability for Jump to ART and Graded, the models capture the shock lapse variations by gender and premium jump appropriately. In the second panel of Figure 3-11, the 100% A/E falls within the 95% confidence interval for all premium jump bands with the exception of the premium jump in the lowest range. This illustrates that apparent variation by gender can be captured by including the other variables in the model.

Figure 3-11
SHOCK LAPSE PROBABILITY BY GENDER AND INITIAL PREMIUM JUMP BAND



3.4 VARIATION BY EXTERNAL VARIABLES

In addition to drivers captured in the shock lapse modeling, the predictive modeling allows for further investigation into residual variation by other variables after fitting the models. This approach allows for analysis of variation by external variables measured through comparing predicted results to actual PLT experience. Variation over time can be investigated for each study year. Similarly, data not used in fitting the model can be analyzed to identify if the model is a good predictor for this business. For example, where substandard business was not included in the modeling, the actual PLT experience for substandard business can be compared to the model predictions to provide insights for substandard business relative to data issued at standard rates. Another interesting example is T20 actual lapse experience (which was also not included in the model) compared to model predictions based on T10 and T15 data. In this way, predictive modeling provides insights into lapse experience for T20 relative to the other term plans, accounting for variation by other variables to ensure a consistent comparison. These and other external variables are analyzed below.

3.4.1 STUDY YEAR

The lapse study was completed on a policy year basis with exposures calculated from policy anniversary to policy anniversary as described in section 2.3. The study year measure is based on the end of the policy year, i.e., the year of the policy anniversary at the end of each duration. For shock lapse analysis, this corresponds to the calendar year when the policy reached the end of the last duration in level term.

In Figure 3-12, the first panel displays the predicted shock lapse probabilities by study year and level term plan for both premium structures. Since T15 data were only observable since 2008, while T10 data were available since 2000, the shock lapse variations by study year are also split by term plan.

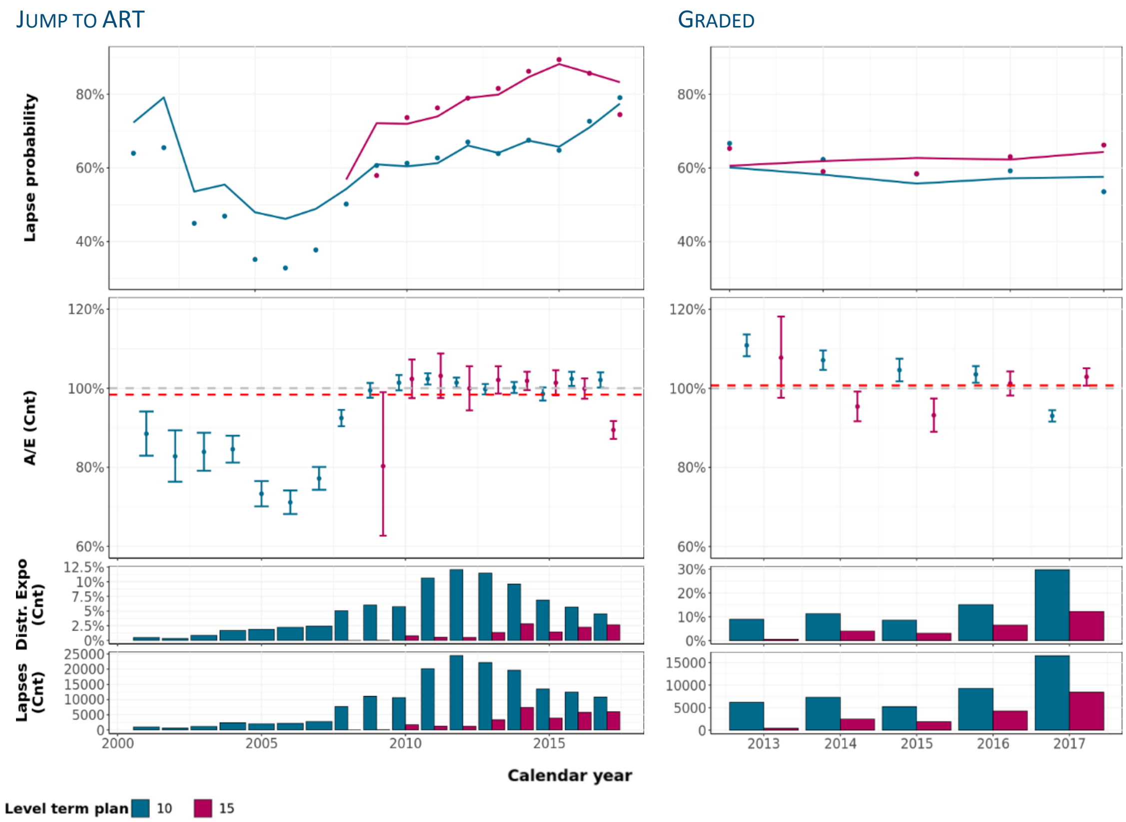
For Jump to ART and both T10 and T15, the shock lapse probabilities increased across study years since 2008. However, when controlling for the effects of the variables discussed in section 3.2.2, no trend is visible in the actual over expected number of lapses (see second panel in Figure 3-12). This shows that the upward trend seen is not originating from a study year effect but rather from the combinations of changes among the other variables over time.

T15 shows higher shock lapse probabilities than T10 by study year for the period 2008-2017 for Jump to ART, and this is captured by the predictive model highlighting that the difference is explained by the combination of variables included in the model.

In addition, the overall A/E ratio is about 98% due to the model not capturing the shock lapse variations for T10 specifically in the period 2000-2007. There are less data available each year for the period 2000-2008, as seen in the third and fourth panels of Figure 3-12, and there are fewer study participants contributing data for this period which leads to heterogeneity in the results. For the period 2008-2017, the 100% A/E falls within the 95% confidence interval for each study year and level term plan. This illustrates that the model is adequately predicting the number of lapses by study year after 2008.

For Graded, the variation by study years 2013 to 2017 is not well captured by the model (see first panel of Figure 3-12). Variation can also be observed where the 100% A/E does not fall within the 95% confidence interval (see second panel of Figure 3-12). The period 2013 to 2017 is too short to observe a trend over time and this is noted as an area of further investigation in future studies.

Figure 3-12
SHOCK LAPSE PROBABILITY BY STUDY YEAR AND LEVEL TERM PLAN



3.4.2 SUBSTANDARD INDICATOR

Substandard data was not used in the model development but is analyzed here by comparing the actual shock lapse rates for substandard to the model predictions for the characteristics of the policies.

The model (which is fitted on standard mortality) underestimates the number of lapses for substandard policyholders for Jump to ART and Graded as illustrated in the first panel of Figure 3-13. The fitted lapse probabilities in the last duration of the level term period are lower than those observed for all the initial premium jump bands.

As a result, the corresponding actual over expected number of lapses for substandard policyholders is larger than 100% for all initial premium jump bands for both premium structures (see second panel in Figure 3-13).

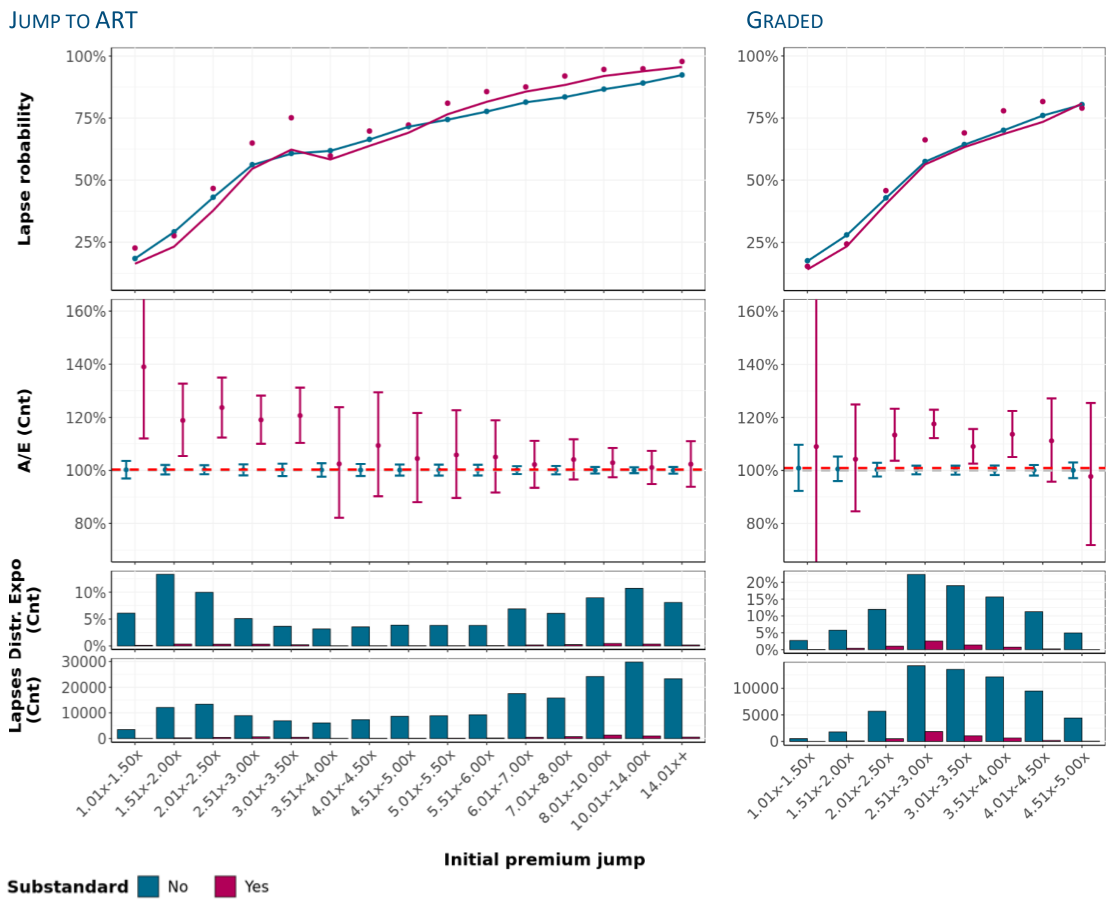
Regarding Jump to ART data, for initial premium jump bands above 3.50x, the 100% A/E falls within the 95% confidence interval. This shows that the shock lapse variations for substandard policyholders above initial premium jump 3.50x can be captured by the combination of variables included in the model calibrated on standard mortality. For the lowest range 1.01x-3.50x, the 100% A/E falls outside the 95% confidence interval. This illustrates that the sensitivity to the premium increase for substandard policyholders is significantly higher than for standard policyholders over this premium jump range.

Regarding Graded data, for premium increases in the lowest 1.01x-2.00x and highest 4.01x-5.00x ranges, the 100% A/E falls within the 95% confidence intervals. This shows that the shock lapse variations for substandard policyholders in these initial premium jump ranges can be captured by the combination of variables included in the model calibrated on standard mortality. For moderate ranges 2.01x-4.00x, the 100% A/E falls outside the 95% confidence intervals. As a result, sensitivity to the premium increase in moderate ranges for substandard policyholders is significantly higher than for standard policyholders.

For both PLT structures, substandard policies have higher shock lapses compared to standard business over the lower premium jump range. There is little difference in shock lapse behavior between standard and substandard policies for higher premium jumps where the shock lapse model built based on standard business data only provides a good fit.

Figure 3-13

SHOCK LAPSE PROBABILITY BY SUBSTANDARD INDICATOR AND INITIAL PREMIUM JUMP BAND



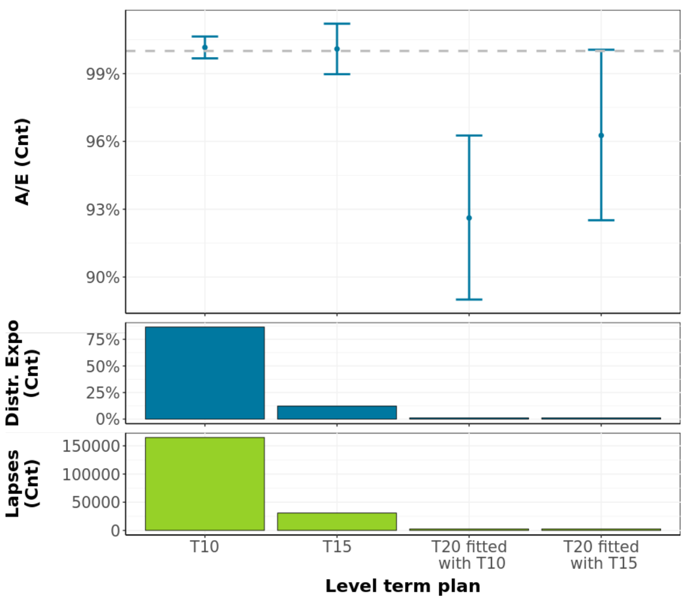
3.4.3 LEVEL TERM PLAN 20

The model for Jump to ART was fitted on T10 and T15 data. T20 data were excluded from the modeling for credibility reasons. In Figure 3-14, the first panel displays the actual over expected number of lapses by level term plan. The expected number of lapses for T20 is obtained by fitting T20 data either with T10 or T15 model predictions. The corresponding A/E for T20 is 93% and 96% when fitted with T10 and T15 predicted values, respectively. When using T15 fitted values, the 100% A/E (illustrated by the grey dashed line) falls within the 95% confidence interval. It shows that the model built using T10 and T15 data adequately predicts the number of lapses for T20 with better fit when the term plan effect is captured on T15.

No T20 data are observable for Graded.

Figure 3-14

ACTUAL OVER EXPECTED NUMBER OF LAPSES BY LEVEL TERM PLAN FOR JUMP TO ART



3.4.4 PROMOTION AT THE END OF LEVEL TERM

As part of the industry study, a survey was sent out in the spring of 2019 in conjunction with the initial data request sent to U.S. term insurance writers. The survey included questions that aimed to provide insight into how practices related to post-level term vary across the industry. The detailed survey results are presented in section 8 of the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience.*

The survey included a question on whether companies had an organized effort to promote persistency at the end of level period. Based on the survey responses, the companies were grouped into two categories - 'no promotion' and 'with communication'. Companies in the 'with communication' category used a range of promotion approaches including policyholder communication at the end of term and/or encouraging policyholders to exercise conversions options. If no information was provided in the survey, the data were excluded as unknown for this analysis. The exclusion represents 15% of exposure. The shock lapse experience was compared between the groups that had 'no promotion' at the end of term compared to those 'with communication' using the model predictions to ensure a more consistent comparison.

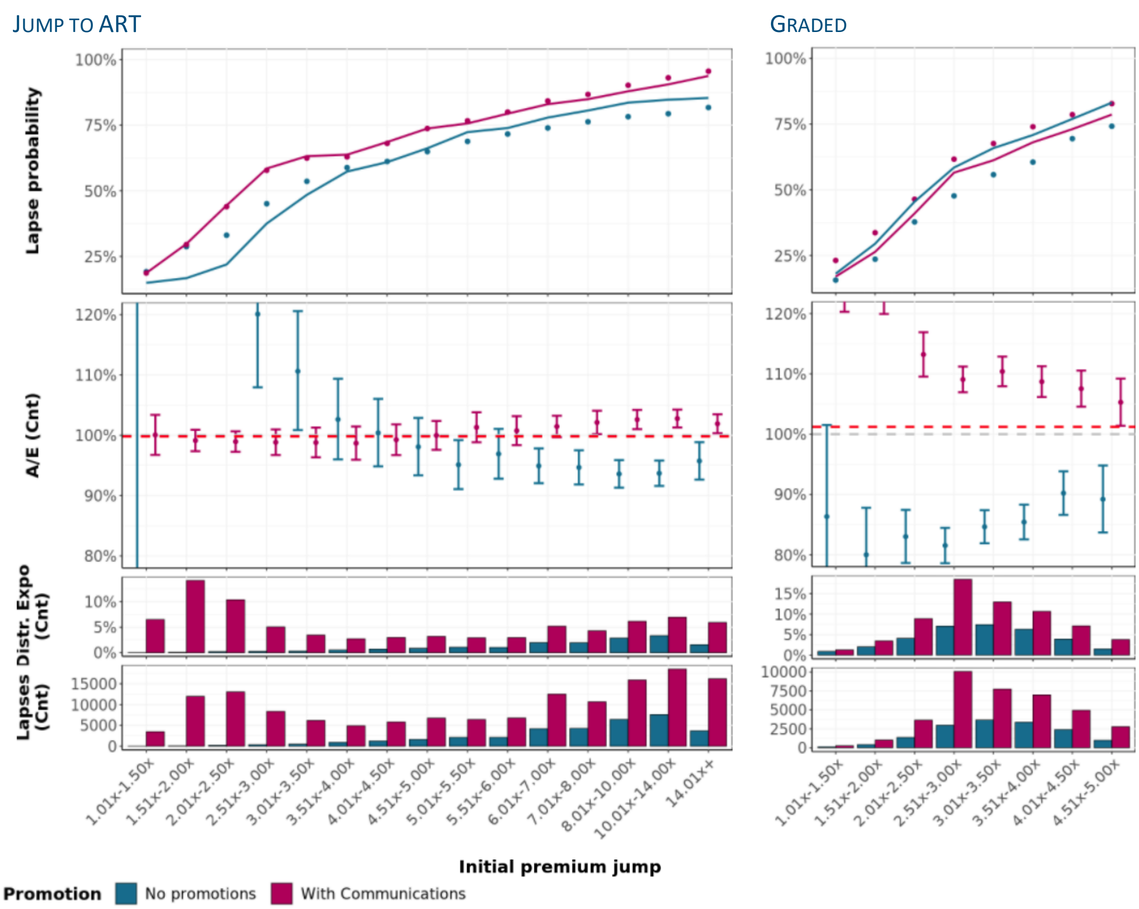
The model fit is shown in Figure 3-15 with results presented for Jump to ART (left panel) and Graded (right panel).

For Jump to ART, some variation in the shock lapse probabilities for each category was observed where sufficient data were available. No reliable result can be seen for the initial premium jumps below 3.01x for the 'no promotions' category due to limited data. For premium jumps above 6.00x, there is some evidence that shock lapses are higher when there was a communication at end of term, although the difference is small as represented by A/Es ranging from 101%-103%. The 'no promotions' category shows A/Es less than 100% over this premium jump range.

For Graded, the model has a significant overestimation for the 'no promotions' category and an underestimation on the 'with communications' category. This illustrates that the variations in shock lapse between the two categories cannot be captured sufficiently by the combination of variables included in the model. For companies that have communication at end of term, shock lapses are higher than for those with no promotion effort. The difference is significant, highlighted by A/Es ranging from 105% to 113% for the premium jump range over which data were sufficient for both groups. At the same time, companies that have no promotion at the end of term show lower shock lapses than expected based on A/Es ranging from 82% to 90% by premium jump group.

Figure 3-15

SHOCK LAPSE PROBABILITY BY PROMOTION PERSISTENCY AND INITIAL PREMIUM JUMP BAND



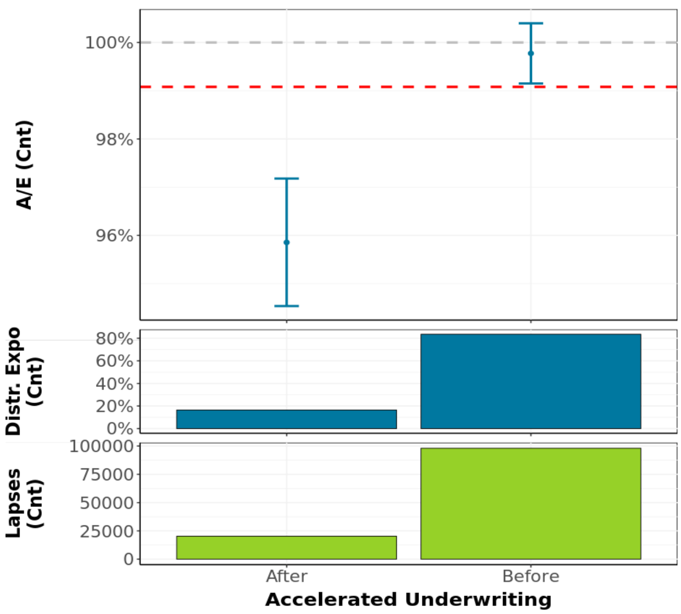
There is some evidence that communication at the end of term and/or promotion of conversion options may be driving higher shock lapse behavior, especially for Graded premium structure.

3.4.5 ACCELERATED UNDERWRITING

The survey also included a question regarding the company's implementation of accelerated underwriting programs. Based on the responses, the PLT data by study year for each company is classified as 'before' or 'after' their accelerated underwriting program became available. If no information was provided in the survey, the data were excluded as unknown for this analysis. The exclusion represents 28% of exposure. The purpose of this analysis is to identify whether the introduction of accelerated underwriting for new business impacted the policyholder behavior at the end of term.

The actual over expected number of lapses for Jump to ART is shown in the first panel of Figure 3-16. When filtering out the unknowns, the overall A/E (illustrated by the red dashed line) is 99%. The A/E for shock lapses before implementation of accelerated underwriting is close to 100% and the A/E for shock lapses after implementing accelerated underwriting is 96%. The model leads to a slight overestimation of the number of lapses for the 'after accelerated underwriting' group.

Figure 3-16
ACTUAL OVER EXPECTED NUMBER OF LAPSES BY ACCELERATED UNDERWRITING FOR JUMP TO ART



There is no indication of higher shock lapses after the implementation of an accelerating underwriting program. The same pattern was also observed for Graded.

Section 4: Lapse by Duration in PLT

The policyholders who decide to remain after having a premium increase continue to have higher lapses in post-level term. Modeling the lapse rates by duration in PLT is of interest to understand the behavior of policyholders who remain and continue to pay PLT premiums.

The shock lapse is the pivotal point at the end of term and influences the lapse experience in PLT. Predictive modeling provides the capability to directly capture this relationship. The Generalized Linear Model (GLM) built to model shock lapse probabilities, as described in section 3, provides a predicted shock lapse for each model point based on the combination of variables. This predicted shock lapse probability was added as a new variable in the dataset to assess how lapse rates in PLT vary depending on the shock lapse at the end of term.

As a first step in the modeling exercise, lapse rates in PLT were modeled by duration using the predicted shock lapse as the only input variable. This model for lapse rates by duration in PLT is referred to as the *shock lapse relationship model*. As a second step, a logistic regression approach was applied to model any significant variations by the other variables that were not captured by the shock lapse variable. The model built in the second step is referred to as the *final model*. Section 4.1 specifies the data available for lapse in PLT analysis and the modeling approaches used in each step.

Models were built separately for each PLT premium structure. The shock lapse relationship models for Jump to ART and Graded are shown in section 4.2 with model predictions compared side-by-side in Figure 4-3. The adjustment of the shock lapse relationship model by additional variables using GLM techniques was carried out for Jump to ART only. A comparison of the shock lapse relationship model and the final model for Jump to ART is shown in section 4.3. Section 4.4 illustrates the Jump to ART final model results for selected variables. This analysis provides an illustration of the ability of the model to explain all deviations observed in the experience data. The figures presented also help to visualize the relationship between variables that are captured by the predictive model.

Using the Jump to ART final model, the variation in lapse rates in PLT was assessed by external variables not included in the model. As described in section 4.5, a more consistent comparison was achieved by adjusting for modeled variation. This approach was applied to investigate whether there are differences in lapse experience for substandard policies and to investigate variation over time in terms of patterns by study year. Though only the shock lapse relationship model was built for Graded, model fit analysis provides insights into variation by other variables in section 4.6.

4.1 DATA AND MODELING APPROACH

4.1.1 DATA

For post-level term lapse analysis, 12 variables were considered. Most are categorical variables with the exception of attained age, duration in PLT and predicted shock lapse probability, which are modeled as numerical variables. Table 4-1 describes the variables and the exposure distribution for both PLT premium structures.

Table 4-1
VARIABLES

Variable	Class	Description	Exposure in PLT (%)	
			Jump to ART	Graded
Level term plan	Categorical	10	97	77
		15	3	23
Gender	Categorical	Male	59	62
		Female	41	38
Attained age	Numerical	18-49	45	28
		50-59	38	38
		60-69	14	28
		70+	3	6
Risk class	Categorical	Residual SM	5	5
		Preferred SM	4	5
		Residual NS	35	34
		Preferred NS	45	26
		Super Preferred NS	11	30
Face amount	Categorical	$0-100K	35	30
		$101-250K	39	32
		$251-500K	19	25
		$501K+	7	13
Initial premium jump	Categorical	1.01x-1.50x	16	4
		1.51x-2.00x	39	11
		2.01x-2.50x	17	20
		2.51x-3.00x	6	24
		3.01x-3.50x	4	20
		3.51x-4.00x	3	12
		4.01x-4.50x	3	6
		4.51x-5.00x	2	3
		5.01x-5.50x	2	NA
		5.51x-6.00x	1	NA
		6.01x-7.00x	2	NA
		7.01x-8.00x	1	NA
		8.01x-10.00x	2	NA
		10.01x-14.00x	1	NA
		14.01x+	1	NA
Cumulative premium jump	Categorical	1.01x-1.50x	5	1
		1.51x-2.00x	19	2
		2.01x-2.50x	23	3
		2.51x-3.00x	16	5
		3.01x-3.50x	9	7
		3.51x-4.00x	6	8
		4.01x-4.50x	4	10
		4.51x-5.00x	3	11
		5.01x-5.50x	2	9
		5.51x-6.00x	2	8
		6.01x-7.00x	3	13
		7.01x-8.00x	2	9
		8.01x-10.00x	3	8
		10.01x-14.00x	2	5
		14.01x+	1	1

Table 4-1 (Continued)
VARIABLES

Variable	Class	Description	Exposure in PLT (%) Jump to ART	Graded
Next Premium jump	Categorical	1.01x-1.10x	85	1
		1.11x-1.20x	14	3
		1.21x-1.30x	1	11
		1.31x-1.40x	>1	17
		1.41x-1.50x	>1	14
		1.51x-1.60x	>1	15
		1.61x-1.70x	>1	24
		1.71x-1.80x	>1	15
		1.81x-1.90x	>1	>1
		1.91x-2.00x	>1	>1
		2.01x+	>1	>1
Billing type	Categorical	Automatic payment	78	40
		Bill Sent	21	60
		Automatic payment changed to Bill Sent	1	NA
Premium mode	Categorical	Annual	18	39
		Semi-annual	5	5
		Quarterly	12	17
		Monthly	65	39
Duration in PLT	Numerical	1	30	65
		2	18	22
		3	14	10
		4	12	3
		5	9	NA
		6	6	NA
		7	4	NA
		8	3	NA
		9	2	NA
		10	2	NA
Predicted lapse probability in the shock duration	Numerical	<30%	37	13
		30-39%	17	14
		40-49%	13	17
		50-59%	10	17
		60-69%	8	18
		70-79%	6	16
		80-89%	6	5
		90-100%	3	NA

Initial premium jump refers to the premium increase from the level term premium to the first PLT duration premium. This is the only premium jump variable relevant for shock lapse modeling. The initial premium jump at the end of the level term is the largest increase, but the premium continues to increase each year in PLT. Two additional premium jump variables are considered when modeling behavior in PLT to capture these subsequent premium increases. Cumulative premium jump is calculated as the ratio of the next duration PLT premium compared to the level term premium. Next premium jump is calculated as the ratio of the PLT premium due in the next duration compared to the PLT premium paid in the current duration.

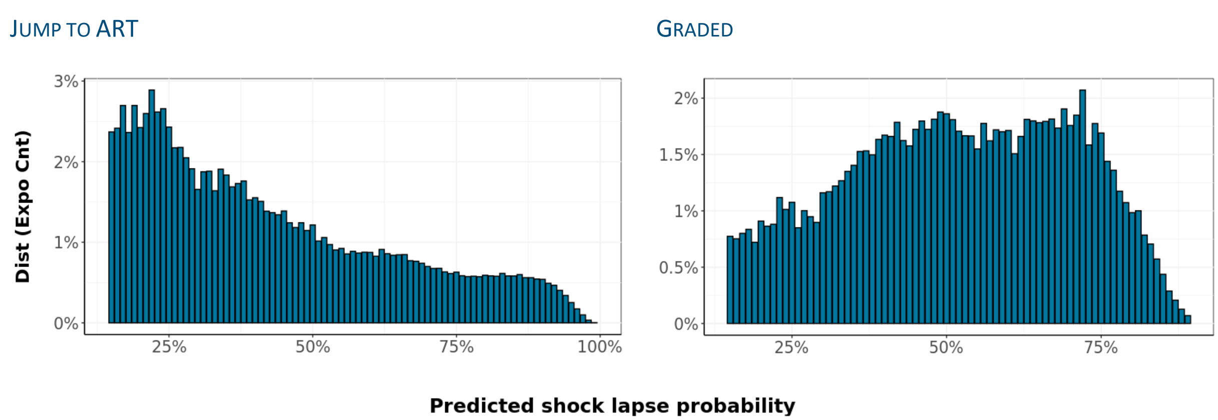
Based on the characteristics of the business, a predicted shock lapse is calculated using the shock lapse model described in section 3. This predicted shock lapse is included as a variable in the study and the PLT data can be reviewed by predicted shock lapse group.

Figure 4-1 illustrates the distribution of exposure by predicted shock lapse probability for Jump to ART and Graded.

Most of the Jump to ART data in the subsequent durations are at the lower predicted shock lapse ranges. When the shock lapse is higher, a smaller amount of business remains in PLT and it follows that less data are available to study lapse in PLT, especially at the later durations.

Jump to ART data were available for ten durations in PLT, while Graded PLT data were available for only four durations, with 65% in PLT duration 1. For Graded, the data are more evenly spread across the shock lapse range. The difference is due to the concentration of Graded data at early durations in PLT. Also, the premium jump range for Graded is more limited and shock lapse in the 50-70% range is most common, which provides a concentration of data at this range. Due to differences in the premium jump range, and the fact that most Graded data were at early durations in PLT, the distribution of available data for PLT analysis differs between the structures as shown in Figure 4-1 below.

Figure 4-1
DISTRIBUTION OF THE EXPOSURE BY PREDICTED SHOCK LAPSE PROBABILITY



4.1.2 MODELING APPROACH

Lapse by duration in PLT is predicted using a two-step approach. The first step assesses the relationship between the predicted shock lapse probabilities and the lapse rates in the subsequent durations in PLT through the *shock lapse relationship model*. The second step (which is applied only for Jump to ART in this report) allows for modeling any significant deviations of additional drivers of the lapse experience that are not captured in the predicted shock lapse probabilities by means of a logistic regression. The model built in the second step is referred to as the *final model*.

The shock lapse relationship model captures the relationship between predicted shock lapses and lapses in the subsequent durations in PLT by means of a nonparametric approach.

The changes in the lapse rates in PLT are analyzed as a function of the duration in PLT u and the shock lapse probability v:

$$C_{u,v} \sim Binomial\left(E_{u,v}\, \rho_{u,v}\right),$$

where

- $C_{u,v}$ is the lapse count for duration u and predicted shock lapse probability v.
- $E_{u,v}$ is the exposure for duration u and predicted shock lapse probability v.
- $\rho_{u,v} = \psi(u, v)$ is an unspecified smoothing function.

The form of the function $\psi(u, v)$ of the duration in PLT and shock lapse probability is estimated nonparametrically. In contrast to a parametric approach, a specific function is not defined in advance, but the data determines its optimal form. Methods used for nonparametric estimation include regression and smoothing splines or local methods. Following the approach taken by Tibshirani and Hastie (1987), local kernel weighted log-likelihood models are fitted to the lapse rates in PLT for Jump to ART and Graded separately.

Local fitting techniques combine excellent theoretical properties with conceptual simplicity and flexibility. They are very adaptable and convenient statistically. See Appendix B for a technical description of the approach and Loader (1999) for an extensive discussion of the strengths of local modeling. For Jump to ART and Graded data, a locally adaptive smoothing method using the intersection of confidence intervals rule is applied. The approach provides an adaptative optimal method to choose the smoothing parameters according to the regularity of the data. See Appendix C for a detailed presentation of the approach and Tomas and Planchet (2013) for a comparison of the methods applied to a mortality study.

For Jump to ART, the variables described in Table 4-1 are then included by means of a logistic regression allowing the model to detect any significant deviations from the estimated lapses in PLT that are not explained by the predicted shock lapse variable.

Each cell is determined by a unique combination of variables,

$$C_i \sim Binomial\,(E_i\, \rho_i),$$

whereas

$$\operatorname{logit} \rho_i = \beta_0 + \beta_1 \operatorname{logit} \rho_i^{\mathrm{SLR}} + \sum_{j=2}^{r+1} \beta_j x_{ij}$$

where

- C_i is the lapse count in the post-level term period for cell $\boldsymbol{i}$.
- E_i is the exposure in the post-level term period for cell $\boldsymbol{i}$.
- ρ_i^{SLR} is the lapse in PLT probability estimated by the Shock Lapse Relationship (SLR) model in the first step for cell i, which is a function of the duration and the predicted shock lapse probability only.
- $x_{ij}'s$ are the variables for cell i.

It is worth noting that the model predicts exactly the total actual number of lapses in PLT for each category of the variables included in the model. By equating the partial derivative of the log-likelihood with respect to β_j,

$$\sum_{i|x_{ij}=1} C_i = \sum_{i|x_{ij}=1} E_i\, \rho_i.$$

It follows that the ratio between the actual and expected number of lapses in PLT is 100% for each category of the variables included in the model.

4.2 SHOCK LAPSE RELATIONSHIP MODEL

The changes in the lapse rates in PLT are analyzed as a function of the duration in PLT and the shock lapse probability.

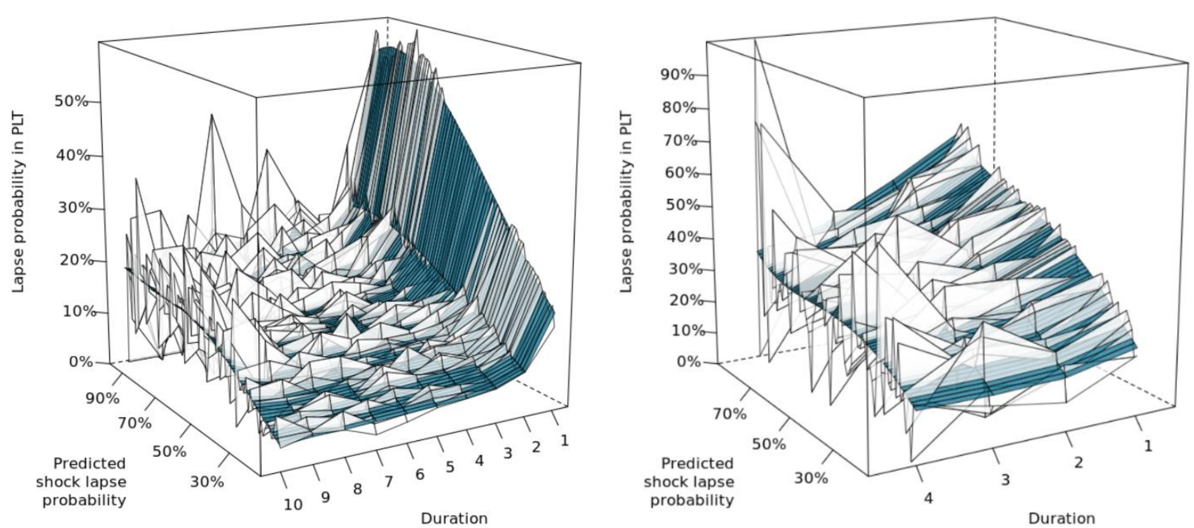
4.2.1 ILLUSTRATION OF SHOCK LAPSE RELATIONSHIP

The lapse rates in PLT as a function of the duration in PLT and the predicted shock lapse probabilities are illustrated in Figure 4-2 for Jump to ART and Graded. Predictive modeling allows this relationship to be captured directly by including predicted shock lapse as a variable in the study. The observed lapse rates are displayed in white while the smooth predictions are represented in blue.

Figure 4-2

OBSERVED AND PREDICTED LAPSES IN PLT BY SHOCK LAPSE AND DURATION IN PLT

JUMP TO ART GRADED

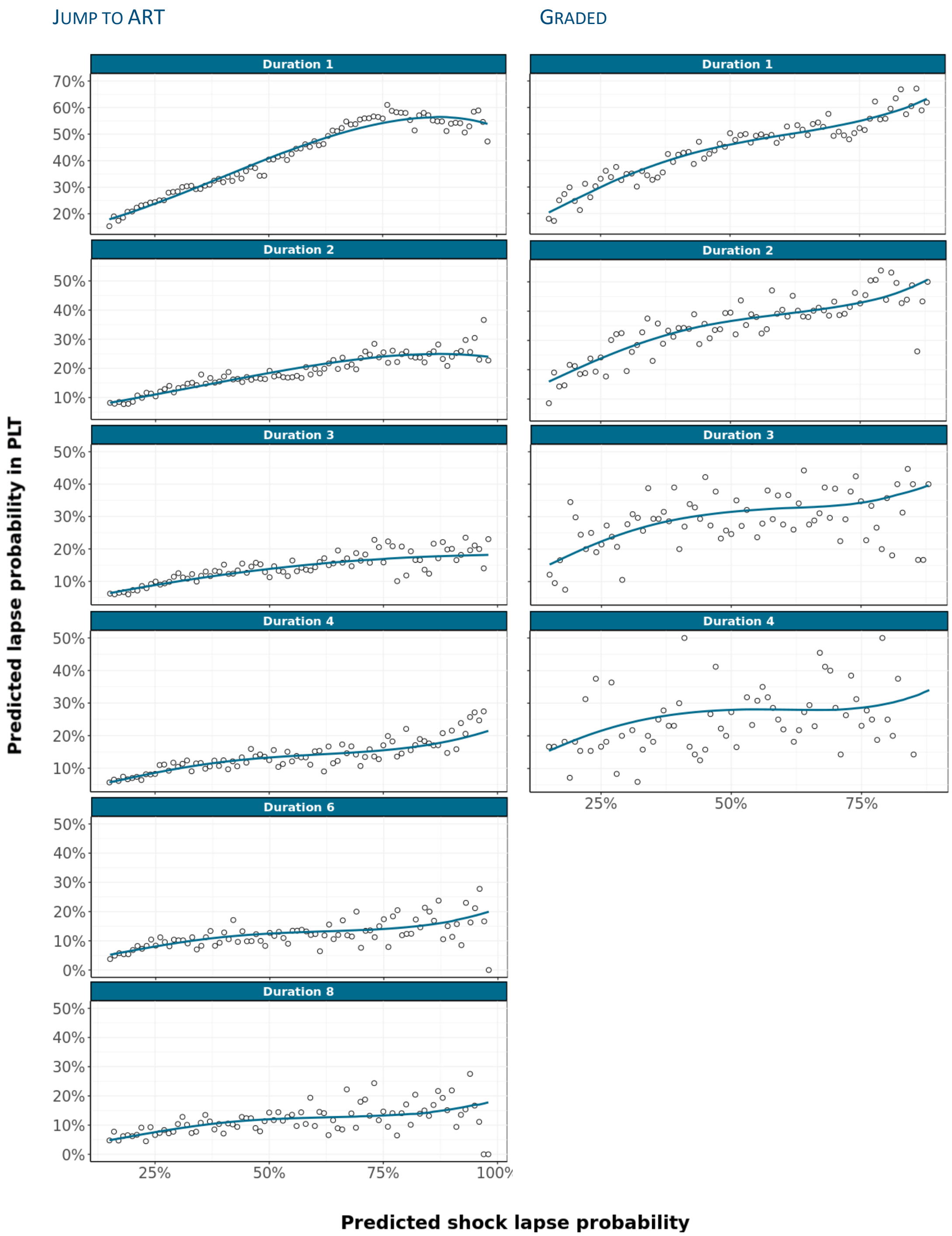


The irregularities in the progression of the actual lapse rates (in white) have been reduced in the smooth predictions (in blue). Spikes in the observed lapses that are attributed to limited lapse counts have been graduated using data from surrounding observations. Data for several observations on either side of a point have been used to augment the basic information, and an improved estimate has been obtained by smoothing the individual estimates. The actual lapse rates (represented in white) are particularly volatile at later durations for higher predicted shock lapses. This is not an occurrence specific to this dataset but a limitation for PLT studies in general as fewer policyholders remain when the shock lapse is high. The locally adaptive smoothing method (represented in blue) helps to define the relationship and overcome sampling fluctuations due to data limitations for specific segments.

Figure 4-3 presents the modeled PLT lapses rates by predicted shock lapse for each duration in PLT for Jump to ART and Graded, where the dots represent the actual lapse rates and the blue line represents the model predictions. These graphics give a first indication about the quality of the fit of the shock lapse relationship model and provide new insights into the lapse rate patterns in PLT.

Figure 4-3

LAPSES IN PLT BY PREDICTED SHOCK LAPSE FOR SELECTED DURATIONS IN PLT



The lapse rate in PLT is higher when the predicted shock lapse is higher and this holds across all durations for both PLT structures. The relationship is most pronounced in PLT duration 1. For both PLT structures, the model fit is best in PLT duration 1 where sampling fluctuations are limited. Observe that the actual data points are clustered closely around the fitted line. At later durations, there is more variation in the actual lapse rates and the data points are more dispersed over a wider range. Despite this increase of the variance at later durations, these graphics demonstrate that the shock lapse relationship model is capturing the pattern well at each duration.

For Jump to ART, the fitted lapse rates in the initial duration in PLT period are increasing gradually from 18% to 55% for predicted shock lapse probabilities 15% to 75%. For higher shock lapse rates, the lapses in the initial duration in PLT period plateau around 55% for shock lapse probabilities in the 75-100% range. The high lapse rate in duration 1 does not persist into later durations in the PLT period where lapse rates appear to be slowly decreasing. For example, in the 75-100% shock lapse probabilities range, lapse rates wear off quickly with around 25% in PLT duration 2 and 18% in PLT duration 3. The pattern of fitted lapse rate by predicted shock lapse is less steep at later durations as lapse rates vary over a smaller range, falling between 5% and 20% for PLT duration 4 and later. There is still variation by initial shock lapse group in these later durations but over a smaller range.

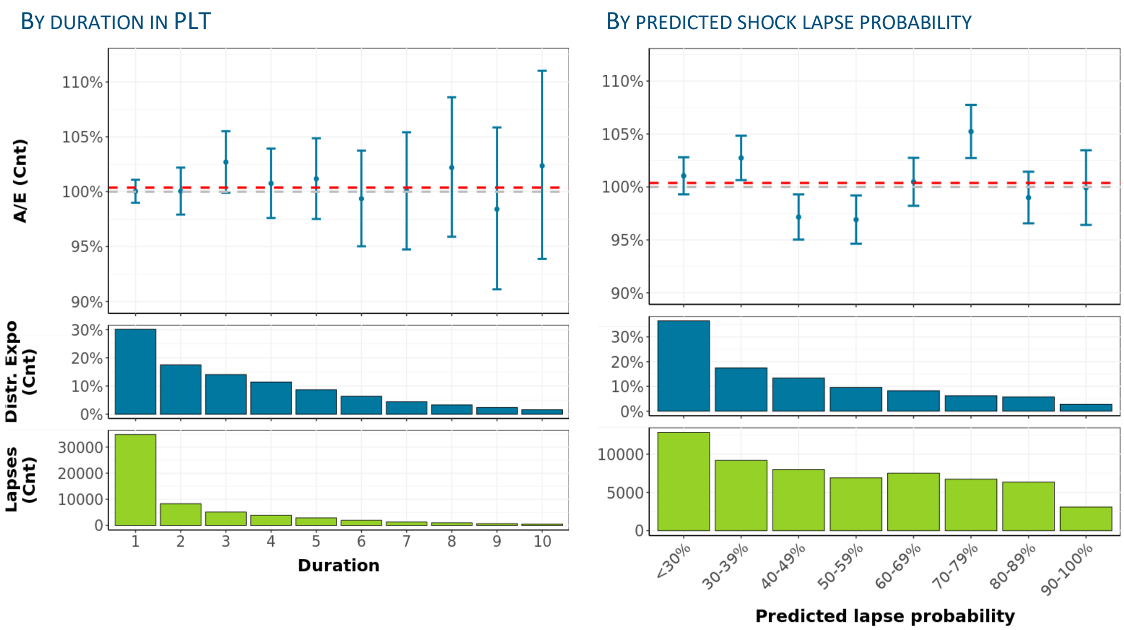
For Graded, the fitted lapse rates in each duration are increasing gradually overall for predicted shock lapse probabilities 15% to 89%, while the slope of each of the fitted lines across durations is gradually decreasing. The fitted lapse rates rise sharply from 20% to 64% in the initial duration in PLT period. The fitted lapse rates vary from 16% to 52% for PLT duration 2 and from 15% to 40% for PLT duration 3, having an increment of 36% and 25%, respectively. In PLT duration 4, the increment in the fitted lapse rates is only 19%, varying from 15% to 34%.

These views also allow for a comparison of the fitted PLT lapse rates between Jump to ART and Graded. In PLT durations 2, 3 and 4, the lapse rates for Graded are higher than the lapse rates for Jump to ART and vary over a wider range.

4.2.2 MODEL FIT ANALYSIS

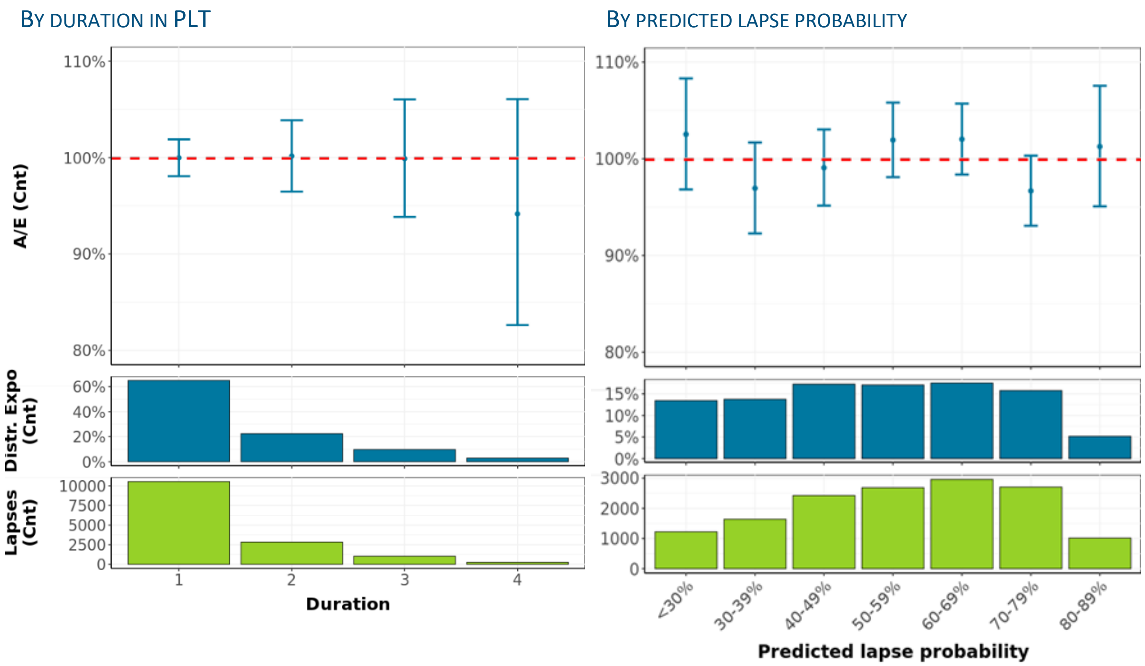
The model fit is further investigated through an A/E analysis where the expected represents the model predicted lapse rate in PLT derived from the shock lapse relationship model. Figures 4-4 and 4-5 show the actual over expected lapse count ratio in the post-level term period with the associated 95% confidence intervals for Jump to ART and Graded, respectively. The left panels present the A/E ratio by duration, while the right panels display the A/E by predicted shock lapse probability. The dashed grey line represents 100%, while the dashed red line shows the overall A/E ratio.

Figure 4-4
ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART



The shock lapse relationship model for Jump to ART adequately captures the variations of the lapse rates by duration in PLT and predicted shock lapse probabilities. The overall A/E (illustrated by the red dashed line) is 100.3% for Jump to ART. The 100% A/E (illustrated by the grey dashed line) falls within the 95% confidence interval for every duration. For predicted shock lapse bands 40-49% and 50-59%, the A/E is less than the 100%, suggesting the model overestimates the lapse rates in PLT, while for 70-79% band, the A/E ratio is 105%, suggesting the model underestimates lapse in PLT. While the 100% A/E does not fall within the confidence interval for these bands, the A/Es are very close to 100% confirming the shock lapse relationship model is a good fit.

Figure 4-5
ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR GRADED



The shock lapse relationship model for Graded adequately captures the variations of the lapse rates by duration in PLT and predicted shock lapse probabilities. The overall A/E (illustrated by the red dashed line) is 99.9%. The 100% A/E (illustrated by the grey dashed line) falls within the 95% confidence interval for every duration and every predicted shock lapse probability band, which confirms that the shock lapse relationship model is a good fit for Graded.

4.3 MODELING WITH ADDITIONAL VARIABLES FOR JUMP TO ART

Although the lapse rates in the subsequent durations are captured by the shock lapse relationship model at the overall level for Jump to ART, as seen in Figure 4-4, some variations at a more granular level are not estimated adequately. The second step of the approach is designed to model, by means of a logistic regression, any significant deviations of additional drivers of the lapses in subsequent durations that are not captured in the shock lapse relationship model.

4.3.1 SELECTING VARIABLES

The main steps in selecting the variables described in Table 4-1 are discussed in the following section. The final model includes the following variables: lapse rates estimated by the shock lapse relationship model, duration in PLT, shock lapse probability, initial premium jump, risk class, face amount, billing type and premium mode.

In this section, the fit for the shock lapse relationship model is compared to the fit of the final model for each of the key variables. In reviewing the fit of the shock lapse relationship model, it is possible to identify which variables have a specific impact on lapse in PLT that cannot be captured by the shock lapse variable. Then, comparing that to the final model highlights the improvement in the fit after adjusting for the additional variables. A saturated model is set at the start by including all main effects and interactions. The model also includes, as a variable, the lapse rates estimated by the shock lapse relationship model as a function of the duration in PLT and predicted shock lapse probability. The insignificant effects of the additional variables are then excluded by comparing the models with and without the variables using the likelihood-ratio test.

Level term plan

The likelihood-ratio test comparing the model without level term plan to the model with this variable gives a *p*-value of 21%. This indicates that excluding level term plan as a variable in the model is statistically justified. The variations of lapses in PLT by level term plan are, on average, well captured by the predicted shock lapse probability.

Gender

Comparing the model with and without the gender variable leads to a *p*-value of the likelihood-ratio test of 59%. It shows that the model without the gender effect is justified.

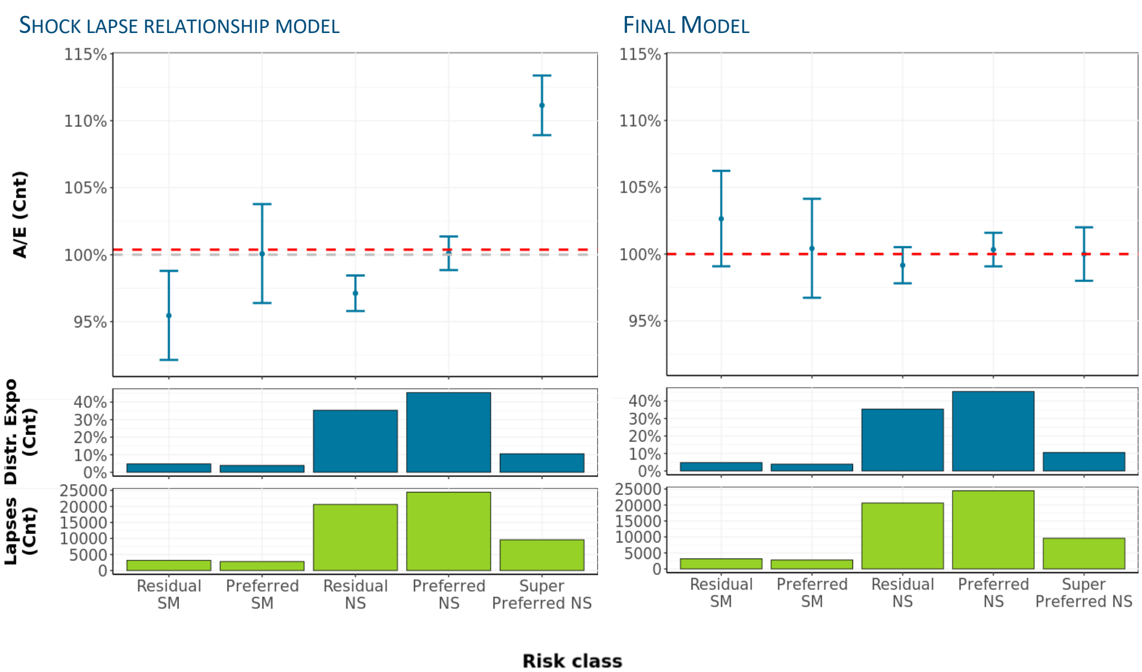
Attained age

The likelihood-ratio test comparing the model without attained age to the model with this variable gives a *p*-value of 72%. It indicates that the model without attained age is statistically justified. The predicted shock lapse probability captures the lapse variations in the subsequent durations by attained age.

Risk class

The likelihood ratio test supports including the risk class effect in the model as its corresponding p-value is lower than 0.1%. Therefore, risk class is included as a variable in the logistic regression for the final model. Figure 4-6 compares the actual over expected model fit analysis by risk class using the shock lapse relationship model as the expected basis (left panel) to the same A/E analysis using the final model as the expected basis (right panel).

Figure 4-6
ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY RISK CLASS



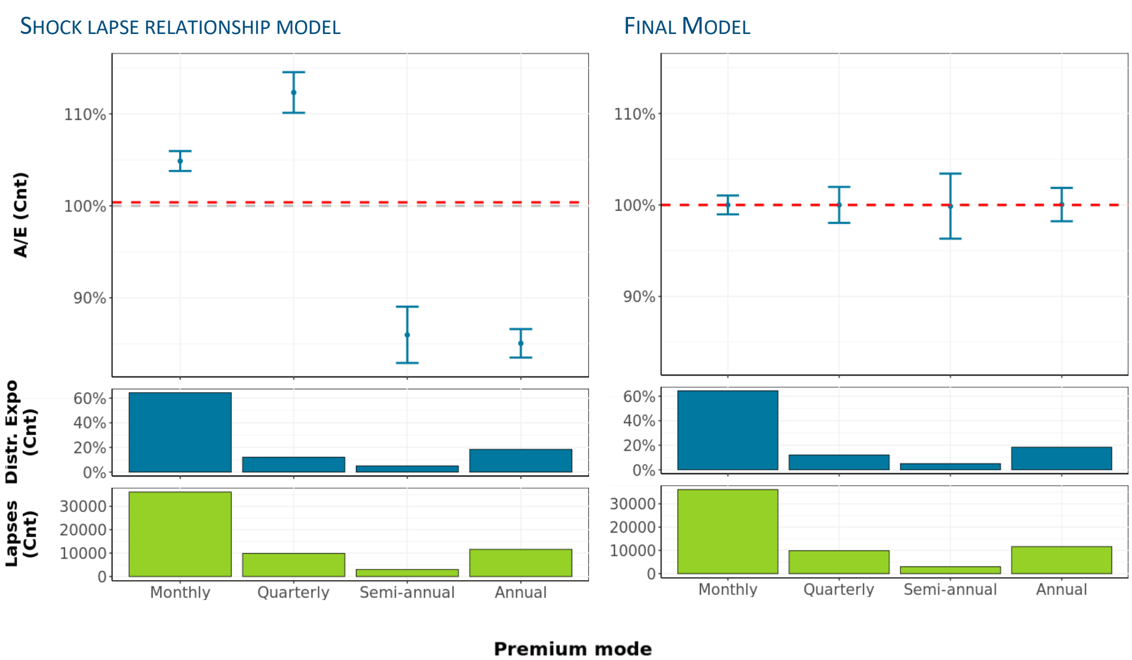
The shock lapse relationship model predictions lead to an overestimation of the number of lapses for the Residual SM and Residual NS and, reciprocally, to a significant underestimation of the lapses for the Super Preferred NS. This is illustrated by the 100% A/E falling outside the 95% confidence interval for these three categories in the left panel of Figure 4-6. Upon investigation, modeling separately the Super Preferred NS from the other risk class categories is found to be statistically justified. The likelihood-ratio test comparing the model with the two categories (Residual SM, Preferred SM, Residual NS, and Preferred NS grouped together and Super Preferred NS alone) to the model with the five categories of risk classes gives a *p*-value of 12%. Therefore, only two categories are considered for the risk class variable used in the final model – Super Preferred NS and all others grouped combined. The right panel of Figure 4-6 illustrates the quality of the fit of the model, including the risk class effect, when Super Preferred NS has been modeled separately from the other categories. The A/E ratio varies within a 99%-103% range and highlights that lapse variations in PLT for Residual SM, Residual NS, Preferred SM and Preferred NS can be captured by the combined effects of the other variables included in the model.

Premium mode

The likelihood-ratio test supports including the premium mode effect in the model as its corresponding *p*-value is lower than 0.1%. The lapse rates in PLT modeled by the shock lapse relationship model leads to a significant underestimation of the number of lapses for the Monthly and Quarterly premium payment modes and an overestimation for the Semi-annual and Annual modes. This is illustrated by the 100% A/E falling outside the 95% confidence interval in the left panel of Figure 4-7. Through further analysis, grouping the Semi-annual and Annual modes is found to be statistically justified. The likelihood-ratio test comparing a model without this grouping to the final model with this grouping gives a *p*-value of 73%. The premium mode is included in the model as a variable with three categories (Monthly, Quarterly and Annual/Semi-annual). By including the premium mode, the model predicts exactly the observed number of lapses for each category included in the model. The A/E ratios for each category are 100%, as shown in the right panel of Figure 4-7.

Figure 4-7

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY PREMIUM MODE

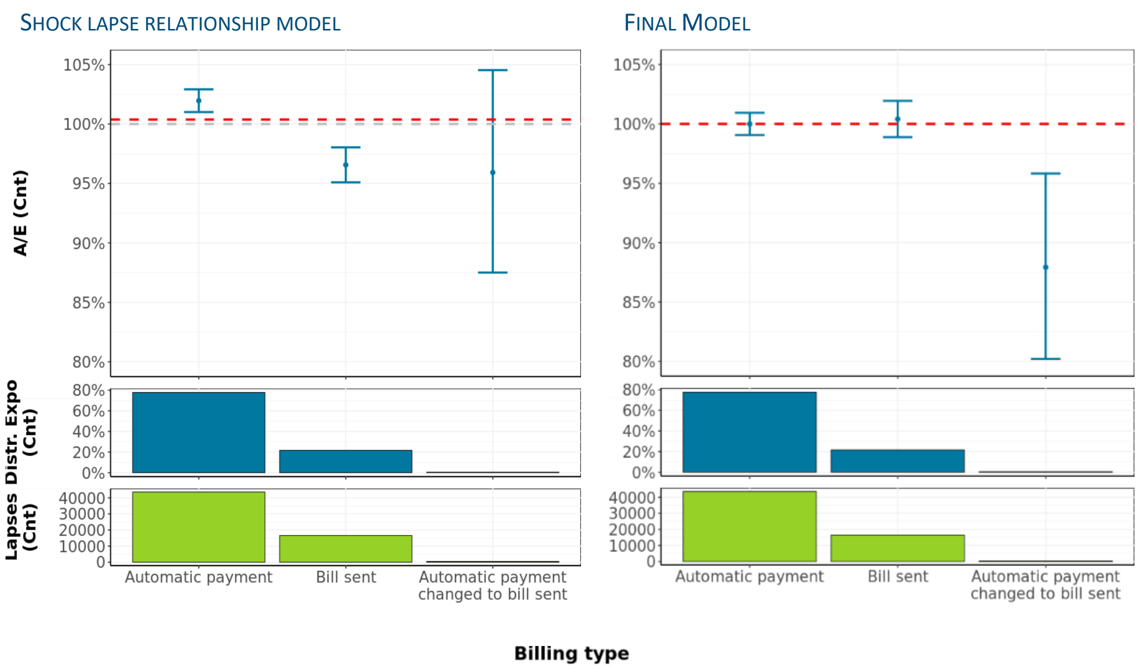


In the post-level term period, lapses continue to be higher for Annual premium mode policies compared to the more frequent premium mode policies, but the difference is not as pronounced as in the shock lapse at the end of term. The shock lapse relationship model predicts a wider variation between Annual and Monthly modes leading to a mis-estimation of lapses by premium mode in PLT. By including premium mode in the final model, this relationship between premium mode and lapse in PLT is captured.

Billing type

The likelihood-ratio test does not support including billing type as its corresponding *p*-value is 55%. Significant deviations between the actual number of lapses and expected as modeled by the shock lapse relationship model can be visualized for billing type categories, Automatic payment and Bill Sent, in the left panel of Figure 4-8. The number of lapses is significantly underestimated for Automatic payment and overestimated for Bill Sent as illustrated by the 100% A/E falling outside the 95% confidence intervals. The A/Es for Bill Sent and Automatic payment changed to Bill Sent categories are at a similar level, being 97% and 96%, respectively. This shows that the lapse variation in PLT for the categories Bill Sent and Automatic payment changed to Bill Sent are similar. While the change in billing type was shown to impact behavior at the end of term, once the policyholder is paying premiums in PLT, the change has been made and the billing type is simply Bill Sent throughout the PLT period.

Figure 4-8
ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY BILLING TYPE



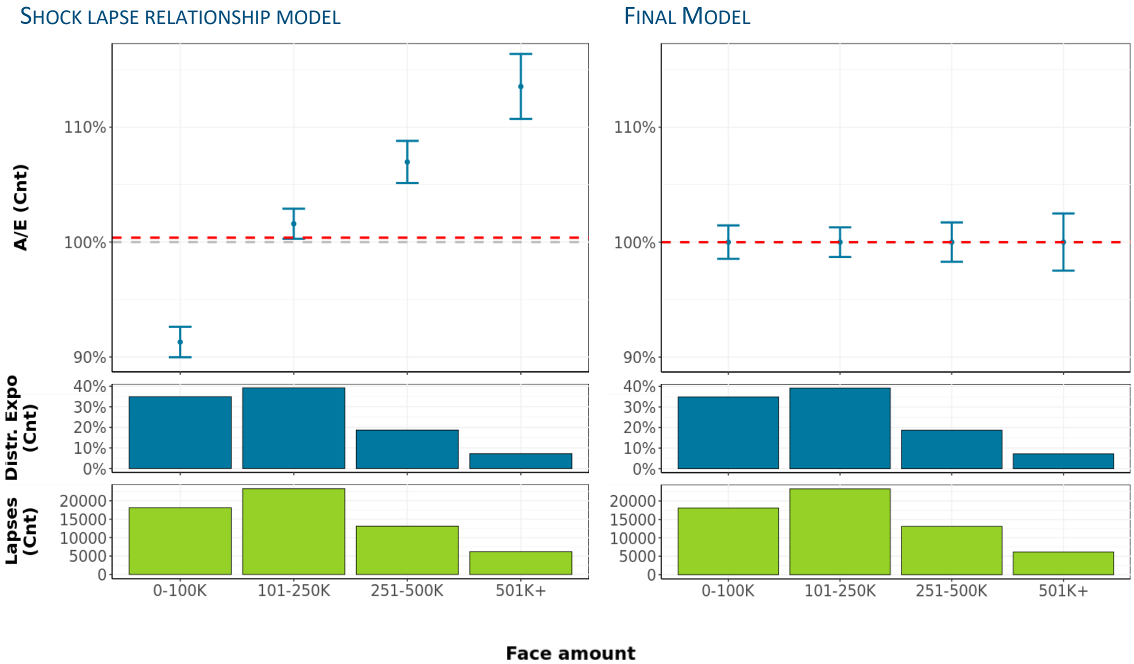
The final model does not include the variable Billing type. The lapse variations in PLT are captured adequately by the combined effects of the other variables included in the final model. This is illustrated in the right panel of Figure 4-8 by the 100% A/E falling inside the 95% confidence interval for Automatic payment and Bill Sent. While the fit is improved for categories Bill Sent and Automatic payment, which each have A/E ratios of 100% based on the final model, the Automatic payment changed to Bill Sent now falls outside the 95% confidence interval. However, variation is not significant given the small amount of data for this category and the reduced importance placed on the change in billing type once the policyholder is already paying premiums in PLT.

Face amount

The likelihood-ratio test supports including the face amount effect in the model as the corresponding *p*-value is lower than 0.1%. Significant deviations in the A/E ratios are observed by face amount band in the left panel of Figure 4-9.

Figure 4-9

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY FACE AMOUNT



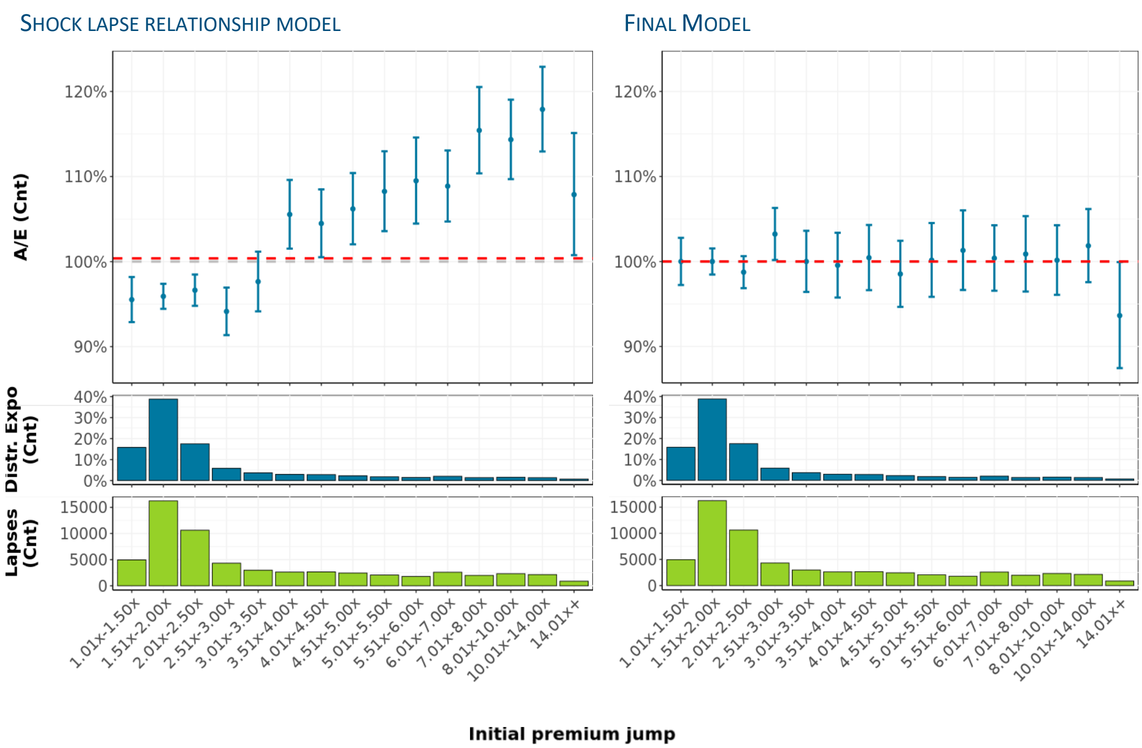
The number of lapses is significantly overestimated for face amount band $0-100K and underestimated for bands $250-500K and $501K+. This is illustrated by the 100% A/E falling outside the 95% confidence interval. By including the face amount variable, the model predicts exactly the observed number of lapses for each band. As a result, the A/E ratio for each category is 100% in the right panel of Figure 4-9. There continues to be an increasing relationship between face amount and lapse in PLT and, in fact, the variation appears to be wider for lapse in PLT than for shock lapse as the shock lapse relationship model does not capture the relationship sufficiently. After including face amount as a variable, the relationship between face amount and lapse in PLT is captured by the final model.

Initial premium jump

The likelihood-ratio test supports including the initial premium jump effect in the model as its corresponding *p*-value is lower than 0.1%. A significant overestimation of the number of lapses for initial premium jump bands lower than 3.00x and underestimation of initial premium jumps higher than 3.51x can be seen in the left panel of Figure 4-10. The 100% A/E falls outside the 95% confidence interval. This highlights that including shock lapse as a variable does not fully capture variation by initial premium jump for lapse rates in PLT. Based on further analysis, grouping initial premium jump into seven bands (1.01x-1.50x, 1.51x-2.00x, 2.01x-3.00x, 3.01x-3.50x, 3.51x-4.50x, 4.51x-7.00x and 7.01x+) is found to be statistically justified. These groupings are applied for the initial premium jump variable included in the final model. The fit by premium jump category is improved in the final model even when reviewed by more granular initial premium jump groups as shown is Figure 4-10. This shows that variation in lapses in PLT is impacted by the initial premium jump, especially over the lower premium jumps. Over the higher premium jumps (7.01x+), initial premium jump is a less important variable as lapse rates in PLT for this broad category can be explained by shock lapse and the other variables included in the model. Note from the lapse count distribution charts that less data were available in PLT for higher premium jump categories as fewer policyholders paid the high premiums. However, lapse counts are still in the thousands for these higher premium jump categories.

Figure 4-10

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY INITIAL PREMIUM JUMP

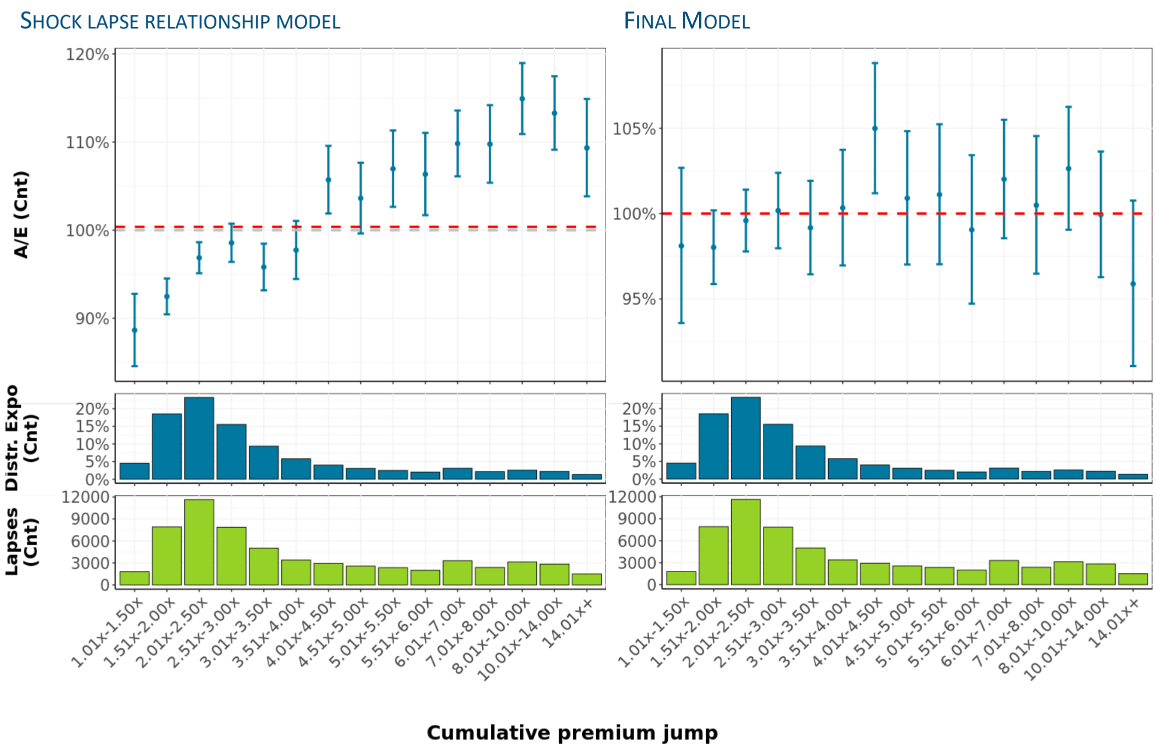


Cumulative premium jump

While the initial premium jump is the key driver of shock lapse at the end of term, lapses in PLT may be impacted by the subsequent premium increases in PLT. Cumulative premium jump is defined as the premium in a given duration in PLT relative to the level term premium. In this way, the cumulative premium jump variable captures the subsequent premium increases in PLT. The likelihood-ratio test supports including the cumulative premium jump effect in the model as its corresponding p-value is lower than 0.1%. Significant deviations in the A/E ratios can be seen by cumulative premium jump band in the left panel of Figure 4-11. However, initial premium jump and cumulative premium jump include some of the same information and, with that in mind, consideration was given to whether both variables or just one of those variables was needed in the model to adequately capture lapse in PLT patterns.

Figure 4-11

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR JUMP TO ART BY CUMULATIVE PREMIUM JUMP



Similar to initial premium jump, the predicted number of lapses by the shock lapse relationship model is significantly overestimated for jumps lower than 3.50x and underestimated for jumps larger than 4.01x. The 100% A/E falls outside the 95% confidence interval. Cumulative premium jump is not included in the final model, however. Lapse rate variations by cumulative premium jump are captured adequately by the initial premium jump and the combined effects of the other variables included in the final model. This is illustrated in the right panel of Figure 4-11 by the 100% A/E falling inside the 95% confidence interval for most of the cumulative premium jump bands. This highlights that the initial premium jump at the end of term is the most important driver of lapse behavior and continues to have an impact in later durations in PLT. For Jump to ART, the premium increase at the end of term is the largest increase with subsequent increases being in the 105%-115% range of the prior year premium, in line with age-related increases on the ART scale. Due to this narrow range over which subsequent duration premium increases vary and the relative size compared to the large premium jump at the end of term, the subsequent duration premium increases are not required to model PLT lapse experience for Jump to ART business.

Duration in PLT

The likelihood-ratio test comparing the model without the duration in PLT to the model with this variable gives a *p*-value lower than 0.1%. This suggests that the model with the duration in PLT variable is statistically justified. An adjustment by duration is needed in addition to the variations captured in the shock lapse relationship model.

Predicted shock lapse probability

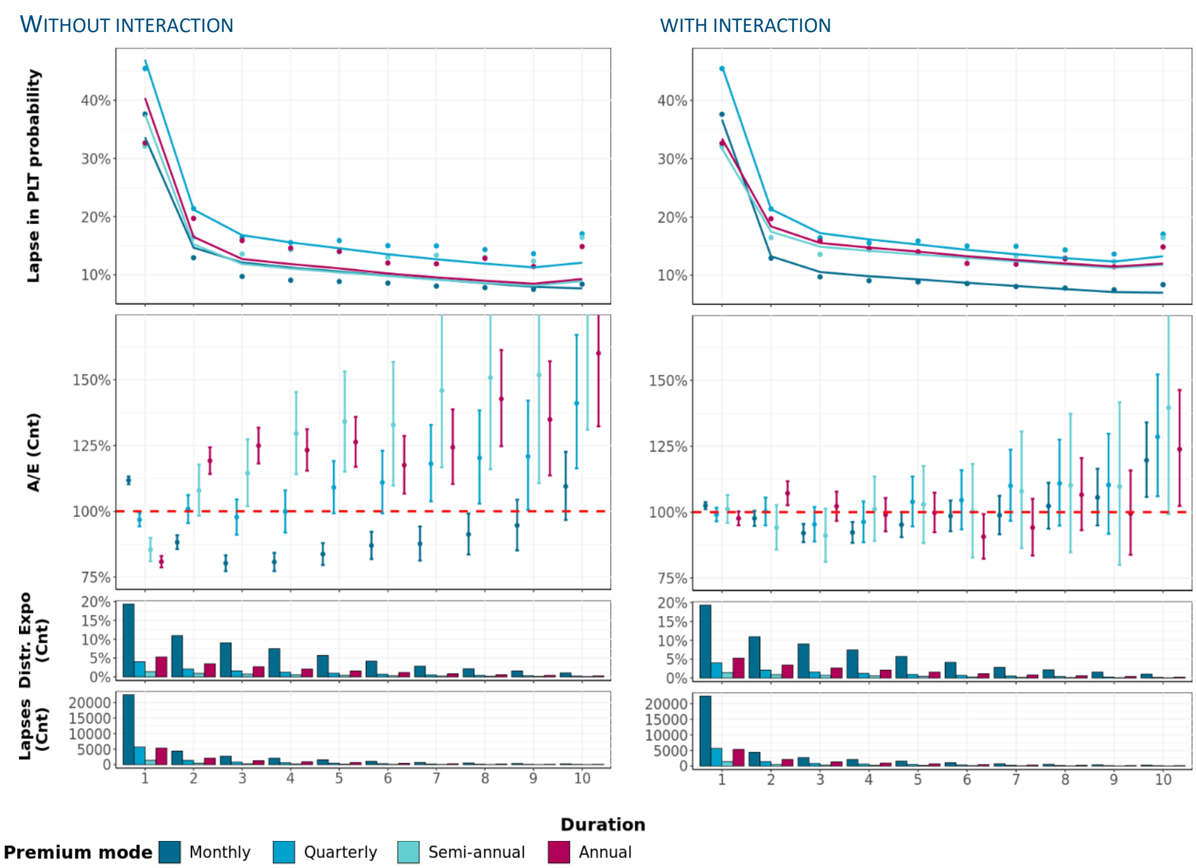
The model allowing an adjustment by predicted lapse probability is favored as the *p*-value of the corresponding likelihood-ratio test is lower than 0.1%. This suggests that predicted shock lapse probability must be included as a variable in the model. An adjustment by shock lapse is needed in addition to the variations captured in the shock lapse relationship model.

Interaction terms

A significant interaction is observed between the lapses in PLT as predicted by the shock lapse relationship model and premium mode. This means that lapses in PLT show significant differences across durations by premium mode. The model fit with and without this interaction term is compared in Figure 4-12 where the model without the interaction term is illustrated in the left panel and the model including the interaction term is illustrated in the right panel.

Figure 4-12

LAPSES VARIATIONS IN PLT BY DURATION AND PREMIUM MODE FOR JUMP TO ART



Without this interaction, the same relationship between premium modes is modeled across all durations. The lapse variations in PLT across all durations for the Monthly, Semi-annual and Annual modes are not captured by the model without the interaction. This is illustrated in the second left panel in Figure 4-12 above where the A/E 100% is not falling within the confidence interval. The model without the interaction term underestimates Monthly premium mode lapses in PLT duration 1 and overestimates Monthly lapse rates in PLT durations 2+, with mis-estimation in the opposite direction for Annual and Semi-annual premium mode business. After including the interaction term, the model captures the higher lapse for Monthly premium mode compared to Annual in PLT duration 1 and then the lower lapses for Monthly premium mode in all later durations. The A/E analysis also shows an improved fit for all premium modes across the durations.

4.3.2 INTERPRETATION OF THE JUMP TO ART REGRESSION MODEL OUTPUT

The main effects and interactions included in the final model fitted to Jump to ART data are displayed in Table E-1 of Appendix E. A reference category is selected for each of the categorical variables that corresponds to the category where the largest exposure is observed. For this model, the reference categories of the categorical variables are given in Table 4-2.

Table 4-2
REFERENCE CATEGORIES FOR CATEGORICAL VARIABLES FOR THE JUMP TO ART FINAL MODEL

Categorical Variables	Reference Categories
Risk class	Residual and Preferred
Initial premium jump band	2.01x-3.00x
Face amount	$101-250K
Premium payment mode	Monthly

From the estimated regression coefficients displayed in Table E-1, the predicted lapse rates can be derived allowing an analysis of how these differ with a change in each variable. As an example, taking the reference categories for a policyholder in PLT duration 1 with a predicted shock lapse of 50%, these effects with their associated 95% confidence intervals are summarized Table 4-3.

Table 4-3

LAPSE PROBABILITIES WITH THEIR ASSOCIATED 95% CONFIDENCE INTERVALS AND RELATIVE RISK FOR THE MAIN EFFECTS AND INTERACTION TERM WITH RESPECT TO A POLICYHOLDER WITH CHARACTERISTICS CORRESPONDING TO THE REFERENCE CATEGORIES IN PLT DURATION 1 AND PREDICTED SHOCK LAPSE 50% FOR JUMP TO ART

Main Effects and Interaction Terms	Lapse Probability with 95% CI	Relative Risk
Reference categories: *Face amount band $101-250K, Residual and Preferred, initial premium jump band 2.01x-3.00x, Monthly premium mode, PLT duration 1 and Predicted shock lapse 50%.*	43% [38%,47%]	100%
Duration: 2	16% [14%,19%]	37%
Duration: 3	12% [11%,14%]	28%
Duration: 4	12% [10%,13%]	28%
Duration: 6	10% [9%,12%]	23%
Duration: 8	10% [8%,11%]	23%
Predicted shock lapse: 30%	28% [25%,30%]	65%
Predicted shock lapse: 45%	39% [35%,43%]	91%
Predicted shock lapse: 60%	50% [45%,55%]	116%
Predicted shock lapse: 75%	58% [52%,63%]	135%
Predicted shock lapse: 90%	58% [52%,64%]	135%
Initial premium jump: 1.01x-1.50x	34% [29%,39%]	79%
Initial premium jump: 1.51x-2.00x	39% [34%,44%]	91%
Initial premium jump: 3.01x-3.50x	45% [40%,51%]	105%
Initial premium jump: 3.51x-4.50x	49% [44%,55%]	114%
Initial premium jump: 4.51x-7.00x	51% [45%,56%]	119%
Initial premium jump: 7.01x+	53% [48%,59%]	123%
Risk class: Super Preferred NS	45% [40%,50%]	105%
Face amount $0-100K	39% [40%,44%]	91%
Face amount $251-500K	45% [40%,50%]	105%
Face amount $501K+	48% [42%,53%]	112%
[Duration 1, shock lapse 50%] × Premium mode: Quarterly	43% [36%,50%]	100%
[Duration 1, shock lapse 50%] × Premium mode: Semi-annual and Annual	31% [26%,38%]	72%
[Duration 2, shock lapse 50%] × Premium mode: Quarterly	22% [18%,26%]	138%[1]
[Duration 2, shock lapse 50%] × Premium mode: Semi-annual and Annual	19% [16%,23%]	119%[1]

[1]Relative risk with respect to [Duration 2, shock lapse 50%] × Premium mode: Monthly

From Table 4-3, the relative risk for the main effects of the model can be interpreted. Below, three examples of the computation of the estimated risk factors and interpretation of the corresponding predicted lapse probabilities are given.

- **Intercept / Reference categories**: A policyholder with characteristics corresponding to the reference categories has a $\exp\left(\hat{\beta}_0 + \hat{\beta}_1 \times \rho^{\mathrm{SLR}}_{1,50\%} + \hat{\beta}_2 \times 50 + \hat{\beta}_3 \times 1\right) / \left(1 + \exp\left(\hat{\beta}_0 + \hat{\beta}_1 \times \rho^{\mathrm{SLR}}_{1,50\%} + \hat{\beta}_2 \times 50 + \hat{\beta}_3 \times 1\right)\right) = \exp(-0.295)/(1 + \exp(-0.295)) \approx 43\%$ probability of lapse during duration 1 in PLT. Additionally, based on the standard errors, the corresponding 95% confidence interval is [38%,47%].
- **Duration**: The lapse probability of a policyholder with characteristics corresponding to all of the reference categories except PLT duration 2 is 16% (95% CI [14%, 19%]). The lapse probability decreased dramatically from PLT duration 1 to 2. The corresponding relative risk of lapse of a policyholder with characteristics corresponding to the reference categories in PLT duration 2 compared to PLT duration 1 is 37%. For the subsequent durations, the lapse probability stagnates. The lapse probabilities of a policyholder in PLT durations 3, 4, 6 and 8 are 12% (95% CI [11%, 14%]), 12% (95% CI [10%, 13%]), 10% (95% CI [9%, 12%]) and 10% (95% CI [8%, 11%]), respectively. The corresponding relative risks of lapse compared to PLT duration 1 are 28% for PLT durations 3 and 4, and 23% for PLT durations 6 and 8.
- **Premium Mode:** Premium mode interacts with the lapses in PLT as predicted by the shock lapse relationship model. The lapse probability of a policyholder with characteristics corresponding to the reference categories but having an Annual or Semi-annual premium mode is:

$$\frac{\exp\left(\hat{\beta}_0 + \left(\hat{\beta}_1 + \hat{\beta}_{17}\right) \times \rho^{\mathrm{SLR}}_{1,50\%} + \hat{\beta}_2 \times 50 + \hat{\beta}_3 \times 1 + \hat{\beta}_{15}\right)}{1 + \exp\left(\hat{\beta}_0 + \left(\hat{\beta}_1 + \hat{\beta}_{17}\right) \times \rho^{\mathrm{SLR}}_{1,50\%} + \hat{\beta}_2 \times 50 + \hat{\beta}_3 \times 1 + \hat{\beta}_{15}\right)} \approx 31\%$$

  The relative risk of lapse compared to a policyholder having a Monthly premium mode is 72% in PLT duration 1. However, the lapse probability of a policyholder in PLT duration 2 having an Annual or Semi-annual premium mode is 19%, while lapse probability of a policyholder having a Monthly mode is 16%. The relative risk of a policyholder having an Annual or Semi-annual premium mode compared to a Monthly mode becomes 119% in PLT duration 2. The interaction term allows the model to capture the higher lapse for Monthly mode in PLT duration 1 but lower lapse for Monthly mode in PLT duration 2.

4.4 MODEL FIT ANALYSIS FOR JUMP TO ART

The final model for Jump to ART lapse in PLT includes the variables risk class, premium mode, initial premium jump group and face amount, as well as an adjustment by predicted shock lapse probability and duration in PLT, which is in addition to the lapse in PLT estimated by the shock lapse relationship model. Furthermore, the final model includes an interaction term between the modeled lapses in PLT and premium mode. In this section, the model output for lapse in PLT for Jump to ART is reviewed by additional variables. It provides insights into the relationships and an assessment of the model fit.

4.4.1 PREDICTED SHOCK LAPSE PROBABILITY AND DURATION IN PLT

Figures 4-13 and 4-14 present the predicted lapse probability in PLT based on the final model by predicted shock lapse and duration in PLT.

Figure 4-13

PREDICTED LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY SHOCK LAPSE PROBABILITY FOR SELECTED DURATIONS IN PLT

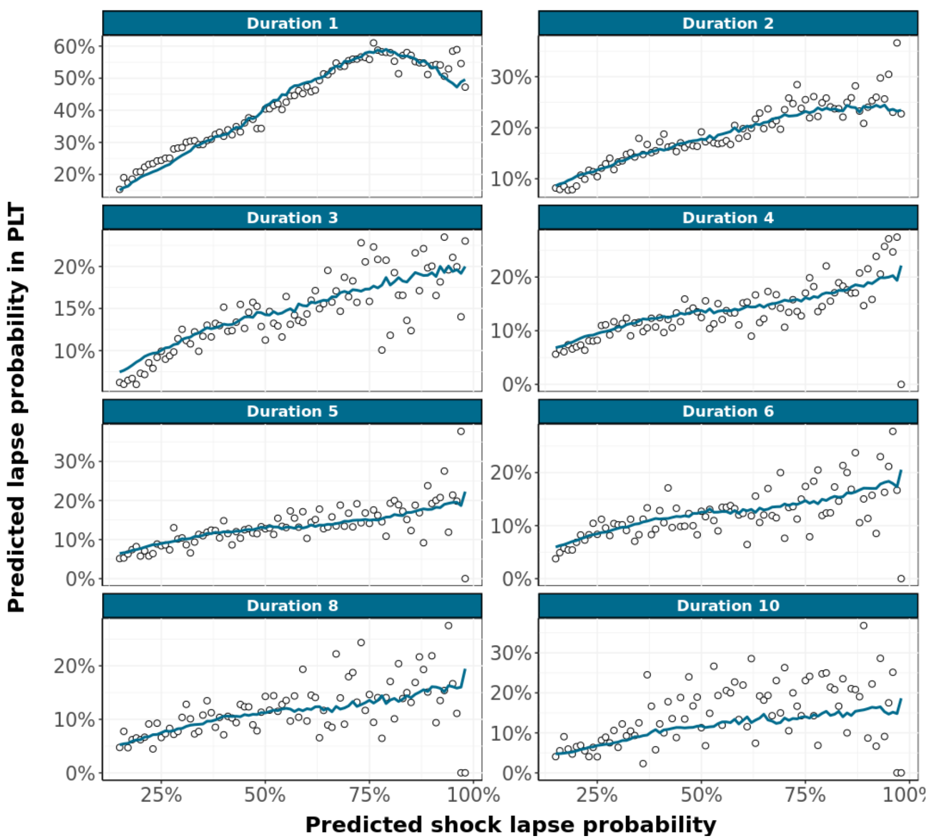
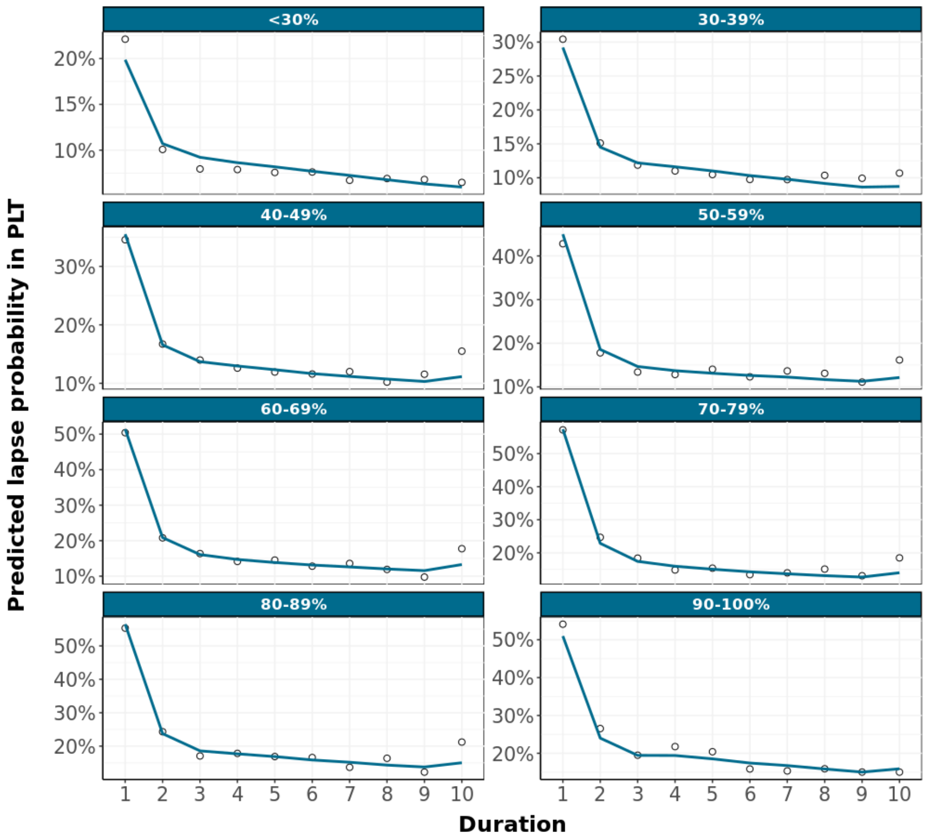


Figure 4-14
PREDICTED LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY DURATION FOR SOME SHOCK LAPSE PROBABILITY BANDS



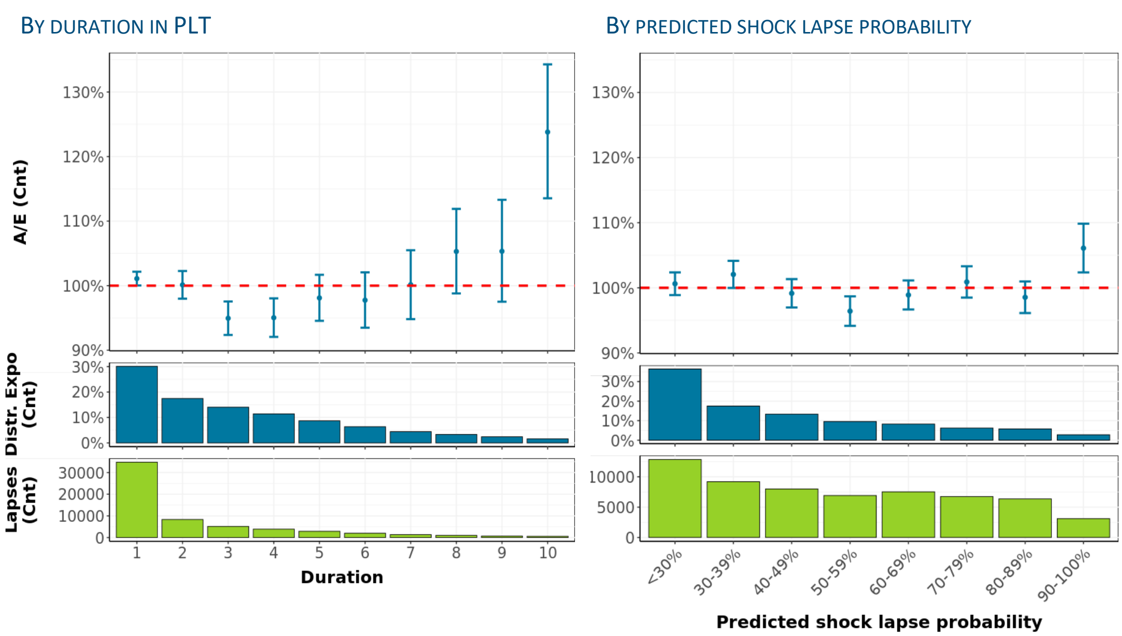
The lapses in PLT estimated by the final model for Jump to ART show that the modeled lapse probability in the first post-level term duration is increasing gradually from 15% to 60% over the predicted shock lapse probability range of 15% to 80%. For extreme shock lapse rates, the lapse probability in PLT seems to decrease slowly, to approximately 50%, for predicted shock lapse probabilities in the 90-100% range as illustrated in the top left panel in Figure 4-13.

The high initial lapse rate in PLT does not persist into later durations in the post-level term period. The lapse rate reduces quickly for all the shock lapse probability ranges. For shock lapse probabilities in the 90-100% range, the lapse rate in PLT dramatically decreases to 24% in PLT duration 2 and approximately 17% for post-level term duration 3+ (see the bottom right panel in Figure 4-14). For lapse probabilities lower than 50%, the decreasing pattern is less steep, reducing from 27% in the initial duration in PLT to 14% in PLT duration 2 and 10% on average for duration 3+.

Figure 4-15 shows the actual over expected number of lapses in the post-level term period as predicted by the final model by duration (left panel) and predicted shock lapse probability (right panel), with the associated 95% confidence intervals for Jump to ART. The dashed grey line representing 100% A/E ratio and the dashed red line showing the overall A/E ratio are superimposed as the model has the ability to predict exactly the actual number of lapses.

Figure 4-15

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR THE FINAL MODEL FOR JUMP TO ART



The number of lapses in PLT predicted by the final model for Jump to ART captures adequately the variations by duration in PLT and predicted shock lapse probability, as seen in Figure 4-15. The 100% A/E falls within the 95% confidence interval for most of the durations and predicted shock lapse probability bands. The A/E ratio is relatively close to 100% for the first seven durations in PLT, with the exception of durations 3 and 4 where A/Es are 95% as shown in the left panel of Figure 4-15. The A/E ratios by shock lapse are within a 99-102% range, with the exception of the lapse bands 50-59% and 90-100% where A/Es are 96% and 106%, respectively.

Similar figures are presented for a selected number of variables. Insights by additional drivers of mortality experience can be viewed using the Tableau dashboards[4].

Each figure contains four panels with results shown side by side by duration in PLT and predicted shock lapse probability derived from the shock lapse model. The first panel provides a visual indication of the quality of the fit and allows a comparison of the predicted lapses in PLT within some of the relevant variables by duration in PLT and predicted shock lapse probability. The dots represent the observed lapse rates, while the full lines illustrate the predictions. The second panel displays the corresponding actual experience over expected number of lapses as predicted by the final model, where an A/E ratio close to 100% represents a good fit of the model to the

[4] https://tableau.soa.org/t/soa-public/views/USPost-LevelTermPredictiveModelingInteractiveTool/2-LapsePLTOverview

observations. The third and fourth panels present the distribution of the exposure and number of lapses, respectively.

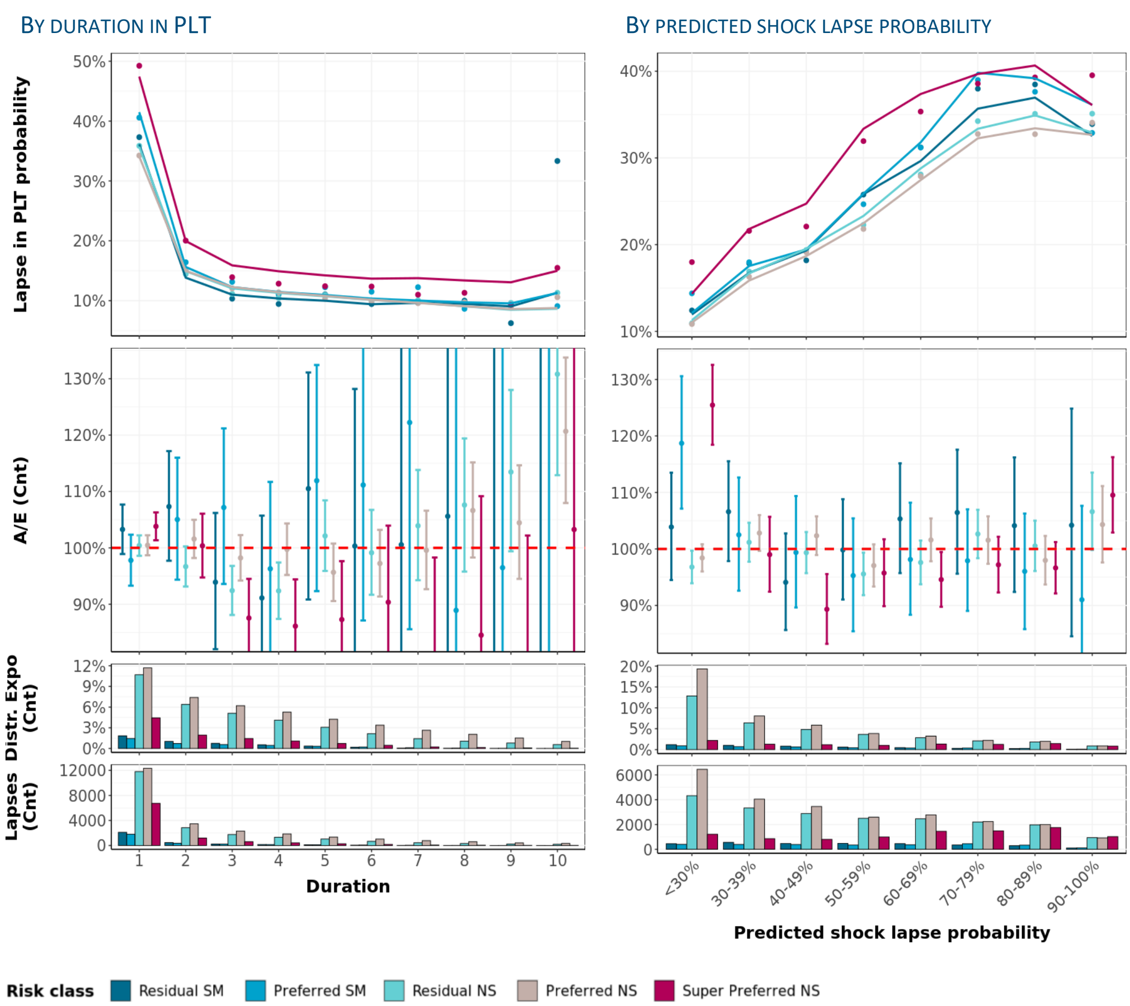
4.4.2 RISK CLASS

Risk class is included as a variable in the final lapse in the PLT model. The predicted lapse probability in PLT is larger for Super Preferred NS, while the pattern of Residual SM, Residual NS, Preferred SM and Preferred NS is similar by duration as illustrated in the top panel left of Figure 4-16. The variable included in the final model captures separately the Super Preferred NS variations to the other risk class categories. This highlights that predicted lapses in PLT do not vary by other risk classes across durations, while the Super Preferred NS class stands out. Variations are visible by predicted shock lapse probability. It shows that the other variables included in the final model explain these apparent variations by risk class across shock lapse bands.

The lapse in PLT variations by duration and predicted shock lapse probability are captured adequately for each risk class. In the second panels of Figure 4-16, the 100% A/E falls within the 95% confidence intervals, with the exception of duration and lapse bands for which no sufficient data can be observed.

Figure 4-16

LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY RISK CLASS

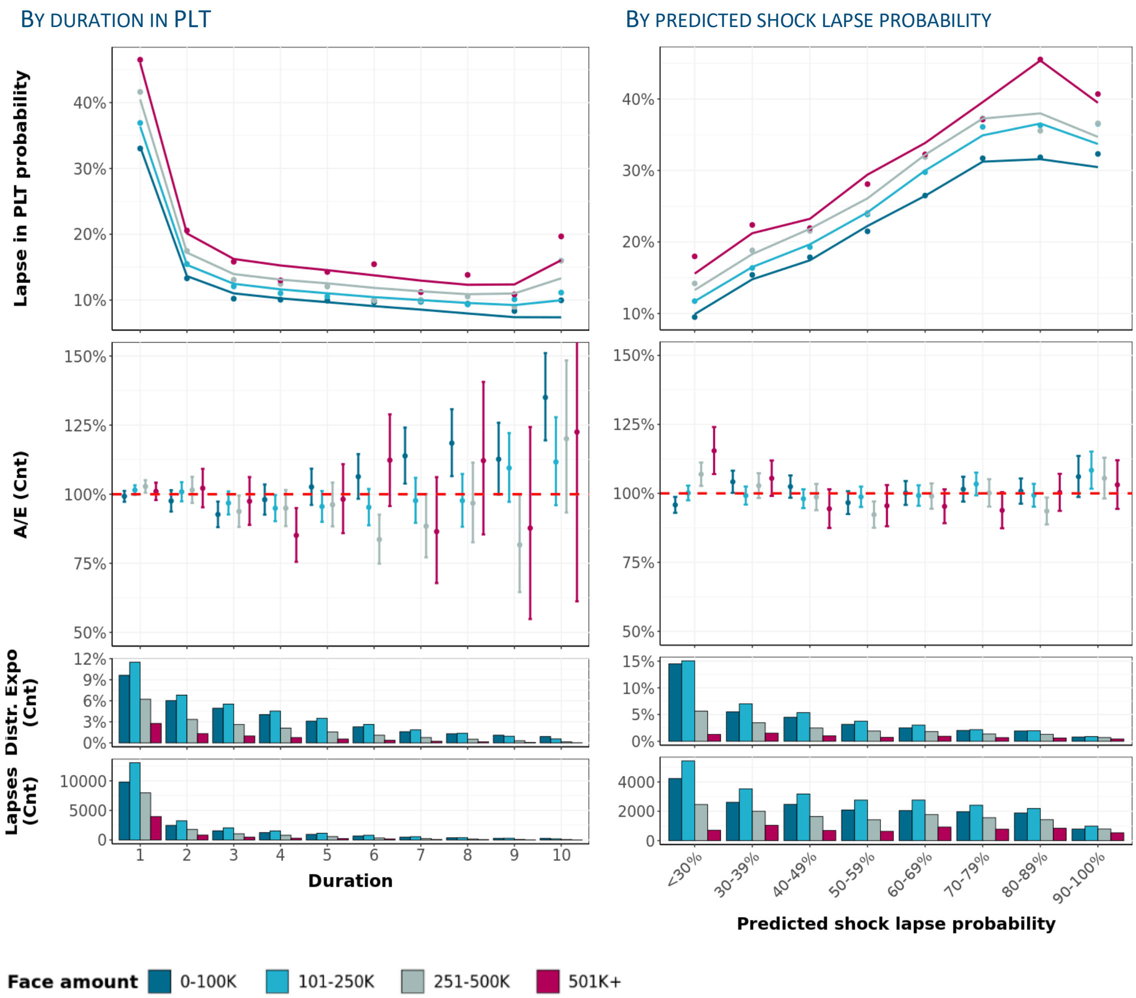


4.4.3 FACE AMOUNT

Face amount is included as a variable in the final model. Predicted lapses in PLT increase with face amount, as shown in the top panels of Figure 4-17. For a given duration or shock lapse probability, policyholders with large face amounts experience higher dollar amounts of premium increase than individuals with lower face amounts. Differences between face amount bands continue to be observed in later durations and remain stable across shock lapse probabilities.

The lapse variation in PLT by duration and predicted shock lapse probability is captured adequately for each face amount band, as illustrated by the 100% A/E falling within most of the 95% confidence intervals in the second panels of Figure 4-17.

Figure 4-17
LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY FACE AMOUNT



4.4.4 BILLING TYPE

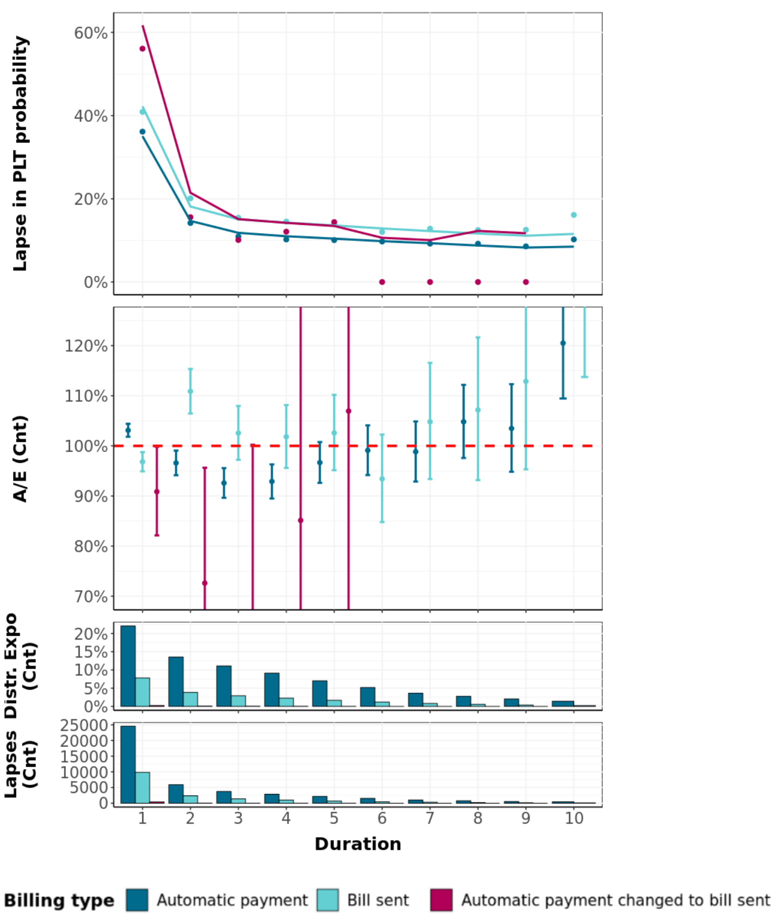
Billing type is not included as a variable in the final model. Predicted lapse probabilities in PLT are lower for Automatic payment across all durations compared to Bill Sent, as shown in the top left panel of Figure 4-18. For the billing type Automatic payment changed to Bill Sent, there is little data available in PLT as shown in the third and fourth panels on distribution. The change in billing type occurred at the end of term and, therefore, has less impact after the first duration in PLT. The predicted lapse probabilities in PLT for Automatic payment changed to Bill Sent converge to the Bill Sent lapse probabilities in duration 3 and remain similar for later durations.

For PLT durations 1 and 2, the 100% A/E falls outside of the 95% confidence interval in the second panels of Figure 4-18. The confidence interval is narrow due to the high data volumes. In the first panel, the final model fits the lapse pattern by duration in PLT for each billing type. This shows that the billing type effect can be captured by modeling lapses in PLT by predicted shock lapse probability including the other additional variables and, in particular, premium payment mode as premium mode and billing type are related.

Figure 4-18

LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY BILLING TYPE

BY DURATION IN PLT



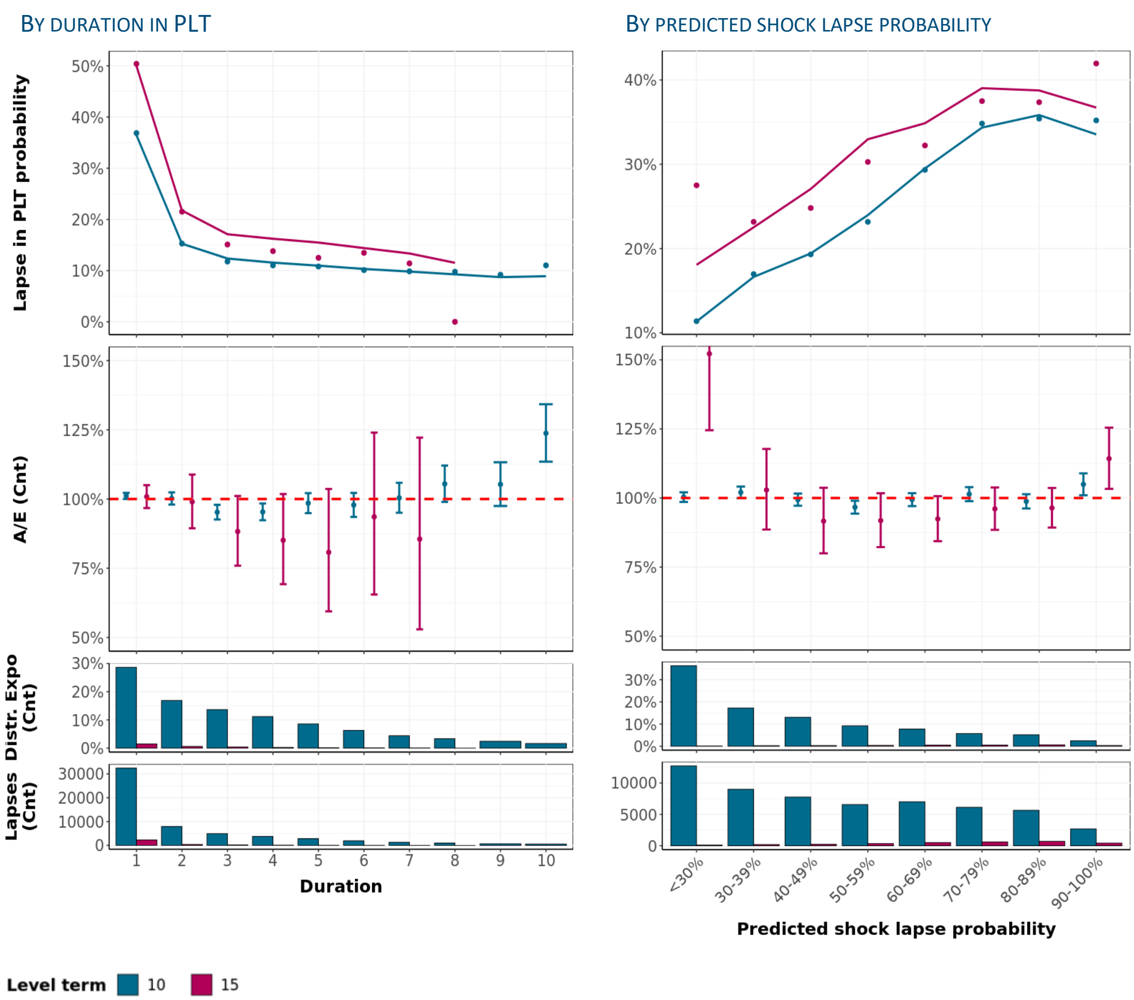
4.4.5 LEVEL TERM PLAN

Level term plan variable is not included in the model. Nevertheless, the model predicts adequately the lapses in PLT variations by level term plan. Predicted lapses are larger for T15 than for T10 on average across all durations in the post-level term period and all shock lapse bands, as seen in the top panels of Figure 4-19. Differences between T15 and T10 lapses in PLT are similar across the durations, while the gap is larger for the lowest predicted shock lapse bands and smaller at extreme shock lapses.

Despite level term plan information not being included in the model, the lapse variations in PLT by duration and predicted lapse probability are properly captured. This is shown for T10 by the 100% A/E falling within most of the 95% confidence intervals in the second panels of Figure 4-19. For T15, an overestimation can be noticed as most of the A/Es by duration and shock lapse are lower than 100%. However, due to the data limitation, the 95% confidence intervals are wide and most include the 100% A/E. This illustrates that the level term plan effect can be captured by modeling lapses in PLT by predicted shock lapse probability and including the additional variables.

Figure 4-19

LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY LEVEL TERM PLAN



4.5 VARIATIONS BY EXTERNAL VARIABLES FOR JUMP TO ART

In addition to drivers captured in the lapse in PLT modeling, further investigation into residual variation by other variables after fitting the model can be done. Variation over time can be investigated for each study year by comparing model predicted results to actual lapses in PLT. Similarly, data not used in fitting the model can be analyzed to identify if the model is a good predictor for this business. For example, since substandard business is not included in the modeling, the actual lapse in PLT for substandard business can be compared to the model predictions to provide insights for substandard business relative to policies issued at standard rates.

4.5.1 STUDY YEAR

The lapse study was completed on a policy year basis with exposures calculated from policy anniversary to policy anniversary as described in section 2.3. The study year measure is based on the end of the policy year. For the lapse study, this corresponds to the calendar year when the policy reached the end of the current duration in PLT.

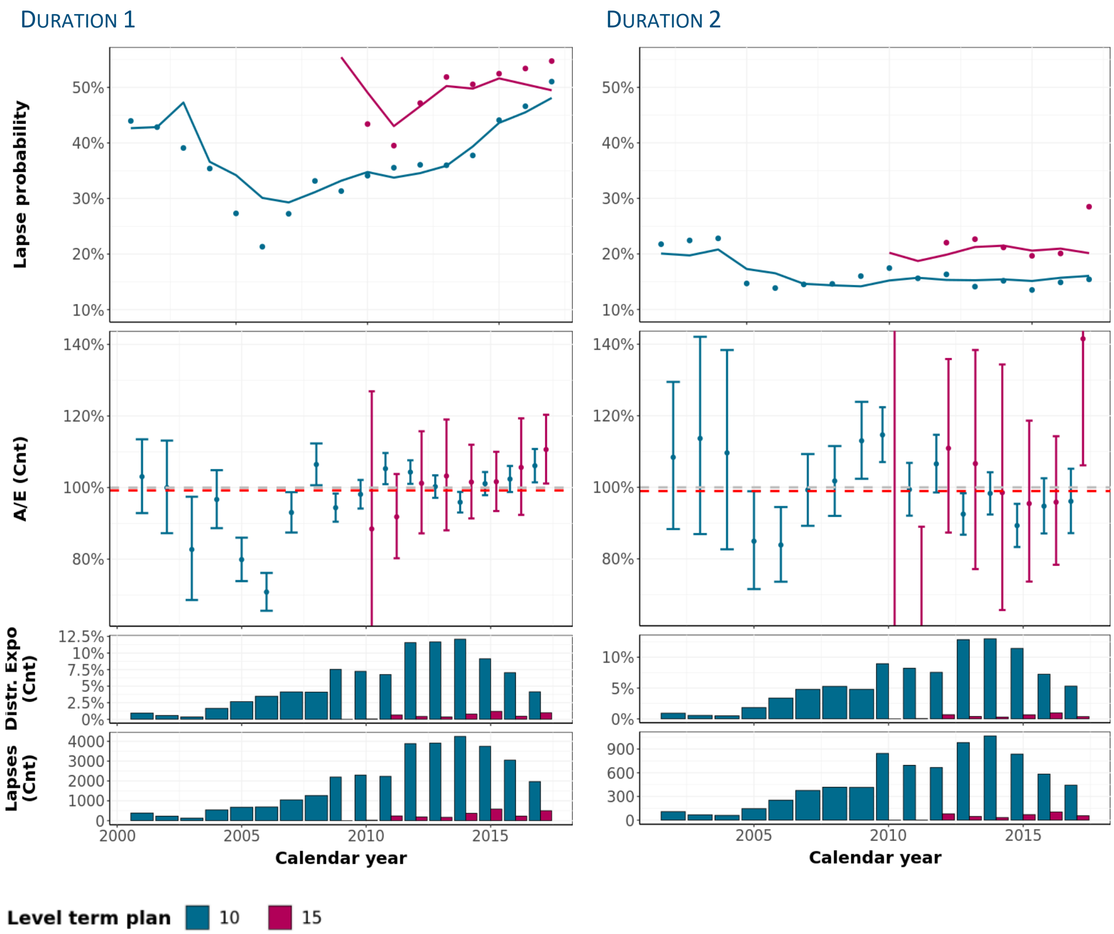
In Figure 4-20, the first panel displays the predicted lapse probabilities in PLT by study year and level term plan for the two first durations in the post-level term period. The lapse variations in PLT by study year are shown by term plan as T15 data have only been observable since 2008, while T10 data have been available since 2000.

T15 presents higher lapse probabilities than T10 by study year for the period 2008-2017. For both T10 and T15, the lapse probabilities have increased across study years since 2008 in the first PLT duration. However, the model is capturing this pattern as shown in the first panel where the fitted line tracks closely the actual lapse rates. When controlling for the effects of the variables included in the final model, no trend is visible in the actual over expected number of lapses as seen in the second panel in Figure 4-20 where A/E ratios are clustered closely around 100%. This shows that the combinations of changes among the variables over time explain the upward trend seen in the lapse probabilities in the first duration in the post-level term period. For PLT duration 2, no trend is apparent in the lapse probability shown in the first panel or in the A/Es for both T10 and T15 shown in the second panel.

The overall A/E ratio is about 99% due to the model not capturing the shock lapse variations for T10 specifically in the period pre-2009. There were less data available each year for the period 2000-2008, and less study participants contributing data for that period, which led to heterogeneity in the results. The 100% A/E falls outside the confidence interval for some years, showing that T10 experience is not explained by the variables included in the final model. For the period 2009-2017, the 100% A/E falls within the 95% confidence interval for most of the study years for both level term plans. This illustrates that the model is adequately predicting the number of lapses by study year after 2008, even if the study year effect is not included in the modeling.

Figure 4-20

LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY STUDY YEAR



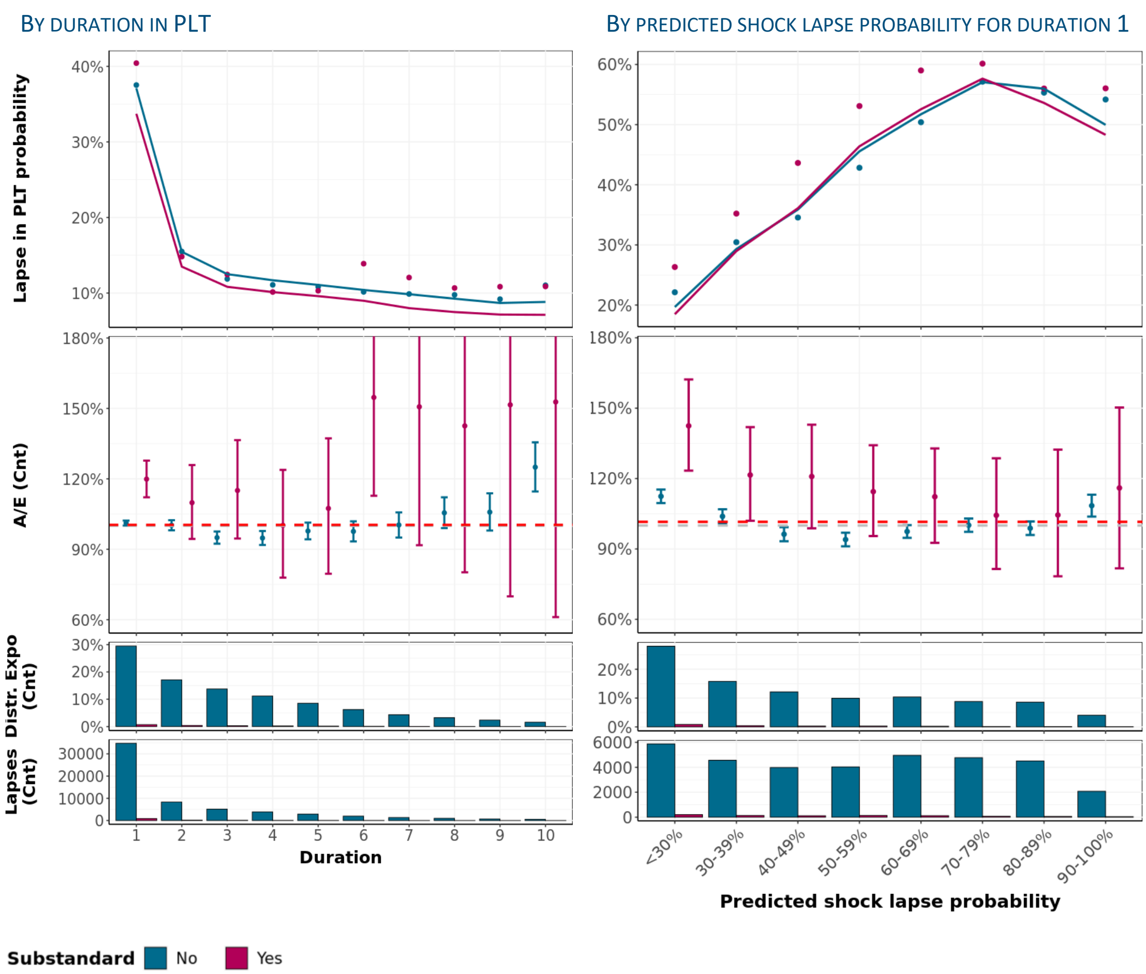
4.5.2 SUBSTANDARD INDICATOR

The lapse in PLT model is built based on standard policy data, similar to the shock lapse model. The actual lapses in PLT for substandard policies are included to assess the fit of the model for substandard business.

Predicted lapse variations in PLT for standard and substandard policyholders are similar by predicted shock lapse probability for the first duration in the post-level term period, as illustrated in the top right panel of Figure 4-21. Predicted lapses are slightly lower for substandard policies by duration in post-level term. The final model underestimates the number of lapses for substandard policyholders, as illustrated in the first panels of Figure 4-21. The corresponding actual over expected number of lapses for substandard policyholders is larger than 100% for all durations in PLT and shock lapse probability bands, as seen in the second panels in Figure 4-21. In particular for predicted shock lapse lower than 50%, the A/E is over 120% suggesting higher lapses in PLT for substandard policies. However, the confidence intervals are wide due to limited data for substandard policies, and the 100% A/E falls within the 95% confidence interval for most of the durations and predicted lapse probabilities.

Figure 4-21

LAPSE PROBABILITY IN PLT FOR JUMP TO ART BY SUBSTANDARD INDICATOR



4.6 MODEL OUTPUT BY ADDITIONAL VARIABLES FOR GRADED

For Graded, the lapse rates in PLT are modeled by the shock lapse relationship model, which includes shock lapse as a variable and predicts a lapse rate for each duration in PLT. The lapse rates in the subsequent durations for Graded are captured adequately by the shock lapse relationship model at the overall level, as seen earlier in Figure 4-5. More insights on the lapse variations by additional variables are reviewed in this section.

4.6.1 MODEL FIT ANALYSIS

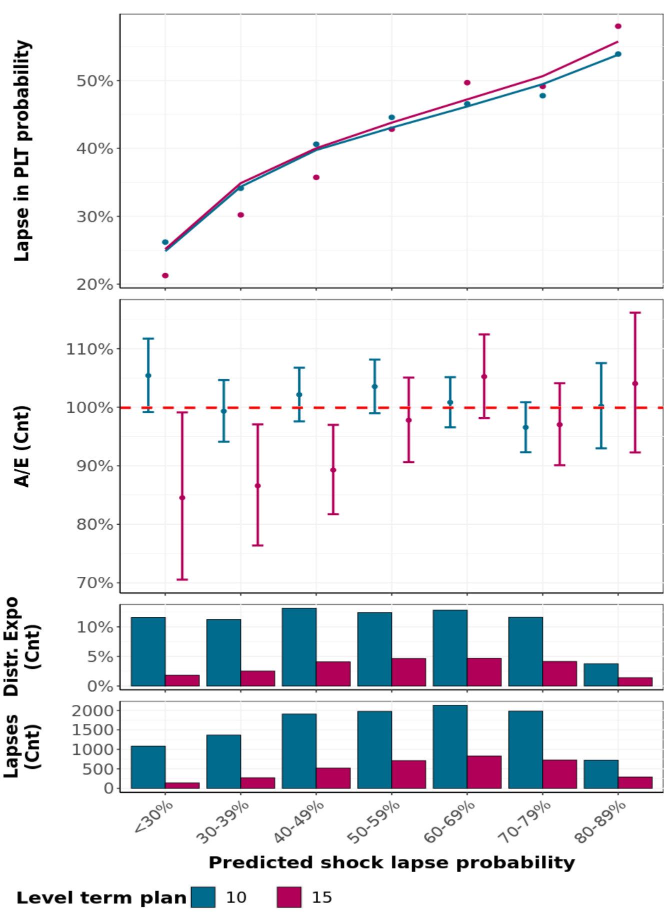
In this section, the fit for the Graded shock lapse relationship model is discussed by additional variables.

Level term plan

The fit of the shock lapse relationship model for a level term plan is shown by predicted shock lapse probability in Figure 4-22. For T10 and T15 in high shock lapse bands, the lapse variations in PLT are captured adequately by the shock lapse relationship model. When the predicted shock lapse is less than 50%, the model overestimates the lapse in PLT for T15, as shown in the first panel by the actual T15 lapse falling below the fitted line and, in the second panel, by the A/E falling outside the 95% confidence interval over the lower shock lapse range. For longer term plans, if the premium increase at the end of term is at the lower end of the Graded premium jump range, the premium may be a good value for the policyholder's attained age. This may explain some differences in behavior between term plans over lower premium jump/lower shock lapse ranges. Overall, the shock lapse relationship model captures the behavior for T10 and T15 with any differences in behavior limited to the lower shock lapse range. The fitted lapse in PLT increases with the predicted lapse probability for both level term plans.

Figure 4-22

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR GRADED BY LEVEL TERM PLAN

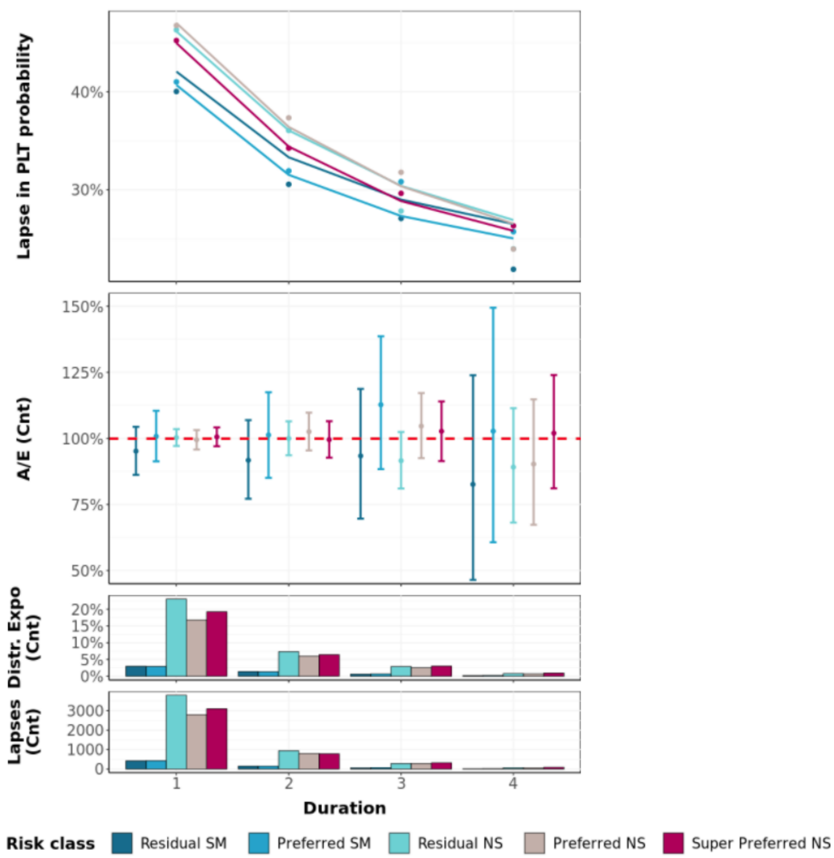


Risk class

The fitted lapses in PLT modeled by the shock lapse relationship model for risk class are shown in Figure 4-23. The model captures the lapse variations adequately by each risk class in each PLT duration. This is illustrated by the 100% A/E falling within the 95% confidence intervals for all groups. The lapse probability in PLT decreases with PLT duration and is higher for NS risk classes than for SM risk classes (in decreasing order, Preferred NS, Residual NS, Super Preferred NS, Residual SM, Preferred SM). For Jump to ART, the Super Preferred NS risk class shows the highest lapse rates, as illustrated in Figure 4-6. The different pattern observed for Graded is attributed to the fact that the PLT rates vary by risk class for Graded. In Figure 4-23, differences in lapse by risk class can be observed at each duration in PLT and this is captured by the shock lapse relationship model.

Figure 4-23

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR GRADED BY RISK CLASS

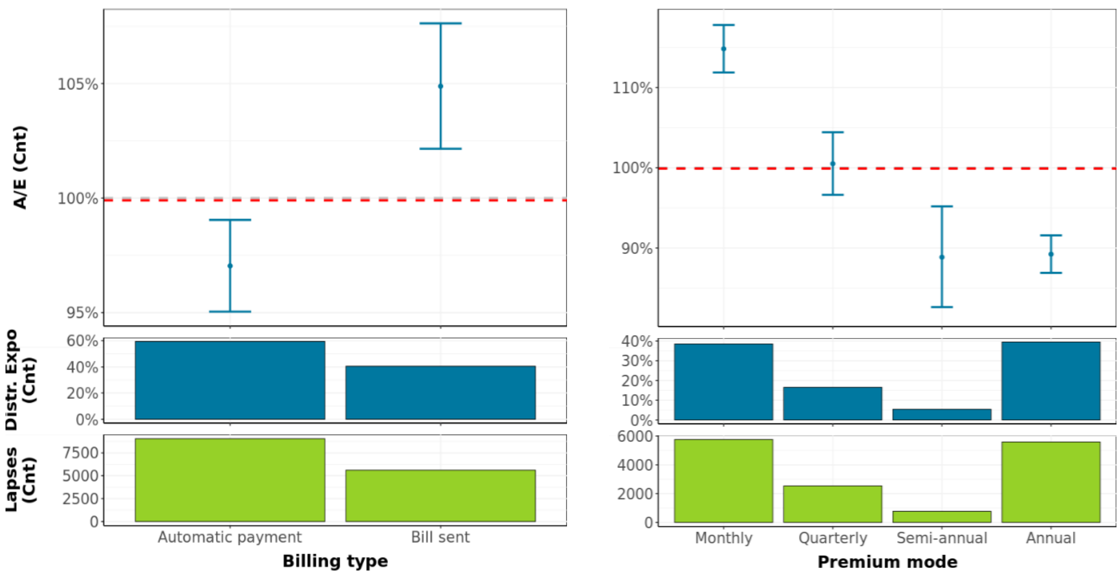


Billing type and premium mode

The actual over expected number of lapses fit as predicted by the shock lapse relationship model for both billing type and premium mode, as shown in Figure 4-24. The A/Es falling outside the confidence internal show that the shock lapse relationship model is not a good fit for PLT lapse rates by premium mode and billing type. This suggests that the lapse patterns by premium mode and billing type are not the same in PLT as captured in the shock lapse relationship model based on the shock lapse patterns. The model underestimates the lapse rates for billing type Bill Sent and overestimates lapses for Automatic payment, suggesting that there is a bigger difference between lapse rates by billing type than estimated by the shock lapse relationship model. The model has a significant underestimation of the number of lapses for the Monthly premium payment mode and an overestimation for the Semi-annual and Annual premium payment modes. In the Jump to ART modeling, a similar pattern was observed for the shock lapse relationship model fit by premium mode (Figure 4-7) and, in particular, the premium mode pattern varied by duration in PLT (Figure 4-12). Though the shock lapse relationship model is a good fit overall for lapse by duration in PLT, it is not adequately capturing variation by premium mode and billing type.

Figure 4-24

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR GRADED BY BILLING TYPE AND PREMIUM MODE

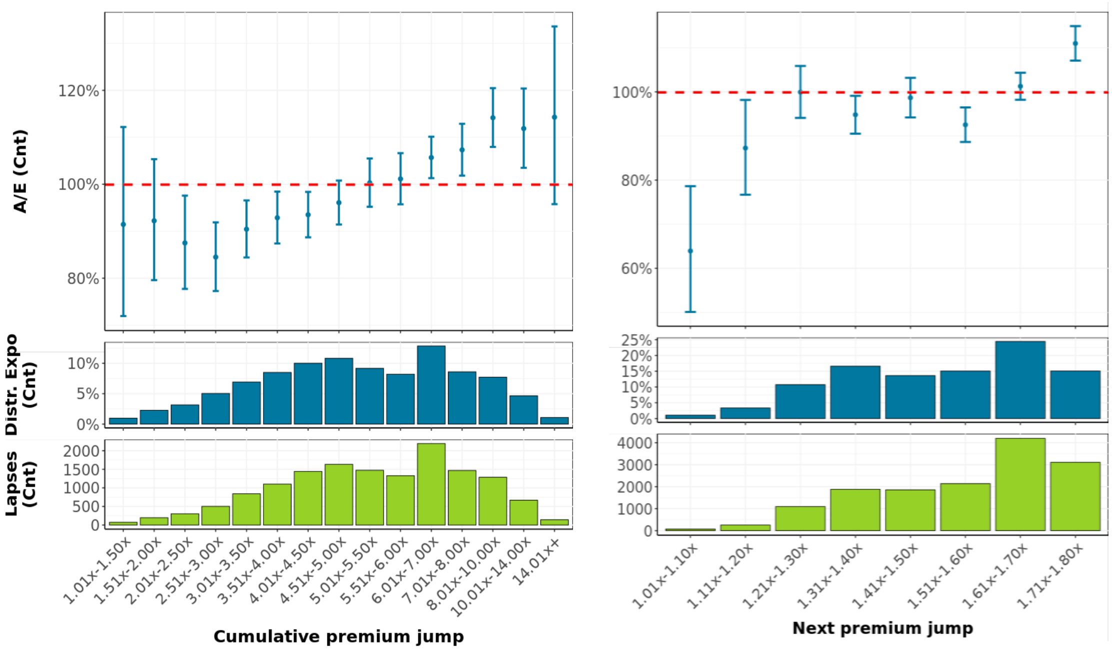


Cumulative premium jump and Next premium jump

Lapses in PLT may be impacted by the subsequent premium increases, especially for Graded premium structures where the premium increases in large steps each year in PLT. Two further premium jump variables are considered to capture the impact of premium increases. Cumulative premium jump is defined as the premium due in the next duration in PLT relative to the level term premium. Next premium jump is defined as the premium due in the next duration in PLT relative to the current duration premium. The fit of the shock lapse relationship model for both cumulative premium jump and next premium jump is shown in Figure 4-25. In the left panel, the predicted number of lapses by the shock lapse relationship model is significantly overestimated for cumulative premium jumps 2.01-4.50x and underestimated for cumulative premium jumps 6.01x-14.00x. Lapses in PLT are higher when the cumulative premium jump faced by the policyholder is higher, and this is not well-captured by the shock lapse relationship model. In the right panel, the shock lapse relationship model does not fully capture the pattern by next premium jump bands with some underestimation in the1.51x-1.60x band (A/E of 93%) and overestimation in the 1.71x-1.80x band (A/E of 111%). The deviation is also illustrated by the 100% A/Es falling outside the 95% confidence interval. This is an important consideration for Graded premium structures as differences in the grading period and the ultimate level the premiums are grading towards lead to differences in next premium jumps. While the shock lapse varies by initial premium jump, these subsequent duration premium jumps will not be captured in the shock lapse relationship model.

Figure 4-25

ACTUAL OVER EXPECTED NUMBER OF LAPSES FOR GRADED BY CUMULATIVE PREMIUM JUMP AND NEXT PREMIUM JUMP



4.6.2 INTERPRETATION OF SHOCK LAPSE RELATIONSHIP MODEL OUTPUT FOR GRADED

The fitted lapse probability in PLT as a function of the predicted shock lapse probabilities and PLT durations is illustrated in Table 4-4 for Graded. The fitted lapse probability in PLT increases gradually with the predicted shock lapses, from 25% to 85%, and with PLT durations 1 to 4. At the initial duration in PLT period, the fitted lapse rates increase sharply from 30% to 61% between predicted shock lapses 25% and 85%. Across subsequent durations, the fitted lapse rates appear to be slowly increasing with predicted shock lapse probabilities. At PLT duration 4, the fitted lapse rates only vary from 22% to 32%. Additional insights for other predicted shock lapse probabilities can be viewed using the Tableau dashboards[5].

Table 4-4

PREDICTED LAPSE PROBABILITY IN PLT BY DURATION AND PREDICTED SHOCK LAPSE PROBABILITY FOR GRADED

PLT	Predicted Shock Lapse Probability												
Duration	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%
1	30%	34%	38%	41%	44%	46%	48%	49%	51%	53%	55%	57%	61%
2	24%	27%	30%	33%	35%	37%	38%	39%	40%	41%	43%	45%	48%
3	22%	25%	28%	29%	31%	31%	32%	33%	33%	33%	34%	36%	38%
4	22%	24%	26%	27%	28%	28%	28%	28%	28%	28%	29%	30%	32%

This model provides an overall shape of the lapse patterns by shock lapse and duration in PLT for Graded premium structure. As highlighted in section 4.4.1, the lapse rates in PLT may vary by premium mode, billing type, premium jumps in PLT and other variables. This shock lapse relationship model provides a baseline model for lapse in PLT that can be adjusted to capture specific premium jump and premium payment features of the business.

[5] https://tableau.soa.org/t/soa-public/views/USPost-LevelTermPredictiveModelingInteractiveTool/2-LapsePLTOverview

Section 5: Mortality Deterioration in PLT

The policyholders who decide to remain after having a premium increase substantially modify the portfolio risk profile. By not lapsing despite an extreme premium increase, these policyholders indirectly show a higher desire for the life insurance policy and this anti-selection leads to higher mortality.

The shock lapse is the pivotal point at the end of term and influences the lapse experience in PLT. Predictive modeling provides the capability to directly capture the relationship between shock lapse at the end of term and mortality deterioration in PLT. The Generalized Linear Model (GLM) built to model shock lapse probabilities (described in section 3) provides a predicted shock lapse for each model point based on the combination of variables. This predicted shock lapse probability was added as a new variable in the dataset, allowing for analysis of the mortality experience in PLT by predicted shock lapse probability.

As a first step in the modeling exercise, mortality deterioration in PLT was modeled by duration using the predicted shock lapse as the only input variable. This model for mortality deterioration in PLT is referred to as the *shock lapse relationship model*. In a second step, a Poisson regression approach was applied to model any significant variations by the other variables that were not captured by the shock lapse variable. The model built in the second step is referred to as the *final model*. Section 5.1 specifies the data available for mortality analysis and the modeling approaches used in each step.

Models were built separately for each PLT premium structure and results are presented for Jump to ART in sections 5.2 through 5.5, and for Graded in section 5.6.

For Jump to ART, the relationship between shock lapse and mortality deterioration by duration in PLT as captured in the shock lapse relationship model is shown in section 5.2. The adjustment of the shock lapse relationship model by additional variables using GLM techniques was carried out for Jump to ART only. The selection of the additional variables and a comparison of the shock lapse relationship model to the final model for Jump to ART is presented in section 5.3. The two-step approach provides insights into the variables for which the patterns of mortality deterioration are captured by the shock lapse relationship and those that require further adjustment to improve the model fit.

Section 5.4 illustrates the Jump to ART final model results for selected variables. This analysis provides a view of the ability of the model to explain all deviations observed in the experience data. The figures presented also help to visualize the relationship between variables that are captured by the predictive model. Using the Jump to ART final model, the variation in mortality deterioration in PLT was assessed by external variables. As described in section 5.5, a more consistent comparison was achieved by adjusting for modeled variation. This approach was applied to investigate whether there are differences in mortality deterioration for substandard policies and to investigate variation over time in terms of patterns by study year.

For Graded, mortality data across the four durations in PLT was combined to build a model for mortality deterioration with only predicted shock lapse probability as an input variable. Variation by duration was studied through A/E analysis to identify whether there is a significant difference in the mortality deterioration by duration in PLT. The Graded mortality deterioration modeling is presented in section 5.6.

5.1 DATA AND MODELING APPROACH

5.1.1 DATA

For post-level term mortality analysis, ten variables were considered. Most are categorical variables with the exception of attained age, duration in PLT and predicted shock lapse probability, which are modeled as numerical variables. Table 5-1 describes the variables and the exposure distribution.

Table 5-1
VARIABLES

Variable	Class	Description	Exposure in PLT (%)	
			Jump to ART	Graded
Level term plan	Categorical	10	88	77
		15	12	23
Gender	Categorical	Male	65	62
		Female	35	38
Attained age	Numerical	18-49	35	30
		50-59	32	37
		60-69	24	26
		70+	9	7
Risk class	Categorical	Residual SM	5	5
		Preferred SM	5	5
		Residual NS	34	35
		Preferred NS	34	25
		Super Preferred NS	22	30
Face amount	Categorical	$0-100K	31	29
		$101-250K	35	32
		$251-500K	22	25
		$501K+	12	14
Initial premium jump	Categorical	1.01x-1.50x	6	5
		1.51x-2.00x	14	13
		2.01x-2.50x	10	20
		2.51x-3.00x	5	25
		3.01x-3.50x	4	18
		3.51x-4.00x	3	11
		4.01x-4.50x	4	6
		4.51x-5.00x	4	2
		5.01x-5.50x	4	NA
		5.51x-6.00x	4	NA
		6.01x-7.00x	7	NA
		7.01x-8.00x	6	NA
		8.01x-10.00x	9	NA
		10.01x-14.00x	11	NA
		14.01x+	9	NA
Billing type	Categorical	Automatic payment	55	40
		Bill Sent	41	60
		Automatic payment changed to Bill Sent	4	NA
Premium mode	Categorical	Annual	29	38
		Semi-annual	6	14
		Quarterly	16	6
		Monthly	49	42

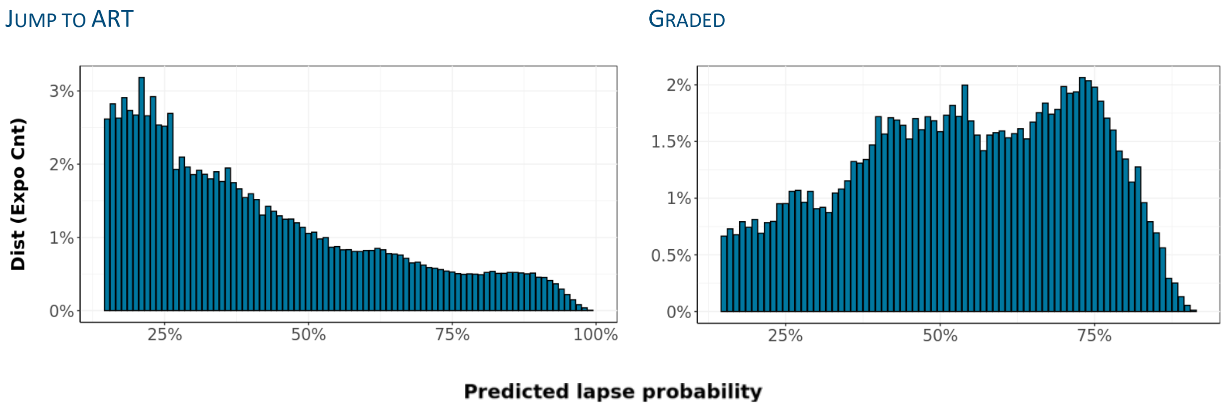
Table 5-1 (Continued)
VARIABLES

Variable	Class	Description	Exposure in PLT (%)	
			Jump to ART	Graded
Duration in PLT	Numerical	1	25	65
		2	18	22
		3	14	9
		4	12	3
		5	10	1
		6	7	NA
		7	5	NA
		8	4	NA
		9	3	NA
		10	2	NA
Predicted shock lapse probability	Numerical	<30%	39	13
		30-39%	18	11
		40-49%	13	17
		50-59%	9	17
		60-69%	8	17
		70-79%	5	19
		80-89%	5	7
		90-100%	2	NA

The Generalized Linear Model (GLM) built to model shock lapse probabilities (described in section 3) provides a predicted shock lapse for each model point based on the combination of variables. This predicted shock lapse probability was added as a new variable in the dataset. Most of the Jump to ART mortality data (58%) are based on a predicted shock lapse lower than 40%. When the shock lapse is higher, a smaller amount of business remains in PLT, and it follows that less data are available to study mortality in PLT for Jump to ART in higher shock lapse bands. On the other hand, the mortality data for Graded is more evenly spread across the predicted shock lapse bands. Due to the lower premium jump range for Graded, shock lapses in the 50-70% range is most common, and the concentration of experience over this range provides more mortality data for this segment.

Jump to ART data were available for ten durations in PLT, while Graded PLT data were available for four durations only with 65% in PLT duration 1. The fact that most Graded data were at early durations in PLT also explains why the distribution of available data for PLT analysis differs compared to Jump to ART. Figure 5-1 illustrates the distribution of exposure by predicted shock lapse probability for Jump to ART and Graded.

Figure 5-2
DISTRIBUTION OF THE EXPOSURE BY PREDICTED SHOCK LAPSE PROBABILITY



5.1.2 MODELING APPROACH

For Jump to ART, mortality deterioration is predicted in a two-step approach. The first step assesses the relationship between the predicted shock lapse probabilities and the mortality deterioration through the *shock lapse relationship model*. The second step (applied only for Jump to ART in this report) allows for modeling any significant deviations of additional drivers of the mortality experience that are not captured in the predicted shock lapse probabilities by means of a Poisson regression. The model built in the second step is referred to as the *final model*.

For Graded, there are insufficient data to capture the mortality deterioration by duration in PLT. The mortality is modeled by predicted shock lapse probability only, based on mortality data aggregated across all durations in PLT. For Graded, credible mortality data are only available for the first three durations in PLT as described in Table 5-1. Variation by duration is reviewed at a high level using the actual-to-expected (A/E) analysis discussed in section 5.6.

The mortality deterioration is calculated as the A/E ratio in the post-level term period divided by the A/E ratio in the level term period. See section 2.4 for the mortality study specification, and the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience,* published by the Society of Actuaries for more details on the computation.

For both Jump to ART and Graded, the actual over expected number of deaths in the level term period is first estimated. The death count in the level term period is modeled with a Poisson distribution where the expected deaths according to 2015 VBT are included as an offset. More technical details about Generalized Linear Models can be found in Appendix A.

Each cell is determined by a unique combination of variables,

$$D_I^{\mathrm{LT}} \sim Poisson\left(E_I^{\mathrm{LT}}\,\theta_i^{\mathrm{LT}}\right),$$

whereas

$$\ln \theta_i^{\mathrm{LT}} = \beta_0 + \sum_{j=1}^{r} \beta_j x_{ij}$$

where

- D_I^{LT} is the death count computed over durations 6 to 10 and 6 to 15 in the level term period for T10 and T15, respectively, for cell i.
- E_I^{LT} is the expected death according to the 2015 VBT calculated over durations 6 to 10 in the level term period for T10 and T15 for cell i.
- θ_i^{LT} is the A/E ratio for cell i in the level term period.
- x_{ij} is the set of variables described in Table 5-1.

The shock lapse relationship model captures the relationship between predicted shock lapses and the PLT mortality by means of a nonparametric approach.

For Jump to ART, the changes in mortality deterioration were analyzed as a function of the duration in PLT u and the shock lapse probability v:

$$D_{u,v}^{\mathrm{PLT}} \sim Poisson\left(E_{u,v}^{\mathrm{PLT}}\,\hat{\theta}_{u,v}^{\mathrm{LT}}\,\mu_{u,v}\right),$$

where

- $D_{u,v}^{\mathrm{PLT}}$ is the death count for duration u and predicted shock lapse probability v.
- $E_{u,v}^{\mathrm{PLT}}$ is the expected death according to the 2015 VBT for duration in u and predicted shock lapse probability v.
- $\hat{\theta}_{u,v}^{\mathrm{LT}}$ is the A/E ratio in the level term period estimated previously for duration u and predicted shock lapse probability v.
- $\mu_{u,v} = \psi(u, v)$ is an unspecified smoothing function.

The death count in the post-level term, $D_{u,v}^{\mathrm{PLT}}$, is assumed to be Poisson distributed where the estimated A/E ratio in the level term, $\hat{\theta}_{u,v}^{\mathrm{LT}}$, times the expected deaths in the post-level term, E_I^{PLT}, was used as an offset. With this approach, the mortality deterioration is modeled as the A/E in the post-level period divided by the A/E ratio in the level term period, as defined in section 2.4.

The form of the function $\psi(u, v)$ of the duration in PLT and shock lapse probability for Jump to ART is estimated nonparametrically.

For Graded, the changes in mortality deterioration were analyzed as a function of the shock lapse probability v only. Due to data limitations, the duration effect is not captured. The changes in mortality deterioration based on data across all PLT durations were analyzed as a function of the shock lapse probability and the form of the function is written $\psi(v)$.

Applying the same approach as in the lapse in PLT modeling (described in section 4), local kernel weighted log-likelihood models are fitted to the mortality deterioration for Jump to ART and Graded. See Appendix B for a technical description of the approach. For Jump to ART, a locally adaptive smoothing method using the intersection of confidence intervals rule is applied. The approach provides an adaptative optimal method to choose the smoothing parameters according to the regularity of the data. See Appendix C for a detailed presentation of the approach fitted to Jump to ART, and Tomas and Planchet (2013) for a comparison of the methods applied to a mortality study. For Graded, a local likelihood model is fitted as described in Appendix B.

For Jump to ART, the variables described in Table 5-1 are then included by means of a Poisson regression to model any significant deviations from the estimated mortality deterioration that are not captured in the predicted shock lapse probabilities.

Similarly, the death count in the post-level term is assumed to be Poisson distributed where the estimated A/E ratio in the level term period times the expected deaths in the post-level term is used as an offset. With this approach, the mortality deterioration is modeled as the A/E in the post-level period divided by the A/E ratio in the level term period.

Each cell is determined by a unique combination of variables,

$$D_i^{\mathrm{PLT}} \sim Poisson\left(E_i^{\mathrm{PLT}}\, \hat{\theta}_i^{\mathrm{LT}}\, \mu_i\right),$$

whereas

$$\ln \mu_i = \beta_0 + \beta_1 \ln \mu_i^{\mathrm{SLR}} + \sum_{j=2}^{r+1} \beta_j x_{ij}$$

where

- D_i^{PLT} is the death count in the post-level term period for cell $\boldsymbol{i}$.
- E_I^{PLT} is the expected death according to the 2015 VBT for cell i.
- μ_i^{SLR} is the mortality deterioration estimated by the Shock Lapse Relationship (SLR) model in the first step for cell i which is a function of the duration and the predicted shock lapse probability only.
- $\hat{\theta}_i^{\mathrm{LT}}$ is the estimated A/E ratio in the level term period for cell i.
- $x_{ij}{}'s$ are the variables for cell $\boldsymbol{i}$.

It is worth noting that the model predicts exactly the total actual number of deaths in PLT for each category of the variables included in the model. By equating the partial derivative of the log-likelihood with respect to β_j,

$$\sum_{i|x_{ij}=1} D_i^{\mathrm{PLT}} = \sum_{i|x_{ij}=1} E_i^{\mathrm{PLT}}\, \hat{\theta}_i^{\mathrm{LT}}\, \mathrm{MD}_i.$$

It follows that the ratio between the actual and expected number of deaths in PLT is 100% for each category of the variables included in the model.

5.2 SHOCK LAPSE RELATIONSHIP MODEL FOR JUMP TO ART

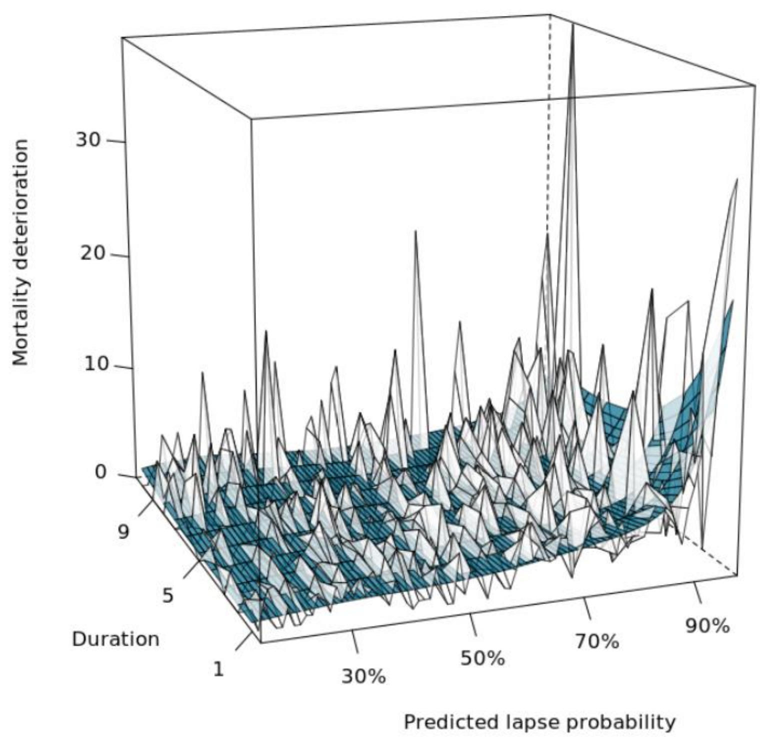
The changes in mortality deterioration for Jump to ART were analyzed as a function of both the duration in PLT and the shock lapse probability.

5.2.1 ILLUSTRATION OF THE SHOCK LAPSE RELATIONSHIP MODEL

The mortality deterioration as a function of the duration in PLT and the predicted shock lapse probabilities is illustrated in Figure 5-2 for Jump to ART. The observed mortality deterioration is displayed in white and the smooth predictions are represented in blue.

Figure 5-2

OBSERVED AND PREDICTED MORTALITY DETERIORATION FOR JUMP TO ART

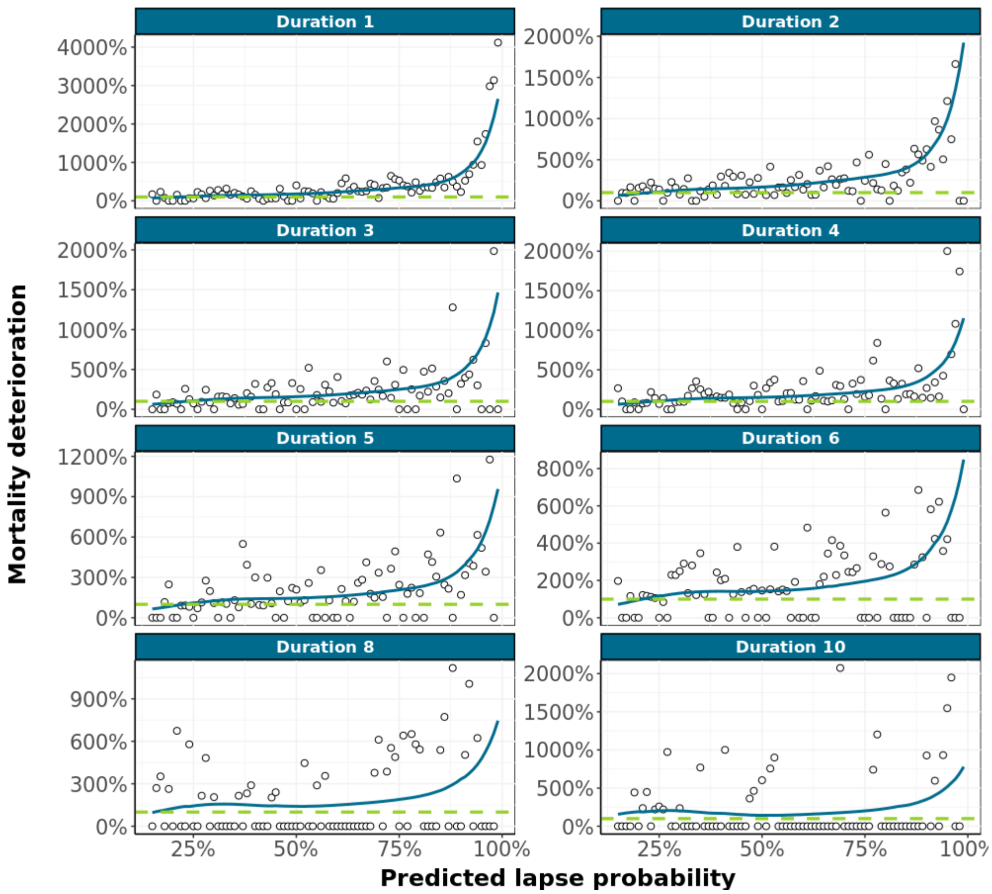


The irregularities in the progression of the actual mortality deterioration (in white) have been reduced in the smooth predictions (in blue). Spikes in the observed mortality that are attributed to limited death counts have been graduated using data from surrounding observations. The locally adaptive smoothing method (represented in blue) helps to define the relationship between shock lapse probabilities, duration in PLT and mortality deterioration and to overcome sampling fluctuations due to data limitations for specific segments.

Figure 5-3 presents the predicted mortality deterioration by predicted shock lapse probabilities for selected durations in PLT for Jump to ART. A green dashed line illustrates 100% mortality deterioration, which is equivalent to level term period mortality, i.e., no deterioration in PLT. These graphics give a first indication about the quality of the fit where the dots represent the actual mortality deterioration and the blue line represents the model predictions.

Figure 5-3

MORTALITY DETERIORATION BY PREDICTED SHOCK LAPSE PROBABILITY FOR SELECTED DURATIONS IN PLT



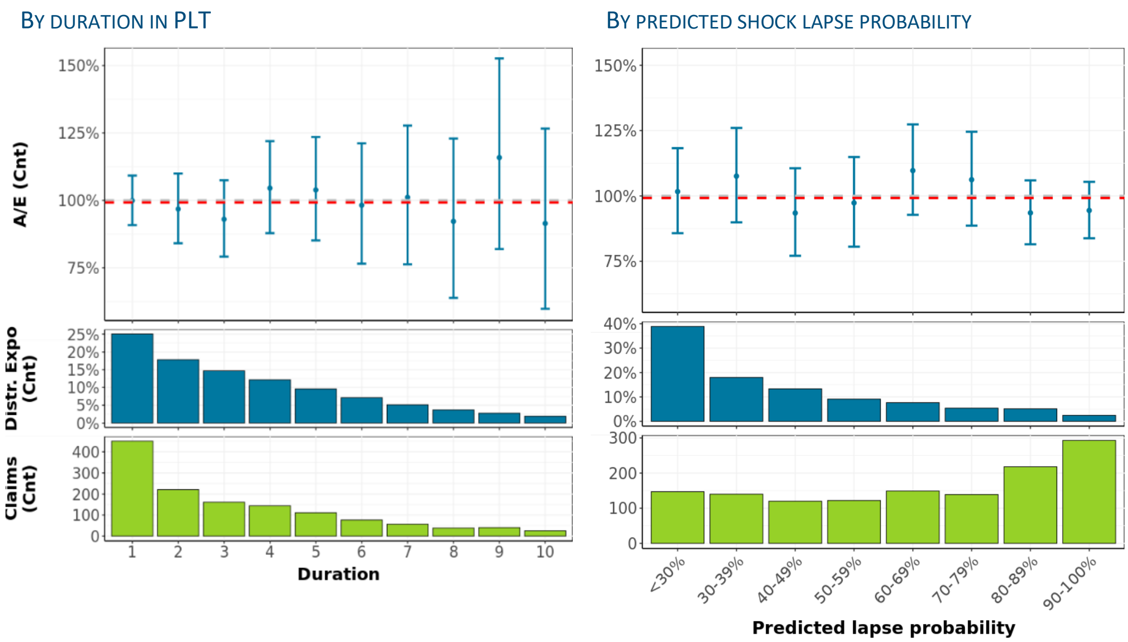
The fitted mortality deterioration shows that, on average, the initial post-level mortality deterioration in PLT duration 1 is increasing gradually to 400% for predicted shock lapse probabilities up to 80%. For higher shock lapse rates, the mortality deterioration increases dramatically reaching 1400% on average for lapse probabilities in the 90-100% range. The high initial mortality deterioration does not persist into later durations in the PLT period. Mortality deterioration wears off quickly in the 90-100% shock lapse probabilities range to around 500% for PLT duration 5+.

5.2.2 QUALITY OF THE FIT

Figure 5-4 shows the actual over expected death count ratio in the post-level term period by duration (left panel) and predicted shock lapse probability (right panel) with the associated 95% confidence intervals. The expected is the shock lapse relationship model predictions for mortality deterioration, and these are compared to the actual mortality deterioration results. The dashed red line shows the 99% overall A/E ratio indicating that the model captures the mortality deterioration accurately at the overall level.

Figure 5-4

ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR JUMP TO ART



The shock lapse relationship model for Jump to ART captures adequately the variations by duration in PLT and predicted shock lapse probabilities. The overall A/E is 99% (illustrated by the red dashed line) and the 100% A/E falls within the 95% confidence interval for every duration and predicted lapse probability band. The A/E ratio is relatively close to 100% for the first seven durations in PLT and deviates when it reaches the later durations where less data are available, as shown in the left panel of Figure 5-4. Looking at predicted shock lapse probability, the A/E varies within a 94%-110% ratio range, with 94% for the extreme shock lapse 90-100% band where less claims are available.

5.3 MODELING WITH ADDITIONAL VARIABLES FOR JUMP TO ART

Mortality deterioration variations are captured by the shock lapse relationship model at the overall level, as seen in Figure 5-4. Some variations at a more granular level are not estimated adequately. The second step of the approach is designed to model any significant deviations of additional drivers of the mortality experience that are not captured in the shock lapse relationship model by means of a Poisson Generalized Linear Model.

5.3.1 SELECTING VARIABLES

The main steps in selecting the variables described in Table 5-1 are discussed in this section. The final model includes the variables' mortality deterioration estimated by the shock lapse relationship model, shock lapse probability, initial premium jump, risk class, billing type and premium mode.

In this section, the fit for the shock lapse relationship model is compared to the fit for the final model for each of the key variables. In reviewing the fit of the shock lapse relationship model, variables having an impact on mortality deterioration that are not captured by the shock lapse model can be identified. Then, a comparison of the final model to the shock lapse relationship model highlights the improvement in the fit after adjusting for the additional variables.

A saturated model is set at the start by including all main effects and interactions. The model also included, as a variable, the estimated mortality as a function of the duration in PLT and predicted shock lapse probability. The decision to include or exclude each additional variable is made by comparing the models with and without the variables using the likelihood-ratio test.

<u>Level term plan</u>

The likelihood-ratio test comparing the model without level term plan to the model with this variable gives a *p*-value of 35%. This indicates that excluding the level term plan variable from the model is statistically justified. The mortality deterioration variation by level term plan is well captured by the predicted shock lapse probability.

<u>Gender</u>

Comparing the model with and without the gender variable leads to a *p*-value of the likelihood-ratio test of 7%. It shows that at a 95% significance level, the model without the gender effect is preferred. The mortality deterioration variation by gender is adequately captured by the predicted shock lapse probability.

<u>Attained age</u>

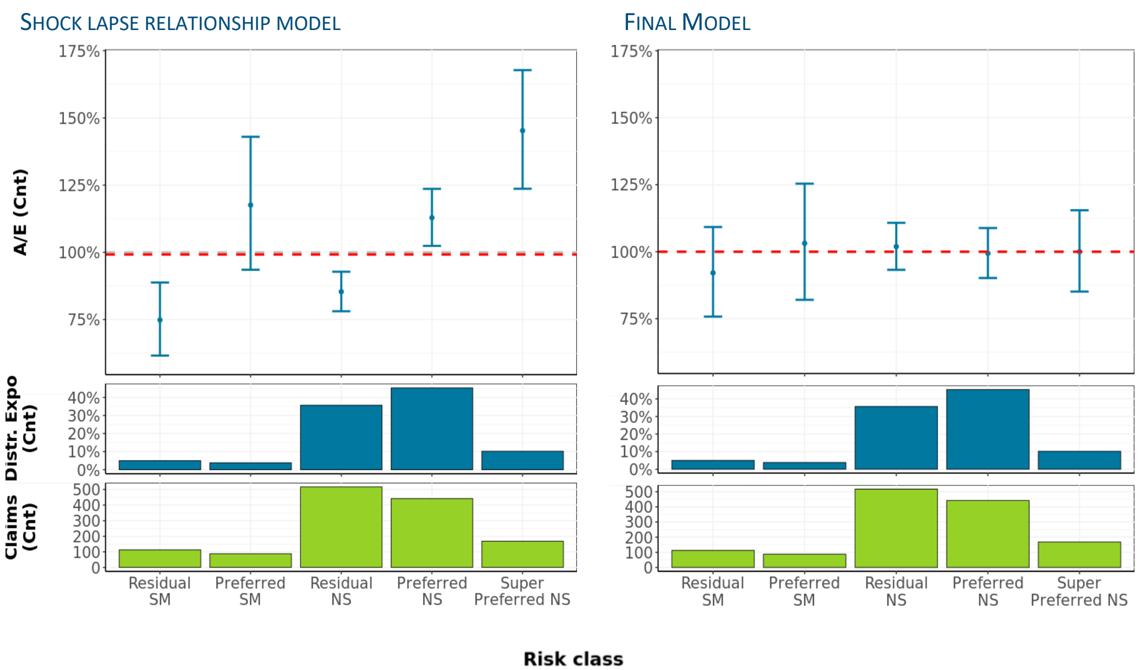
The likelihood-ratio test comparing the model without attained age to the model with this variable gives a *p*-value of 19%. This indicates that excluding the attained age variable from the model is statistically justified. The predicted shock lapse probability captures the mortality deterioration variations by attained age.

Risk class

The likelihood-ratio test supports including the risk class effect in the model as its corresponding p-value is lower than 0.1%. Figure 5-5 compares the actual over expected number of deaths by risk class using the shock lapse relationship model as the expected basis (left panel) to the same A/E analysis using the final model as the expected basis (right panel).

Figure 5-5

ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR JUMP TO ART BY RISK CLASS



The mortality deterioration modeled by the shock lapse relationship model leads to a significant overestimation of the number of deaths for Residual SM and Residual NS and an underestimation of the mortality for Preferred NS and Super Preferred NS. This is illustrated by the 100% A/E falling outside the 95% confidence interval in the left panel of Figure 5-5. Analysis of the risk class categories showed that grouping across smoking status is statistically justified. The likelihood-ratio test comparing the model with the categories (Residual, Preferred and Super Preferred) to the model with the five categories of risk classes gives a *p*-value of 54%. The right panel of Figure 5-5 illustrates the quality of the fit of the model, including the risk class effect when risk classes have been grouped into three categories. The A/E ratio varies within a 93%-103% range highlighting that a risk class variable with three categories is sufficient to capture mortality deterioration variation and differences by smoking status are not significant.

Billing type

The likelihood ratio test supports including billing type as its corresponding *p*-value is lower than 0.1%. Significant deviations between the actual mortality deterioration and expected as modeled by the shock lapse relationship model were also observed. The number of deaths is significantly overestimated for Automatic payment and underestimated for Bill Sent. Recall that shock lapse was higher for Bill Sent than Automatic payment (see section 3.3.3). However, the shock lapse relationship model does not capture the mortality deterioration variation by billing type. This highlights that the difference in mortality deterioration by billing type is more exaggerated than the shock lapse deviation. By including the billing type variable, the model predicts exactly the observed number of deaths for each category and the A/E ratios are 100%.

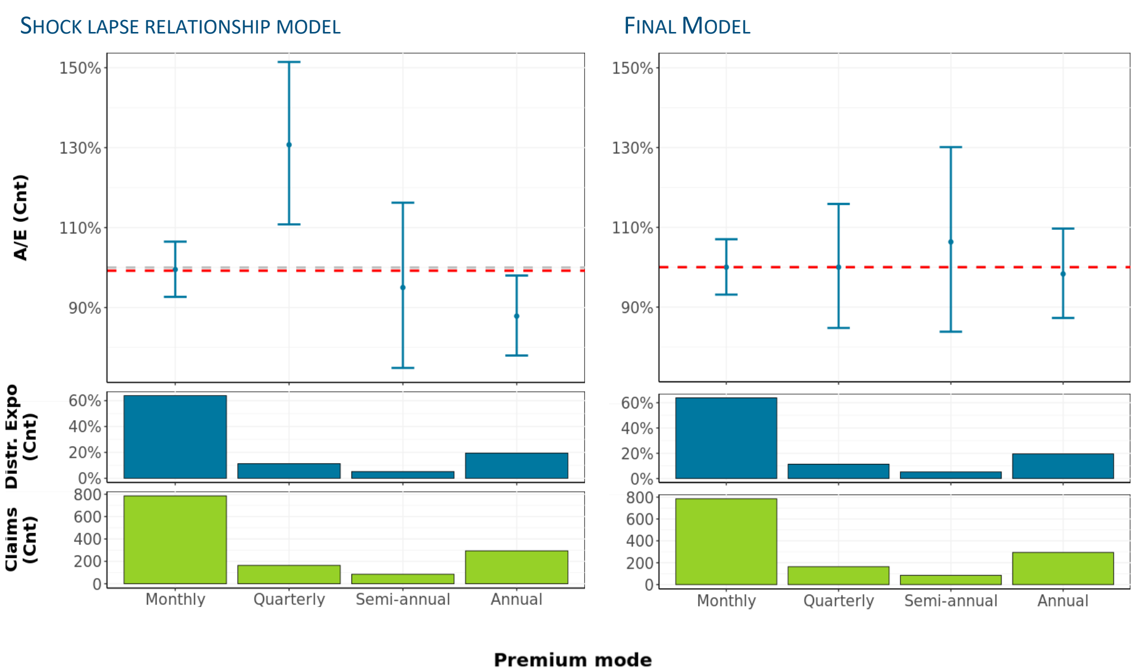
Premium mode

The likelihood-ratio test supports including the premium mode effect in the model as its corresponding *p*-value is lower than 0.1%. The estimated mortality deterioration modeled by the shock lapse relationship model leads to a significant underestimation of the number of deaths for the Quarterly premium payment mode and an overestimation for the Annual mode. This is illustrated by the 100% A/E falling outside the 95% confidence interval in the left panel of Figure 5-6. Recall that shock lapse was higher for Annual premium mode policies (section 3.3.4). The shock lapse relationship model overestimates the mortality deterioration for Annual mode policies, highlighting that the variation in mortality deterioration by premium mode is less pronounced than the shock lapse variation.

When including the premium mode variable in the model, grouping the Semi-annual and Annual modes is found to be statistically justified. The likelihood-ratio test comparing the model without and with the grouping of Semi-annual and Annual modes gives a *p*-value of 79%. By including the premium mode, the model predicts exactly the observed number of deaths for each category included in the model. The A/E ratios for Monthly and Quarterly modes are 100% as shown in the right panel of Figure 5-6. The A/E ratios for Semi-annual and Annual modes are 106% and 99%, respectively. The 100% A/E falls inside the 95% confidence interval, illustrating that no significant mortality deterioration variation can be found between the Semi-annual and Annual modes.

Figure 5-6

ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR JUMP TO ART BY PREMIUM MODE



Initial premium jump

The likelihood-ratio test supports including the initial premium jump effect in the model as its corresponding *p*-value is lower than 0.1%. A significant underestimation of the number of deaths for initial premium jump band 8.01x+ was observed based on an A/E ratio of 130% and the 100% A/E fell outside the 95% confidence interval. This highlights that mortality deterioration at the higher premium jumps is more extreme than captured by the shock lapse relationship model. Based on analysis, grouping initial premium jump into three bands (1.01x-4.00x, 4.01x-8.00x and 8.01x+) is found to be statistically justified. The likelihood-ratio test comparing the model without and with the grouping gives a p-value of 26%. The initial premium jump continues to have an impact on mortality deterioration in PLT that is not captured by shock lapse alone.

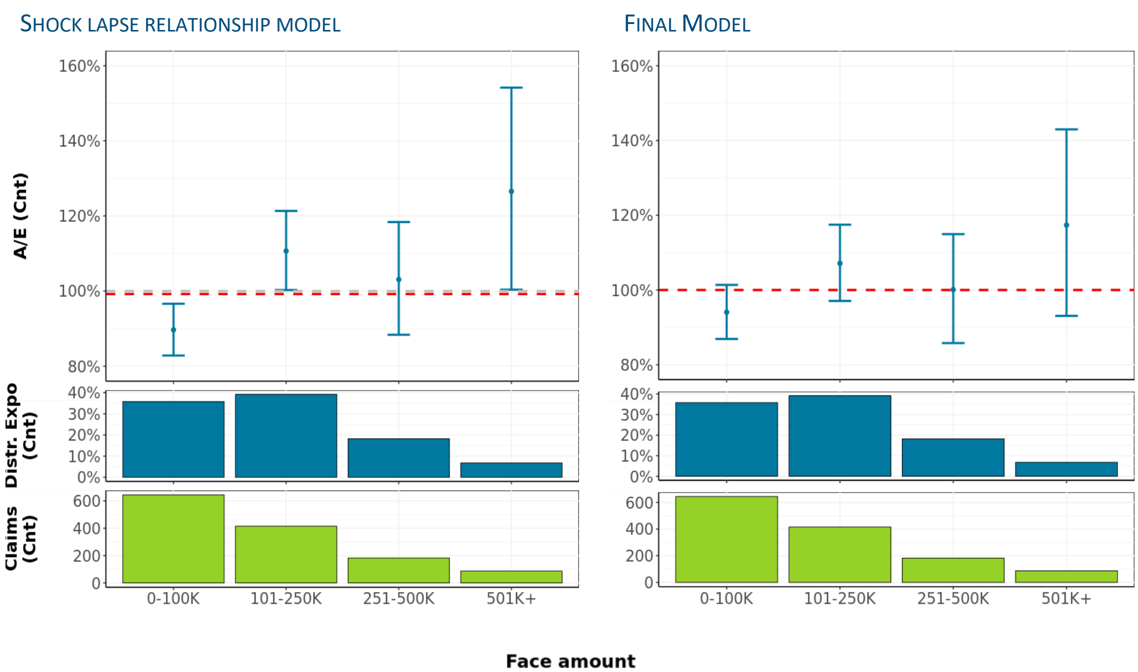
Face amount

The likelihood-ratio test does not support including the face amount effect in the model as the corresponding *p*-value is 33%. Significant deviations in the A/E ratios are observed by face amount band in the left panel of Figure 5-7. The number of deaths is significantly overestimated for face amount band $0-100K and underestimated for bands $101-250K and $501K+ based on the shock lapse relationship model predictions. However, the final model, without including the face amount as a variable, captures the mortality deterioration patterns by face amount. This is illustrated in the right panel of Figure 5-11 by the 100% A/E falling inside the 95% confidence interval for each face amount band for the final model.

This means that the mortality deterioration variations by face amount are captured adequately by the combined effects of the variables included in the model, including risk class, billing type, premium mode and initial premium jump.

Figure 5-7

ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR JUMP TO ART BY FACE AMOUNT



Duration in PLT

The likelihood-ratio test comparing the model without the duration in the level term period to the model with this variable gives a *p*-value of 17%. It suggests that the model without the duration in PLT variable is statistically justified. No further adjustment by duration is needed on top of the variations captured in the mortality deterioration estimated by the shock lapse relationship model.

Predicted shock lapse probability

The model allowing an adjustment by predicted shock lapse probability is favored as the *p*-value of the corresponding likelihood-ratio test is lower than 0.1%. The predicted shock lapse probability is included as a variable in the model, with a further adjustment applied on top of the variations captured in the mortality deterioration estimated by the shock lapse relationship model.

5.3.2 INTERPRETATION OF THE JUMP TO ART REGRESSION MODEL OUTPUT

The main effects included in the final model fitted to Jump to ART data are displayed in Figure F-1 in Appendix F. A reference category is selected for each of the categorical variables that corresponds to the category where the largest exposure is observed. For this model, the reference categories of the categorical variables are given in Table 5-2.

Table 5-2

REFERENCE CATEGORIES FOR CATEGORICAL VARIABLES FOR THE JUMP TO ART FINAL MODEL

Categorical Variables	Reference Categories
Risk class	Residual
Initial premium jump band	1.01x-4.00x
Billing type	Automatic payment
Premium payment mode	Monthly

From the estimated regression coefficients displayed in Table F-1, the effect of risk factors can be derived. These effects with their associated 95% confidence intervals are summarized in Table 5-3.

Table 5-3

ESTIMATED RELATIVE RISK OF MAIN EFFECTS WITH THEIR ASSOCIATED 95% CONFIDENCE INTERVALS FOR JUMP TO ART

Variable – Main Effects	Relative Risk with respect to the Reference Level with 95% CI
Risk class: Preferred	133% [118%,150%][1]
Risk class: Super Preferred	186% [155%,223%][1]
Initial premium jump 4.01x-8.00x	128% [106%,153%][2]
Initial premium jump 8.01x+	166% [131%,212%][2]
Billing type: Bill Sent	158% [136%,184%][3]
Billing type: Automatic payment changed to Bill Sent	209% [136%,322%][3]
Premium mode: Quarterly	136% [114%,163%][4]
Premium mode: Semi-annual and Annual	85% [72%,100%][4]

[1]Relative risk with respect to Residual risk class.
[2]Relative risk with respect to 1.01x-4.00x initial premium jump band.
[3]Relative risk with respect to Billing type Automatic payment.
[4]Relative risk with respect to Monthly premium mode.

From Table 5-3, the relative risk for the main effects of the model can be interpreted. Below, two examples of the computation of the estimated effect of the risk factors and interpretation of the corresponding relative risk with respect to the reference category are given. For example, other things being equal:

- **Risk Class**: Mortality deterioration for Preferred is $\exp(\hat{\beta}_3) = \exp(0.286)$ ≈ 133% of the mortality deterioration of Residual, which is the reference level. Additionally, based on the standard error, the corresponding 95% confidence interval is:

  $$\left[\exp\left(\hat{\beta}_3 - 1.96 \times s.e.\left(\hat{\beta}_3\right)\right), \exp\left(\hat{\beta}_3 + 1.96 \times s.e.\left(\hat{\beta}_3\right)\right)\right] \approx [118\%, 150\%].$$

  The relative risk for Super Preferred is $\exp(\hat{\beta}_4) = \exp(0.286)$ ≈ 186% (95% CI [155, 223%]) of Residual.
- **Billing type**: Mortality deterioration for billing type Bill Sent is $\exp(\hat{\beta}_7)$ ≈ 158% (95% CI [136%, 212%]) of the risk of the reference level Automatic payment. Mortality deterioration for billing type Automatic payment changed to Bill Sent is expected to be more than twice as large as the mortality deterioration of billing type Automatic payment. The corresponding relative risk is 209% (95% CI [136%,322%]).

5.4 MODEL FIT ANALYSIS FOR JUMP TO ART

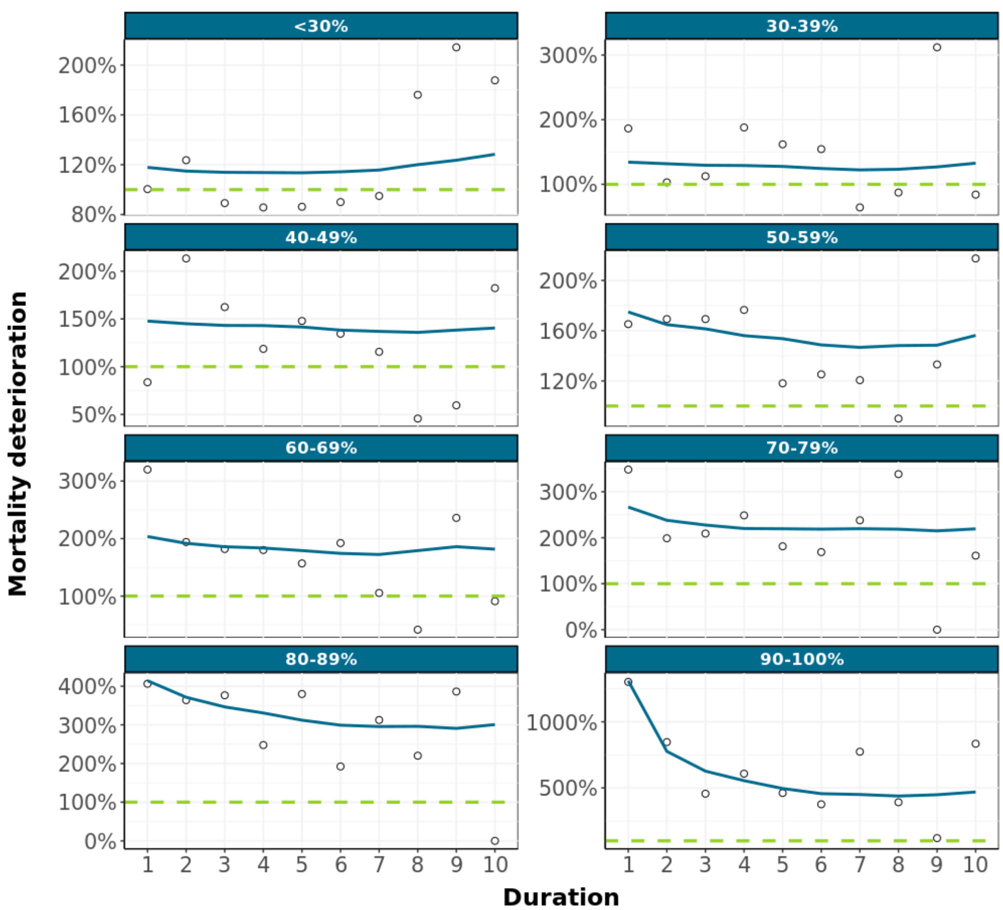
The final model includes the variables risk class, billing type, premium mode and initial premium jump group, as well as an adjustment by predicted shock lapse probability, which is in addition to the mortality deterioration captured by the shock lapse relationship model. In this section, the model output for Jump to ART is reviewed by the additional drivers of the mortality experience to provide insights into the relationships and assess the model fit.

5.4.1 PREDICTED SHOCK LAPSE PROBABILITY AND DURATION IN PLT

Figure 5-8 presents the final model predicted mortality deterioration by predicted shock lapse probability and duration in PLT. A green dashed line illustrates 100%, which represents no mortality deterioration relative to the level term.

Figure 5-8

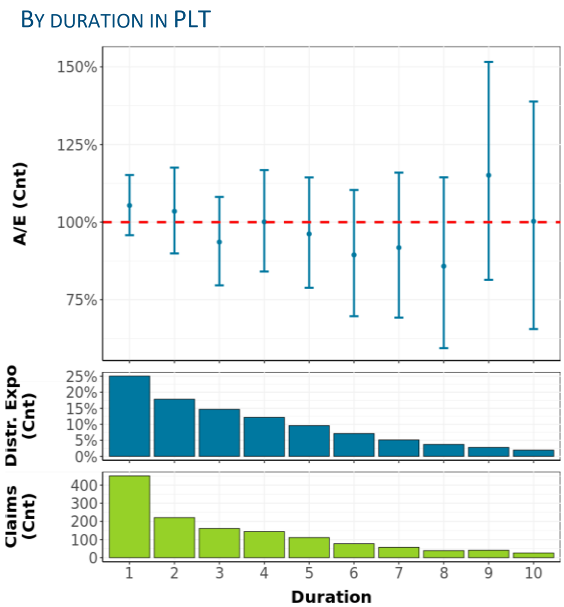
MORTALITY DETERIORATION FOR JUMP TO ART BY DURATION IN PLT FOR PREDICTED SHOCK LAPSE PROBABILITY BANDS

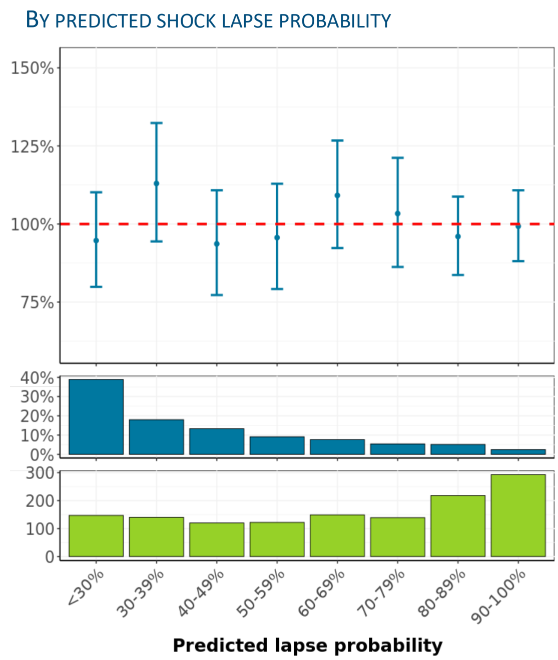


The predicted mortality deterioration based on the final model for Jump to ART shows that the mortality deterioration in the initial post-level term duration is increasing gradually from 120% when predicted shock lapse probability is less than 30% to 400% when predicted shock lapses ranges from 80-89%. For extremely high shock lapse rates in the 90-100% range, the mortality deterioration increases dramatically, hitting 2000% on average. The high initial mortality deterioration does not seem to persist into later durations in the post-level term period. Mortality deterioration wears off quickly in the 90-100% shock lapse probabilities range, dropping to 1300% in PLT duration 2 and staying around the 490% level for post-level term duration 5+. For shock lapse probabilities lower than 50%, deterioration wear-off is less steep and appears to be relatively flat across later PLT durations.

Figure 5-9 shows the actual over expected number of deaths in the post-level term period by duration (left panel) and predicted shock lapse probability (right panel), with the associated 95% confidence intervals for Jump to ART. The dashed red line represents the overall A/E ratio at 100% as the model predicts exactly the number of deaths at an overall level. The expected basis is the final model mortality deterioration predictions.

Figure 5-9
ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR JUMP TO ART





The predicted mortality deterioration adjusted for additional drivers of the mortality experience for Jump to ART captures adequately the variations by duration in PLT and predicted shock lapse probabilities. The 100% A/E falls within the 95% confidence interval for every duration and predicted shock lapse probability band. The A/E ratio is relatively close to 100% for the first seven durations in PLT and deviates to be in the range of 85-115% when reaching the later durations where less data were available, as shown in the left panel of Figure 5-9.

5.4.2 ADDITIONAL VARIABLES

In this section, similar analysis and figures are presented for a selected number of variables to assess the impact on the mortality deterioration. Insights by additional drivers of mortality experience can be viewed using the Tableau dashboards[6].

Each figure contains four panels with results shown side by side by duration in PLT and predicted shock lapse probability. The first panel provides a visual indication of the quality of the fit and allows a comparison of the predicted mortality deterioration within some of the relevant drivers of the mortality experience by duration in PLT and predicted shock lapse probability. The dots represent the observed mortality, while the full lines illustrate the predictions. The second panel displays the corresponding actual experience over expected number of deaths as predicted by the model, where an A/E ratio close to 100% represents a good fit of the model to the observations. The third and fourth panels present the distribution of the exposure and the number of deaths, respectively.

Risk class

Risk class is included as a variable in the final mortality model. The variable applied in the model is grouped into three categories (Residual, Preferred, Super Preferred) and therefore, not split by smoking status.

The predicted mortality deterioration is higher for risk classes with preferred policyholders (in increasing order, Residual SM, Residual NS, Preferred SM, Preferred NS and Super Preferred NS), as illustrated in the top panels of Figure 5-10. Super Preferred mortality deterioration stands out as the highest by both duration and predicted shock lapse probability. Mortality deterioration reaches 850% in the initial duration in PLT and declines to 400% by duration 5. In addition, while it gradually increases from 200% to 400% for predicted lapse probability bands <30% to 70-79%, mortality deterioration escalates to 1400% on average in the highest band, 90-100%.

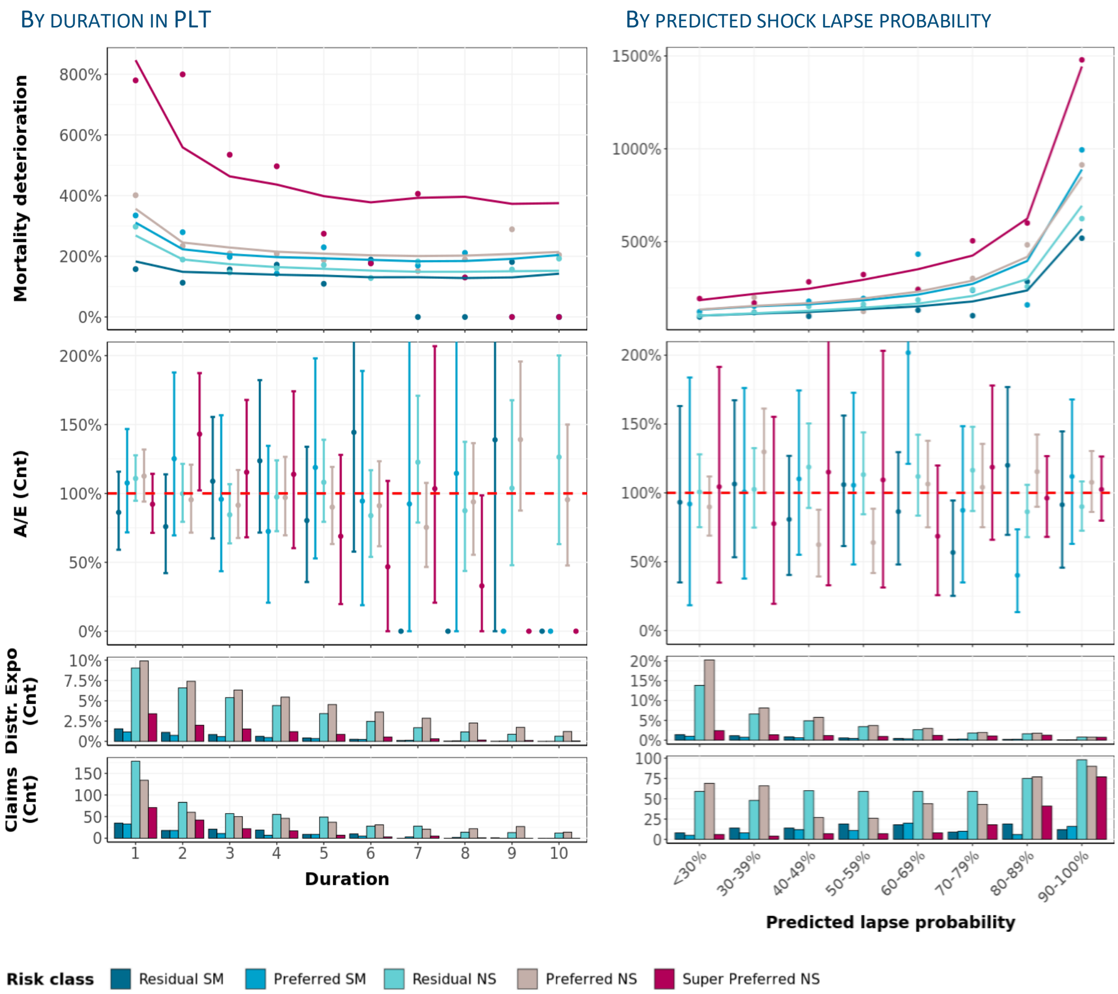
The pattern by predicted shock lapse is similar for other risk classes, though less steep at the highest predicted shock lapse bands. Mortality deterioration for Residual SM is relatively flat across durations after the initial duration in PLT, as shown in the top left panel in Figure 5-10. Residual NS mortality, on the other hand, decreases more heavily from PLT duration 1 to PLT duration 4 and remains flat through the following durations. Mortality deterioration variation for Preferred SM and Residual NS is very similar by duration in PLT, as well as by predicted shock lapse probability.

The mortality variations by duration and predicted shock lapse probability are captured adequately for each risk class. In the second panels of Figure 5-10, the 100% A/E falls within the 95% confidence interval with the exception of duration and shock lapse bands for which data were not sufficient.

[6] https://tableau.soa.org/t/soa-public/views/USPost-LevelTermPredictiveModelingInteractiveTool/3-MortalityDetOverview

Figure 5-10

MORTALITY DETERIORATION FOR JUMP TO ART BY RISK CLASS

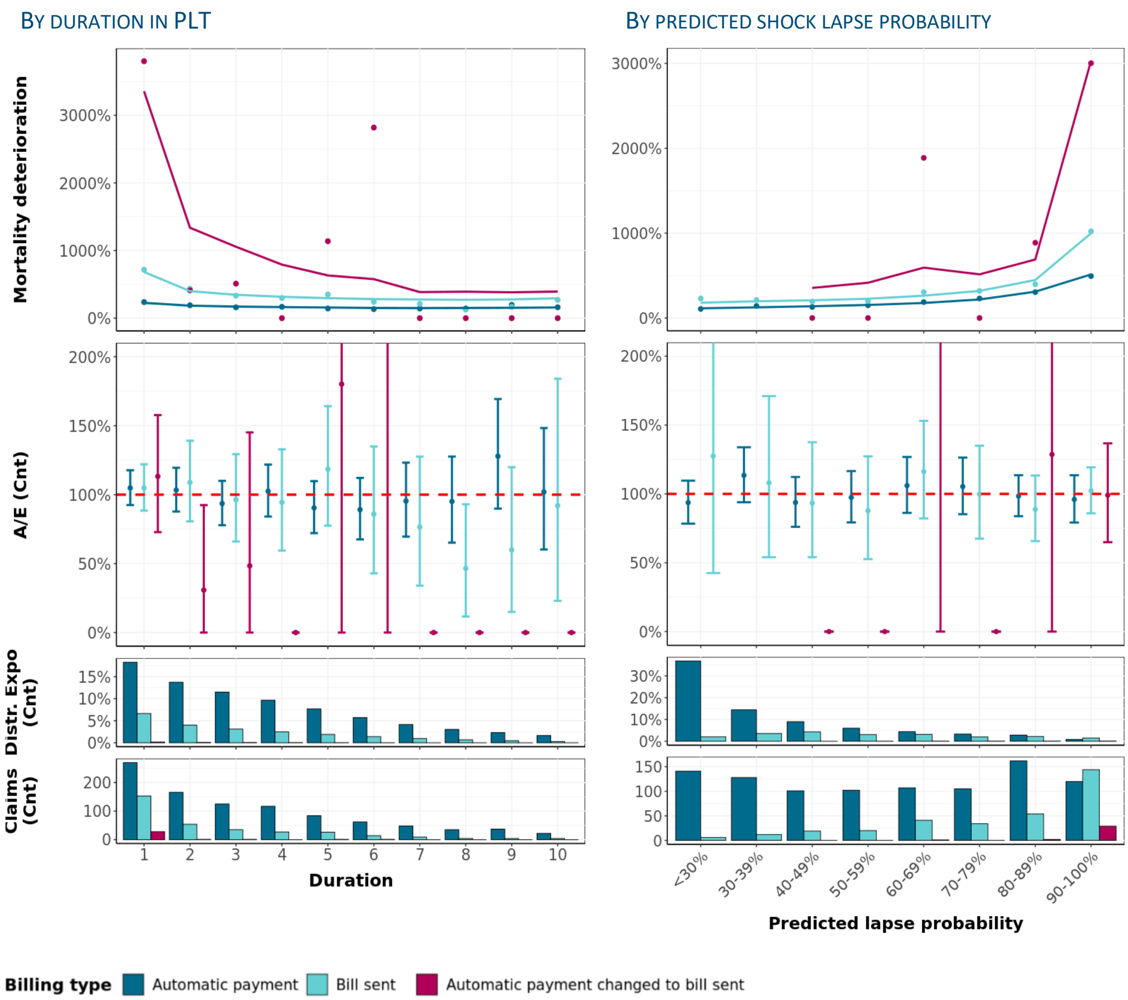


Billing type

Billing type is included as a variable in the mortality model. Predicted mortality deterioration is lower for Automatic payment compared to Bill Sent across all durations and predicted shock lapse probability ranges, as shown in the top panels of Figure 5-11. Differences between Automatic payment and Bill Sent mortality are larger in the initial duration of PLT and at the highest predicted shock lapse probability band. For Automatic payment changed to Bill Sent, the difference is most important for the first duration in PLT and predicted shock lapse band 90-100%. This is where most of the data are available and the model captures these variations.

The mortality variations by duration and predicted shock lapse probability are captured adequately for each billing type, as illustrated by the 100% A/E falling within the 95% confidence intervals in the second panels of Figure 5-11.

Figure 5-11
MORTALITY DETERIORATION FOR JUMP TO ART BY BILLING TYPE



Initial premium jump

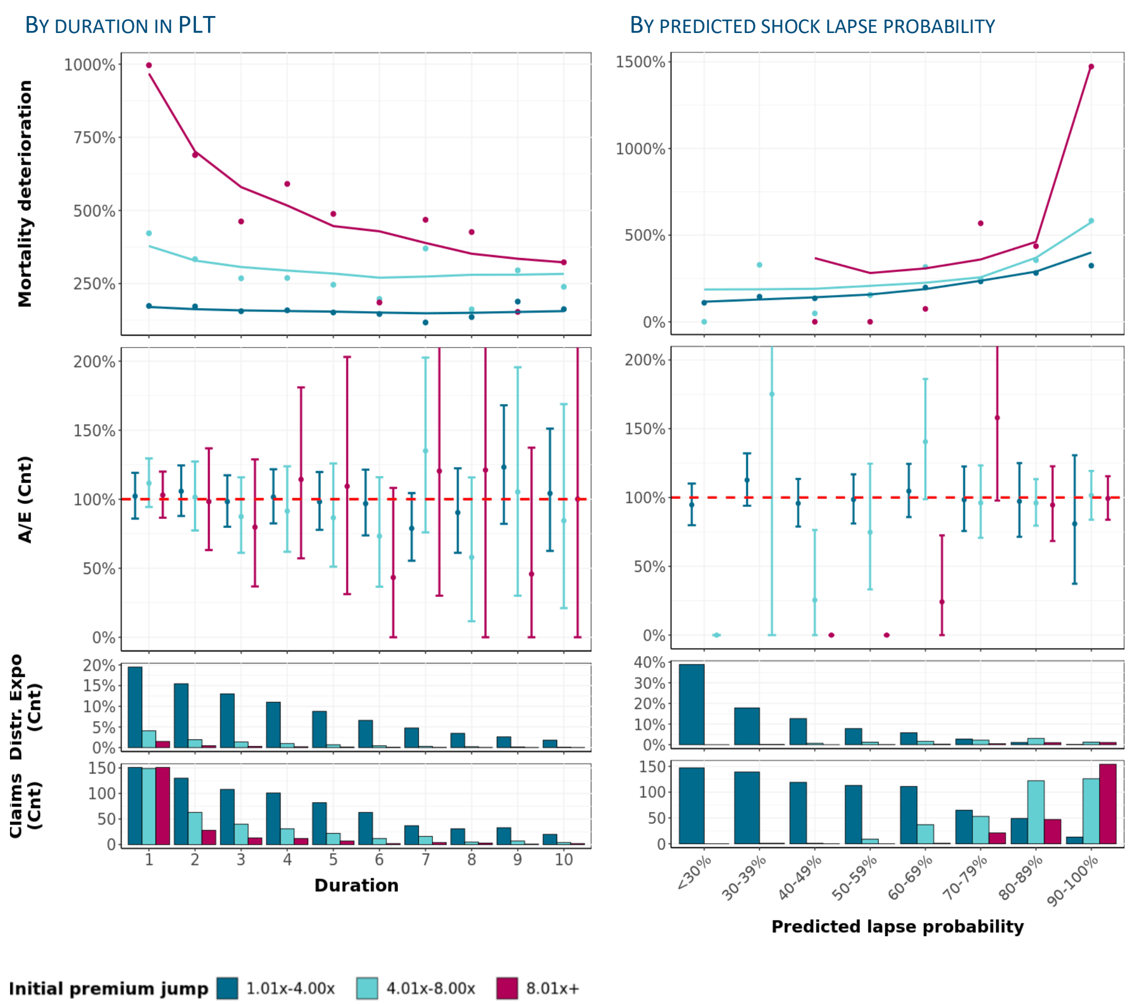
Initial premium jump is included as a variable in the mortality model to specifically capture the differences in mortality deterioration pattern by duration for the three premium jump groups. The top panels in Figure 5-12 show that mortality deterioration for the lowest band 1.01x-4.00x is relatively flat across durations, while mortality deterioration in the moderate premium increase range 4.01x-8.00x drops from 370% in PLT duration 1 to 280% in

PLT duration 5 and remains flat through the following durations. Mortality variations for the lowest and moderate initial premium jump bands by predicted lapse probability are very similar, except for the extreme lapse band 90-100%. The largest differences by duration and predicted shock lapse probability are estimated for the largest premium increase 8.01x+. Starting from 1000% in the initial duration, mortality deterioration slowly converges to the level of the moderate premium jump 4.01x-8.00x in duration 10. Variations by predicted shock lapse probability show a dramatic increase of mortality deterioration for the largest premium increase 8.01x+, reaching 1500% in the highest band 90-100%.

The mortality variations by duration and predicted shock lapse probability are captured adequately for the initial premium jump band. In the second panels of Figure 5-12, the 100% A/E falls within the 95% confidence interval across all durations and the relevant predicted lapse probability ranges. When considering results by predicted shock lapse probability, the lower premium jump business tends to have lower shock lapse, while the higher premium jump business has only higher shock lapse, as shown by the exposure and claims distributions in the third and fourth panels of Figure 5-12. When data are available for the three premium jump groups within a given shock lapse band, differences in mortality deterioration are observed. In the 80-89% shock lapse range, mortality deterioration is higher for the higher premium jump bands. The initial premium jump continues to have an impact on mortality deterioration in PLT that is not captured by shock lapse alone.

Figure 5-12

MORTALITY DETERIORATION FOR JUMP TO ART BY INITIAL PREMIUM JUMP

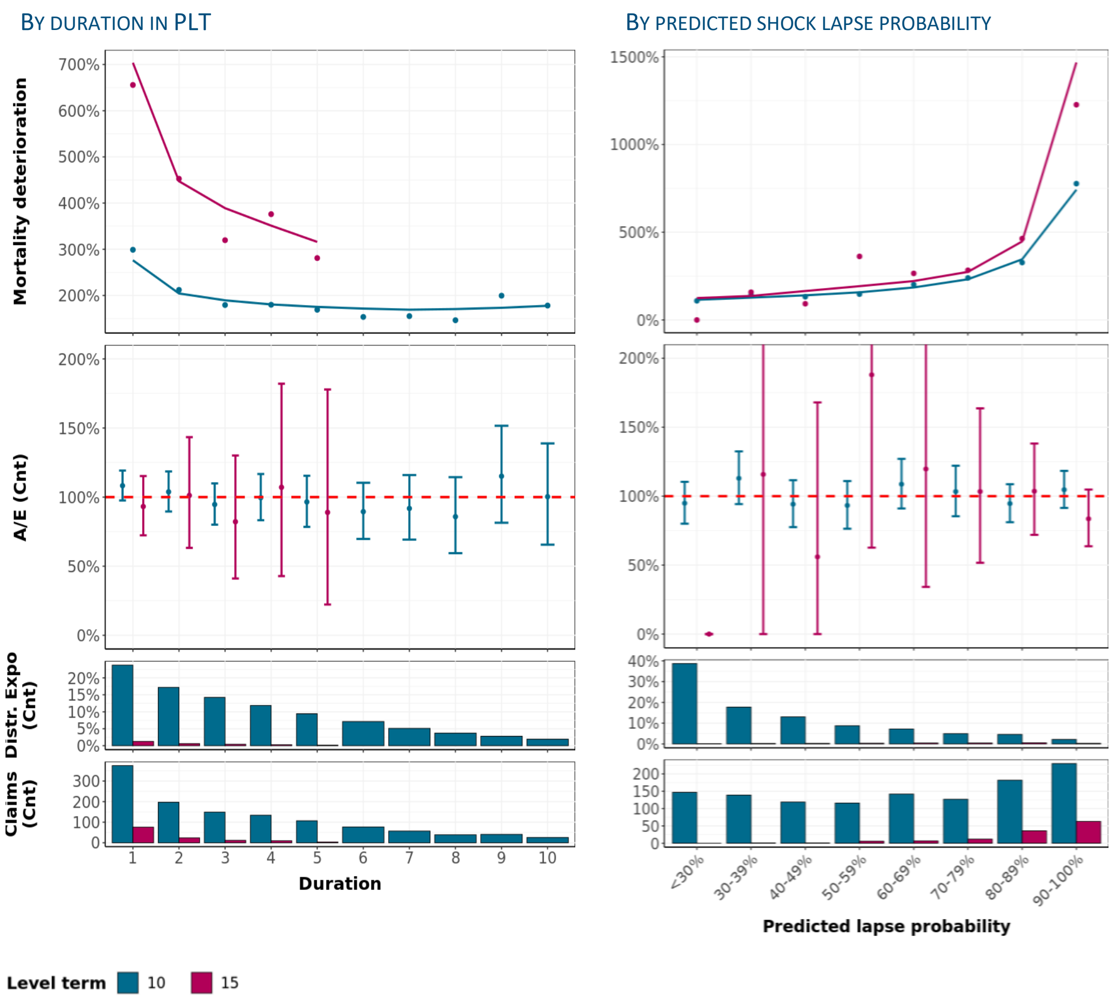


Level term plan

The level term plan variable is not included in the model. Nevertheless, the model predicts adequately the mortality deterioration variations by level term plan. Predicted mortality deterioration is larger for T15 than for T10 on average across all durations in the post-level term period, as seen in the top panels of Figure 5-13. Mortality deterioration variation by predicted shock lapse probability is similar, gradually increasing from 120% for shock lapse rates <30% to 230% and 270% for T10 and T15, respectively, in the 70-79% band. Differences become larger for extreme shock lapse rates where mortality deterioration reaches 740% for T10 and around 1500% for T15 in the 90-100% band (see the top right panel of Figure 5-13).

Despite level term plan information not being included in the model, the mortality variations by duration and predicted shock lapse probability are properly captured, as shown by the 100% A/E falling within the 95% confidence interval in the second panels of Figure 5-13. This illustrates that the level term plan effect can be captured by modeling mortality by predicted shock lapse probability and including the other variables of the mortality experience.

Figure 5-13
MORTALITY DETERIORATION FOR JUMP TO ART BY LEVEL TERM PLAN



5.5 VARIATION BY EXTERNAL VARIABLES FOR JUMP TO ART

In addition to drivers captured in the mortality modeling, predictive modeling allows for further investigation into residual variation by other variables after fitting the model. Variation over time can be investigated for each study year by comparing predicted results to actual mortality experience. Similarly, data not used in fitting the model can be analyzed to identify whether the model is a good predictor for this business. For example, while substandard business is not included in the modeling, the actual mortality experience for substandard business can be compared to the model predictions to provide insights for substandard business relative to policies issued at standard rates. In this section, the expected basis is the final model mortality deterioration prediction for each variable.

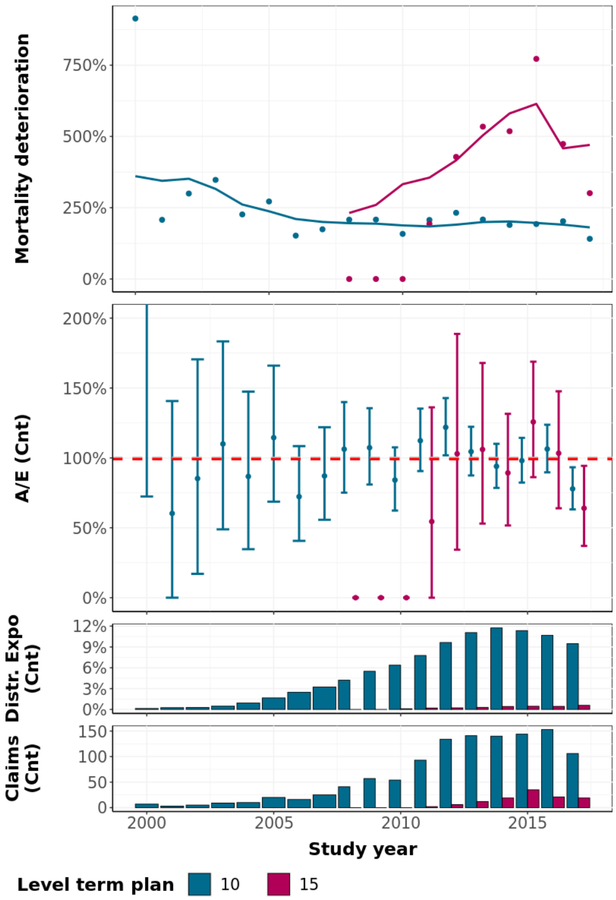
5.5.1 STUDY YEAR

The mortality study was completed on a calendar year basis as described in section 2.4. The study year in this analysis corresponds to the calendar year of mortality experience. This differs from the study year definition in the lapse analysis described in section 3.4.1. As T15 data were only observable since 2008, while T10 data have been available since 2000, the mortality deterioration variations by study year were split by term plan.

For T10, mortality deterioration decreases across study years from 360% to 200% during the period 2000-2007 and remains constant around 200% for the period 2008-2017. On the other hand, T15 mortality deterioration appears to increase sharply from 230% in 2008 to 610% in 2015. However, the mortality model fits this pattern well despite not including a variable for study year. When controlling for the effects of the variables such as risk class, initial premium jump, billing type and premium payment mode, no trend is visible. See the second panel in Figure 5-14 where the A/E results each year are clustered around the 100% line. Some variation year on year can be seen but no specific trend is observed on the A/E ratios. This shows that the apparent downward trend for T10 during the period 2000-2007 and the apparent upward trend seen for T15 during the period 2008-2015 are not originating from a study year effect but rather from the combinations of changes among the other variables captured in the final mortality model.

Figure 5-14

MORTALITY DETERIORATION FOR JUMP TO ART BY STUDY YEAR



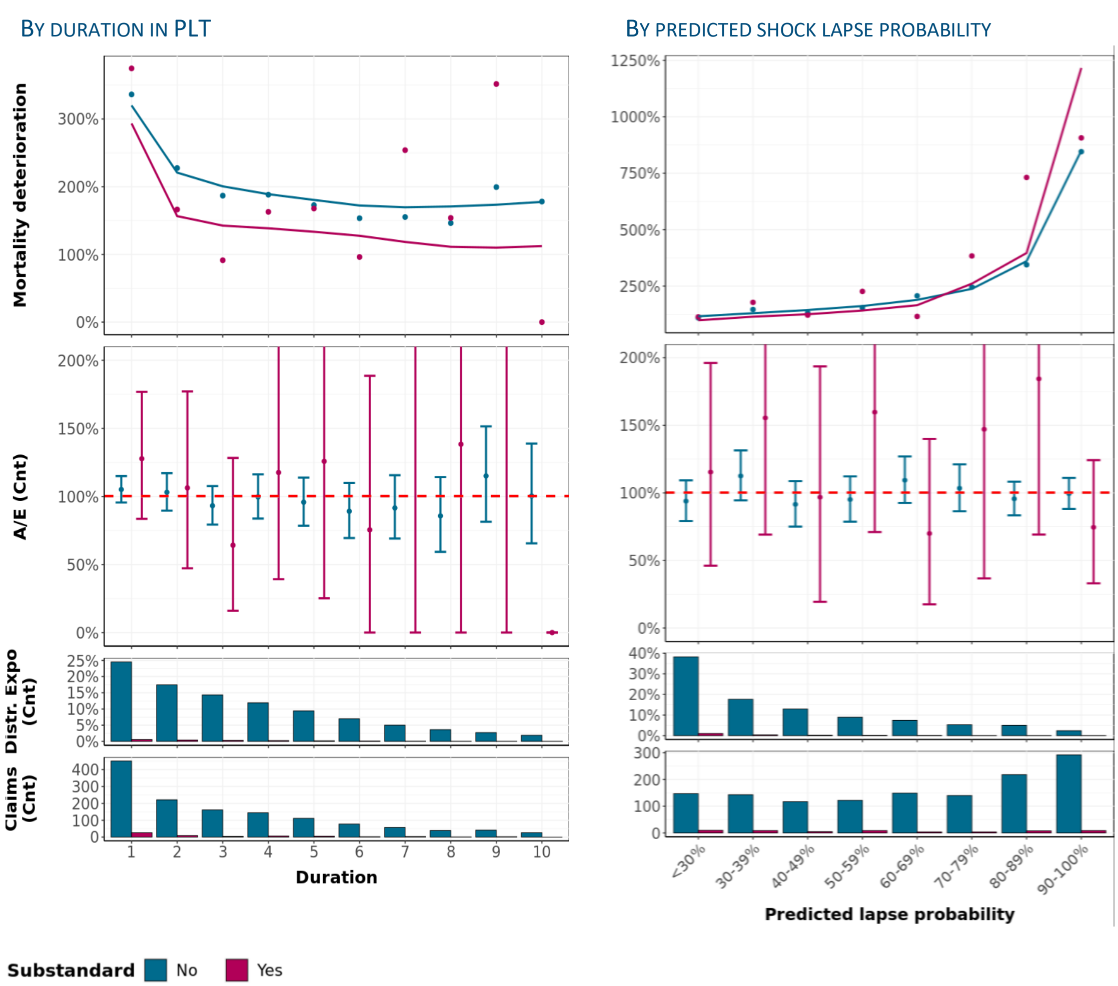
5.5.2 SUBSTANDARD INDICATOR

The mortality model is built on standard policy data. The actual mortality experience for substandard policies is included to assess the fit of the model for substandard business. Predicted mortality deterioration variations for standard and substandard policyholders are similar by predicted shock lapse probability, as illustrated in the top right panel of Figure 5-15. Predicted mortality deterioration is slightly lower for substandard policies by duration in post-level term. Mortality deterioration starts at 320% and 300% in the first PLT duration, decreases to 170% and 110% in duration 7 and remains constant in the following durations for standard and substandard policyholders, respectively.

The mortality deterioration model fitted on standard mortality is capturing adequately the number of deaths for substandard policyholders as illustrated in the top panels of Figure 5-15. Though the confidence intervals are wide due to limited data for substandard policies, the 100% A/E falls within the 95% confidence interval for all durations and predicted lapse probabilities. See the second panels in Figure 5-15, which illustrate that the mortality deterioration variations for substandard can be captured by the combination of variables included in the model calibrated on standard mortality. Substandard policies are expected to have higher mortality, but this analysis suggests there is no higher anti-selection for substandard compared to standard policies.

Figure 5-15

MORTALITY DETERIORATION FOR JUMP TO ART BY SUBSTANDARD INDICATOR



5.6 SHOCK LAPSE RELATIONSHIP MODEL FOR GRADED

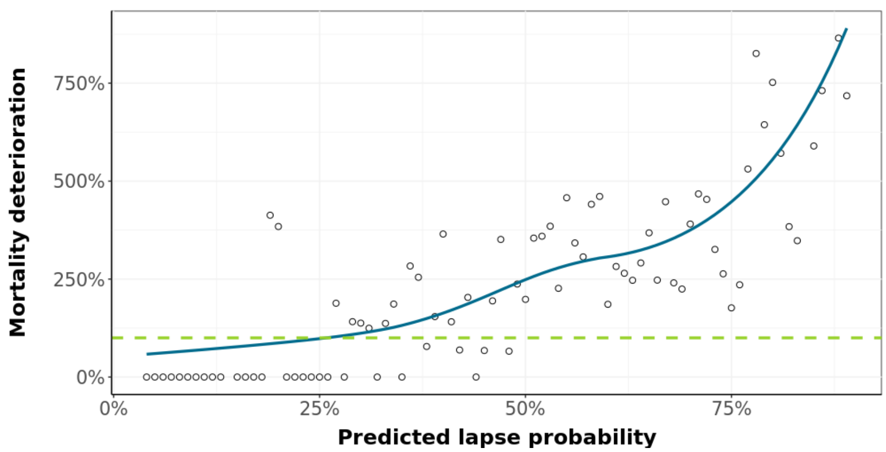
Mortality deterioration for Graded was modeled as a function of the predicted shock lapse probability only. There are insufficient data to capture variations by duration in the post-level term period. Mortality was instead aggregated across all durations and modeled by predicted shock lapse probability. Insights on the mortality deterioration variations by duration are presented through the A/E model fit analysis in this section.

5.6.1 ILLUSTRATION OF THE MORTALITY DETERIORATION BY PREDICTED SHOCK LAPSE PROBABILITY

The fitted mortality deterioration as a function of the predicted lapse probabilities is illustrated in Figure 5-16 for Graded. The observed mortality deterioration is displayed in dots, while the smooth predictions are represented by a blue line. A green dashed line illustrates 100%, which represents no mortality deterioration relative to the level term.

Figure 5-16

OBSERVED AND PREDICTED MORTALITY DETERIORATION BY PREDICTED SHOCK LAPSE PROBABILITY FOR GRADED



The nonparametric smoothing has reduced the variability in the progression of the mortality deterioration due to the sampling fluctuations. The fitted mortality deterioration progresses smoothly by predicted shock lapse probability and its dependence on predicted shock lapse probability is captured without introducing an undue distortion.

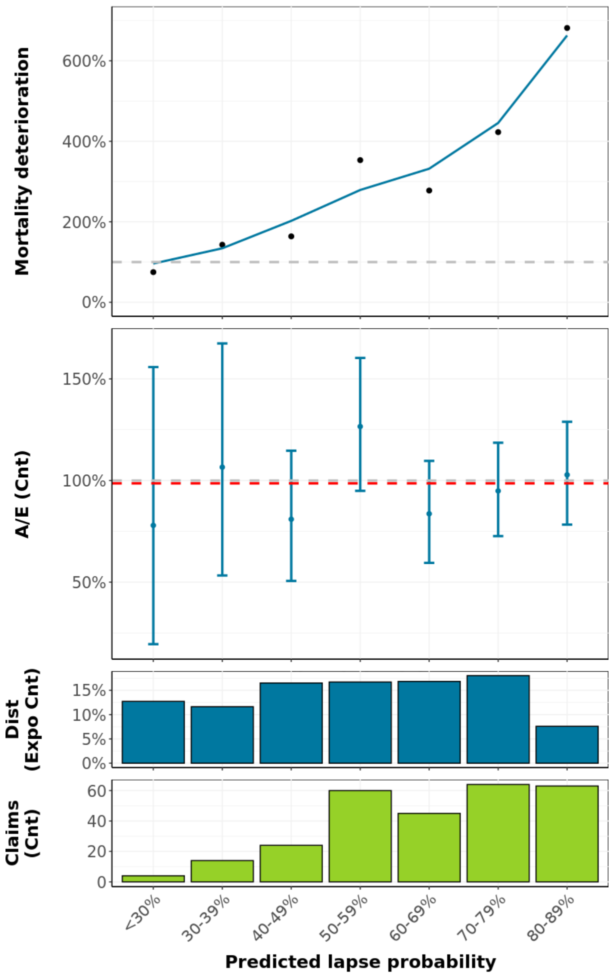
The fitted mortality deterioration increases gradually to 300% over the 30% to 60% predicted shock lapse range. For higher shock lapse rates, the mortality deterioration increases sharply, reaching 660% on average in the 80-89% range.

5.6.2 QUALITY OF THE FIT

The first panel of Figure 5-17 illustrates the fit. The dots represent the observed mortality, while the solid line shows the predictions. The second panel displays the actual over expected death count ratio in the post-level term period by predicted shock lapse probability with the associated 95% confidence intervals. The dashed grey line represents 100%, while the dashed red line shows the 99% overall A/E ratio.

Figure 5-17

ACTUAL OVER EXPECTED NUMBER OF DEATHS BY PREDICTED SHOCK LAPSE PROBABILITY FOR GRADED



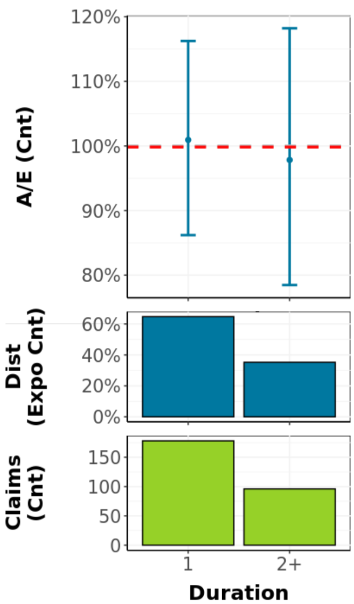
The model estimated mortality deterioration for Graded captures adequately the variations by predicted shock lapse probability. The overall A/E is 99% (illustrated by the red dashed line) and the 100% A/E (illustrated by the grey dashed line) falls within the 95% confidence interval for every predicted lapse probability band. The A/E ratios are 95% and 103% for the highest shock lapse bands 70-79% and 80-89%, respectively, where most of the claims are observed. The model by predicted shock lapse probability only provided a good fit for Graded mortality in PLT.

5.6.3 ANALYSIS BY DURATION IN PLT

To investigate the variation in mortality deterioration between the first duration in PLT and subsequent durations, post-level term period data were split into PLT durations 1 and 2+ for analysis. Recall from Table 5-1, there is very little data after PLT duration 3 (4% of claims). The mortality model built using predicted shock lapse as the only variable is used to derive predicted mortality deterioration for each of the PLT duration groups. Figure 5-18 presents the actual over expected number of deaths as estimated by the model. The A/E ratio for durations 1 and 2+ are 101% and 98%, respectively, and the 100% A/E falls within the 95% confidence intervals. This illustrates that, on average, no significant variations can be observed between durations 1 and 2+. Mortality deterioration variations for durations 1 and 2+ are properly captured by the fitted mortality deterioration estimated by aggregating data across all available PLT durations.

Figure 5-18

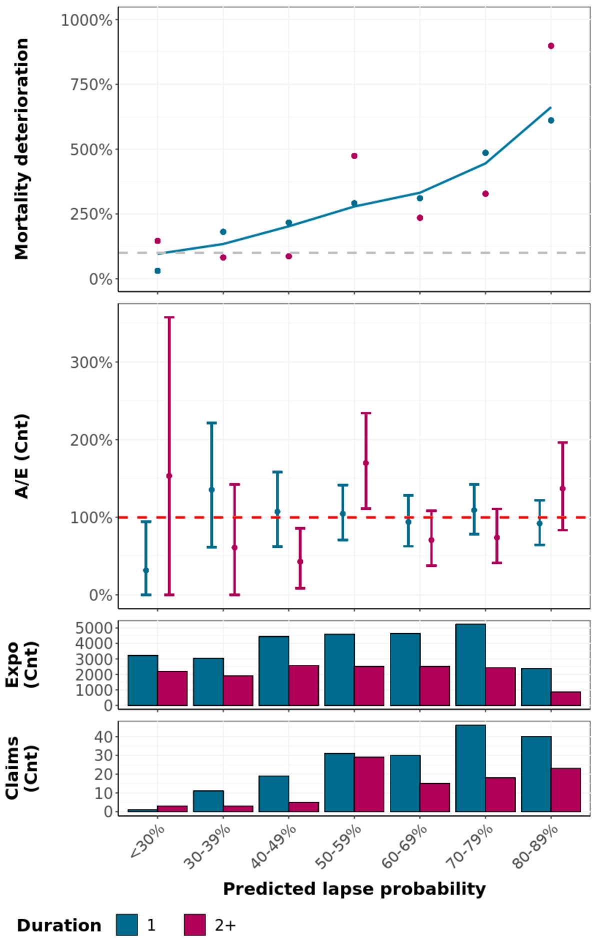
ACTUAL OVER EXPECTED NUMBER OF DEATHS FOR DURATIONS 1 AND 2+ FOR GRADED



The first panel of Figure 5-19 compares the fitted mortality deterioration (blue line) to the actual for durations 1 (blue dots) and 2+ (red dots). The second panel displays the actual over expected death count ratio in the post-level term period by predicted shock lapse probability with the associated 95% confidence intervals. The dashed grey line represents 100%, while the dashed red line shows the 99% overall A/E ratio.

Figure 5-19

ACTUAL OVER EXPECTED NUMBER OF DEATHS BY PREDICTED SHOCK LAPSE PROBABILITY FOR DURATIONS 1 AND 2+ FOR GRADED



The 100% A/E falls within the 95% confidence interval for most predicted shock lapse probability bands. For duration 1, the A/E is only outside the confidence interval for band <30% where there is very little claims data, as shown in the fourth panel. In PLT duration 2+, band 40-49% has an A/E below 100% and band 50-59% has an A/E above 100%. While there is some variation for PLT duration 2+, there is no clear pattern.

In the Jump to ART mortality data seen in section 5.4, the first duration in PLT shows the highest mortality deterioration with lower deterioration observed in PLT duration 2 and later durations. This model for Graded shows PLT duration 2+ mortality deterioration is similar to the first duration mortality deterioration. While there are variations, the A/E for PLT duration 2+ is higher at some predicted shock lapse bands and lower at others. No clear evidence of wear-off is identified when comparing mortality deterioration between the first duration and the available later durations in PLT for Graded.

5.7 COMPARISON WITH THE DUKES MACDONALD APPROACH

The Dukes MacDonald (1980) approach is a well-known method to model mortality deterioration. The approach aims to predict how anti-selective lapsation affects expected mortality by linking the shock lapse at the end of term and the mortality deterioration in PLT. The formula can be written:

$$\mathrm{A} = \mathrm{B} \times \mathrm{S\%} + \mathrm{C} \times (1 - \mathrm{S\%})$$

Before the end of the level term period, mortality of policyholders is known in aggregate (A). When policyholders enter the end of the level term period, the healthy lives lapse as they can find cheaper premiums elsewhere. The policyholders who lapse and take out new policies are called reverters (B) and are assumed to experience newly select mortality. The remaining lives (C) are the persisters and their mortality can be calculated by balancing this equation. $\mathrm{S\%}$ represents the percentage of policyholders who have newly select mortality. This can be set as the shock lapse rate to assume that all those who lapse are going to take out new policies but is usually adjusted by an effectiveness rate to assume that less than 100% of lapsers have newly select mortality.

The core assumption is that, starting from any insured population, the total aggregate deaths from in-force policies ("persisters") and lapsed policies ("reverters") in any year is the same as the aggregate year assumptions. Those who lapse are assumed to exhibit better mortality and those who remain have worse mortality. Three methods of applying the Dukes MacDonald approach exist and the difference is based on the definition of persisters as illustrated by Doll (2003).

Method 1: Persisters are those who continue their policy in-force.
Method 2: Persisters are those who continue in-force, plus the non-select excess lapsers.
Method 3: Persisters are those who continue in-force, plus the non-select excess lapsers, plus the base rate lapsers.

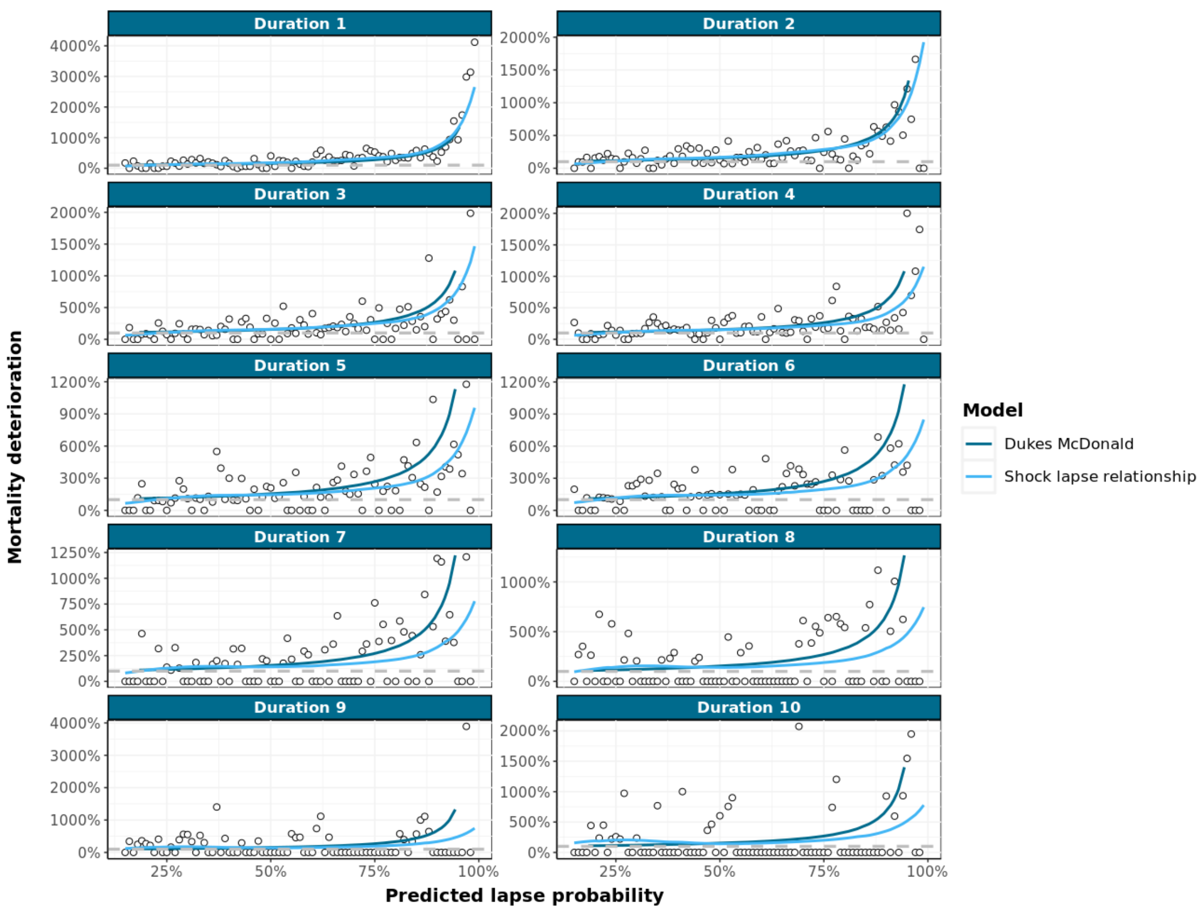
Mortality deterioration will be highest under method 1 and lowest under method 3. For the purpose of this analysis, method 2 is used.

The Dukes MacDonald approach defines a relationship between shock lapse and mortality deterioration. In this report, the shock lapse relationship model captures the relationship between shock lapse and mortality deterioration. A comparison of the mortality deterioration predictions between the approaches was carried out for Jump to ART.

Figure 5-20 presents the mortality deterioration by predicted shock lapse probability and duration in PLT with two lines fitted to represent mortality deterioration modeled by the Dukes MacDonald approach and the predictive modeling shock lapse relationship model, respectively. A green dashed line illustrates 100% mortality deterioration. The Dukes MacDonald predictions are sensitive to the choice of an effectiveness rate assumption. An effectiveness rate of 100% assumes that all policyholders who lapse have newly select mortality, i.e., all lapses are anti-selective. It is unlikely that all policyholders will take out new term life insurance, and some lapse because they no longer need coverage. For this reason, in practice the effectiveness rate is assumed to be less than 100%. For comparison purposes, the effectiveness rate was varied to find the best fit to the data. The Dukes MacDonald predictions in Figure 5-20 are based on an effectiveness rate of 80%.

Figure 5-20

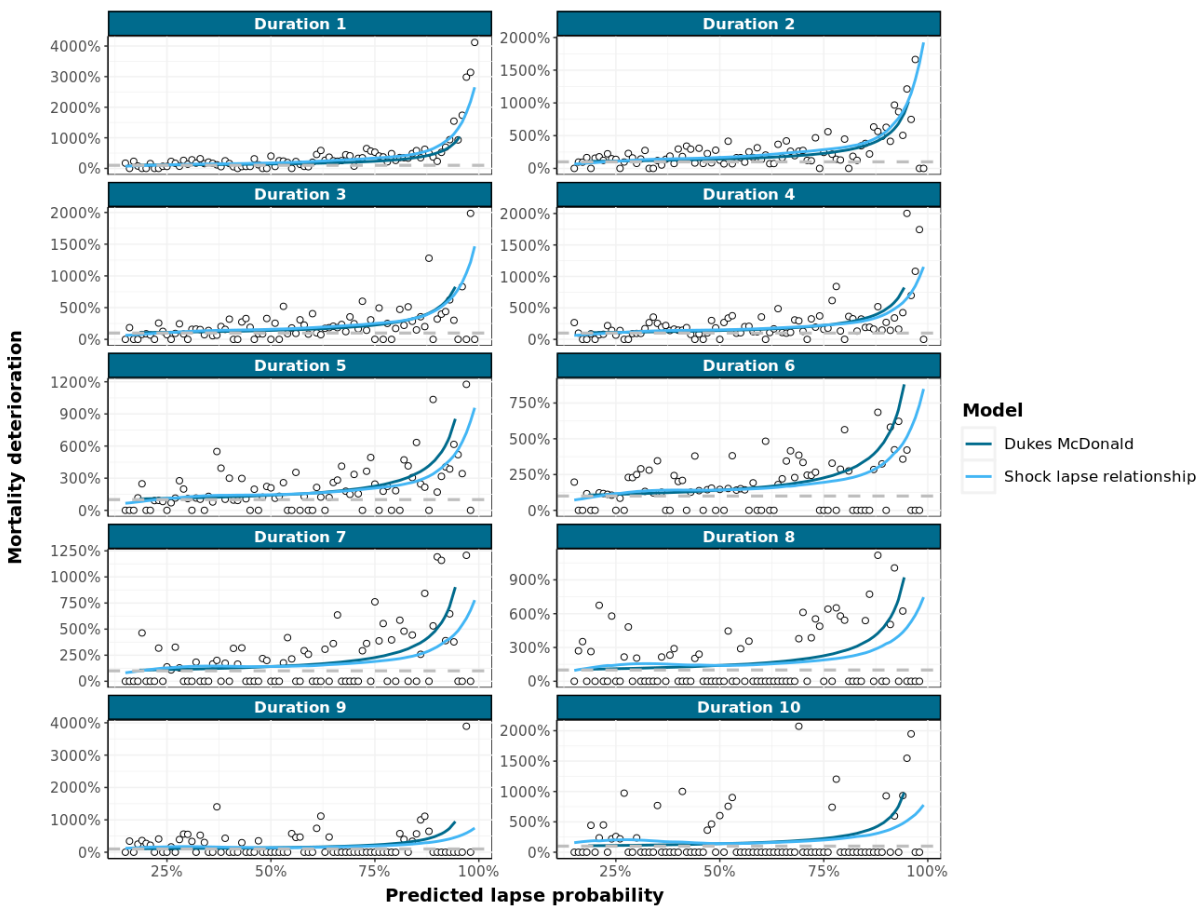
COMPARISON OF DUKES MACDONALD APPROACH AT EFFECTIVENESS RATE 80% AND SHOCK LAPSE RELATIONSHIP MODEL PREDICTIONS FOR MORTALITY DETERIORATION FOR JUMP TO ART



At an effectiveness rate of 80%, the Dukes MacDonald mortality deterioration is a good fit to the data in PLT duration 1 and produces a prediction very close to the shock lapse relationship model. The same pattern of mortality deterioration by shock lapse is captured by both models. The predictions also closely aligned between the two models for PLT duration 2 but, in later durations, the Dukes MacDonald approach predicts higher mortality deterioration than the predictive modeling shock lapse relationship model for shock lapses above 75%. A lower effectiveness rate assumption provides a better fit at later durations in PLT. Figure 5-21 presents the Dukes MacDonald predictions based on an effectiveness rate of 60% in comparison to the shock lapse relationship model.

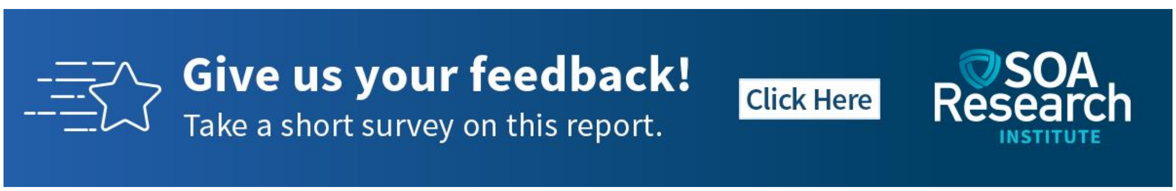
Figure 5-21

COMPARISON OF DUKES MACDONALD APPROACH AT EFFECTIVENESS RATE 60% AND SHOCK LAPSE RELATIONSHIP MODEL PREDICTIONS FOR MORTALITY DETERIORATION FOR JUMP TO ART



The predicted mortality deterioration aligns closely between the models for PLT durations 3, 4 and 5. The Dukes MacDonald approach predicts lower mortality deterioration than the shock lapse relationship model in PLT durations 1 and 2 when the effectiveness rate is set to 60%.

The initial mortality deterioration is captured by the Dukes MacDonald approach with the effectiveness rate at 80%. The wear-off pattern differs by predicted shock lapse group as shown in Figure 5-8 where the mortality deterioration reduces quickly by duration in PLT for higher shock lapses and decreases more gradually or remains level for the lowest shock lapses. This is not captured by the Dukes MacDonald model. Sensitivity analysis at different effectiveness rates shows that there is a wear-off of anti-selection as a higher effectiveness rate is a better fit at early durations and a lower effectiveness rate is better at later durations.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Section 6: Acknowledgments

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Appendix A: Generalized Linear Framework

During the last 30 years, the use of Generalized Linear Models (GLMs) (Nelder and Wedderburn (1972)) has received a lot of attention since the applications of McCullagh and Nelder (1989). GLMs are ideally suited for the analysis of non-Normal data typically encountered when interested in insurance-related topics. Modeling differs from Gaussian linear models in two important aspects:

- The distribution of the dependent variable is chosen from the exponential family and is, therefore, not specifically Normal but can be explicitly non-Normal.
- A transformation of the expectation of the dependent variable is linearly related to the explanatory variables.

Generalized Linear Models have three characteristics:

- A random element, which establishes that the observations are independent random variables $Y_i,\ i = 1, \dots, n$ with a density belonging to the linear exponential family.
- A systematic element which attributes to each observation of linear predictor η_i.
- A third element which connects the first two components: μ_i the expectation of Y_i is linked to the linear predictor η_i by a link function.

The GLM technique can be applied to all distributions belonging to the exponential family, i.e., when the dependent variable Y_i has a probability law of the form:

$$f(y_i|\theta_i, \phi) = \exp\left\{\frac{y_i\theta_i - b(\theta_i)}{a(\phi)} + c(y_i, \phi)\right\},$$

for specific functions $a(\cdot)$, $b(\cdot)$ and $c(\cdot)$. The functions a and c are such that $a(\phi) = \phi$ and $c = c(y_i, \phi)$. The parameter θ_i is the canonical parameter (or natural parameter) and ϕ is the dispersion parameter. Table A-1 presents an example of a Poisson GLM.

Table A-1
POISSON DISTRIBUTION BELONGING TO THE EXPONENTIAL FAMILY

Distribution of y_i	θ_i	$a(\phi)$	$b(\theta_i)$	$c(y_i, \phi)$	$\mathrm{E}[Y_i]$	$\mathrm{V}[\mu_i] = \mathrm{V}[Y_i]/a(\phi)$
Poisson (μ_i)	$\ln(\mu_i)$	1	$\exp(\theta_i)$	$-\log(y_i)!$	μ_i	μ_i

"Linear" in Generalized Linear Models means that the explanatory variables are combined linearly to model the expectation. If $x_1, x_2, \dots, x_P$ are explanatory variables, then linear combinations of the form $\beta_0 + \beta_1 x_1 + \cdots + \beta_P x_P$ serve as linear predictors of the expectation of the dependent variable. Linearity in GLMs refers only to linearity in coefficients β_j, not in the explanatory variables. For example, $\beta_0 + \beta_1 x_1 + \beta_2 x_1^2$ and $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_3$ are "linear" in the sense defined by the GLMs, but $\beta_0 + \beta_1 x_1 + \exp(\beta_2 x_2)$ is not.

The link function $g(\,)$, which is monotonic and differentiable, links the expectation $\mu_i = \mathrm{E}[Y_i], i = 1, 2, \dots, n$ to the linear predictor η_i:

$$g(\mu_i) = \eta_i \Leftrightarrow \mu_i = g^{-1}(\eta_i).$$

The link function is said to be canonical when $\theta_i = \eta_i$, where θ_i is the canonical parameter. The canonical link function, therefore, ensures that $g(\mu_i) = \theta_i$ and $g^{-1} = b'(\,)$, since $\mu_i = b'(\theta_i)$. The canonical link for the Poisson distribution is $\eta_i = \log(\mu_i)$.

In a GLM, each step of the solving algorithm constitutes a weighted least squares type of adjustment. It is a generalization of ordinary least squares which takes into account the non-constancy of the variance of the observations. The observations collected at points where the variability is lower are given greater weight in determining the parameters. At each iteration, the weights are updated. The algorithm is called iteratively re-weighted least squares or IRWLS.

When modeling lapse and mortality experience data, the exposure is taken into account. The linear predictor becomes

$$\eta_i = \log(\mu_i) = \log(E_i \varphi_i) = \log(E_i) + \log(\varphi_i)$$

The term E_i is called the offset and can be easily incorporated into the regression. It is an element of the linear predictor whose coefficient is constrained to 1.

Appendix B: Regression Model Output

The main effects and interactions included in the final models fitted separately to Jump to ART and Graded data are displayed in Tables B-1 and B-2, respectively. For these models, the reference categories are given in Table 3-5.

Table B-1

SHOCK LAPSE JUMP TO ART REGRESSION MODEL OUTPUT

Variable	Regression Coefficient	Parameter Estimate	Standard Error	P-value
Intercept	β_0	0,239	0.029	< 0.1%
Term 15	β_1	-0.185	0.017	< 0.1%
Attained age	β_2	0.570	0.008	< 0.1%
Attained age^2	β_3	0.049	0.005	< 0.1%
Risk class: Residual SM	β_4	0.558	0.021	< 0.1%
Risk class: Preferred SM	β_5	0.410	0.022	< 0.1%
Risk class: Residual NS	β_6	0.085	0.011	< 0.1%
Risk class: Super Preferred NS	β_7	0.143	0.014	< 0.1%
Face amount $0-100K	β_8	-0.210	0.012	< 0.1%
Face amount $251-500K	β_9	0.087	0.013	< 0.1%
Face amount $501K+	β_{10}	0.173	0.016	< 0.1%
Premium mode: Quarterly	β_{11}	0.638	0.013	< 0.1%
Premium mode: Semi-annual	β_{12}	1.109	0.022	< 0.1%
Premium mode: Annual	β_{13}	1.270	0.014	< 0.1%
Billing type: Bill Sent	β_{14}	0.484	0.046	< 0.1%
Billing type: Automatic payment changed to Bill Sent	β_{15}	0.800	0.145	< 0.1%
Premium jump 1.01x-1.50x × Billing type: Automatic payment	β_{16}	-1.310	0.037	< 0.1%
Premium jump 1.51x-2.00x × Billing type: Automatic payment	β_{17}	-1.198	0.030	< 0.1%
Premium jump 2.01x-2.50x × Billing type: Automatic payment	β_{18}	-0.908	0.030	< 0.1%
Premium jump 2.51x-3.00x × Billing type: Automatic payment	β_{19}	-0.540	0.033	< 0.1%
Premium jump 3.01x-3.50x × Billing type: Automatic payment	β_{20}	-0.413	0.035	< 0.1%
Premium jump 3.51x-4.00x × Billing type: Automatic payment	β_{21}	-0.375	0.037	< 0.1%
Premium jump 4.01x-4.50x × Billing type: Automatic payment	β_{22}	-0.212	0.037	< 0.1%
Premium jump 5.01x-5.50x × Billing type: Automatic payment	β_{23}	0.071	0.039	< 0.1%
Premium jump 5.51x-6.00x × Billing type: Automatic payment	β_{24}	0.280	0.040	< 0.1%
Premium jump 6.01x-7.00x × Billing type: Automatic payment	β_{25}	0.427	0.036	< 0.1%
Premium jump 7.01x-8.00x × Billing type: Automatic payment	β_{26}	0.469	0.039	< 0.1%
Premium jump 8.01x-10.00x × Billing type: Automatic payment	β_{27}	0.570	0.038	< 0.1%
Premium jump 10.01x-14.00x × Billing type: Automatic payment	β_{28}	0.353	0.040	< 0.1%
Premium jump 14.01x+ × Billing type: Automatic payment	β_{29}	0.040	0.052	44%
Premium jump 1.01x-1.50x × Billing type: Bill Sent	β_{30}	-0.772	0.064	< 0.1%
Premium jump 1.51x-2.00x × Billing type: Bill Sent	β_{31}	-0.666	0.053	< 0.1%
Premium jump 2.01x-2.50x × Billing type: Bill Sent	β_{32}	-0.548	0.054	< 0.1%
Premium jump 2.51x-3.00x × Billing type: Bill Sent	β_{33}	-0.229	0.062	< 0.1%
Premium jump 3.01x-3.50x × Billing type: Bill Sent	β_{34}	0.001	0.068	98%
Premium jump 3.51x-4.00x × Billing type: Bill Sent	β_{35}	0.197	0.067	< 0.1%
Premium jump 4.01x-4.50x × Billing type: Bill Sent	β_{36}	0.050	0.065	44%
Premium jump 5.01x-5.50x × Billing type: Bill Sent	β_{37}	0.136	0.065	4%
Premium jump 5.51x-6.00x × Billing type: Bill Sent	β_{38}	-0.052	0.066	43%
Premium jump 6.01x-7.00x × Billing type: Bill Sent	β_{39}	-0.007	0.059	90%
Premium jump 7.01x-8.00x × Billing type: Bill Sent	β_{40}	0.038	0.061	54%
Premium jump 8.01x-10.00x × Billing type: Bill Sent	β_{41}	0.098	0.059	9%
Premium jump 10.01x-14.00x × Billing type: Bill Sent	β_{42}	0.461	0.059	< 0.1%
Premium jump 14.01x+ × Billing type: Bill Sent	β_{43}	0.772	0.071	< 0.1%
Premium jump 1.01x-1.50x × Billing type: Automatic payment changed to Bill Sent	β_{44}	1.648	0.476	97.6%

Premium jump 1.51x-2.00x × Billing type: Automatic payment changed to Bill Sent	β_{45}	1.664	0.293	7.9%
Premium jump 2.01x-2.50x × Billing type: Automatic payment changed to Bill Sent	β_{46}	0.781	0.245	1.5%
Premium jump 2.51x-3.00x × Billing type: Automatic payment changed to Bill Sent	β_{47}	0.477	0.221	4.6%
Premium jump 3.01x-3.50x × Billing type: Automatic payment changed to Bill Sent	β_{48}	0.683	0.223	0.5%
Premium jump 3.51x-4.00x × Billing type: Automatic payment changed to Bill Sent	β_{49}	0.304	0.213	15%
Premium jump 4.01x-4.50x × Billing type: Automatic payment changed to Bill Sent	β_{50}	0.368	0.214	9%
Premium jump 5.01x-5.50x × Billing type: Automatic payment changed to Bill Sent	β_{51}	0.122	0.200	54%
Premium jump 5.51x-6.00x × Billing type: Automatic payment changed to Bill Sent	β_{52}	0.422	0.217	5%
Premium jump 6.01x-7.00x × Billing type: Automatic payment changed to Bill Sent	β_{53}	0.642	0.192	< 0.1%
Premium jump 7.01x-8.00x × Billing type: Automatic payment changed to Bill Sent	β_{54}	0.701	0.193	< 0.1%
Premium jump 8.01x-10.00x × Billing type: Automatic payment changed to Bill Sent	β_{55}	0.712	0.174	< 0.1%
Premium jump 10.01x-14.00x × Billing type: Automatic payment changed to Bill Sent	β_{56}	1.305	0.173	< 0.1%
Premium jump 14.01x+ × Billing type: Automatic payment changed to Bill Sent	β_{57}	1.956	0.187	< 0.1%

Table B-2

SHOCK LAPSE GRADED REGRESSION MODEL OUTPUT

Variable	Regression Coefficient	Parameter Estimate	Standard Error	P-value
Intercept	β_0	0.937	0.019	< 0.1%
Term 15	β_1	0.036	0.017	3%
Attained age	β_2	0.401	0.011	< 0.1%
Attained age^2	β_3	-0.028	0.008	< 0.1%
Risk class: Residual SM	β_4	0.107	0.045	1.6%
Risk class: Preferred SM	β_5	0.218	0.042	< 0.1%
Risk class: Preferred NS	β_6	-0.120	0.018	< 0.1%
Risk class: Super Preferred NS	β_7	-0.180	0.018	< 0.1%
Face amount $0-99K	β_8	-0.827	0.050	< 0.1%
Face amount $100K	β_9	-0.368	0.022	< 0.1%
Face amount $101-249K	β_{10}	-0.153	0.023	< 0.1%
Premium jump 1.01x-1.50x	β_{11}	-0.802	0.062	< 0.1%
Premium jump 1.51x-2.00x	β_{12}	-0.675	0.036	< 0.1%
Premium jump 2.01x-2.50x	β_{13}	-0.355	0.025	< 0.1%
Premium jump 3.01x-3.50x	β_{14}	0.164	0.021	< 0.1%
Premium jump 3.51x-4.00x	β_{15}	0.370	0.023	< 0.1%
Premium jump 4.01x-4.50x	β_{16}	0.583	0.028	< 0.1%
Premium jump 4.51x-5.00x	β_{17}	0.816	0.039	< 0.1%
Premium mode: Monthly	β_{18}	-1.065	0.028	< 0.1%
Premium mode: Quarterly	β_{19}	-0.404	0.021	< 0.1%
Premium mode: Semi-annual	β_{20}	-0.139	0.029	< 0.1%
Billing type: Automatic payment	β_{21}	-0.136	0.027	< 0.1%

Appendix C: Local Kernel Weighted Log-Likelihood Model

Following the approach taken by Tibshirani and Hastie (1987), local kernel weighted log-likelihood models apply the local fitting technique to data where the relationship can be expressed through a likelihood function. For simplicity, $x_i = (u_i, v_i)$ denotes the vector of the predictor variables.

The bivariate local likelihood fits a polynomial model locally within a bivariate smoothing window. The function ψ is supposed to have (p+1)*th* continuous derivative at the point $x_i = (u_i, v_i)$. For data point $x_j = (u_j, v_j)$ in a neighborhood of $x_i = (u_i, v_i)$, the function $\psi(x_j)$ is approximated via a Taylor expansion by a polynomial of degree p.

If locally linear fitting is used, the fitting variables are just the independent variables. If locally quadratic fitting is used, the fitting variables are the independent variables, their squares and their cross-products. For example, a local quadratic approximation is

$$\begin{aligned}\psi(x_j) = \psi(u_j, v_j) &\approx \beta_0(x_i) + \beta_1(x_i)(u_j - u_i) + \beta_2(x_i)(v_j - v_i)\\ &+ \frac{1}{2}\beta_3(x_i)(u_j - u_i)^2 + \beta_4(x_i)(u_j - u_i)(v_j - v_i)\\ &+ \frac{1}{2}\beta_5(x_i)(v_j - v_i)^2.\end{aligned}$$

The local log-likelihood can be written as

$$\ell(\beta|\lambda, x_i) = \sum_{j=1}^{n} l(y_j, \boldsymbol{x}^{\mathbf{T}}\boldsymbol{\beta})\ w_j,$$

where in the case of locally quadratic fitting,

$$\boldsymbol{x} = \left(u_j - u_i, v_j - v_i, (u_j - u_i)^2, (u_j - u_i)(v_j - v_i), (v_j - v_i)^2\right)^{\mathbf{T}},$$

and

$$\boldsymbol{\beta} = (\beta_0, \dots, \beta_5)^{\mathbf{T}}.$$

The weights are defined on the bivariate space. The nonnegative weight function,

$$w_j = \begin{cases} W(\rho(x_i, x_j)/h) & \text{if } \rho(x_i, x_j)/h \le 1, \\ 0 & \text{otherwise.} \end{cases}$$

depends on the distance $\rho(x_i, x_j)$ between the observations $x_j = (u_j, v_j)$ and the fitting point $x_i = (u_i, v_i)$. A common choice is the Euclidean distance,

$$\rho(x_i, x_j) = \sqrt{(u_j - u_i)^2 + (v_j - v_i)^2}.$$

In addition, it contains a smoothing parameter $h = (\lambda - 1)/2$, which determines the radius of the neighborhood of x_i. $W(.)$ is some weight function like those given in Table C-1.

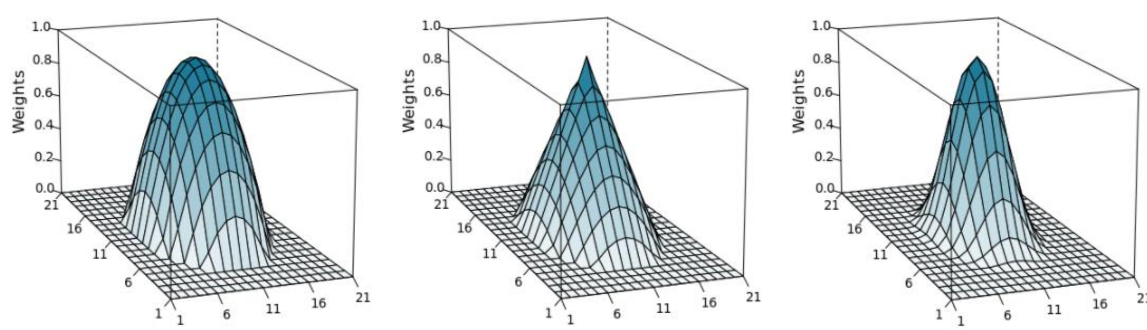
Table C-1
EXAMPLES OF WEIGHT FUNCTION WITH $a = \rho(x_i, x_j)/h$.

Weight Function	W(a)
Uniform	$\frac{1}{2}\,\mathbb{I}(\lvert a\rvert \leq 1)$
Triangular	$(1 - \lvert a\rvert)\,\mathbb{I}(\lvert a\rvert \leq 1)$
Epanechnikov	$\frac{3}{4}(1 - a^2)\,\mathbb{I}(\lvert a\rvert \leq 1)$
Quartic (biweight)	$\frac{15}{16}(1 - a^2)^2\,\mathbb{I}(\lvert a\rvert \leq 1)$
Triweight	$\frac{35}{32}(1 - a^2)^3\,\mathbb{I}(\lvert a\rvert \leq 1)$
Tricube	$(1 - \lvert a\rvert^3)^3\,\mathbb{I}(\lvert a\rvert \leq 1)$
Gaussian	$\frac{1}{\sqrt{2\pi}}\exp\left(\frac{1}{2}a^2\right)$

Figure C-1 displays some of the weight functions presented. For a weight function $W(a)$, the weights decrease with increasing distance $\rho(x_i, x_j)$. The window-width or bandwidth λ determines how fast the weights decrease. For small λ, only values in the immediate neighborhood of x_i will be influential; for large λ, values more distant from x_i may also influence the estimate.

Figure C-1
WEIGHTING SYSTEM SHAPE OF SOME WEIGHT FUNCTIONS WITH RADIUS h=7

EPANECHNIKOV TRIANGULAR TRIWEIGHT



Maximizing the local log-likelihood with respect to $\boldsymbol{\beta}$ gives the vector of estimators $\widehat{\boldsymbol{\beta}} = (\hat{\beta}_0, \ldots, \hat{\beta}_5)^{\mathbf{T}}$. Estimator $\psi(x_i)$ is given by $\hat{\psi}(x_i) = \hat{\beta}_0$.

Graduation, and hence the model selection issue, is a very effective compromise between two objectives, the elimination of irregularities and the achievement of a desired mathematical shape to the progression of the mortality deterioration. This underlines the importance of experience and, above all, thorough investigation of data as the prerequisites of reliable judgment, as the data must be first inspected and a decision about the type of irregularity to be retained has been made. To quote Hickman and Miller (1977, p.15), "*without prior information, smoothing is an unjustified process.*"

To find the constellation of smoothing parameters (which are the smoothing bandwidth λ, the degree of approximation p and the weight function $W(.)$), the strategy is to compute a number of candidate fits and use criteria to select, among the fits, the one with the lowest score. One possible loss function is the deviance D for a Poisson GLM. This leads to a generalization of the Akaike information criterion (AIC) based directly on the deviance function:

$$\mathrm{AIC} = \sum_{i=1}^{n} \mathrm{D} + 2\upsilon,$$

where υ is the number of fitted degrees of freedom.

Local fitting techniques combine excellent theoretical properties with conceptual simplicity and flexibility. They are very adaptable and convenient statistically; see Loader (1999) for an extensive discussion on the strengths of local modeling.

Appendix D: Adaptive Local Kernel Weighted Log-Likelihood Model: Intersection of Confidence Intervals

The intersection of confidence intervals rule provides an adaptative optimal method to choose the smoothing parameters according to the regularity of the data. The approach is implemented in the R (2020) package locfit by Loader (2010).

The intersection of confidence intervals (ICI) was introduced by Goldenshulger and Nemirovski (1997) and further developed by Katkovnik (1999). Application of the ICI rule in the case of Poisson local likelihood for mortality has been studied by Tomas and Planchet (2013).

In the estimation of the mortality deterioration of reference, only the window width varies. The approximation is set to be quadratic and the weight function to Gaussian. It is well known that, of the smoothing parameters, the weight function has much less influence on the bias and variance tradeoff than the bandwidth or the order of approximation. The choice is not too crucial: at best it changes the visual quality of the regression curve.

At the start, a finite set of window sizes is defined,

$$\Lambda = \{\lambda_1 < \lambda_2 < \cdots < \lambda_k\}$$

and the optimal bandwidth is determined by evaluating the fitting results.

Let $\hat{\psi}(x_i, \lambda_k)$ be the estimate at x_i for window λ_k. To select the optimal bandwidth, the ICI rule examines a sequence of confidence intervals of the estimates $\hat{\psi}(x_i, \lambda_k)$:

$$\begin{aligned}
\widehat{I}(x_i, \lambda_k) &= \left[\widehat{L}(x_i, \lambda_k), \widehat{U}(x_i, \lambda_k)\right], \\
\widehat{U}(x_i, \lambda_k) &= \widehat{\psi}(x_i, \lambda_k) + c\,\widehat{\sigma}(x_i)\|\boldsymbol{s}(x_i, \lambda_k)\|, \\
\widehat{L}(x_i, \lambda_k) &= \widehat{\psi}(x_i, \lambda_k) - c\,\widehat{\sigma}(x_i)\|\boldsymbol{s}(x_i, \lambda_k)\|,
\end{aligned}$$

where c is a threshold parameter of the confidence interval and $\hat{\sigma}(x_i)\|\boldsymbol{s}(x_i, \lambda_k)\|$ the standard deviation. Then, from the confidence intervals, we define

$$\begin{aligned}
&\overline{\widehat{L}}(x_i, \lambda_k) = \max\left[\widehat{L}(x_i, \lambda_{k-1}), \widehat{L}(x_i, \lambda_k)\right], \\
&\underline{\widehat{U}}(x_i, \lambda_k) = \min\left[\widehat{U}(x_i, \lambda_{k-1}), \widehat{U}(x_i, \lambda_k)\right], \\
&k = 1, 2, \ldots, K \quad \text{and} \quad \overline{\widehat{L}}(x_i, \lambda_0) = \underline{\widehat{U}}(x_i, \lambda_0) = 0.
\end{aligned}$$

The largest value from these *k* for which

$$\underline{\widehat{U}}(x_i, \lambda_k) \geq \overline{\widehat{L}}(x_i, \lambda_k)$$

gives k^*, and it yields a bandwidth λ_k^*, which is the required optimal ICI bandwidth.

In other words, denoting

$$\ell_j = \bigcap_{j=k}^{K} \widehat{I}(x_i, \lambda_j)$$

for $k = 1, 2, \ldots, K$, k^* is chosen such that

$$\begin{cases} \ell_j \neq \emptyset, & \forall j \geq k^*, \\ \ell_{k^*-1} = \emptyset. \end{cases}$$

As the bandwidth λ_k is increased, the standard deviation of $\hat{\psi}(x_i, \lambda_k)$ decreases. The confidence intervals become narrower. If λ_k is increased too far, the estimate $\hat{\psi}(x_i, \lambda_k)$ will become heavily biased, and the confidence intervals will become inconsistent in the sense that the intervals constructed at different bandwidths have no common intersection. The optimal bandwidth λ_k^* is the largest k for which the relation is still satisfied, i.e.,

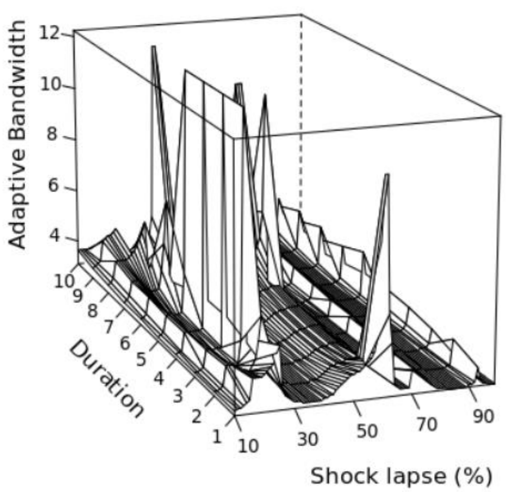
$$\underline{\widehat{U}}(x_i, \lambda_k) \geq \overline{\widehat{L}}(x_i, \lambda_k)$$

when $\ell \neq \emptyset$.

In the estimation of the lapses in the post-level term period and mortality deterioration, only the window width varies. As an illustration, Figure D-1 displays the resulting optimal local bandwidths for the mortality deterioration modeling smoothing step.

Figure D-1

OPTIMAL LOCAL BANDWIDTHS DERIVED FROM THE INTERSECTION OF CONFIDENCE INTERVALS RULE



Appendix E: Logistic Regression Output for Lapses in Subsequent Durations

The main effects included in the final model fitted to Jump to ART data are displayed Table E-1. For this model, the reference categories of the categorical variables are given in Table 4-2.

Table E-1

JUMP TO ART PREMIUM STRUCTURE REGRESSION MODEL OUTPUT

Variable	Regression Coefficient	Parameter Estimate	Standard Error	P-value
Intercept	β_0	-2,307	0,029	< 0.1%
ρ^{SLR}, the lapse in PLT probability estimated by the SLR model in the first step	β_1	5,931	0,066	< 0.1%
Predicted shock lapse probability	β_2	-0,008	0,001	< 0.1%
Duration in PLY	β_3	-0,034	0,003	< 0.1%
Risk class: Super Preferred NS	β_4	0,088	0,015	< 0.1%
Face amount $0-100K	β_5	-0,154	0,012	< 0.1%
Face amount $251-500K	β_6	0,080	0,013	< 0.1%
Face amount $501K+	β_7	0,196	0,018	< 0.1%
Initial premium jump 1.01x-1.50x	β_8	-0,359	0,024	< 0.1%
Initial premium jump 1.51x-2.00x	β_9	-0,156	0,016	< 0.1%
Initial premium jump 3.01x-3.50x	β_{10}	0,096	0,025	< 0.1%
Initial premium jump 3.51x-4.50x	β_{11}	0,262	0,021	< 0.1%
Initial premium jump 4.51x-7.00x	β_{12}	0,333	0,023	< 0.1%
Initial premium jump 7.01x+	β_{13}	0,430	0,028	< 0.1%
Premium mode: Quarterly	β_{14}	0,660	0,029	< 0.1%
Premium mode: Semi-annual and Annual	β_{15}	0,769	0,027	< 0.1%
$\rho^{\mathrm{SLR}} \times$ Premium mode: Quarterly	β_{16}	-1,589	0,088	< 0.1%
$\rho^{\mathrm{SLR}} \times$ Premium mode: Semi-annual and Annual	β_{17}	-3,080	0,073	< 0.1%

Appendix F: Sensitivity of the Shock Lapse Relationship Model to the Shock Lapse Model Specification

The output of the shock lapse model is included as a new variable in the dataset to allow for analysis of the lapse experience in PLT by predicted shock lapse probability through the shock lapse relationship model.

This section studies the sensitivity of the shock lapse relationship model to the shock lapse model specifications.

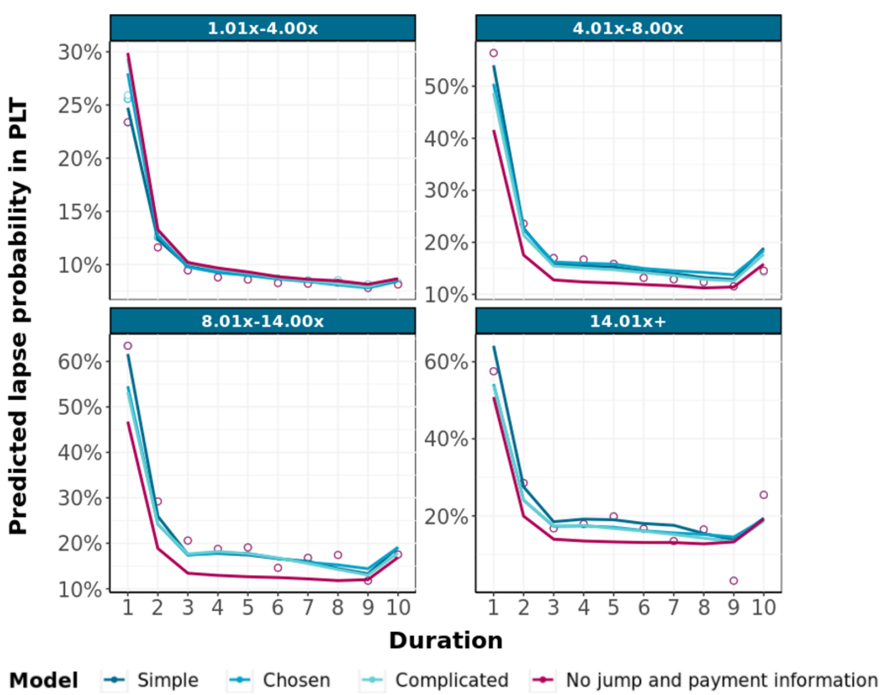
Four shock lapse models are studied and their impacts on the predicted lapse probability in PLT modeled by the shock lapse relationship discussed. The shock lapse model framework is described in section 3.1.2.

- Simple: This model only includes the two most important variables in predicting the shock lapse: initial premium jump and attained age. Variable importance was studied in section 5.2 of the traditional report, *U.S. Post-Level Term Lapse & Mortality Experience*.
- Chosen: This model is the one illustrated in section 3.2. It includes initial premium jump, attained age, billing type, premium mode, risk class, face amount and level term plan, as well as an interaction term between initial premium jump and billing type.
- Complicated: This model includes all the variables (initial premium jump, attained age, billing type, premium mode, risk class, face amount and level term plan), as well as their piecewise interactions.
- No jump and payment information: Conversely to the first three models, this model does not include premium jump information or payment information but consists of attained age, risk class, face amount and level term plan.

Figure F-1 presents the model fit for the four shock lapse model specifications for four initial premium jump bands by duration in PLT. The dots represent the observed lapse probability, while the full lines illustrate the model predictions.

Figure F-1

LAPSE PROBABILITY BY INITIAL PREMIUM JUMP BAND AND DURATION FOR FOUR SHOCK LAPSE MODEL SPECIFICATIONS



For initial premium jump band 1.01x-4.00x, no major differences can be seen in the fit between the four model specifications. At the lower initial premium jump band, the model without premium information captures the lapse in PLT variations without distortion. In addition, initial premium jump band 1.01x-4.00x represents 78% of the study exposure in PLT (see Table 4-1). Therefore, at an aggregated level, when summarizing the data by duration, the fit was similar for the four models specified.

Differences become apparent at moderate and high premium increases. For initial premium jump bands 4.01x-8.00x and 8.01x-14.00x, the model without jump and payment information does not capture the pattern by duration and underestimates the lapse probability. Premium information is needed to capture the lapse in PLT variations at moderate and high premium jump bands.

At extreme initial premium increase 14.01x+, the model without jump and premium information is still underestimating substantially the lapse probability in PLT. Conversely, the simple model, which only includes the variables initial premium jump and attained age, seems to overestimate the probability of lapse. It illustrates that, for extreme premium increases, the other variables included in the chosen and complicated models, such as risk class or face amount, capture additional variations that cannot be explained by attained age and initial premium jump only.

Finally, the fit resulting from the chosen and complicated shock lapse models are almost identical as their associated full lines are superimposed. This confirms the shock lapse model selection of variables and interactions discussed in section 3.1.3.

Appendix G: Poisson Regression Output for Mortality Deterioration

The main effects included in the final model fitted to Jump to ART data are displayed in Table G-1. For this model, the reference categories of the categorical variables are provided in Table 5-2.

Table G-1

JUMP TO ART PREMIUM STRUCTURE REGRESSION MODEL OUTPUT

Variable	Regression Coefficient	Parameter Estimate	Standard Error	P-value
Intercept	β_0	-0.318	0.102	0.2%
Average mortality deterioration	β_1	0.085	0.010	< 0.1%
Predicted shock lapse probability	β_2	0.009	0.002	< 0.1%
Risk class: Preferred	β_3	0.286	0.060	< 0.1%
Risk class: Super Preferred	β_4	0.620	0.092	< 0.1%
Initial premium jump 4.01x-8.00x	β_5	0.243	0.092	0.8%
Initial premium jump 8.01x+	β_6	0.509	0.123	< 0.1%
Billing type: Bill Sent	β_7	0.460	0.076	< 0.1%
Billing type: Automatic payment changed to Bill Sent	β_8	0.739	0.219	< 0.1%
Premium mode: Quarterly	β_9	0.308	0.092	< 0.1%
Premium mode: Semi-annual and Annual	β_{10}	-0.163	0.082	4.6%

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