Research paper

Accident Benefits Long-Term Disability

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1 Executive summary

Ontario automobile accident benefits (AB) long-term disability (LTD) has received increased attention for setting appropriate case reserves for claims on file. It has been over 20 years since the Canadian Institute of Actuaries (CIA) last published a research paper on the topic of Ontario automobile AB LTD claims. The purpose of this research paper is to provide an actuarially sound approach to valuate AB LTD reserves.

The estimation of individual claim case reserve comprises thoughtful, well-reasoned evaluation of costs of a given claim over time, based on a critical assessment of facts, laws and societal and behavioral issues. In addition to these considerations, this research paper attempts to consider and account for the features, strengths and weaknesses revealed in the Ontario Statutory Accident Benefits Statistical Plan (OSABSP) data, publicly available literature on modelling and the recommendations mentioned in the "Accident Benefits Long-Term Disability Losses"[1] (Christie 1992) and "Ontario Automobile LTD Losses: The OMPP Cliff, and Bill 164"[2] Machtinger and Brown (1994) research papers.

For the purpose of this paper, survival curves represent the relationship between the percentage of claimants that remain disabled as a function of time since first payment (in months) based on claimant counts from the OSABSP data. Over time, claimants are expected to recover or die, or their coverage reaches termination. Consequently, survival curves for a given cohort of claimants are expected to monotonically decrease. However, the empirical survival curves exhibited reversals in curvature, mainly due to recording processes. Survival models in this paper were developed to produce smoother and more stable predictive survival curves.

The final selected survival models were developed using Generalized Linear Models (GLMs) assuming a Poisson distribution with log link function and hinge point(s). In an effort to balance homogeneity and credibility, four separate survival models were built to reflect the settlement patterns for claimants belonging to age groups <= 50 years old. The models differentiate insurer type (e.g., Non-group insurers and Group membership/affinity business), as well as region (e.g., Greater Toronto Area (GTA) and Non-GTA). The fifth survival model reflects the settlement patterns for all claimants older than 50 years old, combining insurer type and region. Table 1 summarizes the final selected survival models. Note that duration is counted in months.

[1] James K. Christie, "Accident Benefits Long-Term Disability Losses", July 1992. Accessed March 11, 2019. www.cia-ica.ca/docs/default-source/1992/9246ed9dc2ca281924e69aebc433e914ce053.pdf.

[2] Jason K. Machtinger and Robert L. Brown, "Ontario Automobile LTD Losses: The OMPP Cliff, and Bill 164", December 1994. Accessed March 11, 2019. www.cia-ica.ca/docs/default-source/1995/9515e.pdf?sfvrsn=0.

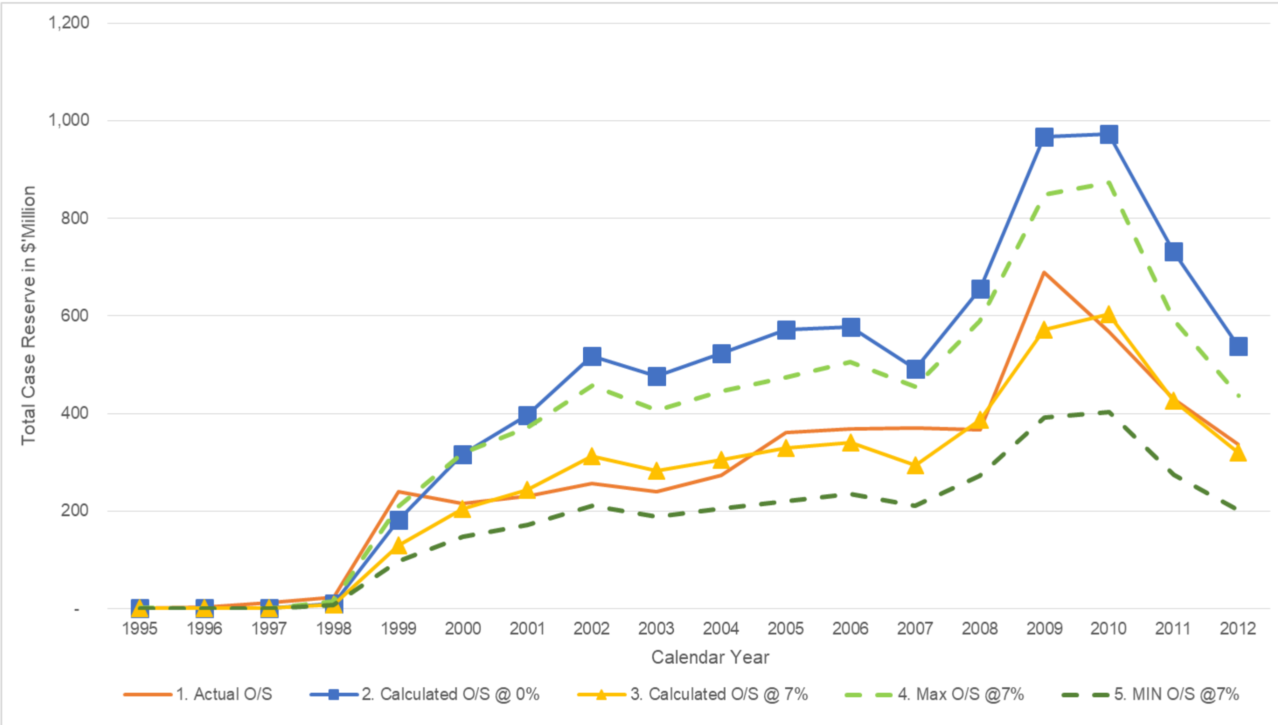
Table 1: Selected Models

Insurer Type	Region	Age Group	Selected GLM
Non-group	GTA	Age <= 50	Variables used: age, gender and duration; Age interaction with duration before duration 14; Age interaction with ln(duration) after duration 14; Hinge points at duration 14 and ln(14)
Non-group	Non-GTA	Age <= 50	Variables used: age, gender and duration; Age interaction with ln(duration) before and after duration 14; Hinge point at duration ln(14)
Group	GTA	Age <= 50	Same as Non-group GTA
Group	Non-GTA	Age <= 50	Same as Non-group Non-GTA
All Insurers Combined	All Regions Combined	Age > 50	Variables used: age and duration; Age interaction with ln(duration) before and after duration 14 and 60; Hinge points at duration ln(14) and ln(60)

In addition to standard goodness-of-fit statistics and graph inspections comparing the selected survival curves vs. actual data, annuity curves were derived. Note that annuity factors were not designed nor intended to set initial case reserves at the time claims are first reported to the insurer. The premise for this decision was that when a given incident is first reported, there is not enough information to determine whether the AB LTD coverage will be triggered. The annuity factors developed in this paper do not encompass the probability that a claim against AB LTD coverage will be initiated or not. Rather, they assume that the AB LTD claim is activated.

As part of the model validation process, the annuity factors were scrutinized for reasonableness, and the sum of fitted annuity factors was compared to the actual case reserves.

Figure 1: Actual vs. Fitted Case Reserves



In the above figure, the orange line 1 with no markers represents the actual AB LTD case reserves as collected from the OSABSP dataset. The blue line 2 with square markers reflects the undiscounted fitted case reserves. The yellow line 3 with triangle marker shows the total fitted case reserves discounted at 7%, which is enclosed within upper (light green line 4) and lower (dark green line 5) bounds reflecting the minimum ($185) and maximum ($400) weekly payments. A 7% discount rate was used to calculate the total case reserve for comparison as it was used in both the Christie (1992) and Machtinger and Brown (1994) research papers. According to the above figure, the fitted case reserves discounted at 7% are well matched to the actual AB LTD case reserves. Note that the actual AB LTD case reserves represent a mix of structured settlements and past tabular annuities, as well as undiscounted case reserves. As the interest environment changes to lower rates, the case reserves are expected to move up.

The adoption of the selected survival models provided in this research paper to establish AB LTD case reserves is expected to affect the provisions for claims incurred but not reported (IBNR) of each insurer to a different degree. The influence of assumptions such as maximum attainable age and treatment of structured settlements is uneven across insurers' claim portfolios. The proposed AB LTD case reserves tend to be slightly more prudent for claim portfolios that have a larger Non-GTA proportion, are in older age groups or have more group business when compared to the proportions underlying the OSABSP dataset.

Moreover, as the proposed survival curves differ significantly from the past survival curves, the rate of build-up and amortization of AB LTD case reserves is expected to change. Consequently, the adoption of the selected survival models to establish AB LTD case reserves may distort an insurer's triangles of incurred losses and the associated loss development factors (LDFs). Thus, additional analyses and adjustments may be required to determine the IBNR post adoption of proposed models.

Further aspects should be considered when adopting the selected AB LTD survival models, such as the requirements stemming from the implementation of International Financial Reporting Standard 17 (IFRS 17). The proposed survival models allow frequent updates to the assumed discount rate underlying the AB LTD case reserves and the ability to project expected future cash flows as needed. Notably, the discount rate used to derive case reserves will have significant impacts for insurers, and it is up to each insurer to pick appropriate discount rates while valuating the AB LTD reserve. As a result, this study provides an opportunity for insurers to reflect the interest rate environment rigorously. In order to incorporate the risk margin under IFRS 17, future studies (exploiting advancement in computing power) could consider stochastic simulations of annuity factors.

The remainder of this research paper describes the methodology, assumptions and parameterization underlying the AB LTD survival models. It discusses key findings and observations, and details the effect of legislative reforms and data transformations on the modelling. Finally, it offers some suggestions for future improvements.

2 Introduction

In September 1992, James K. Christie presented "Accident Benefits Long-Term Disability Losses" (Christie 1992) to the CIA, which provides tabular reserves for AB LTD. In December 1994, the CIA published "Ontario Automobile LTD Losses: The OMPP Cliff, and Bill 164" authored by Jason K. Machtinger and Robert L. Brown (Machtinger and Brown 1994), which produced tabular reserves using three years of actual data from the Ontario Motorist Protection Plan (OMPP) with cliff factors due to legislative changes.

Machtinger and Brown (1994) described the early history of AB LTD as follows:

> Long-term disability (LTD) coverage in Ontario automobile insurance first became available in 1968, as part of the optional Accident Benefits section. This section became compulsory in 1972. The weekly indemnity limit was raised in 1972, and was raised again in 1978, at which level it remained until OMPP came into force on June 22, 1990. Prior to this date, accident benefits were paid on a no-fault basis.

Machtinger and Brown (1994) concluded:

> The models given in this paper can be used for reserving LTD claims under OMPP. Some of the underlying assumptions are subject to modification as seen fit by each individual actuary. At the present time, the models are of limited use for reserving Bill 164 claims, although further studies should definitely be carried out once more data become available.

Since Bill 164 was adopted in 1993, multiple product reforms affecting AB LTD were enacted, namely: Bill 59 in 1996, a Statutory Accident Benefits Schedule (SABS) in 2010 and a revised SABS in 2016.

In addition to changes in legislation, the economic environment has evolved significantly since 1994. One key factor is the interest rate influencing the assumed discount rate used to present value future LTD payments used to set case reserves. For example, the nominal yields to maturity compounded semi-annually for Government of Canada securities with a term of five to 10 years decreased from 8.26% to 1.61% between 1994 and 2017[3].

The Research Council of the CIA issued a request for proposal (RFP) in the spring of 2014 for a research paper updating methodologies and parameters used for establishing case reserves for AB LTD claims. In response to the RFP, this research paper exploits industry data from the OSABSP from its inception in 1995 until 2012 to obtain annuity factors applicable to income replacement, caregiver and non-earner benefits respectively. Permission was received to use data from eight insurers that include 23 independent legal entities.

Funding for this research project is provided by the Research Council of the CIA.

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[3] CIA, "Report on Canadian Economic Statistics 1924–2017", May 2018. Accessed July 10, 2019. www.cia-ica.ca/docs/default-source/members/218067e.pdf (CIA members only).

3 Final Selected Survival Models

As mentioned in Table 1, five models were developed to obtain survival curves. These survival models are segregated into the following three sets:

- Insurer type, which identifies Non-group vs. Group business;
- Region, which segregates GTA and Non-GTA claims; and
- Claimant age, which classifies the claimant by their age at the time of the accident by
    - Claimant age <= 50; and
    - Claimant age > 50.

The survival models also depend on the following three explanatory variables:

- Age_Bin, which classifies the claimant by their age at the time of the accident. The Age_Bins are
    - Age_Bin<=20;
    - Age_Bin21-25;
    - Age_Bin26-30;
    - Age_Bin31-35;
    - Age_Bin36-40;
    - Age_Bin41-45;
    - Age_Bin46-50;
    - Age_Bin51-55;
    - Age_Bin56-60; and
    - Age_Bin>=60.
- Duration, which represents the time elapsed since the first payment date in months; and
- Gender, which identifies the claimant by gender as male (M) or female (F). Note that gender is a statistically significant indicator for the survival models, but it has a minimal impact on the annuity factors for a given combination of insurer type, region and Age_Bin. However, if an insurer assumes a different maximum attainable age (e.g., 120 years) by gender, the annuity factors will show visible differences for each gender. Differences in annuity factors are more prevalent for younger claimants who are expected to receive more future payments.

3.1 Survival Models

This section details the closed-form formula for each survival model. Note that the selected survival models include hinge functions, which are explained in more detail in Section 8.2. The hinge feature[4] allows for the model to change its slope at the hinge points. Different coefficients are used before and after the hinge points.

[4] Mark Goldburd, Anand Khare and Dan Tevet, "Generalized Linear Models For Insurance Rating", 2016. Accessed March 11, 2019. www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

3.1.1 Non-group and Group, GTA Region, Claimant Age <= 50

$$S_{Age\_Bin,duration,gender} = exp(Intercept + \beta_1 X_{Age\_Bin} * \max(0, 14 - duration) + \beta_2 X_{Age\_Bin} + \beta_3 X_{Age\_Bin} * \max(0, \ln(duration) - \ln(14)) + \beta_4 X_{gender} + \beta_5 \max(0, 14 - duration) + \beta_6 \max(0, \ln(duration) - \ln(14)))$$

This formula represents the models for both Non-group and Group insurers, where

$S_{Age\_Bin,duration,gender}$ is the survival rate;

β_1 is the coefficient for Age_Bin * max(0, 14 – duration), which is only triggered when duration ≤14;

β_2 is Age_Bin coefficient, where 36-40 is the base class;

β_3 is the coefficient for Age_Bin * max(ln(duration) – ln(14)), which is only triggered when duration > 14;

β_4 is the coefficient for gender, where male is the base class;

β_5 is the coefficient for max(0, 14 – duration), which is only triggered when duration ≤ 14; and

β_6 is the coefficient for max(0, ln(duration) – ln(14)), which is only triggered when duration > 14.

3.1.2 Non-group and Group, Non-GTA Region, Claimant Age <= 50

$$S_{Age\_Bin,duration,gender} = exp(Intercept + \beta_1 X_{Age\_Bin} * \ln(duration) + \beta_2 X_{Age\_Bin} + \beta_3 X_{Age\_Bin} * \max(0, \ln(duration) - \ln(14)) + \beta_4 X_{gender} + \beta_5 \ln(duration) + \beta_6 \max(0, \ln(duration) - \ln(14)))$$

This formula represents the models for both Non-group and Group insurers, where

$S_{Age\_Bin,duration,gender}$ is the survival rate;

β_1 is the coefficient for Age_Bin * ln(duration);

β_2 is the Age_Bin coefficient, where 36-40 is the base class;

β_3 is the coefficient for Age_Bin * max(0, ln(duration) – ln(14)), which is only triggered when duration > 14;

β_4 is the coefficient for gender, where male is the base class;

β_5 is the coefficient for ln(duration); and

β_6 is the coefficient for max(0, ln(duration) – ln(14)), which is only triggered when duration > 14.

3.1.3 All Insurers and Regions Combined, Claimant Age > 50

$$S_{Age\_Bin,duration,gender,region} = exp(Intercept + \beta_1 X_{Age\_Bin} * \ln(duration) + \beta_2 X_{Age\_Bin} + \beta_3 X_{Age\_Bin} * \max((0, \ln(duration) - \ln(14)) + \beta_4 X_{Age\_Bin} * \max(0, \ln(duration) - \ln(60)) +$$

$\beta_5 \ln(duration) + \beta_6 \max(0, \ln\,(duration) - \ln(14)) + \beta_7 \max(0, \ln\,(duration) - \ln(60)) + \beta_8 X_{region})$

where

$S_{Age\_Bin,duration,gender,region}$ is the survival rate;

β_1 is the coefficient for Age_Bin * ln(duration);

β_2 is the coefficient for Age_Bin, where 36-40 is the base class;

β_3 is the coefficient for Age_Bin * max(0, ln(duration) – ln(14)), which is only triggered when duration > 14;

β_4 is the coefficient for Age_Bin * max(0, ln(duration) – ln(60)), which is only triggered when duration > 60;

β_5 is the coefficient for ln(duration);

β_6 is the coefficient for max(0, ln(duration) – ln(14)), which is only triggered when duration > 14;

β_7 is the coefficient for max(0, ln(duration) – ln(60)), which is only triggered when duration > 60; and

β_8 is the coefficient for region, where GTA is the base class.

As all formulae contain hinge points, users should pay special attention to the transformation of the duration variable when applying the formula.

3.2 Selected Model Coefficients

This section details the coefficients for the selected models. While the tables show coefficients with four digits, it is highly recommended to use the full coefficients set in the adjoining Excel workbook for accuracy.

3.2.1 Non-group and Group, GTA Region, Claimant Age <= 50

	Variable βs	Non-group	Group
	Intercept	-1.9651	-1.6369
β_2	Age_Bin<=20	-0.2722	-0.2910
	Age_Bin21-25	-0.2764	-0.2689
	Age_Bin26-30	-0.0942	-0.0786
	Age_Bin31-35	-0.0507	-0.0596
	Age_Bin36-40 [base]	0.0000	0.0000
	Age_Bin41-45	0.0965	0.0481
	Age_Bin46-50	0.2392	0.2101
β_5	max(0,14 – duration)	0.1451	0.1209
β_6	max(0,ln(duration) – ln(14))	-1.2661	-1.2462
β_4	Gender male [base]	0.0000	0.0000
	Gender female	-0.0314	-0.0116
β_1	Age_Bin<=20 * max(0,14 – duration)	0.0177	0.0164
	Age_Bin21-25 * max(0,14 – duration)	0.0222	0.0160
	Age_Bin26-30 * max(0,14 – duration)	0.0079	0.0039
	Age_Bin31-35 * max(0,14 – duration)	0.0052	0.0030
	Age_Bin36-40 * max(0,14 – duration) [base]	0.0000	0.0000
	Age_Bin41-45 * max(0,14 – duration)	-0.0079	-0.0046
	Age_Bin46-50 * max(0,14 – duration)	-0.0185	-0.0187
β_3	Age_Bin<=20 * max(0,ln(duration) – ln(14))	-0.1124	-0.1349
	Age_Bin21-25 * max(0,ln(duration) – ln(14))	-0.1667	-0.1406
	Age_Bin26-30 * max(0,ln(duration) – ln(14))	-0.1554	-0.2335
	Age_Bin31-35 * max(0,ln(duration) – ln(14))	-0.0798	-0.1889
	Age_Bin36-40 * max(0,ln(duration) – ln(14)) [base]	0.0000	0.0000
	Age_Bin41-45 * max(0,ln(duration) – ln(14))	-0.0300	0.0076
	Age_Bin46-50 * max(0,ln(duration) – ln(14))	0.1263	0.0021

3.2.2 Non-group and Group, Non-GTA Region, for Claimant Age <= 50

	Variable βs	Non-group	Group
	Intercept	0.1487	0.0935
β_2	Age_Bin<=20	-0.0340	-0.0096
	Age_Bin21-25	-0.0004	-0.0148
	Age_Bin26-30	-0.0117	-0.0037
	Age_Bin31-35	-0.0111	-0.0244
	Age_Bin36-40 [base]	0.0000	0.0000
	Age_Bin41-45	-0.0141	0.0060
	Age_Bin46-50	-0.0201	-0.0066
β_5	ln(duration)	-0.5414	-0.4965
β_6	max(0,ln(duration) – ln(14))	-0.4472	-0.5785
β_4	Gender male [base]	0.0000	0.0000
	Gender female	-0.0775	-0.0251
β_1	Age_Bin<=20 * ln(duration)	-0.1777	-0.1818
	Age_Bin21-25 * ln(duration)	-0.1434	-0.1120
	Age_Bin26-30 * ln(duration)	-0.0558	-0.0731
	Age_Bin31-35 * ln(duration)	-0.0261	-0.0356
	Age_Bin36-40 * ln(duration) [base]	0.0000	0.0000
	Age_Bin41-45 * ln(duration)	0.0290	-0.0249
	Age_Bin46-50 * ln(duration)	0.0490	0.0278
β_3	Age_Bin<=20 * max(0,ln(duration) – ln(14))	0.1344	0.3228
	Age_Bin21-25 * max(0,ln(duration) – ln(14))	-0.0006	-0.0982

	Age_Bin26-30 * max(0,ln(duration) – ln(14))	-0.1210	0.1430
	Age_Bin31-35 * max(0,ln(duration) – ln(14))	-0.0651	0.0111
	Age_Bin36-40 * max(0,ln(duration) – ln(14)) [base]	0.0000	0.0000
	Age_Bin41-45 * max(0,ln(duration) – ln(14))	0.0322	0.1552
	Age_Bin46-50 * max(0,ln(duration) – ln(14))	-0.0247	0.0649

3.2.3 All Insurers and Regions Combined, for Claimant Age > 50

	Variable βs	Non-group and Group Combined
	Intercept	0.0566
β_2	Age_Bin51-55 [base]	0.0000
	Age_Bin56-60	-0.0152
	Age_Bin>60	-0.0609
β_5	ln(duration)	-0.5740
β_6	max(0,ln(duration) – ln(14))	-0.4230
β_7	max(0,ln(duration) – ln(60))	-0.3839
β_8	Location GTA [base]	0.0000
	Location Non-GTA	0.2370
β_1	Age_Bin51-55 * ln(duration) [base]	0.0000
	Age_Bin56-40 * ln(duration)	0.0198
	Age_Bin>60 * ln(duration)	0.0793
β_3	Age_Bin51-55 * max(0,ln(duration) – ln(14)) [base]	0.0000
	Age_Bin56-60 * max(0,ln(duration) – ln(14))	-0.0215
	Age_Bin>60 * max(0,ln(duration) – ln(14))	-0.7033
β_4	Age_Bin51-55 * max(0,ln(duration) – ln(60)) [base]	0.0000
	Age_Bin56-60 * max(0,ln(duration) – ln(60))	-0.8379
	Age_Bin>60 * max(0,ln(duration) – ln(60))	-1.1163

The survival rates can be determined for a given combination of model set and explanatory variables. For example, given a Non-group male at Age_Bin31-35 in the GTA region with a duration of 16 months, the corresponding survival rate can be calculated as:

$$Survival\ rate = exp(-1.9651 - 0.0507 - 1.2661 * (ln(16) - ln(14)) - 0.0798 * (ln(16) - ln(14))) = 11.13\%$$

Survival rates for each combination of insurer type, region, gender, age and duration can be calculated using all coefficients provided in the same manner. Note that there are differences between the survival rates obtained from the coefficients listed in the above tables and the survival rates in the adjoining Excel workbook due to rounding.

3.3 Annuity Calculations

After calculating survival rates, annuity factors can be calculated on both an undiscounted and discounted basis. For the discounted basis, a user could apply varying discount rates by duration. The adjoining Excel workbook allows a user to pick a constant force of interest between 0 and 0.2. For example, a constant force of interest c = 0.02 is equivalent to an annual spot rate of r_1 = exp(0.02) - 1 = 2.02%.

In general, the annuity factor represents the sum of all future cash flow given that the claimant has survived to the period being measured. The weekly annuity factor is obtained by multiplying the monthly factor by 4.3333, the approximated number of weekly payments per month. It assumes that each undiscounted weekly cash flow equals 1. The weekly annuity factor corresponds to the multiplier applicable to the weekly payment. The annuity factor formula is described as follows:

$$AnnuityAmount_t = WeeklyPayment * \left(4.3333 * AdjustmentFactor * \frac{\sum_{j=t}^{n} S_j * \left(1 + r_{\frac{(j-t+1)}{12}}\right)^{-(j-t+0.5)/12}}{S_{t-1}}\right) \text{ and}$$

$$AnnuityFactor_t = 4.3333 * AdjustmentFactor * \frac{\sum_{j=t}^{n} S_j * \left(1 + r_{(j-t+1)/12}\right)^{-(j-t+0.5)/12}}{S_{t-1}}$$

where

> $AnnuityAmount_t$ is the annuity amount at duration month t (since first payment) for a claimant of a given gender, age, region and insurer type;
>
> AdjustmentFactor adjusts the weekly payment, varying by coverage and claimant age;
>
> $AnnuityFactor_t$ is the annuity factor at duration month t for a claimant of a given gender, age, region and insurer type;
>
> WeeklyPayment is the weekly payment amount;
>
> S_j is the survival rate at duration month j;
>
> r_j is the annual spot rate at month j used for discounting; and
>
> n =

- (120 – age at accident) * 12 months, if age at accident is before the 65th birthday and assuming that the maximum attained age is 120 years for income replacement benefits and caregiver benefits;
- 48 months if age at accident is after the 65th birthday; and
- 24 months, assuming that the maximum attained age is 120 years for non-earner benefits.

AdjustmentFactor varies by coverage and age. For income replacement, claimants with entitlement before 65 years old and who remain disabled after 65 years old, or if entitlement first arises on or after the 65th birthday, are subject to an adjustment. AdjustmentFactor also varies by year of injury if the entitlement is before 65 years old, which is 0.02 * D, where D is the lesser of 35 and the number of years during which the person qualified for the income replacement benefit. If the entitlement first arises on or after the 65th birthday, the insured person will receive the benefits for no more than 48 months, and AdjustmentFactor will follow the following table:

Table 2 – Adjustment Factors (Entitlement after 65)

Number of months since entitlement arose	AdjustmentFactor
Less than 12 months	1
12 months or more but less than 24 months	0.8
24 months or more but less than 36 months	0.6
36 months or more but less than 48 months	0.3

For both caregiver and non-earner, AdjustmentFactor is 1. More details related to the AdjustmentFactor are specified in Appendix A – Legislative Changes.

The annuity factor assumes a mid-month payment. The discounting process recognizes the time value of money to the beginning of month t.

Both undiscounted and discounted annuity factors for each combination of insurer type, region, gender, age and duration can be obtained in the same manner in the adjoining Excel workbook with discounted annuity factors using a selected force of interest between 0 and 0.2.

In the adjoining Excel workbook, survival probabilities are rounded to 10 digits and annuity factors are rounded to two digits (cents). Instructions for the Excel workbook can be found in the adjoining document, “Excel Workbook Guide.pdf”.

Additional information regarding legislation, data, assumptions and the survival models are provided in the following appendices:

- Appendix A – Legislative Changes;
- Appendix B – Data Validation, Cleansing and Transformation Process; and
- Appendix C – Model Specification and Validation.

4 Future Considerations

Future considerations under this research paper focus on two aspects: data collection and monitoring, and modelling improvements.

The collection of OSABSP data terminated at the end of 2012. A repository of industry data would be desirable to update and refine the AB LTD models. Insurers may consider using their own data to determine their own annuity factors after consideration of credibility.

Disability income exhibits very long payment streams, and data from an individual insurer at longer durations may lack the credibility to produce stable and reliable results. Additionally, individual insurers need to consider the modelling granularity while using their own data. Depending on the volume of data, it may be difficult for individual insurers to reconstruct the analysis at the same granularity level as this research paper.

Assuming that future datasets resemble the OSABSP data layout, additional improvements should be considered. In the current model, only 15 years of data were used, since OSABSP data contain 18 years of transactions. The data used for modelling only included claims with a duration of at least 14 months but no longer than 180 months (15 years) to avoid underestimating the annuity factors. More information is included in Section 6.5.

Additionally, the study is not able to capture any abrupt trend change after 15 years of payments. Furthermore, the data are limited to analyze the legislative changes enacted shortly before the data collection was terminated or after the data collection period. For future study, the data collection should consider longer durations for completeness.

Automobile disability income coverage tends to be the last payer for claimants when there are other benefits available, such as employee benefits. The current model was split by Non-group and Group insurers. It is assumed that most group businesses benefit from these other sources of indemnities. However, for more accuracy it would be better to classify claimants with/without first payer. Future improvements could consider the use of first payer as a category, and thus it needs to be collected within the dataset.

Also, some OSABSP transactions were missing data fields, in particular the specific OSABSP coverage code. This study mapped the Automobile Statistical Plan (ASP) coverage code to OSABSP coverage code, which may not be accurate. Future improvements could incorporate a more consistent coverage code system so that accident benefit transactions can be easily classified.

The severity of the injury (i.e., catastrophic impairment vs. non-cat non-Minor Injury Guideline) is not separately considered in this research paper due to lack of data. In a future study, a synthesized medical code indicator could be used to estimate how long a claimant remains disabled.

Neither occupation nor income are considered in this study, also due to lack of data. Future studies could test the significance of these two categories, especially if the maximum weekly payment increases. In addition, insurers could consider merging their database with external data sources, such as census data, to build a more robust model.

This study excludes data from non-earner coverage due to significant legislative changes in 2016. A future study could separately model non-earner coverage under the new regulation, which may result in different survival rates than the ones currently approximated.

The annuity factors in this research paper were derived from fitted survival curves using survival models. With advancements in computing power, a future study could incorporate stochastic modelling to estimate the risk margin associated with these annuity factors to comply with IFRS 17 requirements.

5 Appendix A – Legislative Changes

Many product reforms were enacted since the OMPP, affecting the AB LTD coverage. The main product reforms affecting AB LTD coverage features were:

- Minimum and maximum weekly benefit amounts;
- Percentage of gross or net income;
- Elimination period;
- Revisionary period[5]; and
- Eligibility requirements.

Christie (1992) and Machtinger and Brown (1994) presented tabular factors for disability-income-related claims, but neither discussed coverage of caregiver and non-earner benefits, which are also identified as disability income benefits.

This section discusses the AB LTD coverage in detail.

5.1 Income Replacement Benefits

Income replacement benefits compensate individuals who were either employed or self-employed at the time of accident and suffered substantial inability to return to their own occupation within 104 weeks of an accident, or suffered complete inability to perform any occupation 104 weeks after an accident. The following table summarizes reform changes in the past 20 years:

Table 3: Income Replacement Benefits

Reforms	Weekly Benefit Calculation	Elimination Period	Revisionary Period	Requirements for Eligibility
Bill 68 **(OMPP)** **1990–1993**	80% gross income Min: $185 Max: $600 Optional coverage: maximum benefit may be $750, $900 or $1,050 per week	1 week	156 weeks (3 years)	Suffered inability to perform their own occupation within 156 weeks; inability to perform any occupation to which they are suitable by education, training or experience after 156 weeks
Bill 164 **1993–1996**	90% net income Min: $185	1 week	104 weeks (2 years)	Suffered inability to perform their own occupation within 104 weeks; inability to

[5] Revisionary period: within and after the period, the requirements for eligibility of disability changed.

Reforms	Weekly Benefit Calculation	Elimination Period	Revisionary Period	Requirements for Eligibility
	Max: $1,000			perform any occupation to which they are suitable by education, training or experience after 104 weeks
Bill 59 **1996–2009**	80% net income Min: $185 Max: $400 Adjustment at 65 2% * min(35, 65 - attained age) Accident >= 65 Maximum 208 weeks (4 years) subject to weekly payment adjustment < 52 weeks: 1 >= 52 and < 104: 0.8 >= 104 and < 156: 0.6 >=156 and < 208: 0.3	1 week	104 weeks (2 years)	Same as Bill 164
SABS **2010 to now**	70% gross income Min: $185 Max: $400 Same adjustments as Bill 59	1 week	104 weeks (2 years)	Same as Bill 164

Income replacement benefits were the most frequent transactions within the OSABSP data related to disability income coverage. Legislation indicated a minimum payment of $185/week and a maximum of $400/week for all years included in the OSABSP dataset except for 1995. From 1996 to 2010, the average annual after-tax income in Ontario increased from $27,300 to $36,000 for unattached individuals[6], while the increase was even higher for individuals with families. Therefore, although the calculation of weekly benefits changed over time, it is expected that the majority of claimants received the maximum weekly payment of $400.

5.2 Caregiver Benefits

Caregiver benefits compensate primary caregivers who provided full-time care to dependants and can no longer do so as the result of a car accident. They reimburse the expense of hiring someone else to provide that care. Eligibility has changed over time, as summarized in the table below:

Table 4: Caregiver Benefits

Reforms	Weekly Benefit	Elimination Period	Revisionary Period	Requirements for Eligibility
Bill 68 (OMPP) 1990–1993	$185 for caregiver $50 for each additional person in need of care Optional coverage: $100 per week for each person requiring care	N/A	156 weeks (3 years)	Over 16 years old; disability must commence within 2 years of accident; must be a primary caregiver and have only income from self-employment from work in the home
Bill 164 1993–1996	$250 for the first person in need of care, $50 each additional dependant, if applicable	N/A	104 weeks (2 years)	Suffered inability to carry on caregiving activities within 104 weeks; inability to carry on normal life after 104 weeks. Available for both minor injury and catastrophic impairment
Bill 59 1996–2009	$250 for the first person in need of care, $50 each additional	N/A	104 weeks (2 years)	Same as Bill 164

[6] Data are from Statistics Canada table 202-0603. Accessed November 22, 2019. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1110016701.

Reforms	Weekly Benefit	Elimination Period	Revisionary Period	Requirements for Eligibility
SABS 2010 to now	Same as Bill 59	N/A	104 weeks (2 years)	Same as Bill 164, but only available for catastrophic impairment

Caregiver benefits represent the second largest proportion of disability-income-related transactions. Notably, investigation of the OSABSP data revealed that weekly payments for caregiver benefits did not change much over the years. However, eligibility requirements became stricter from limiting covered losses. Since the enactment of the SABS, only catastrophic impairment caregiver benefits were covered. Consequently, the amount of aggregate caregiver benefits decreased.

5.3 Non-earner Benefits

These benefits compensate individuals who have suffered the inability to carry out a normal life under the following conditions:

- Are not qualified for income replacement;
- Are full-time students; or
- Completed education less than one year before the accident.

The definition of non-earner benefits changed over time. Under Bill 68, there were no specific classes of non-earners, while under Bill 164, non-earner benefits separated coverage for students, loss of earning capacity and other disability benefits. Under Bill 59 and the SABS, non-earner benefits updated the coverage for students, which provided an increase in benefits two years after the accident, for insurable incidents prior to June 2016. The eligibility and elimination period have also changed over the last 20 years, as summarized in the following table:

Table 5: Non-earner Benefits

Reforms	Weekly Benefit	Elimination Period	Revisionary Period	Requirements for Eligibility
Bill 68 1990–1993	$185 less any income that person is entitled to receive under an income continuation plan or under any sick leave plan	N/A	156 weeks (3 years)	Over 16 years old; disability commences within 2 years of accident; must have no entitlement to receive any benefit under the income benefit provision
Bill 164	Education disability:	N/A	104 weeks	Education: payable after age 16 if you are a full-time

Reforms	Weekly Benefit	Elimination Period	Revisionary Period	Requirements for Eligibility
1993–1996	Weekly: 50% of net Ontario average weekly earning Lump sum: provide a lump-sum payment for each of school year missed, if you are unable to attend or successfully complete one or more school years Other disability: $185/week Loss of earning capacity: replacement for all other benefits based on pre- and post-accident earning capacity[7] after 2 years		(2 years)	student and unable to continue your education, or are unable to carry on a normal life Other disability: if you suffer a partial or complete inability to lead a normal life and you do not qualify for any other weekly benefits
Bill 59 **1996–2009**	$185 within first 104 weeks; $320 after, if student	26 weeks	104 weeks (2 years)	Suffer complete inability to carry normal life if: – Not qualified for income replacement; – Full-time student after 16 years old; or – Less than one year since completion of education

[7] This benefit kicks in if you continue to qualify for weekly benefits more than 104 weeks after you first became disabled. It replaces income replacement benefits, weekly caregiver benefits, weekly education benefits, or other disability benefits, and is based on the difference between pre- and post-accident earning capacity.

Reforms	Weekly Benefit	Elimination Period	Revisionary Period	Requirements for Eligibility
SABS **2010 to May 2016**	Same as Bill 59	26 weeks	104 weeks (2 years)	Same as Bill 59
SABS[8] **June 2016 to now**	$185 only for first 104 weeks	4 weeks	N/A	Suffer complete inability to carry normal life if: – Not qualified for income replacement; – Full-time student after 18 years old; or – Less than one year since completion of education

Non-earner benefits represent 9% of disability-income-transactions-related claims within OSABSP, which includes student benefits and other non-earner benefits. For other non-earner benefits, the minimum weekly payment is the same as income replacement ($185). However, the elimination period decreased from 26 weeks to four weeks after June 2016, a contrast with a one-week elimination period for income replacement, but this did not affect the period of this study. The weekly payment was the same for student benefits within the first two years. However, if the claimant suffered complete inability after two years and was eligible for student benefits, weekly benefit increased from $185/week to $320/week. Starting from June 2016, the weekly benefit was $185/week for all non-earner benefits, and all payments terminated after two years regardless of the inability status. Although the elimination period decreased to four weeks, this reform eventually shortened the payment period of non-earner benefits for future emerging claims.

5.4 How Legislative Changes Were Considered

As mentioned previously, caregiver and non-earner benefits comprised 21% of the OSABSP transactions related to disability income, with income replacement being the balance. Thus, the survival curves based on actual data for caregiver and non-earner benefits were less reliable and had more volatility than income replacement, which were considered in the final model. The final model combined caregiver and income replacement for modelling, while non-earner benefits transactions are excluded due to significant legislative changes.

[8] Regulation O. Reg. 251/15, s. 4 (3) is in place to revoke part of non-earner benefits coverage from the SABS.

For this research paper, no attempt was made to adjust the data to reflect the most current legislative and eligibility requirements. The survival rates and annuity factors are insensitive to changes in weekly benefit amounts because weekly benefit is a scalar of the annuity factor. Additionally the survival rates and annuity factors would not be materially affected whether weekly benefit amounts are gross or net of income taxes.

However, the final model was adapted to reflect changes in the coverage period limit for non-earner benefits by capping the payment period to two years. Also, annuity factors for income replacement were adjusted for claimants who reach 65 years old and for claimants who had an accident after 65 years old.

6 Appendix B – Data Validation, Cleansing and Transformation Process

6.1 Description of Data

This research paper and survival models are based on OSABSP data from January 1, 1995 to December 31, 2012. Thus, the data collected contained 18 years of transactional records at the claimant level. At the beginning of this study, sample OSABSP data from four representative insurers were tested for suitability and ultimately the feasibility of expanding the data to include more insurers. The option of a data call was also evaluated as an alternative data source. It was not pursued since the OSABSP appeared sufficiently reliable and suitable for the purpose of this research. Furthermore a data call would have incurred additional uncertainty about data quality, as well as higher costs in collection, validation and cleansing.

After the feasibility study, permissions were obtained from individual insurers to use OSABSP data from 23 legal entities consolidated into eight groups of insurers, representing 65.3% of the property and casualty (P&C) industry direct written premiums as of December 2012[9]. There were over 45 million transactional records available for determining the survival models.

We used Alteryx[10] for data validation and cleansing, and RStudio[11] for modelling. All resulting survival rates and annuity factors are also provided within the Excel file "CIA_AB_LTD_2019_Tables.xlsm", along with documentation and instructions on how to use the workbook.

As individual risk may behave differently compared to affinity groups, this study separated insurers into these two model indicators. Insurers that only underwrite individuals are referred as "Non-group" insurers, while those that underwrite affinity groups are referred as "Group" insurers. Within the 23 legal entities, 14 entities were classified as Non-group insurers, and nine as group insurers.

6.2 Data Validation Process

Data validation steps were conducted for the OSABSP data to test for consistency and field availability. Specifically, the consistency of information for each claimant was tested including gender, age and accident date. Validation procedures were also performed on specific fields to test their suitability for:

- Separating coverages;
- Calculating duration; and
- Identifying weekly payments, etc.

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[9] From www.msaresearch.com/. Accessed March 8, 2019.

[10] Alteryx is a multi-functional data transformation software that is designed in a drag-and-drop workflow manner to minimize programming required. Visit: www.alteryx.com for more information. Accessed November 22, 2019.

[11] RStudio is a comprehensive data analyzing platform based on R that is capable of curve fitting, distribution fit, machine learning and simulations, etc. Visit: www.rstudio.com/ for more details. Accessed November 22, 2019.

Particularly, the OSABSP dataset contained 76 data fields. Validation was done for 32 selected fields based on the relevance of each variable to this study as listed in the following table.

Table 6 - OSABSP Data Structure

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
Submission Type	Indicator for original submission and revised submission	No	Not relevant for this study since no duplicate transactions
Company Number	Company identification code	Yes	Used to differentiate transactions of different companies
Entry Date	Date when transaction date is entered in the system	Yes	Used to validate accident date
Stat Plan	Code for OSABSP	No	All transactions are under the same plan
Transaction Kind	Indicate paid or outstanding transactions	Yes	Used to split paid and outstanding record
Submission Number	Numbers represent partial submissions	No	Not relevant for this study
Record Type	Indicate the record type	No	Not relevant for this study
Transaction Type	Indicator for indemnity/expense/unpaid claims	No	Transaction kind is sufficient enough to select paid vs. outstanding
Claimant Number	Unique claimant number under each claim	Yes	Used as a component to separate claimants under the same claim
Claim Identification	Unique claims number	Yes	Used to identify claims
Policy Effective Date	Date when policy was issued or last renewed	No	Analysis is based on accident date
Type of Business	Indicate if it is individually rated/fleets/miscellaneous	Yes	Use to validate data availability

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
Type of User	Indicate if it is private passenger/commercial/others	Yes	This study only analyzes private passenger vehicles
Driving Record	Drivers or non-owned policy	No	Not relevant for this study
Vehicle Location	Special territory code as defined in ASP	Yes	Used to identify the geographical region
Vehicle Code	Code that indicates the vehicle model	No	Not relevant for this study
Model Year	Model year associated with the vehicle	No	Not relevant for this study
Claimant Residence Location	First three digits of claimant's postal code	Yes	After cross-validation with the vehicle location, it proves vehicle location is useful for this analysis
Gender	Indicate claimant's gender	Yes	Used to separate different genders of claimants
Year of Birth	Claimant's year of birth	Yes	Used to calculate claimant's age when the accident happened
Number of Dependants	Number of persons principally dependent on the claimant for financial support or care at the time of the accident	Yes	Used to validate claimant information. For example, it is not reasonable for a 16-year-old to have three dependants
Marital Status	Marital status at the accident	Yes	Used to validate claimant's marital status
Claimant Status	Indicate claimant status when accident happened	Yes	Used to verify if one claimant is getting the correct coverage

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
	(employed/unemployed/student, etc.)		
Occupation	Indicate the claimant's occupation when the accident happened	Yes	Used to validate occupation
Gross Income	Indicate the claimant's gross income from employment at the time of accident	Yes	Used to estimate % of claimants who received maximum weekly payments
Accident Date	Indicate accident date	Yes	Used to calculate attained age
Type of Injury_1	Indicate type of injuries	No	Not relevant for this study
Type of Injury_2	Same as above	No	Not relevant for this study
Type of Injury 3	Same as above	No	Not relevant for this study
Type of Injury_4	Same as above	No	Not relevant for this study
Type of Injury_5	Same as above	No	Not relevant for this study
Degree of Fault	Degree of fault for each claimant	No	Not relevant for this study
Nature of Involvement	Indicate the nature of involvement of this claimant (driver/passenger/pedestrian, etc.)	No	Not relevant for this study
Date of Onset of Disability for Weekly Indemnity	Indicate the date of commencement of claimant's disability. Only applicable for specific OSABSP code relating to weekly indemnity payments	Yes	Used to validate accident date
Date of Termination of Disability for Weekly Indemnity	Indicate the date when the disability is considered to end	Yes	Used to validate last payment date

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
Reason for Termination of Weekly Indemnity Payments	Explain the reason why the weekly payments have been terminated	No	Only required for entries before January 1, 2003, so it is not useful for this study
Collateral Source	Indicate existing source of income	No	Not relevant for this study
Workers' Compensation	Indicate claimant's eligible for Workers' Compensation	No	Not relevant for this study
Legal Representation	Indicate if one claimant is represented by legal counsel	No	Not relevant for this study
Benefits Jurisdiction	Indicate jurisdiction under which the benefits have been determined	No	Not relevant for this study
Loss Transfer	Indicate whether a loss transfer is applicable	Yes	This study only included the entries without loss transfer
ASP Coverage	ASP coverage as defined under ASP	No	Not relevant for this study
ASP Kind of Loss	ASP kind of loss, indicating if it is related to weekly indemnity	Yes	Used together with OSABSP Kind of Loss Primary
OSABSP Kind of Loss Primary	OSABSP code that indicates the kind of loss (this is only required for indemnity payments)	Yes	Used together with ASP code to identify transactions related to weekly indemnity
OSABSP Kind of Loss Secondary	OSABSP secondary code associated with corresponding primary code	No	Not available for most of the transactions
Designated Assessment Centre	Referred to assessment centre	No	Not relevant for this study
Average Weekly Indemnity	Indicate the weekly indemnity for each claimant if granted	Yes	Used as an indicator for weekly payment amount

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
Claim Status	Indicate claim status: open/close/reopen	Yes	Used to validate claim status
Claim Status Date	Data when the current claim status became effective	No	Not relevant for this study
Transaction Amount	Indicate the transaction amount of that record with sign	Yes	Used as transaction amount
Processing Date	When the business transaction is created and processed	Yes	Used to identify when each payment is processed to calculate duration
Sequence Number	A sequential number assigned by the insurer to identify to Insurance Bureau of Canada (IBC)	Yes	Used to filter latest transaction for each claimant
Policy Identification	Policy identification as used on the premium record	No	Not at the level of granularity the study requires
Type of Injury Latent Effect 1	A latent effect injury is a condition that manifests itself after initial diagnosis during the progression of a claimant's claim	No	Not relevant for this study
Type of Injury Latent Effect 2	Same as above	No	Not relevant for this study
Type of Injury Latent Effect 3	Same as above	No	Not relevant for this study
Optional Benefits – Income Replacement Benefits	Indicating if a claimant is selecting optional weekly benefits under income replacement coverage	Yes	Use to analyze composition of optional coverage
Optional Benefits – Death and Funeral Benefits	Indicating if a claimant is selecting optional weekly benefits under death and funeral coverage	No	Not relevant for this study
Optional Benefits – Medical, Rehabilitation and	Indicating if a claimant is selecting optional weekly benefits under medical,	No	Not relevant for this study

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
Attendant Care Benefits	rehabilitation and attendant care coverage		
Optional Benefits – Caregiver and Dependant Care Benefits	Indicating if a claimant is selecting optional weekly benefits under caregiver and dependant care coverage	Yes	Use to analyze composition of optional coverage
Optional Benefits – Indexation Benefit	Indicating if claimants choose to index their benefits	Yes	Use to analyze composition of optional coverage
Optional Benefits – Other Optional Accident Benefits	Indicating if claimants choose other optional benefits	No	Not relevant for this study
Retiree Discount	Discount applied to basic coverage	No	Lack of data
ICD-10-CA Injury Codes 1	Injury code for accident that happened after January 2004	No	Lack of data
ICD-10-CA Injury Codes 2	Same as above	No	Lack of data
ICD-10-CA Injury Codes 3	Same as above	No	Lack of data
ICD-10-CA Injury Codes 4	Same as above	No	Lack of data
ICD-10-CA Injury Codes 5	Same as above	No	Lack of data
ICD-10-CA Injury Codes 6	Same as above	No	Lack of data
ICD-10-CA Injury Codes 7	Same as above	No	Lack of data
ICD-10-CA Injury Codes 8	Same as above	No	Lack of data
ICD-10-CA Injury Codes 9	Same as above	No	Lack of data

Output Field	Description	Select for Data Validation	Reason for Selection/Drop
ICD-10-CA Injury Codes 10	Same as above	No	Lack of data
Catastrophic Impairment Indicator	Indicate if claimants have catastrophic impairment or not	Yes	This analysis focuses on non-catastrophic impairments
Collateral Source Offset Indicator – Income Replacement	Enter the code to identify whether the Loss Amount has been reduced by a collateral source providing income replacement benefits	No	Not relevant for this study
Collateral Source Offset Indicator – Extended Health Care	Enter the code to identify whether the Loss Amount has been reduced by a collateral source providing extended health care benefits	No	Not relevant for this study

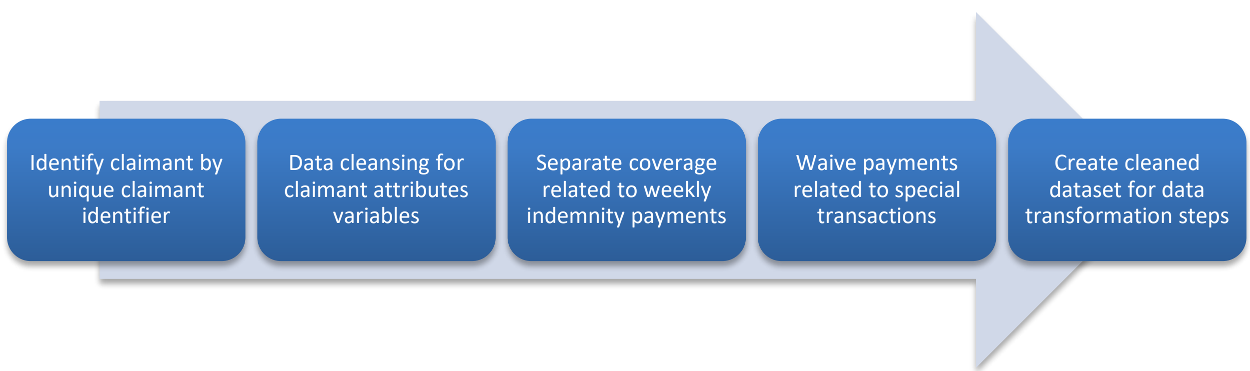
Variables on which validation tests were performed are categorized into the following types:

- Identification variables – variables identifying insurers, unique claims and claimants (e.g., company number, claim identification, claimant number);
- Transactional variables – variables identifying the order of transactions (e.g., processing date, sequence number);
- Claimant attribute variables – variables related to each claimant, which should be consistent over time (e.g., gender, year of birth, accident date, gross income);
- Coverage variables – variables identifying the coverage for which a payment was made (e.g., ASP Kind of Loss, OSABSP Kind of Loss Primary);
- Indicator variables – variables indicating certain special transactions (e.g., optional coverage indicator, loss transfer, catastrophic indicator); and
- Numerical variables – variables indicating the transactional amount.

The data validation process uncovered inconsistencies, such as a change in gender or year of birth and missing data such as OSABSP Kind of Loss Primary. Thus, a data cleansing process was carried out to create a more consistent and complete dataset at the claimant level for this study.

6.3 Data Cleansing Process

In general, the data validation process identified which variables were suitable for this study. Observed inconsistencies of certain fields indicated the need for data cleansing procedures. To better understand the OSABSP dataset and make it useful for the purposes of this study, data cleansing procedures were performed in Alteryx. The following flow chart shows the rationale behind the data cleansing process:



During the data validation process, assumptions were made due to the inconsistency or scarcity of the data under certain fields. The following key assumptions were used as the basis for data cleansing:

- To create a unique claimant identifier, the combination of the fields “company number”, “claim identification” and “claimant number” were used. However, this identifier string could not address the situation when insurers re-use the claim identification for different claims, or when insurers change the claim identification for existing claims if they are converted to a new claim administration system. It is difficult to identify such situations.

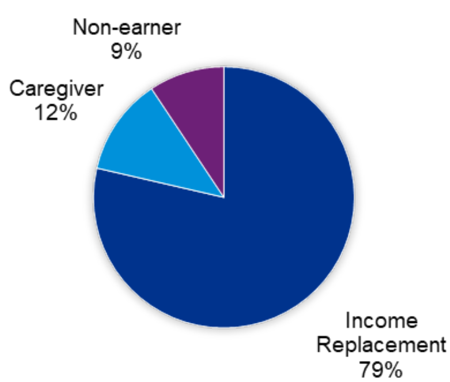
- Claimant gender, year of birth, accident date and vehicle location were considered as claimant attribute variables, which should not change during the life of the claim. However, changes in gender, year of birth and locations were observed. From an insurer's perspective, this may be due to a correction made as more information becomes available. Therefore, information from the most current transaction was taken as the most up-to-date claimant attribute information.

- As this study only analyzes LTD income transactions (i.e., income replacement, caregiver and non-earner benefits), coverage variables within the dataset (described in Section 6.1) were used to identify these coverages. Ideally, the field "OSABSP Kind of Loss Primary" should be used as it defines the coverage for LTD at a more granular level. However, around 30% of paid transactions were missing this field. "ASP Kind of Loss" was used as a complement for selecting coverages. Thus, income replacement, caregiver and non-earner benefits were categorized based on these two fields. Furthermore, as there was no specific code directly identifying non-earner benefits, they were identified using a combination of multiple fields indicating the kind of loss code relevant to non-earner benefits such as student benefits and loss of earning capacity.
- This study only analyzed non-catastrophic transactions and excluded loss transfers.
- Based on the OSABSP dataset, less than 1% of claimants chose to purchase optional income replacement coverage, and no claimant purchased indexation of benefits. Thus, this study only analyzed claimants that chose the base coverage without indexation.

Overall, within the OSABSP dataset, 46.6% of the transactions were attributed to changes in case reserves and 53.4% were paid transactions; 1.7% of the paid transactions were eliminated, and 11.6% of the transactions were cleansed. Only paid transactions were used in this analysis.

The following figure shows the composition of each coverage by transaction percentage. Income replacement had the largest amount of transactions among three coverages. Given the data volume, the resulting survival curves for income replacement would be more stable and reliable when compared to caregiver and non-earner. Conversely, the combined data for caregiver and non-earner benefits comprised 21% of transactions for all three coverages. Consequently, survival curves purely based on caregiver or non-earner benefits would be more volatile and less credible; hence, we combined caregiver with income replacement and excluded non-earner.

Figure 2: Distribution of Benefit Type



In addition, the following figures illustrate the attribute distribution for the three coverages combined in terms of insurers' type, gender, region and Age_Bin, respectively:

Figure 3: Distribution of Insurer Type

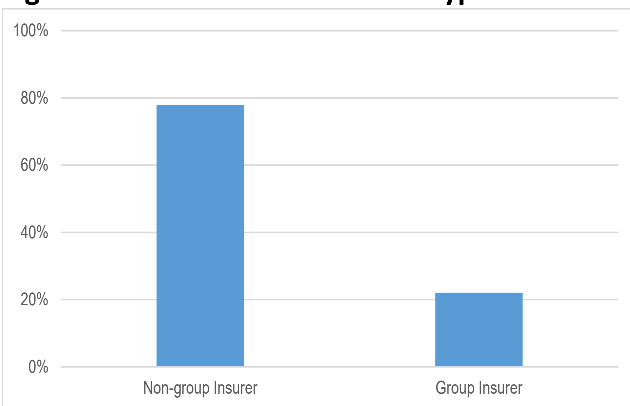


Figure 4: Distribution of Gender

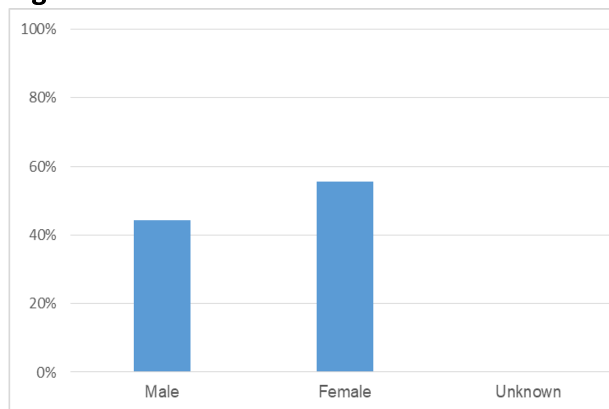


Figure 5: Distribution of Geographical Location

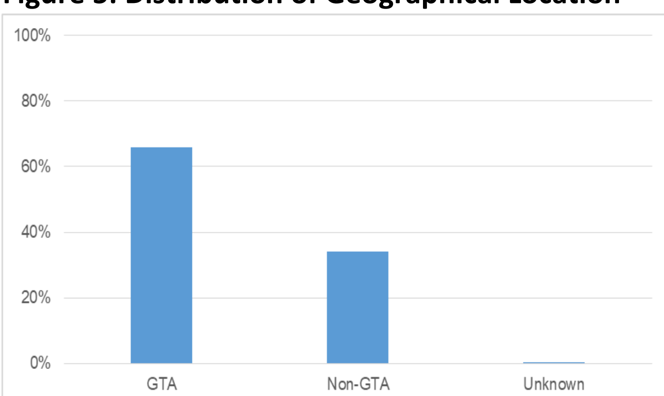
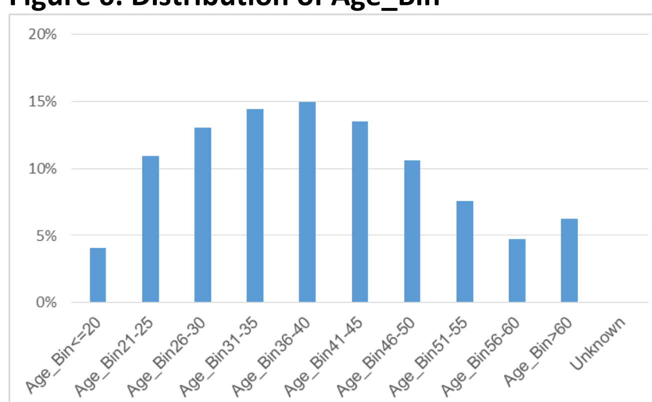


Figure 6: Distribution of Age_Bin



After the data cleansing process, there were still some data idiosyncrasies that led to abnormal trends in the survival curves. The data transformation process was designed to deal with these anomalies.

6.4 Data Transformation Process

The data transformation process was designed to smooth the weekly payments so that abnormally large single payments were transformed to regular weekly payments. This process also determined the starting point for weekly payments. This section describes the circumstances and rationale for the data transformation.

6.4.1 First Payment Date

The final survival curves vary by duration; the time in months since the inception of the claim. The starting point of a claim is crucial for modelling survival rates. Three important dates along a claimant's timeline were monitored:

Accident date: the time when the accident happened

Disability onset date: when the claimant becomes disabled, and onset of the coverage

First processing date: when the first transaction was processed for a specific claimant

In theory, a claimant proceeded through the above dates in chronological order, subject to specific regulations. The onset date and first processing date could coincide with each other. The inclusion of an elimination period for income replacement prevented the accident date being the date of first payment, and thus the actual starting duration point for a claim. Consequently, the survival model did not use accident date to calculate duration. Ideally, the onset date would be the starting point for a claim as weekly payments start after onset. However, half of the transactions were missing an onset date. Moreover, records with an onset date appeared to have that date recorded as being seven days after the accident date. In many instances, claimants have not yet reported the claim, or the coverage has not yet been triggered. Based on interviews with the insurers who provided data for this study, claimants may not report an LTD claim right after the injury. Some claimants may return to work for a few months then declare themselves incapacitated to the insurers, cease work and claim income replacement benefits. Thus, the first processing date reflects the delay between accident date and the actual start date, which is approximately two to three months. As a result, the onset date is not an accurate estimation for the claim starting date. Therefore, the first processing date was selected for duration as it appears the date was an actual input and was determined to be the representative of the most accurate estimate of the claim starting point from the available fields.

6.4.2 Catch-up Process

The data field "Date of Onset of Disability for Weekly Indemnity" was the commencement date of a claimant's disability benefit. Theoretically this date should be highly correlated with the start date of weekly payments. Based on the regulations described in Appendix A – Legislative Changes, the elimination period is one week for income replacement and 26 weeks for non-earner benefits (before June 2016), with no waiting period for caregiver benefits. Therefore, the onset date could be used as a proxy to confirm whether the first payment occurs at the indicated starting date. However, half of the paid transactions were missing the onset date, reinforcing the need to use the first payment date.

From the comparison between the theoretical start date and actual first payment date (i.e., first processing date), there were observed instances of two- or three-month differences between the two dates. With these discrepancies, the transaction amounts tended to aggregate the missing weekly payments. For example, a claimant with income replacement benefits received the first benefit four months after the accident date, with an amount of $2,400. Thus, this claimant qualified for income replacement benefits 10 weeks from the accident date, receiving a lump sum of six weeks of $400 weekly benefits. Table 7 illustrates the catch-up payment process.

Table 7: Catch-up Illustration

Duration since Accident (in Weeks)	0	…	10	11	12	13	14	15	16
Catch-up payment									2,400
Disaggregation				400	400	400	400	400	400

From the observed data, the length of delays mostly ranged from two to six months. However, from a cash flow perspective, these aggregate payments were supposed to be paid on a weekly basis. Therefore, a "catch-up" process was designed to disaggregate the lump-sum payment retrospectively (i.e., to fill in the time gap between date X and date Y based on the weekly payment).

As a consequence of the catch-up process, if the catch-up payment was the first transaction for a claimant, it changed the date of the first payment. Therefore, the first payment date was revised after the catch-up process, as indicated.

6.4.3 Expansion Process

The OSABSP dataset also contained some single large paid transaction amounts as the last transaction of a claim. From the insurers' perspective, there are two reasons to explain such payments:

- Insurers purchased structured settlements to close claims;
- Insurers purchased one-time long-term care insurance from a life insurer to compensate the claimant.

Thus, large settlements would shorten the complete stream of benefit payments. For the purpose of this study, survival curves were created assuming that weekly indemnity payments were paid instead of structured settlements.

To resolve the issue of lump-sum cash flows, a lump-sum expansion process was designed to expand these large settlements prospectively. Note that some large settlements may have also included compensation for coverages other than AB LTD, such as medical rehabilitation. The OSABSP dataset included a number of large settlements that, once converted to streams of weekly payments, would result in a claimant surviving to an unreasonable attained age. Given that weekly payments could not continue to such durations, it was assumed that each claimant could live up to a maximum of 120 years. As the expansion process was sensitive to any assumed discount rate, the 10-year government bond rate effective at the settlement date was used to reflect time value of money[12]. Any residual amounts left after the lump-sum expansion process were allocated to the beginning of the expansion period. Figure 7 shows the distribution of large settlements by size. Although most settlement amounts were under $100,000, they tended to distort the survival curve more than the corresponding counts by increasing the length of payment.

Figure 7: Large Settlement Distribution by Size

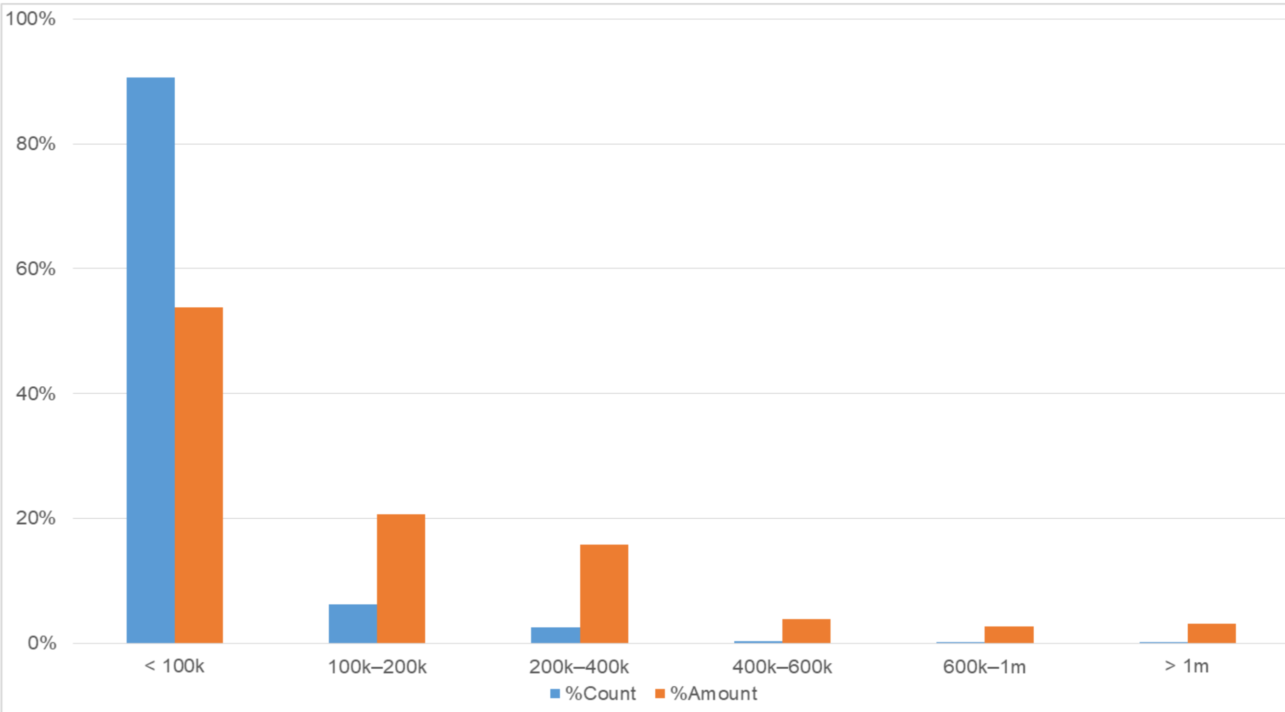
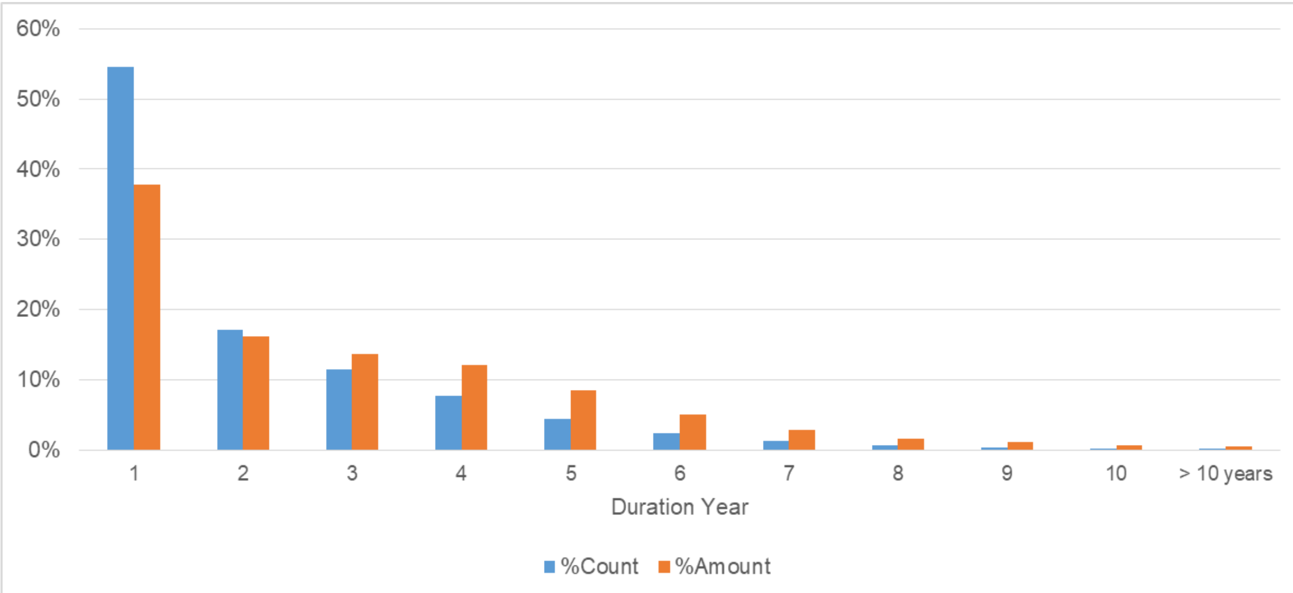


Figure 8 shows the large settlement distribution by duration in years. The majority of large settlements were paid within the first seven years. This could imply that insurers that were made aware of severe claims tended to act quickly to close claims with large settlements.

[12] CIA, "Report on Canadian Economic Statistics 1924-2017: Final Release – Tables", May 2018. Accessed March 11, 2019. www.cia-ica.ca/publications/publication-details/218067t#results. (CIA members only)

Figure 8: Large Settlement Distribution by Duration



The OSABSP dataset presented instances of large positive payments followed by negative payments of the same amount. Based on interviews with insurers, this was due to reversal of incorrect transactions. Thus, both payments were excluded from the analysis.

6.4.4 Weekly Payments

For both the catch-up and lump-sum expansion processes, it was important to select corresponding weekly payments for each claimant to ensure an appropriate expansion period.

For income replacement coverage, the weekly payments were between $185 and $400 for accidents between 1996 and 2012. Hence, weekly payments were selected based on an average of each transaction and the time between transactions for each claimant.

For caregiver benefits, the minimum weekly payment was always $250, with an incremental $50 per additional person in need of care. In theory, the regulation does not specify an upper bound. For this study, the maximum weekly payment was capped at $1,000, which means the caregiver had 15 people in need of care. This cap should be sufficient to cover most of the cases. Weekly payments were selected based on an average of each transaction and the time between transactions for each claimant.

For non-earner benefits, the regular benefit should always be $185, while student benefits could increase to $320 after two years. Considering the “OSABSP Kind of Loss Primary” did not have a specific code for non-earner benefits, and the kind of loss selected could possibly include income replacement benefits, the same logic is applied.

6.5 Duration Constraints

As the OSABSP data included 18 years of data in total (1995–2012), they contained claims with various durations. For example, a claim could happen in 2012 and only have a few months of transaction, while another claim could be opened back in 2000 and have 12 years of transactions. As a result, if all data were analyzed at once, the incomplete short-duration claims increase the number of claim counts at early duration that still may have been open when OSABSP terminated, thus censoring the tail of the payments by duration. To avoid this distortion, data used for modelling only included claims with a duration of at least 14 months but no longer than 180 months (15 years). By doing this, the impact from recent open claims decreased, and the survival curve kept a monotonically decreasing tail from 15 years duration onward. As mentioned before, most of the structured settlements payments were paid within the first seven years, and the impact from structured settlements and the lump-sum expansion process have also been captured.

The following table illustrates the structure of OSABSP data graphically. For example, a claim incurred in 2012 can only have a maximum duration since first payment of 12 months. Thus, data used for modelling only included claims transactions before October 31, 2011. On the other hand, data used for this study have a maximum duration of 180 months (15 years) to avoid fluctuations at the tail due to unusual transactions. As a result, the cells highlighted in green represent data used for modelling, and cells highlighted in gray are excluded data.

Table 8: Data Included Based on Duration Constraints

	Calendar Year							
Monthly Duration	1995	1996	1997	…	2010	10/31/2011	11/1/2011	2012
1*								
2*								
…								
13*								
14								
15								
…								
179								
180								
181								
…								

* Monthly durations 1–13 were included only when claims lasted more than 14 months.

In addition, the data used for modelling include three types of claims:

- Claims closed within 15 years;
- Claims that had payments that were expanded to 15 years; and
- Claims still open at 15 years.

For the first two types of claims, it is assumed that the survival rate curve after 15 years remains the same. In the survival model, the third type of claim did not modify the survival rates, but rather assumed that the historical survival pattern from other types of claims at the same maturity applied to the open claims. Insurers should be cautious while using the model described in this paper if there are a significant amount of claims lasting 15 years or more.

A GLM assumes a linear relationship between the explanatory and response variable. Duration (an explanatory variable) tends to be more right-skewed than the survival rate (the response variable), which implies a non-linear relationship. To improve model fit, duration was sometimes transformed using the log function. More details are provided in Section 7.4.

7 Appendix C – Model Specification and Validation

7.1 Review of Relevant Literature

Prior to modelling the survival curves, relevant literature was reviewed. This section summarizes key points from the main research papers.

Christie (1992) and Machtinger and Brown (1994) provided an aid for actuaries to evaluate tabular case reserves for AB LTD claims ensuing after the introduction of the OMPP in 1990 and Bill 164 in 1993. Both research papers included termination rate and annuity factor tables that were valuable to actuaries, claim adjusters and others working for P&C insurers.

Christie presented termination rate tables based on age, gender and duration since claim inception. In addition, a hypothetical interest rate and termination Provision for Adverse Deviation factor were considered when constructing the corresponding annuity table. However, due to a lack of data representing the disability experience under Canadian AB coverage, Christie used the termination rates derived in “Report of the Committee to Recommend New Disability Tables for Valuation” from the 1985 Transactions of the Society of Actuaries (TSA (1985)), which was modified to reflect the regulatory requirements in Ontario. As Christie’s paper used experience from life insurers, it also discussed concerns stemming from the use of TSA (1985) data when modelling Ontario disability income coverage.

Machtinger and Brown advanced the termination rates developed in Christie (1992). This paper had drawbacks as well due to the lack of publicly available data as well as conservative termination rates compared to insurers’ actual experience. The research paper further developed termination rates and annuity factors using OMPP LTD claims based on data from accident years 1990 through 1993. The dataset represented 10% of the Ontario automobile market, as most insurers did not capture their data at the claimant level. Machtinger and Brown (1994) modelled termination rates using statistical distributions, as well as further measuring a three-year cliff representing Bill 164 experience due to a change in definition of disability. Due to a lack of data with longer durations, Machtinger and Brown suggested the use of Christie (1992) for annuity factors greater than three years.

In 2012, the Individual Disability Experience Committee (IDEC) of the Society of Actuaries (SOA) published “Development of the 2012 IDEC Claim Termination Rate Table”, which used industry data from 1990–2007 to update the termination table developed in TSA (1985). The analysis is based on an actual vs. expected method with Whittaker–Henderson Type B smoothing technique. The Whittaker–Henderson Type B smoothing technique uses multi-degree polynomials to model termination rates, with the objective to balance smoothness and fitness of the termination curve.

Table 9 summarizes the explanatory variables and main model considerations from these research papers. These aspects informed the models selected in this research paper.

Table 9: Summary of Past Literature

TSA 1985 Vol. 37: Report of the Committee to Recommend New Disability Tables for Valuation (Length: 154 pages)	Accident Benefits Long-Term Disability Losses (1992) from J.K. Christie (Length: 29 pages)	Ontario Automobile LTD Losses: The OMPP Cliff, and Bill 164 (1994) from J.K. Machtinger and R.L. Brown (Length: 19 pages)	Development of the 2012 IDEC Claim Termination Rate Table (Length: 17 pages)
Coverage: disability income Analyze by claim counts Used TSA data from life insurers	Coverage: disability income Analyze by claim counts Used termination rate from TSA (1985)	Coverage: disability income Analyze by claim counts Used OMPP 3-year data	Coverage: disability income Analyze at actual vs. expected Used industry data from 1990–2007
Explanatory variables: gender, age, cause, elimination period, class	Explanatory variables: gender, age	Explanatory variables: none; introduced cliff factor Model 3-year termination rate using statistical model	Explanatory variables: same as TSA (1985)
Termination Rate Duration: 1–13 by week, 4–24 by month, 3–10 by year, and over 10 years	Termination Rate Duration: same as TSA (1985)	Termination Rate Duration: first 37 30-day intervals, after used Christie (1992)'s factor	Termination Rate Duration: 1–13 by week, 4–60 by month, 6–10 by year, and over 10 years

7.2 Considerations Underlying the Selection of GLM Modelling

When selecting the GLM family of models, the following aspects were considered:

- Account for interdependencies between explanatory variables;
- Account for distributional biases in explanatory variables;
- Minimize distortions from data outliers;
- Estimate survival rates for combinations of explanatory variables with few or no data;
- Estimate survival rates for tail durations;
- Optimize goodness of fit; and
- Minimize complexities.

Multiple models were tested at the claimant level with both claimant count (frequency) and transactional payments (severity). Several rounds of modelling were done for different combinations of explanatory variables. Eventually, final models were selected from the GLM family assuming Poisson distribution with log link function and hinge points, as they responded well to the above criteria.

7.3 Selection of Model Indicators and Explanatory Variables

Various criteria were considered to assess whether to retain model sets and explanatory variables, such as:

- Practical considerations, including historical use of explanatory variables, accuracy of data entries, cost of collecting the data;

- Differentiation criterion; and
- Balance of homogeneity and credibility criteria.

The differentiation criterion is fulfilled when the value for a given explanatory variable demonstrates significant statistical difference in the survival rate response. Statistical tests such as Kolmogorov–Smirnov[13] and graphs were used to assess the differentiation criterion. With regard to credibility, a standard of 481 was selected for claimant counts at the most granular combination of explanatory variables. This credibility is represented for P = 90% and k = 7.5%; that is, it has 90% chance of being within ±7.5% of the mean assuming that normal approximation applies.

According to these criteria,

- The data for Non-group and Group claims are sufficiently credible and show significantly different actual survival rates, thus justifying the segregation of insurer types;
- The data for GTA and Non-GTA are sufficiently credible and show significantly different actual survival rates, thus justifying segregation of region;
- The data for Urban Non-GTA and Rural regions are not sufficiently credible to justify such segregation;
- The gender and age groups were carried over from Christie (1992). The data confirmed sufficient differentiation and credibility;
- The data for income replacement and caregiver benefits did not show significantly different actual survival rates to justify segregation; and
- The coverage specifics for non-earner benefits are significantly different from income replacement and caregiver benefits, and justify segregation. The empirical survival curve for non-earner coverage does not reflect the actual behavior for claimants under the new SABS 2016 regulation due to changes in the benefits. The survival curve for non-earner benefits is extrapolated from the survival model for income replacement and caregiver combined by capping payment length to two years.

The results from the first iteration of GLM testing show poorer fits for claimant age > 50. The bucketing of explanatory variables was revisited for the second iteration and a separate model was developed for claimant age greater than 50 years with all insurers combined.

7.4 Response Variable

Both payment frequency and severity were considered as potential candidates for a response variable. The final model was based solely on frequency, which allowed the evaluation of the probability of claimants remaining disabled (a.k.a., survival rate). Frequency is calculated as the ratio of number of claimants with payment at a given duration (i.e., claim counts) to total claimants

[13] The Kolmogorov–Smirnov test (K–S test or KS test) belongs to the family of non-parametric goodness-of-fit tests. It allows comparison between two samples (two-sample K–S test), or a sample with a continuous distribution (one-sample K–S test).

at the time of first payment (i.e., exposures). To use a GLM, the OSABSP dataset needed to reflect exposures. Since the dataset only contained transactions with payments, dummy zeros were added to the dataset to reflect the exposures.

As mentioned previously, the OSABSP data used for modelling include three types of claims:

- Claims closed within 15 years;
- Claims that had payments that were expanded to 15 years; and
- Claims still open at 15 years.

For the first two types of claims, it is assumed that the survival rate curve after 15 years remained the same. In the final selected model, the third type of claims do not have any modification of the survival rate but rather assumed the historical survival pattern from other types of claims at the same maturity applied to the open claims. Table 10 illustrates the three types of claims. In order to compute survival probabilities, claim counts only include 1, while exposure counts include 1 and 0 but exclude blanks.

Table 10: Claim and Exposure Counts

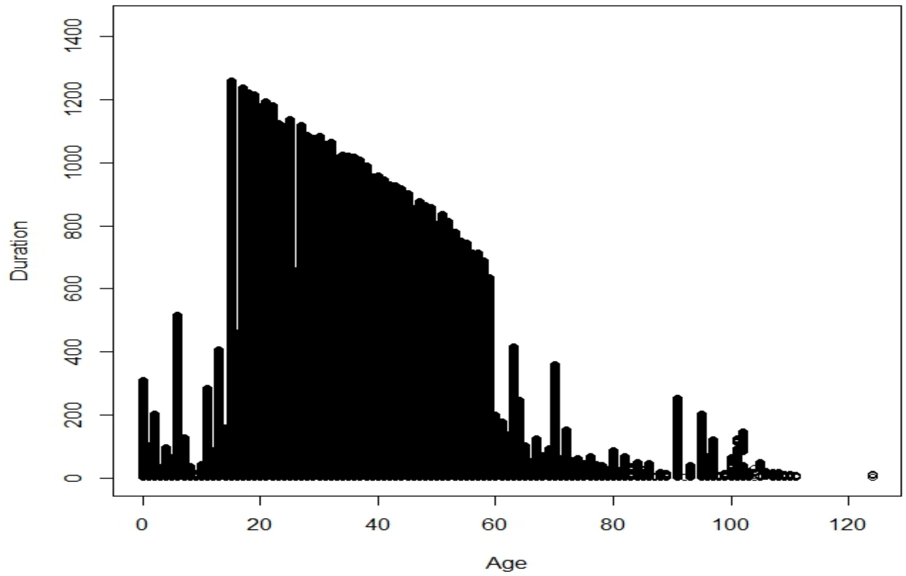
	2011	2012	2013	2014	2015
Expansion	1	1	1	1	1
Closed	1	1	0	0	0
Open	1	1	Blank	Blank	Blank

To model severity, the distributions of existing claimants' weekly payments were analyzed. The OSABSP dataset showed that the majority of weekly payments reach the $400 maximum cap. Additionally, over 40% of the total payments consisted of structured settlements. As a result, severity did not provide additional information regarding claimant behavior that was not already captured by frequency. If future legislative reforms increase the $400 maximum cap, a severity model should be explored.

7.5 Interactions

When determining the best GLM model, interactions between variables were examined. Intuitively, claimant age interacts with duration in terms of length of future payments. For example, an injured 20-year-old is not expected to receive the same length of payment as a 60-year-old similarly injured. The interaction of claimant age and duration may be exacerbated with large structured settlements. Figure 9 shows the relationship between age and duration after the lump-sum expansion of large structured settlements assuming a maximum attainable age of 120 years old.

Figure 9: Duration vs. Age



In the above figure, younger claimants tend to receive payments for longer periods than older claimants. Hence, this interaction term was considered in the model.

7.6 Hinge Points

When examining the survival rate curve, a different curvature was observed before and after 14 months. This behavior could not be modelled effectively with a single equation of explanatory variables. Two approaches were tested to resolve the issue:

- Two-piece model (i.e., use two GLMs for one curve); and
- Hinge function.

The two-piece model is detailed in Section 8.1. It was ultimately not retained as it introduced a discontinuity point from duration 14 to duration 15. The fitted survival rate at duration 14 was lower than the fitted survival rate at duration 15, implying a negative termination rate. In addition to being theoretically incorrect, it distorted the build-up and amortization of the annuity factors.

Instead of the two-piece model, the final selected models incorporate a hinge function. By creating a hinge point, the GLM was able to fit two separate curves to the data, before and after the hinge point, while still obtaining an overall continuous and monotonically decreasing survival rate curve. Furthermore, the hinge function allowed for the transformation of explanatory variables, which improved fits for the tail.

7.7 Criteria for Model Selection and Validation

To select the final model, statistical tests and graph examinations were performed.

7.7.1 Statistical Tests

To validate whether explanatory variables should be retained in the model, p-values were reviewed. A p-value less than 5% was considered to have predictive power. This section details the resulting p-value for retained explanatory variables.

7.7.1.1 Non-group and Group, GTA Region, Claimant Age <= 50

Variable βs	Non-group	Group
Intercept	2.00E-16	2.00E-16
Age_Bin<=20	2.00E-16	2.00E-16
Age_Bin21-25	2.00E-16	2.00E-16
Age_Bin26-30	2.00E-16	0.000002
Age_Bin31-35	0.000001	0.000109
Age_Bin36-40 [base]		
Age_Bin41-45	2.00E-16	0.001896
Age_Bin46-50	2.00E-16	2.00E-16
max(0,14 – duration)	2.00E-16	2.00E-16
max(0,ln(duration)-ln(14))	2.00E-16	2.00E-16
Gender male [base]		
Gender female	2.00E-16	8.90E-03
Age_Bin<=20*max(0,14 –duration)	2.00E-16	1.59E-09
Age_Bin21-25*max(0,14 –duration)	2.00E-16	2.68E-13
Age_Bin26-30*max(0,14 –duration)	1.89E-10	4.16E-02
Age_Bin31-35*max(0,14 –duration)	0.000014	0.097281
Age_Bin36-40*max(0,14 –duration) [base]		
Age_Bin41-45*max(0,14 –duration)	2.62E-11	1.15E-02
Age_Bin46-50*max(0,14 –duration)	2.00E-16	2.00E-16
Age_Bin<=20*max(0,ln(duration)-ln(14))	2.00E-16	7.96E-12
Age_Bin21-25*max(0,ln(duration)-ln(14))	2.00E-16	2.00E-16
Age_Bin26-30*max(0,ln(duration)-ln(14))	2.00E-16	2.00E-16
Age_Bin31-35*max(0,ln(duration)-ln(14))	2.00E-16	2.00E-16
Age_Bin36-40*max(0,ln(duration)-ln(14)) [base]		
Age_Bin41-45*max(0,ln(duration)-ln(14))	0.000347	0.532135
Age_Bin46-50*max(0,ln(duration)-ln(14))	2.00E-16	8.73E-01

7.7.1.2 Non-group and Group, Non-GTA Region, Claimant Age <= 50

Variable βs	Non-group	Group
Intercept	2.00E-16	0.000054
Age_Bin<=20	0.049800	0.801000

Variable βs	Non-group	Group
Age_Bin21-25	0.978825	0.671782
Age_Bin26-30	0.409062	0.911630
Age_Bin31-35	0.429492	0.445781
Age_Bin36-40 [base]		
Age_Bin41-45	0.316328	0.854641
Age_Bin46-50	0.174723	0.850271
ln(duration)	2.00E-16	2.00E-16
max(0,ln(duration)-ln(14))	2.00E-16	2.00E-16
Gender male [base]		
Gender female	2.00E-16	0.000028
Age_Bin<=20*ln(duration)	2.00E-16	2.00E-16
Age_Bin21-25*ln(duration)	2.00E-16	6.18E-10
Age_Bin26-30*ln(duration)	2.31E-14	1.84E-05
Age_Bin31-35*ln(duration)	0.000275	0.027804
Age_Bin36-40*ln(duration) [base]		
Age_Bin41-45*ln(duration)	4.02E-05	0.131000
Age_Bin46-50*ln(duration)	4.09E-11	0.113000
Age_Bin<=20*max(0,ln(duration)-ln(14))	6.49E-16	2.00E-16
Age_Bin21-25*max(0,ln(duration)-ln(14))	0.967000	0.003190
Age_Bin26-30*max(0,ln(duration)-ln(14))	2.00E-16	1.45E-06
Age_Bin31-35*max(0,ln(duration)-ln(14))	1.98E-07	0.694000

Variable βs	Non-group	Group
Age_Bin36-40*max(0,ln(duration)-ln(14)) [base]		
Age_Bin41-45*max(0,ln(duration)-ln(14))	0.007235	3.98E-08
Age_Bin46-50*max(0,ln(duration)-ln(14))	0.049900	0.029900

7.7.1.3 All Insurers and Regions Combined, Claimant Age > 50

Variable βs	Non-group and Group Combined
Intercept	7.90E-15
Age_Bin51-55 [base]	
Age_Bin56-60	0.187000
Age_Bin>60	3.30E-07
ln(duration)	2.00E-16
max(0,ln(duration)-ln(14))	2.00E-16
max(0, ln(duration) – log (60))	2.00E-16
Location GTA [base]	
Location Non-GTA	2.00E-16
Age_Bin51-55*ln(duration) [base]	
Age_Bin56-40*ln(duration)	0.001340
Age_Bin>60*ln(duration)	2.00E-16
Age_Bin51-55*max(0,ln(duration)-ln(14)) [base]	
Age_Bin56-60*max(0,ln(duration)-ln(14))	0.146000
Age_Bin>60*max(0,ln(duration)-ln(14))	2.00E-16

7.7.2 Global Statistics

To compare the overall significance between GLM iterations, statistics such as Akaike Information Criterion (AIC) and deviance were examined. Similar tests were used to assess model performance on the training and hold-out datasets. Low AIC and deviance were preferred.

Models	Training Dataset	
	AIC	Deviance
Non-group, GTA, Age <= 50	2,853,215	1,810,861
Non-group, Non-GTA, Age <= 50	2,704,998	1,761,984
Group, GTA, Age <= 50	1,121,503	709,577
Group, Non-GTA, Age <= 50	516,827	336,015
All Insurers, All Regions, Age > 50	1,641,130	1,029,342

The above table summarizes AIC and deviance for all selected models. As they are the smallest values among all models tested, they point toward the best fits. More statistics regarding other models are listed in Section 8.2.

7.7.3 Single Lift Charts

The single lift chart is a good indicator to assess the fit between the training data and the selected model. It also indicates whether the selected model is appropriate for the hold-out data. Note that for each model, training data contains 70% of the transactions, while hold-out data includes the remaining 30% of transactions. The following figures show the single lift charts for both training data and hold-out data.

The training graph shows the estimated average survival rates using the training data and the selected model coefficients. The dashed red line represents the selected survival model, and the actual (raw) average survival rates based on the training data are represented by black dots.

The hold-out graph shows the estimated average survival rates using the hold-out data and the selected model coefficients. The dashed blue line represents the selected survival model, and the actual (raw) average survival rates based on the hold-out data are represented by black dots.

As shown on the x-axis in the following figures, the respective datasets are bucketed in 10 bands using the ascending ordered magnitude of the fitted survival rates. The y-axis indicates the average survival rates in each band.

Figure 10: Non-group, GTA, Claimant Age <= 50 Training Data

Figure 11: Non-group, GTA, Claimant Age <= 50 Hold-out Data

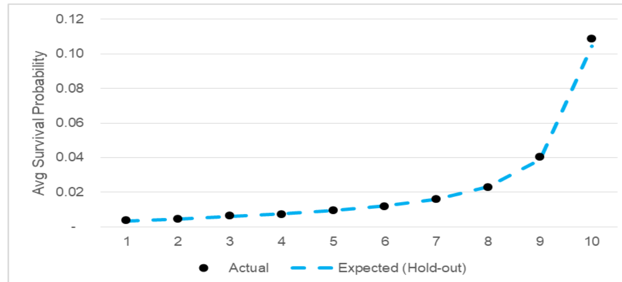


Figure 12: Non-group, Non-GTA, Claimant Age <= 50 Training Data

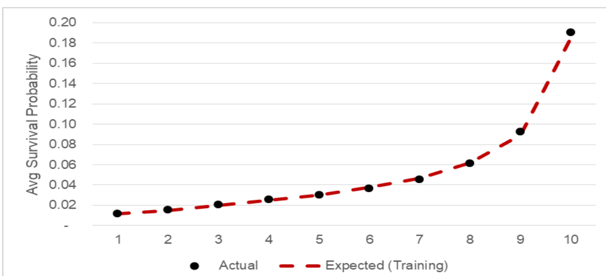


Figure 13: Non-group, Non-GTA, Claimant Age <= 50 Hold-out Data

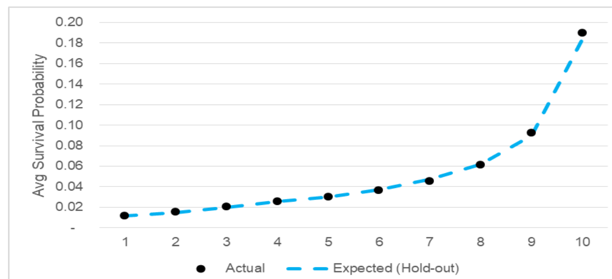


Figure 14: Group, GTA, Claimant Age <= 50 Training Data

Figure 15: Group, GTA, Claimant Age <= 50 Hold-out Data

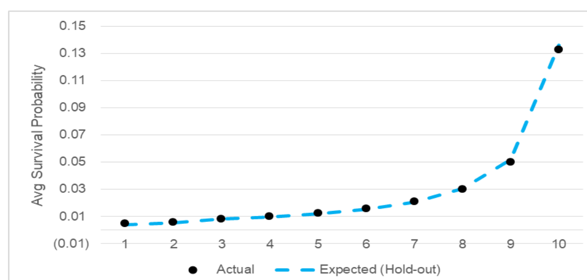


Figure 16: Group, Non-GTA, Claimant Age <= 50 Training Data

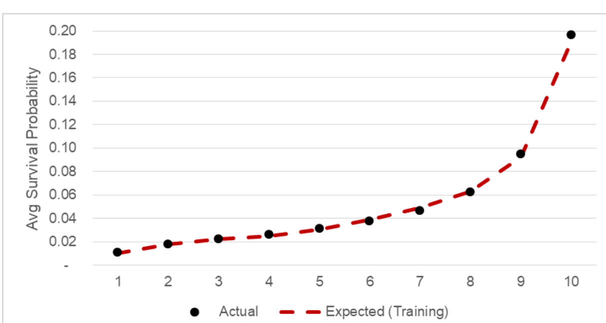


Figure 17: Group, Non-GTA, Claimant Age <= 50 Hold-out Data

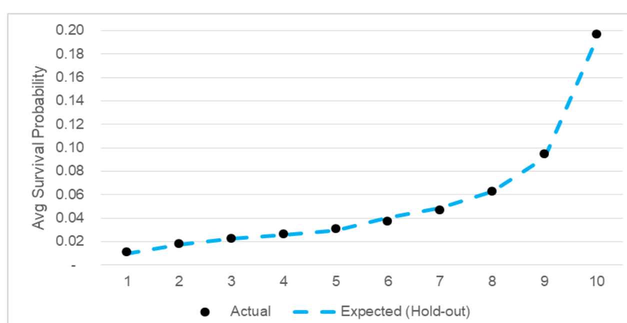


Figure 18: All Insurers, All Regions, Claimant Age > 50 Training Data

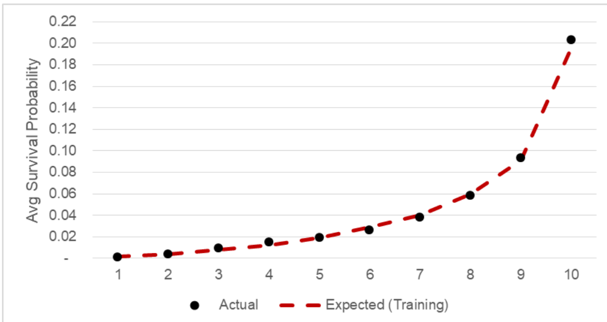
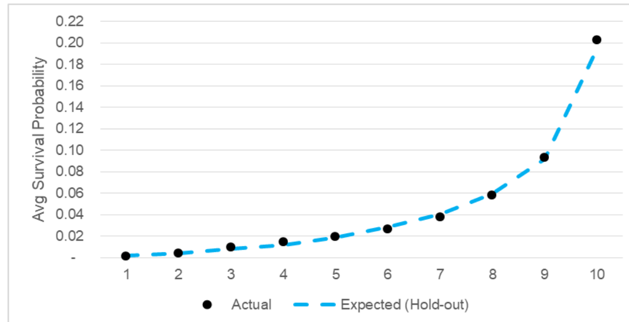


Figure 19: All Insurers, All Regions, Claimant Age > 50 Hold-out Data



As observed from the above charts, the expected survival curves mimic the behaviour of the actual survival rates for both training and hold-out datasets. It indicates that the selected model is appropriate for each dataset given the insurer's type, region and age.

7.7.4 Heat Maps

To balance both credibility and homogeneity, multiple heat maps were created to analyze the distribution of explanatory variables used to decide on the granularity of the model and which variables to group together. The following figure provides an example of a heat map used to determine the final model:

Figure 20: Heat Map Distribution

	Non-group Insurers				Group Insurers			
Age_Bins	GTA M	Non-GTA M	GTA F	Non-GTA F	GTA M	Non-GTA M	GTA F	Non-GTA F
Age_Bin<=20	0.85%	0.67%	0.80%	0.80%	0.31%	0.14%	0.34%	0.18%
Age_Bin21-25	2.68%	1.36%	2.78%	1.86%	0.76%	0.23%	0.88%	0.37%
Age_Bin26-30	2.96%	1.46%	3.54%	2.19%	0.93%	0.25%	1.29%	0.43%
Age_Bin31-35	3.17%	1.52%	3.93%	2.21%	1.11%	0.27%	1.65%	0.53%
Age_Bin36-40	3.30%	1.57%	4.11%	2.48%	1.14%	0.24%	1.61%	0.50%
Age_Bin41-45	3.06%	1.47%	3.70%	2.21%	1.04%	0.25%	1.31%	0.45%
Age_Bin46-50	2.52%	1.25%	2.82%	1.82%	0.74%	0.21%	0.91%	0.34%
Age_Bin51-55	1.84%	0.93%	1.89%	1.40%	0.48%	0.17%	0.60%	0.24%
Age_Bin56-60	1.17%	0.66%	1.08%	0.87%	0.31%	0.10%	0.35%	0.16%
Age_Bin>60	1.71%	0.99%	1.29%	0.99%	0.46%	0.16%	0.44%	0.19%

In Figure 20, each probability represents the percentage of total claimants in a particular category. The color scheme is from dark red to dark green, which represents a low to high percentage. This heat map illustrates that claimants of Non-group insurers are almost triple the size of claimants of Group insurers. This heat map indicates that the models relying on Non-group insurers' data are more credible than those relying on Group insurers'. Also, both types of insurers had more claimants located in the GTA region than the Non-GTA. Furthermore, data was scarce for both insurer types over 50 years old in the Non-GTA region. As a result, the final selected model combined all insurer types and regions to model older claimants.

In addition, heat maps were used to identify overestimation and underestimation of the annuity factors derived from the raw data (i.e., raw annuity factors). Figure 21 shows the expected over raw annuity factors derived from OSABSP data at duration 60 months since first payment. This heat map shows that underestimation is slightly more likely to occur for young females in the GTA Region of Non-group insurers. Conversely, there appears to be a slight overestimation of annuity factors for male claimants between the age of 51 and 60 in the Non-GTA region of Group insurers. As the estimation of annuity factors shows good fit on the overall training dataset, an individual insurer should pay particular attention when using annuity factors derived in this study if their book of business is significantly different from the OSABSP data. That is, if an insurer writes a larger distribution of younger people, it is likely that the case reserve derived using the annuity factors from this study will be understated and would require proportionally more IBNR than an insurer with a more even age distribution.

Figure 21: Expected vs. Raw Annuity Factors at Duration 60 Months

	Non-group Insurers				Group Insurers			
Age_Bins	GTA M	Non-GTA M	GTA F	Non-GTA F	GTA M	Non-GTA M	GTA F	Non-GTA F
Age_Bin<=20	1.062	0.976	0.652	0.747	0.792	0.554	1.595	1.390
Age_Bin21-25	0.733	0.759	0.536	1.257	1.016	0.795	1.181	0.691
Age_Bin26-30	1.256	0.894	0.688	1.513	0.835	1.314	1.183	1.278
Age_Bin31-35	0.792	1.034	1.208	1.156	0.933	1.140	0.981	1.738
Age_Bin36-40	0.990	1.375	1.203	1.328	0.790	1.098	0.742	1.830
Age_Bin41-45	1.082	1.436	1.201	1.639	1.312	0.956	1.299	1.303
Age_Bin46-50	1.137	1.623	1.531	1.889	1.685	1.696	1.824	1.550
Age_Bin51-55	1.564	1.699	2.087	1.523	1.862	2.644	1.727	2.231
Age_Bin56-60	2.031	1.849	1.661	2.730	2.686	3.340	1.969	2.392
Age_Bin>60	1.044	0.797	0.962	0.755	1.759	0.496	0.632	1.216

7.7.5 Survival Graphs

Visual inspections of survival rate curves were performed to inform the selection of final models. This section compares the actual and fitted survival rate curves.

Figure 22: Non-group, GTA

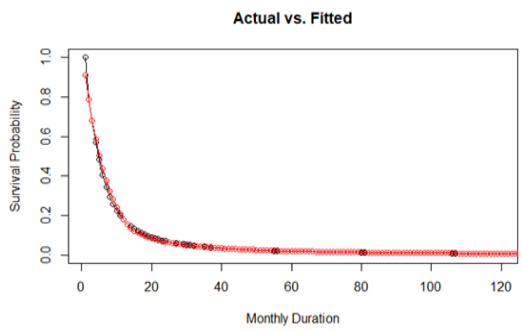


Figure 23: Non-group, Non-GTA

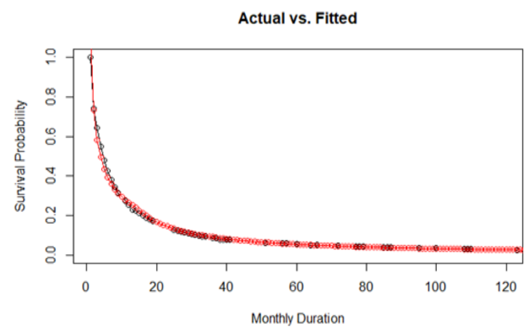


Figure 24: Group, GTA

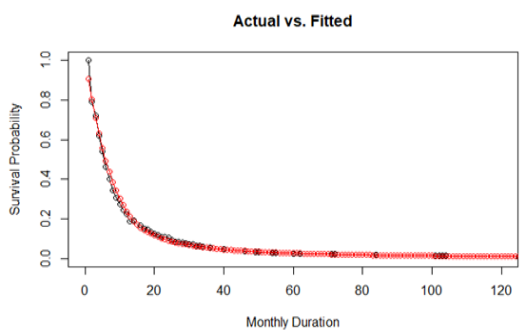
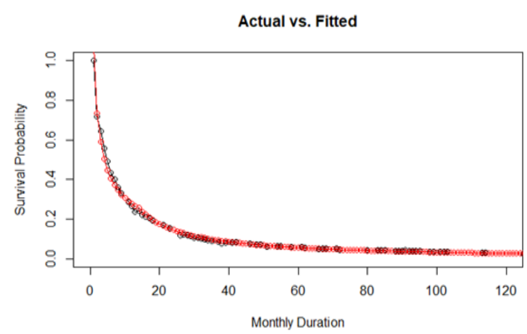


Figure 25: Group, Non-GTA

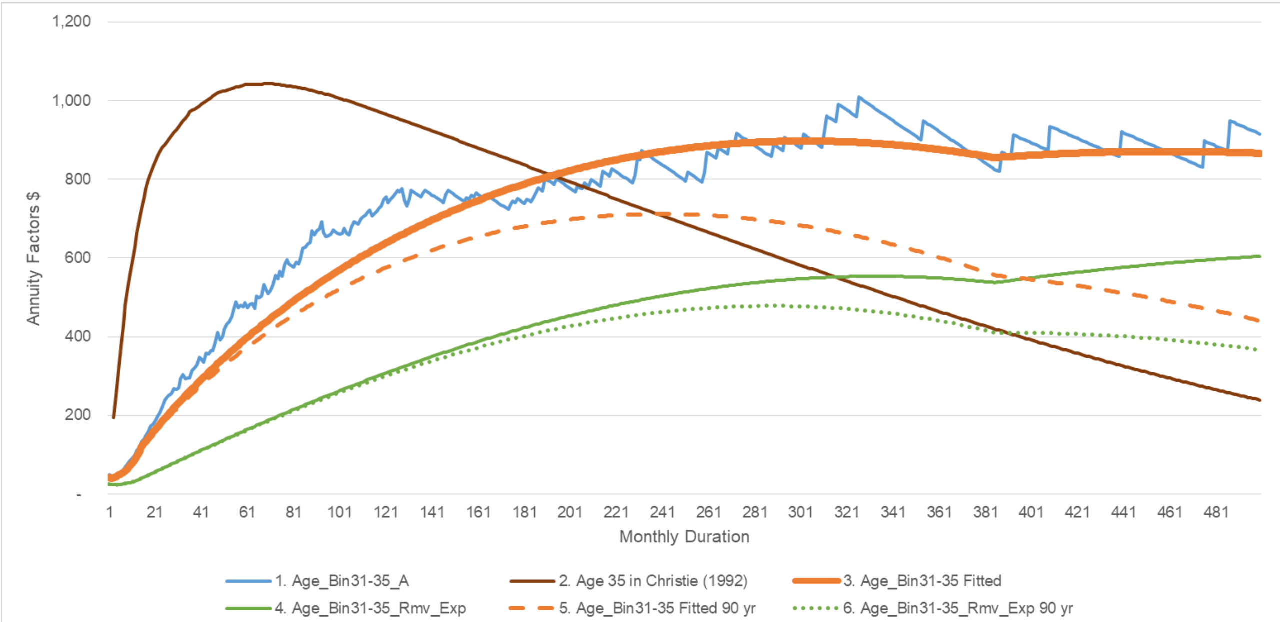


The selected model in Figure 22 is the best fit among all models that were tested, and it captures the curvature of the overall survival model. Although there is some overestimation and underestimation for each explanatory variable (such as gender and Age_Bin), the selected model provides a relatively accurate estimation of the overall portfolio. Similar conclusions can be drawn for Figure 23, Figure 24 and Figure 25.

7.7.6 Annuity Factor Curves

The annuity factor curves can be derived from the fitted survival rates. Annuity factors represent discounted future $1 weekly cash flows assuming the claimant survived the previous period. The annuity factor curve is mainly driven by payments in the tail. Claimant life expectancy plays a central role in the magnitude of the annuity factors. As well, the inclusion of large structured settlements significantly impacts the annuity factor curve. Figure 26 illustrates an annuity factor curve for Non-group, GTA, male, Age_Bin31-35.

Figure 26: Annuity Factors, Non-group, GTA, Male, Age_Bin31-35



The blue curve 1 represents the undiscounted annuity factors using the raw survival rate curve, which has many bumps due to the raw survival rate reacting immediately to unusual transactions. Note that the raw survival rate curve may not be a monotonically decreasing curve. The brown curve 2 shows the Christie (1992) undiscounted annuity factors extended to the ultimate for male. The orange curve 3 represents the undiscounted annuity factor derived from fitted survival rate curve assuming a maximum attained age of 120. The dashed orange curve 5 assumed a maximum attained age of 90. The green curve 4 represents the fitted undiscounted annuity factors after removing all claimants with large structured settlements, and assuming a maximum attained age of 120. The dashed green curve 6 has the same model parameters but assumed a maximum attained age of 90. From the above graph, the conclusion can be made that the LTD curve based on OSABSP data is not comparable with data used in Christie (1992), and the lump-sum expansion process assumption carries significant weight. By disaggregating large structured settlements, the OSABSP dataset shows a much heavier and longer annuity tail. Also, there was an inflection point for each fitted curve (i.e., curves 3, 4, 5 and 6) due to the benefits adjustments applied to a claimant who reached 65 years old or was injured after the age of 65.

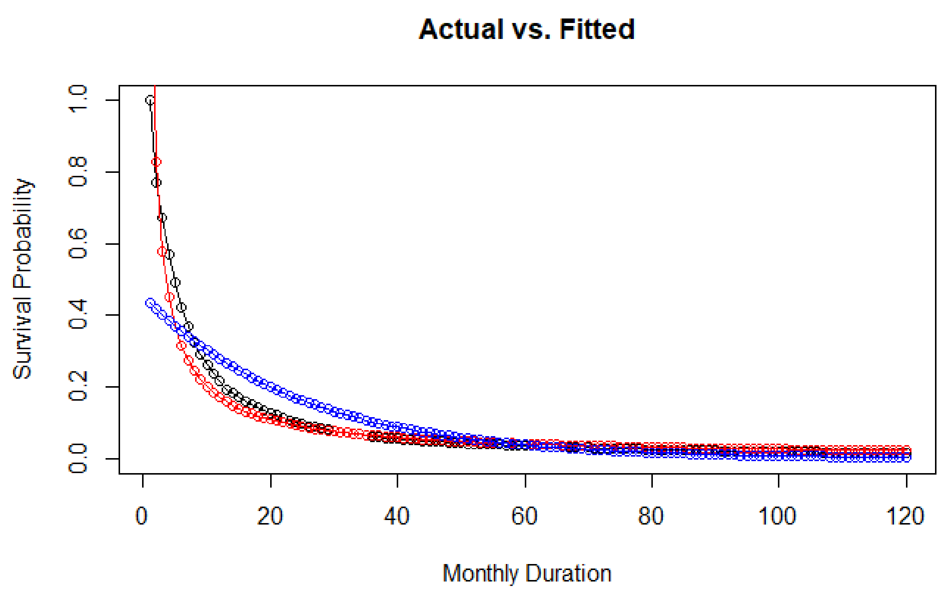
8 Appendix D – Alternative Models

Numerous models were considered for this research paper. This section highlights alternative models that were investigated but were not ultimately retained.

8.1 Two-Piece Survival Model

Using a GLM to model survival rates has the benefit of fitting an entire survival rate curve with a single equation. However, based on inspection of the actual and fitted curves, the curve before duration 14 months exhibited a notable different curvature than the curve after 14 months. Thus, the entire survival curve could not be captured appropriately with a single equation. Figure 27 shows the actual vs. fitted curve for the single survival model.

Figure 27: Single Survival Model



From the above graph, the x-axis represents the monthly duration, and the y-axis represents the probability claimants who remained on claim (i.e., survival rate). The black curve is the actual survival rate, the blue curve is a GLM model with duration as an explanatory variable, while the red curve is a model with ln(duration) as an explanatory variable. On one hand, the curve using duration as a variable does not capture the actual shape at early durations. On the other hand, although the use of ln(duration) provides a better fit of the actual survival rate curve at early durations, it tends to underestimate the survival rates in the first 14 months.

In order to eliminate this underestimation bias, a GLM model with a Poisson link function was developed to fit two separate curves; one for duration 1–14 months and another for duration 15–120 months, respectively.

Figure 28: Survival Model – Duration 1–14

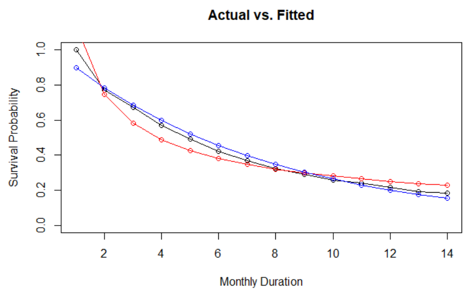
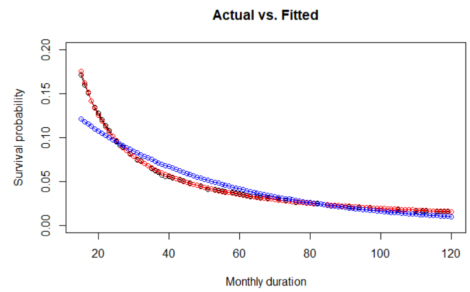


Figure 29: Survival Model – Duration 15–120



Time Variable	Duration	Ln(Duration)	Duration	Ln(Duration)
AIC	2,169,108	2,175,439	3,944,907	3,930,599
Residual Deviance	889,816	896,147	2,897,989	2,883,681

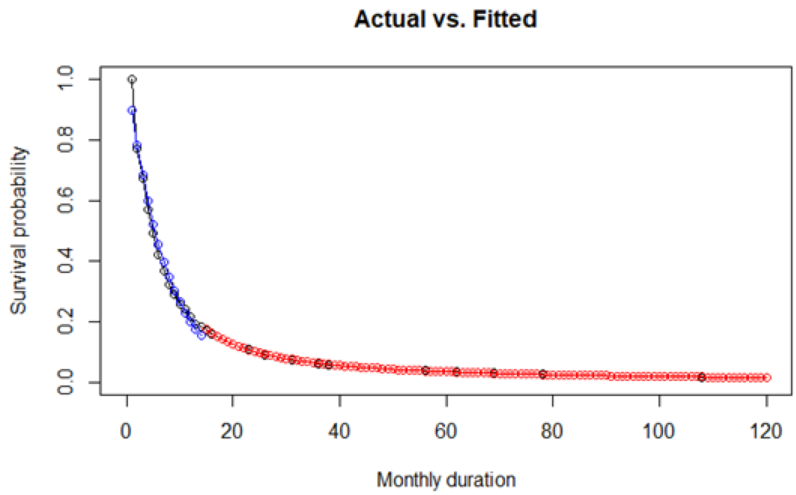
In Figure 28 and Figure 29, the x-axis represents monthly duration, and the y-axis represents the survival rate. The blue curve is the fitted curve with duration as an explanatory variable, and the red curve is the fitted curve with ln(duration) as an explanatory variable.

In Figure 28, the log transformation for duration led to survival rates decreasing at an increasing rate. However, it still underestimated a couple of data points from months 2–8. Thus, the model with log transformation was not optimal for durations 1–14. In contrast, the model without the log transformation better depicted the actual curve. Corroborating the visual interpretation, the model with duration as variable showed a lower AIC and residual deviance as shown above.

In Figure 29, the red curve with ln(duration) as a variable appears to better fit the actual curve. The improvement in fit from using the log transformation is also shown in the AIC and residual deviance tests.

In the two-piece model, the fitted curve with duration as an explanatory variable was used for duration 1–14 months, and the fitted curve with ln(duration) as variable was used for duration 15 months onward. Figure 30 shows the actual and fitted curves for the combined survival rate curve.

Figure 30: Two-Piece Survival Model



In the above chart, the black curve is the actual survival rate curve, and the blue curve uses duration as an explanatory variable, adjoined to the red curve with ln(duration) as an explanatory variable after duration 14 months. It can be observed that the two-piece curve fits the actual curve quite well. However, the discontinuity point at duration 14 months was an inevitable consequence, as neither curve considers the other dataset. With a survival rate at duration 15 months that is higher than the rate at 14 months, it generates a negative termination rate. This discontinuity was resolved by instead using a hinge function.

8.2 Hinge Function with Different Number of Interactions

The hinge function in a GLM is typically a function that adds break points to the underlying model. A GLM with a hinge function captures the change in slope before and after that break point, and reflect interactions between the variables. As the hinge function is a single equation, it solves the discontinuity issue introduced in the two-piece model. Considering that survival rate curves follow different curvatures before and after duration 14 months, the hinge function is an appropriate solution.

When adding hinge functions, multiple models with different interactions and break points were tested, including, but not limited to:

- One interaction (Age_Bin * ln(duration)) and one break point for ln(duration) at ln(14);
- Two interactions (Age_Bin * ln(duration) and Age_Bin * max(0, ln(duration) – ln(14)) and one break point for ln(duration) at ln(14); and
- Two interactions (Age_Bin * max(0, 14 – duration) and Age_Bin * max(0, ln(duration) – ln(14)) and two break points for duration at 14 and ln(duration) at ln(14).

All three models were tested with Non-group and Group insurers as well as for the GTA and Non-GTA regions. Table 11 shows the AIC and residual deviance for each alternative model.

Table 11: Alternative Models with Hinges and Interactions

Insurer Type and Region	Model #	Time Variable	Interaction	AIC	Deviance
Non-group GTA Age <= 50	M1	ln(duration)	1 with 1 break point	2,864,500	1,822,158
	M2	ln(duration)	2 with 1 break point	2,863,934	1,821,580
	M3	ln(duration) and duration	2 with 2 break points	2,853,215	1,810,861
Non-group Non-GTA Age <= 50	M1	ln(duration)	1 with 1 break point	2,705,274	1,762,272
	M2	ln(duration)	2 with 1 break point	2,704,998	1,761,984
	M3	ln(duration) and duration	2 with 2 break points	2,706,918	1,763,904
Group GTA Age <= 50	M1	ln(duration)	1 with 1 break point	1,123,960	712,046
	M2	ln(duration)	2 with 1 break point	1,123,715	711,789
	M3	ln(duration) and duration	2 with 2 break points	1,121,503	709,577
Group Non-GTA Age <= 50	M1	ln(duration)	1 with 1 break point	516,979	336,179
	M2	ln(duration)	2 with 1 break point	516,827	336,015
	M3	ln(duration) and duration	2 with 2 break points	517,221	336,409
All Insurers All Regions	M1	ln(duration)	1 with 1 break point	1,650,251	1,038,473

Age > 50	M2	ln(duration)	2 with 1 break point	1,645,265	1,033,483
	M3	ln(duration) and duration	2 with 2 break points at duration 14 and 60	1,641,130	1,029,342

Based on the above table, for each insurer type and region, the model with lowest AIC was selected as the final model, while the rest was considered as alternative models. Note that the selected models were considered as the best fit for the data available in OSABSP only; alternative models may work better with other datasets.

For all insurer types and regions, the fitted survival rate curves for model 1 and model 2 were similar, while model 3 had a fitted survival rate curve with visible differences compared to the other survival rate curves. The following figures show the actual and fitted survival rate curves for model 1 (M1) compared to model 3 (M3) as an illustration.

Figure 31: Non-group, GTA

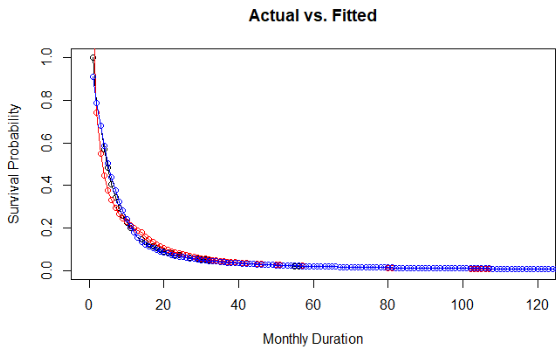


Figure 32: Non-group, Non-GTA

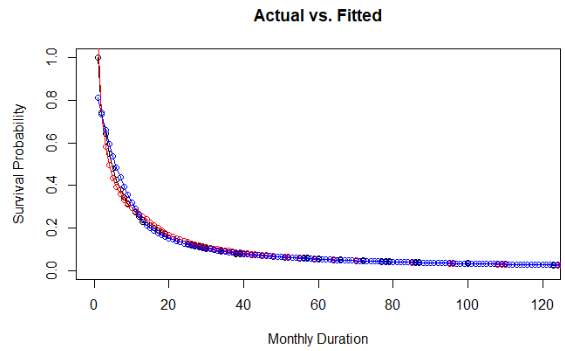


Figure 33: Group, GTA

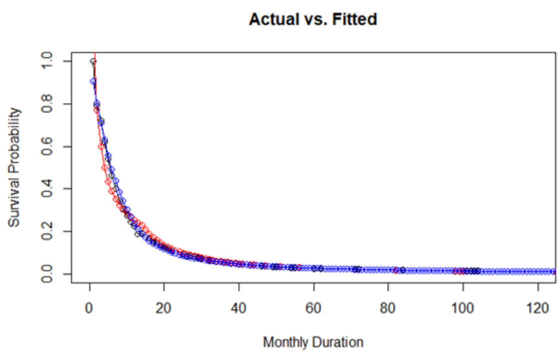
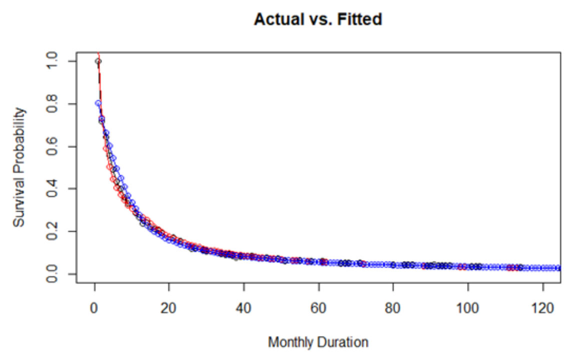


Figure 34: Group, Non-GTA



The black curve is the actual, the red curve is M1, and the blue curve is M3. The x-axis is duration by month, and the y-axis represents the average survival probability in each month. As shown in the above figures, M3 performed well for GTA, while M1 performed relatively better for Non-GTA.

8.3 Excluding Claimants with Structured Settlements

Structured settlements have a significant impact on the survival rate curves. An alternative model was tested by removing all claimants receiving a structured settlement payment. As a result, the alternative survival rate curve was much shorter than the survival rate curve including structured settlements after lump-sum expansion. Consequently, the fitted survival rate curve also shortened. As an illustration, Figure 35, Figure 36 and Figure 37 compare survival rate curves with and without structured settlements for a male in Age_Bin31-35 in GTA, Non-group insurer.

Figure 35: With and without Structured Settlements Duration 1–14 Months

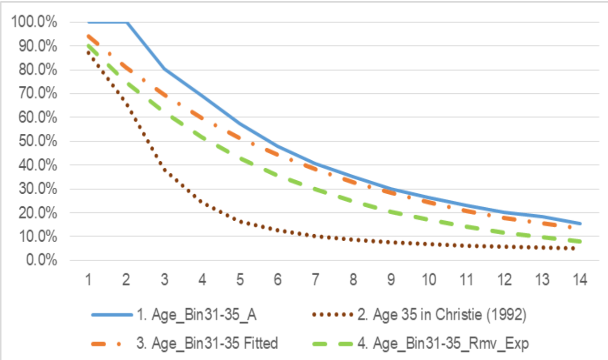


Figure 36: With and without Structured Settlements Duration 15–120 Months

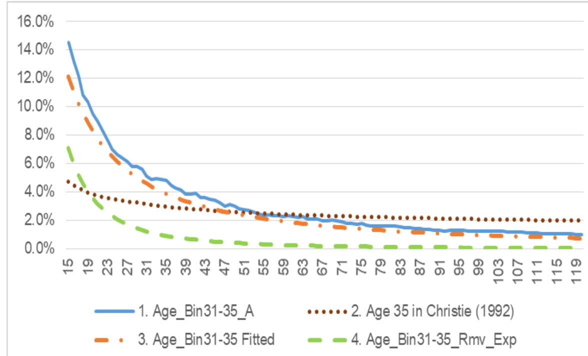
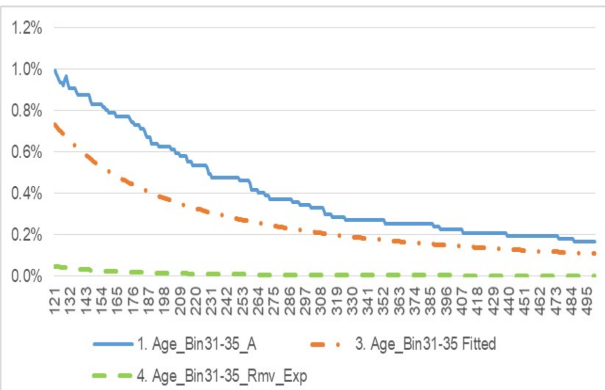


Figure 37: With and without Structured Settlements Duration 121–500 Months



The blue curve 1 represents the raw survival rate curve with structured settlements after lump-sum expansion, while the dashed brown curve 2 is the curve from Christie (1992). The dashed orange curve 3 is the fitted model selected for Non-group insurer, GTA Region, and the dashed green curve 4 is the fitted curve using the OSABSP dataset removing all claimants with structured settlements.

Figure 36 shows that curve 4 starts to deviate from the curve 3 after a year and is much lower than curve 3, reflecting the removal of structured payments. As the GLM model is based on frequency, removing claimants with longer durations prematurely limits the survival rate curve at later durations.

8.4 Sensitivity Tests – Data with/without Lump-Sum Expansion and Discount Rate +100bps

Two additional models were built to provide sensitivity tests on the final selected models. The first model tested the impact of the lump-sum expansion process for structured settlements by modelling a survival rate curve without lump-sum expansion. This dataset counted all structured settlements payments regardless of amount. Thus, this dataset could be considered a right-censored dataset.

The second model tested the effect of +100bps discount rates applied during the lump-sum expansion process. Discount rates underlying structured settlements contained within the OSABSP dataset were unknown. This research paper assumed a discount rate using the Government of Canada 10-year bond rate effective at the time of settlement. Through the lump-sum expansion process, a higher discount rate would lengthen the survival rate curve. Conversely, a lower discount rate would shorten the survival rate curve. For sensitivity testing, an alternative survival rate curve was derived assuming the base discount rate +100bps.

Figure 38, Figure 39 and Figure 40 illustrate the sensitivity of survival rates to the lump-sum expansion and discount rates assumptions for a Non-group insurer, male, Age_Bin31-35 and GTA.

Figure 38: Survival Rates Uncensored/Censored Duration 1–14 Months

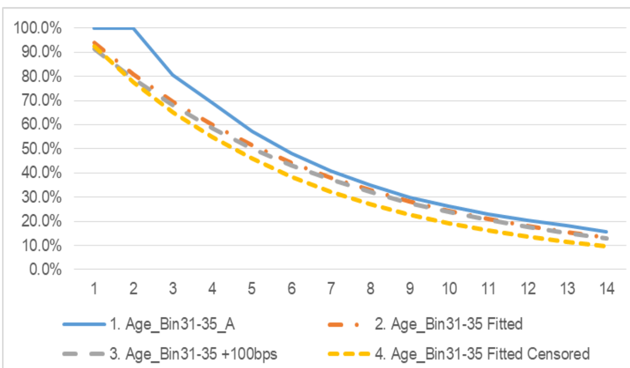


Figure 39: Survival Rates Uncensored/Censored Duration 15–120 Months

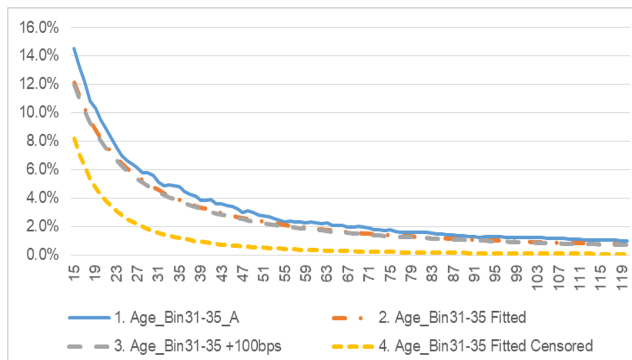
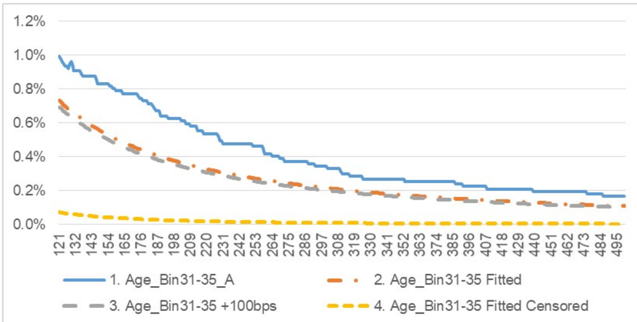


Figure 40: Survival Rates Uncensored/Censored Figure Duration 121–500 Months

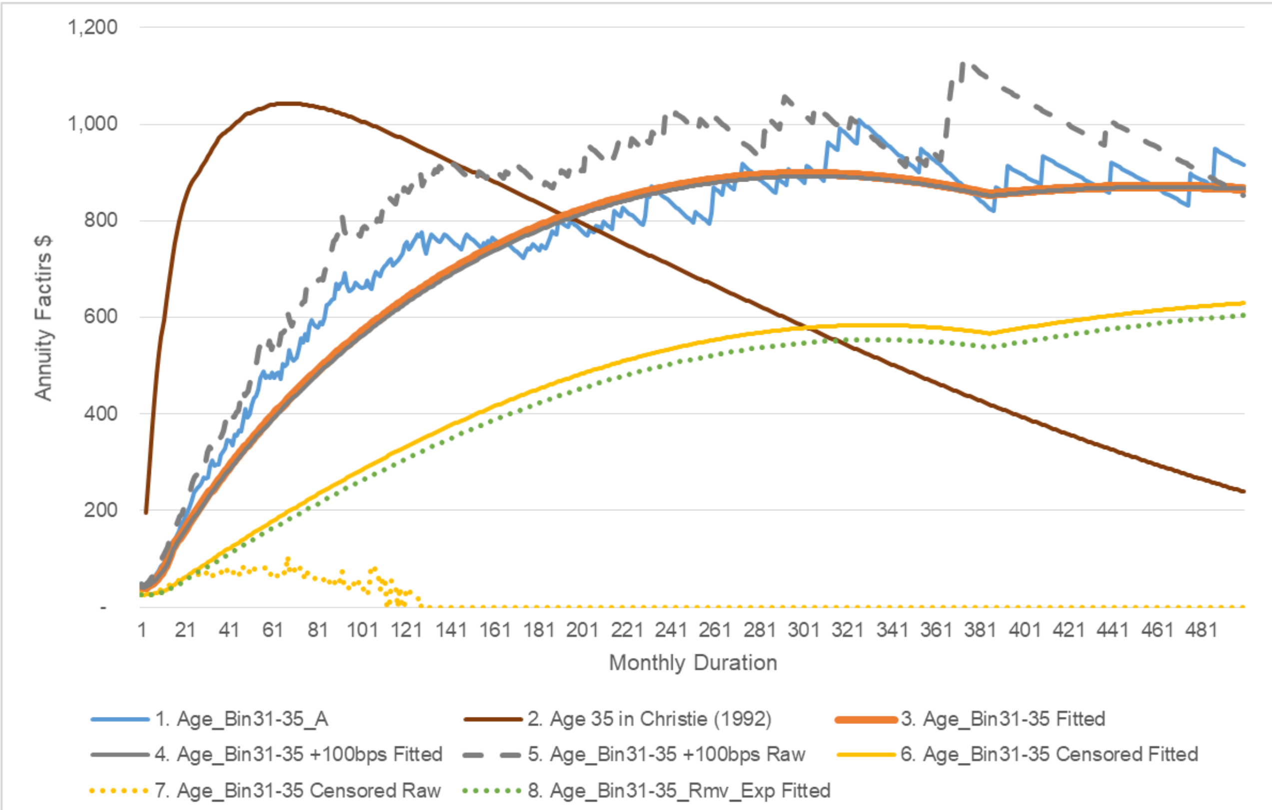


In the above figures, the blue curve 1 represents the raw survival rate, the dashed orange curve 2 represents the fitted survival curve derived from the selected model, the dashed gray curve 3 is the survival rate curve derived from the alternative model with discount rate +100bps, and the dashed yellow curve 4 represents the fitted model with censored data (i.e., counting the structured settlement regardless of amount). All figures show that curve 2 and curve 3 overlap each other with minimal visible differences. In contrast, curve 4 is much lower than the rest of the curves, reflecting the alternative treatment of structured settlements.

Figure 41 below shows the annuity factors derived from the selected models assuming a maximum attained age of 120 years old. All raw curves use the original transactions to determine the attained age, in so far as they ended. This figure contains the following curves:

- Curve 1 is the raw undiscounted annuity factor curve;
- Curve 2 is the annuity factor curve using survival rates from Christie (1992) extended using ultimate undiscounted annuity factors;
- Curve 3 is the final selected undiscounted annuity factor curve;
- Curve 4 is the fitted undiscounted annuity factor curve with discount rate for lump-sum expansion +100bps;
- Curve 5 is the raw undiscounted annuity factor curve with discount rate for lump-sum expansion +100bps;
- Curve 6 is the undiscounted annuity factor curve derived from censored data;
- Curve 7 is the raw undiscounted annuity factor curve derived from censored data; and
- Curve 8 is the fitted undiscounted annuity factor curve removing all claimants with structured settlement payments.

Figure 41: Annuity Factors – Uncensored/Censored – Discount Rate Sensitivity



As can be seen, the fitted discount rate +100bps curve 4 does not have a material impact on the final selected model (curve 3). The raw and fitted undiscounted annuity factors with discount rate +100bps (curve 4 and 5) showed a steeper slope at early durations, as a higher discount rate lengthens the average duration. Also, the fitted censored curve (curve 6) was slightly above the fitted curve excluding any structured settlements (curve 8), which is within expectation. The raw censored annuity factor curve (curve 7) is at the bottom left corner, which reflects the reduction in duration. Note that the use of censored data tends to underestimate the true survival rates. As the annuity factor is a function heavily driven by the tail of the survival rate curve, the removal of structured settlements decreases the annuity factor, as shown by curve 8.

In conclusion, since the actual dataset only contained 18 years of data, it was assumed that all claims would close at 18 years. However, the real world indicates that payments may continue beyond 18 years; thus, using the data with the lump-sum expansion process for modelling was necessary. Also, the two sensitivity tests showed that the selected models appropriately and sufficiently estimated the annuity factor curve in terms of lump-sum expansion and life expectancy.

8.5 Conditional Survival Model

As mentioned in Section 7.4, the OSABSP data included three types of claims:

— Claims closed within 15 years;

— Claims that had payments that were expanded to 15 years; and

— Claims still open at 15 years.

The data for the first two types of claims included the complete stream of transactions and could be used to model similar incidents. The issue at hand was how to forecast the length of payments for the third type of claims past 15 years (as the data were unavailable). In the final selected model, the stream of transactions was not modified for the third type of claims. Rather, it was assumed that the historical survival patterns from claims of the same maturity were applicable to the open claims. For example, a two-year-old claim that was still open at the end of the data on December 31, 2012 was assumed to exhibit the same behavior as any past claims of two years' duration.

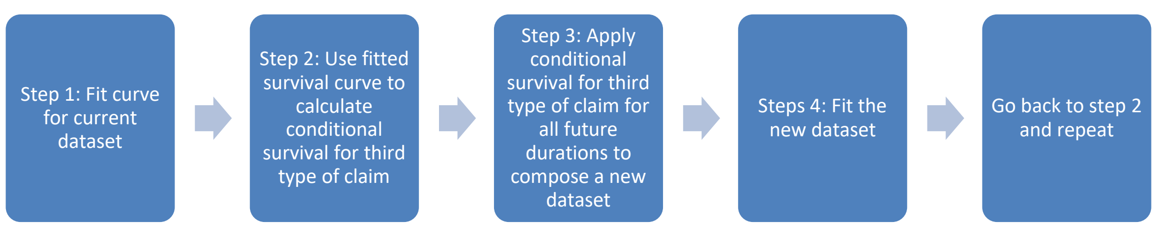
A future alternative model could be built assuming conditional survival for the third type of claims. The conditional survival rates could be based on the proposed selected models in Section 3.

Table 12: Claim and Exposure Counts: Conditional Survival Rates

	2011	2012	2013	2014	2015
Expansion	1	1	1	1	1
Closed	1	1	0	0	0
Open	1	1	S_3 / S_2	S_4/S_2	S_5/S_2

The adjusted data were used as input to re-fit survival curves until they converged to stable curves. The following figure illustrates the process:

Figure 42: Survival Curve Fitting Process



One drawback of this process is that many iterations may be required for the model to converge. It is unclear how this iterative process would affect the frequency of claims and composition of exposures. Therefore, the movement of the survival rate curves from the first to the final iteration cannot be predicted. Thus, due to the number of possible iterations, this model was not selected for the final model, but its use could be investigated in a future study.

9 Commonly Used Acronyms

These following acronyms are used within this research report and used by insurance regulatory bodies and actuarial organizations around the world.

AB	Accident Benefits
AIC	Akaike Information Criterion
ASP	Automobile Statistical Plan
CIA	Canadian Institute of Actuaries
DI	Disability Income
GTA	Greater Toronto Area
IDEC	Individual Disability Experience Committee
LDFs	Loss Development Factors
LTD	Long-Term Disability
OMPP	Ontario Motorist Protection Plan
OSABSP	Ontario Statutory Accident Benefits Statistical Plan
OSFI	Office of the Superintendent of Financial Institutions
P&C	Property and Casualty
RFP	Request for Proposal
SABS	Statutory Accident Benefits Schedule
SOA	Society of Actuaries
TSA	Transactions of the Society of Actuaries

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11 References

Christie, James K., “Accident Benefits Long-Term Disability Losses,” CIA Committee on Property and Casualty Financial Reporting, Research Paper, 1992.

Goldburd, Mark, Anand Khare, Anand and Dan Tevet, Dan, “Generalized Linear Models for Insurance Rating,” CAS Monograph Series Number 5, 2016.

Individual Disability Experience Committee, “Development of the 2012 IDEC Claim Termination Rate Table (Version 1.0),” Society of Actuaries, 2012.

Machtinger, Jason K., and Robert L. Brown, “Ontario Automobile LTD Losses: The OMPP Cliff, and Bill 164,” Institute of Insurance and Pension Research, 1994.

Society of Actuaries, “Report of the Society of Actuaries Committee to Recommend New Disability Tables for Valuation,” *Transactions, Society of Actuaries*, Volume XXXVII, 1985, pp. 449–601.