February 8, 2019

RE: Allstate Property and Casualty Insurance Company
Private Passenger Auto
GA DOI Filing Disapproval Response / R50648

With this filing, Allstate is introducing Table Assignment Number (TAN) Group Rating. This rating enhancement is designed with four goals in mind:

- Adjust current premium in the direction of updated expected loss cost estimates
- Reflect most up-to-date estimates using a new class-based loss model
- Reduce the cost of implementing rating plan structure changes in the future
- Mitigate renewal impacts

Furthermore, this filing will result in:

- 98% of new customers experiencing a lower rate
- No current policyholder experiencing greater than a 5% increase, with 90% of current policyholders experiencing an increase of 2% or less

The following addresses the objections received from the Department of Insurance on February 6, 2019.

DOI Objection: The Department does not allow the use of price optimization.

Allstate Response:

During the phone call with MARS on February 5th, a brief discussion took place when Mr. Moulton asked a question regarding how this filing aligned with Price Optimization. In our response, we noted the ambiguity of that question due to the lack of a consistent definition of Price Optimization.

However, when examining definitions used in the context of regulatory concerns over price optimization, Allstate's TAN rating structure is clearly NOT price optimization. As an example, the Missouri Department of Insurance Bulletin 16-02 states:

> *Price optimization is generally considered to be the use of factors to help determine or to adjust the insured's premium that are not specifically related to the insured's risk or hazard. An example would be using an individual policyholder's responses to previous premium increases to determine how much of a premium increase the policyholder will tolerate at renewal before switching to a different insurer. More plainly, if an insured did not complain about a rate increase or cancel the policy due to such an increase, an insurer may use this information to justify additional rate increases.*

Allstate's proposed rating plan does **not** establish rates without a link to the projected costs of the insured's risk nor does Allstate use the existence of complaints, or lack thereof, to justify rate increases.

Allstate's TAN rating plan builds upon common techniques to project loss costs in a sound manner from both a business and actuarial perspective. As background, Allstate's TAN rating plan improves upon well-established practices of examining factors other than risk when building a rating plan. Insurers have traditionally done this by incorporating a judgmental step in the ratemaking process that examines information including: competitive rate comparisons; close ratios, retention ratios and growth; distributional analysis; and dislocation analysis. See Geoff Werner and Claudine Modlin, Casual Actuarial Society, *Basic Ratemaking 4th ed.* (2010) p. 247 – 261 (Chapter 13 - "Traditional Techniques for Incorporating Marketplace Considerations").

The CAS Statement of Principles Regarding Property and Casualty Insurance Ratemaking, as adopted in 1988, also reflects these considerations noting that:

> *Ratemaking is the process of establishing rates used in insurance or other risk transfer mechanisms. This process involves a number of considerations including marketing goals, competition and legal restrictions to the extent they affect the estimation of future costs associated with the transfer of risk.*

The CAS Statement of Principles concludes by explaining the how the inclusion of marketplace considerations relates to determining the price:

> *The actuary, by applying the ratemaking principles in this Statement, will derive an estimation of the future costs associated with the transfer of risk. Other business considerations are also a part of ratemaking. By interacting with professionals from various fields including underwriting, marketing, law, claims, and finance, the actuary has a key role in the ratemaking process.*

Allstate has structured its TAN rating plan so that it ensures that premiums equitably reflect expected losses and expenses and therefore not impermissible price optimization:

- All rating factors used within TAN comply with state laws and regulations – Allstate will only use variables permitted under applicable state law in developing the TAN factor and any other factor used in the rate calculation process.
- TAN will not be used to raise a customer's rate unless a rate increase is justified by <u>loss considerations</u>.
- TAN is designed to promote rate stability – TAN mitigates rate disruption and promotes rate stability compared to a process of updating rating plan without TAN.
- TAN will not be used to alter the overall level of profitability targeted in Allstate's rate filings – Allstate determines and changes the overall rate level through rate filings supported with an actuarially sound overall rate level indication analysis. With TAN, Allstate only expects to grow profitability by attracting and retaining more customers, not by targeting higher overall returns for customers.

In addition, we expect the TAN rating plan to more accurately predict losses over time. No loss model or projection of losses is perfect. The TAN structure permits Allstate to update loss information while also mitigating renewal price changes associated with those updates. Over time, this should produce more stable rates which benefits consumers, and this rate stability should also improve accuracy from an actuarial perspective.

DOI Objection: The filing does not include details of the retention model analysis or the results from that analysis.

Allstate Response:

Before discussing the technical details of the retention model, the following information may serve as a succinct summary of how the retention model is utilized within the broader ratemaking process. For a more robust overview, please reference Attachment III of the filing.

Allstate uses a factor selection process that is common industry practice – factors are selected between current and indicated based on the results of a loss-based analysis as of a given evaluation date.

Once the actuarially sound range has been determined for each TAN using the class-based loss model detailed in Attachment V of the filing, Allstate considers the estimated propensity to retain in determining movement within the actuarially sound range. The retention probabilities are calculated using the class-based retention model. The list of variables utilized in the retention model is contained in Confidential Attachment I, Exhibit A of the filing and further technical details follow in this response. This process will operate to minimize policyholder disruption by tempering movement towards the fully indicated rate relativity (from the class-based loss model). ***Factors are selected within the actuarially sound range*** of factors in a manner designed to maximize the ***overall*** retention of the book while addressing the need to achieve movement towards the indicated rate. ***Therefore, this process does not attempt to maximize an individual policyholder's likelihood of retaining or find the maximum amount of increase a policyholder will tolerate before defecting.***

Additional technical background on the modeling process can be found on ***Page 4.***

Methodology

Indicated factors were developed via a multivariate analysis using a version of Generalized Linear Models (GLMs). GLMs provide regression-like modeling of the response variable, but provide more flexibility than linear regression, as GLMs allow the response variable to come from an exponential family of distributions, including Normal, Poisson, Binomial, Negative Binomial, Gamma and Tweedie distributions.

A GLM was fit using the Binomial distribution with a logit link function to predict the response variable of expected retention probability. Weights for each GLM were defined as policy counts.

A penalty term can be added to the minimization procedure used in traditional GLM modeling, which takes the form of a regularized GLM, also known as a GLMnet. Within a regularized GLM, the model is rewarded for being able to shrink coefficients or drop them entirely without compromising predictive power, thereby increasing the efficiency of the variable selection process. Thus, this penalty term accomplishes 'regularization' which reduces the risk of over-fitting the model to the modeling dataset. While regularized GLMs are available in a few different forms, Allstate has used the Lasso form of regularization within this analysis.

The Lasso regularized GLM includes a penalty term equal to the sum of the absolute values of the model coefficients multiplied by some scaling value as the method of regularization. As the penalty term scaling value is increased, the Lasso regularized GLM has a different tradeoff between the penalty term and goodness of fit, which results in the automated removal of variables with little predictive value.

Allstate fit Lasso regularized GLMs with an initial list of candidate model variables containing only components of variables found in our currently filed rating plan, as well as premium change and current premium, and evaluated which variables were not dropped as the penalty term scaling value was increased. From this analysis, a list of predictors was selected. Once the predictors were selected, the model was refit using this list of predictors and the original optimized regularization strength was determined based on the full list of variables using the holdout data set. This allows for a reduced variable count while also retaining more of the predictive power than would be obtained by strictly using an increased regularization.

Since regularized GLMs select variables formulaically, many of the metrics used in analyzing GLM variables like p-value do not apply. As an alternative to the use of these metrics, cross validation was used as a measure of coefficient stability. The resulting outputs give the probability of a non-zero value for each variable, measuring the likelihood a variable is predictive given the size of the penalty term, as well as the standard error for non-zero coefficients.

One-way lift charts are an additional method of graphically comparing each coverage GLM model predictions against actual retention experience on the holdout dataset. The holdout data is scored by the model and then sorted from lowest model predictions to highest modeled predictions. The predicted scores are then bucketed into 10 equal groups. For each decile, actual recorded losses and predicted losses are plotted for each group representing the aggregate spread across the data. The closer the actual losses and predicted losses line up, the more accurate the model is predicting on the holdout data for each of the groups.

For more information on GLMs and usage in insurance ratemaking, please see the following reference:

Goldburd, Khare, and Tevet. “Generalized Linear Models for Insurance Rating,” CAS Monograph #5, 2016.

http://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf

Please note that two separate models were created using this methodology. The Renewal model predicts whether a policyholder will defect during the policy renewal cycle while the Midterm model predicts whether a policyholder will defect at any other point in the policy term.

Data

The data used in this analysis was selected in accordance with the considerations listed in Section 3.2 of the Actuarial Standard of Practice No. 23, Data Quality.

Each record in the modeling dataset represents one policy per exposure year, and includes the associated exposures, policy & vehicle characteristics. The data consists of all states except for CA and MI across all open Allstate brand companies. The data includes policies for exposure dates between 12/9/2014 and 10/9/2015, while removing user initiated premium change overlaps, cancel rewrite defections, secondary policies, and other backdated changes.

In order to appropriately assess the model’s performance, the dataset was split by date into two subsets for model development: data from 12/9/2014 to 5/9/2015 made up the Train dataset, while data from 5/10/2015 to 10/9/2015 made up the Validate dataset. These subsets were used in the following manner:

- Train dataset was used to build the model structure
- Validate dataset was used for final assessment and validation of model performance, as well as for selecting the optimal penalty term.

We are happy to provide further detail upon request.