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Casualty Actuarial and Statistical (C) Task Force

Regulatory Review of Predictive Models

White Paper

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I.   INTRODUCTION

Insurers' use of predictive analytics along with big data has significant potential benefits to both consumers and insurers. Predictive analytics can reveal insights into the relationship between consumer behavior and the cost of insurance, lower the cost of insurance for many, and provide incentives for consumers to better control and mitigate loss. However, predictive analytic techniques are evolving rapidly and leaving many regulators, who must review these techniques, without the necessary tools to effectively review insurers' use of predictive models in insurance applications.

When a rate plan is truly innovative, the insurer must anticipate or imagine the reviewers' interests because reviewers will respond with unanticipated questions and have unique educational needs. Insurers can learn from the questions, teach the reviewers, and so forth. When that back-and-forth learning is memorialized and retained, filing requirements and insurer presentations can be routinely organized to meet or exceed reviewers' needs and expectations. Hopefully, this paper helps bring more consistency to the art of reviewing predictive models within a rate filing and make the review process more efficient.

The Casualty Actuarial and Statistical (C) Task Force (CASTF) has been charged with identifying best practices to serve as a guide to state insurance departments in their review of predictive models[1] underlying rating plans. There were two charges given to CASTF by the Property and Casualty Insurance (C) Committee at the request of the Big Data (EX) Working Group:

- **Draft and propose changes to the *Product Filing Review Handbook* to include best practices for review of predictive models and analytics filed by insurers to justify rates.**

- **Draft and propose state guidance (e.g., information, data) for rate filings based on complex predictive models.**

This paper will identify best practices for the review of predictive models and analytics filed by insurers with regulators to justify rates and will provide state guidance for review of rate filings based on predictive models. Upon adoption of this paper by the Executive (EX) Committee and Plenary, CASTF will make a recommendation to incorporate these best practices into the *Product Filing Review Handbook* and will forward that recommendation to the Speed to Market (EX) Working Group.

II.   WHAT IS A "BEST PRACTICE?"

A best practice is a form of program evaluation in public policy. At its most basic level, a practice is a "tangible and visible behavior… [based on] an idea about how the actions…will solve a problem or achieve a goal"[2]. Best practices are used to maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking.[3] Therefore, a best practice represents an effective method of problem solving. The "problem" regulators want to solve is probably better posed as seeking an answer to this question: How can regulators determine that predictive models, as used in rate filings, are compliant with state laws and regulations?

Key Regulatory Principles

In this paper, best practices are based on the following principles that promote a comprehensive and coordinated review of predictive models across states:

1. State insurance regulators will maintain their current rate regulatory authority and autonomy.

2. State insurance regulators will be able to share information to aid companies in getting insurance products to market more quickly across the states.

3. State insurance regulators will share expertise and discuss technical issues regarding predictive models to make the review process in any state more effective and efficient.

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[1] In this paper, references to "model" or "predictive model" are the same as "complex predictive model" unless qualified.

[2] Bardach, E. and Patashnik, E. (2016.) *A Practical Guide for Policy Analysis, The Eightfold Path to More Effective Problem Solving.* Thousand Oaks, CA: CQ Press. See Appendix A for an overview of Bardach's best-practice analysis.

[3] Bogan, C.E. and English, M.J. (1994). Benchmarking for Best Practices: Winning Through Innovative Adaptation. New York: McGraw-Hill.

4. State insurance regulators will maintain confidentiality, in accordance with state law, regarding predictive models.

Best practices are presented to regulators for the review of predictive models and to insurance companies as a consideration in filing rating plans that incorporate predictive models. A by-product of identifying these best practices, general and specific information elements were identified that could be useful to a regulator when reviewing a rating plan that is wholly or in part based on a generalized linear model (GLM). For states that are interested, the information elements are identified in Appendix B, including comments on what might be important about that information and, where appropriate, providing insight as to when the information might identify an issue the regulator needs to be aware of or explore further. Lastly, provided in this paper are glossary terms (Appendix B) and references (contained in the paper's footnotes) that can expand a regulator's knowledge of predictive models (GLMs specifically).

III. SOME ISSUES IN REVIEWING TODAY'S PREDICTIVE MODELS

The term "predictive model" refers to a set of models that use statistics to predict outcomes[4]. When applied to insurance, the model is chosen to estimate the probability or expected value of an outcome given a set amount of input data; for example, models can predict the frequency of loss, the severity of loss, or the pure premium. The generalized linear model[5] is a commonly used predictive model in insurance applications, particularly in building an insurance product's rating plan.

Depending on definitional boundaries, predictive modeling can sometimes overlap with the field of machine learning. In this modeling space, predictive modeling is often referred to as predictive analytics.

Before GLMs became vogue, rating plans were built using univariate methods. Univariate methods were considered intuitive and easy to demonstrate the relationship to costs (loss and/or expense). Today, many insurers consider univariate methods too simplistic since they do not take into account the interaction (or dependencies) of the selected input variables.

Today, the majority of predictive models used in personal automobile and home insurance rating plans are GLMs.[6] According to many in the insurance industry, GLMs introduce significant improvements over univariate-based rating plans by automatically adjusting for correlations among input variables. However, it is not always easy to understand the complex predictive model output's relationship to cost. This creates a problem for the regulator when model results are difficult to explain to someone with little to no expertise in modeling techniques, e.g., a consumer.

Generalized Linear Models

A GLM consists of three elements[7]:

- A target variable, Y, which is a random variable that is independent and follows a probability distribution from the exponential family, defined by a selected variance function and dispersion parameter.
- A linear predictor $\eta = X\beta$.
- A link function g such that $E(Y) = \mu = g^{-1}(\eta)$.

As can be seen in the description of the three GLM components above, it may take more than a casual introduction to statistics to comprehend the construction of a GLM. As stated earlier, a downside to GLMs is that it is more challenging to interpret the GLMs output than with univariate models.

To further complicate regulatory review of models in the future, modeling methods are evolving rapidly and not limited just to GLMs. As computing power grows exponentially, it is opening up the modeling world to more sophisticated forms of data acquisition and data analysis. Insurance actuaries and data scientists seek increased predictiveness by using even more complex predictive modeling methods. Examples of these methods are predictive models utilizing random forests, decision trees, neural networks, or combinations of available modeling methods (often referred to as ensembles). These

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[4] A more thorough exploration of different predictive models will be found in many statistics' books, including Geisser, Seymour (September 2016). *Predictive Inference: An Introduction*. New York: Chapman & Hall or An Introduction to Statistical Learning: with Applications in R, by Gareth James et al., Springer, 2017, pp. 87–90. Accessed at: http://faculty.marshall.usc.edu/gareth-james/ISL/ISLR%20Seventh%20Printing.pdf.

[5] The generalized linear model (GLM) is a flexible family of models that are unified under a single method. Types of GLM include logistic regression, Poisson regression, gamma regression and multinomial regression.

[6] "Generalized Linear Models for Insurance Rating." CAS Monograph Series Number 5, by Mark Goldburd et al., Casualty Actuarial Society, 2016, pp. 52-58. Accessed at: https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

[7] Information on model elements can be found in most statistics' books.

evolving techniques will make the regulators' understanding and oversight of filed rating plans incorporating predictive models even more challenging.

In addition to the growing complexity of predictive models, many state insurance departments do not have in-house actuarial support or have limited resources to contract out for support when reviewing rate filings that include use of predictive models. The Big Data (EX) Working Group identified the need to provide states with guidance and assistance when reviewing predictive models underlying filed rating plans.[8] The Working Group circulated a proposal addressing aid to state insurance regulators in the review of predictive models as used in personal automobile and home insurance rate filings. This proposal was circulated to all of the Working Group members and interested parties on December 19, 2017, for a public comment period ending January 12, 2018.[9] The Big Data Working Group effort resulted in the new CASTF charges (see the Introduction section) with identifying best practices that provide guidance to states in the review of predictive models.

Credibility of GLM Output

If the underlying data is not credible, then no model will improve that credibility, and segmentation methods could make credibility worse. GLM software provides point estimates and allows the modeler to consider standard errors and confidence intervals. GLMs effectively assume that the underlying datasets are 100% credible no matter their size. If some segments have little data, the resulting uncertainty would not be reflected in the GLM parameter estimates themselves (although it might be reflected in the standard errors, confidence intervals, etc.). Even though the process of selecting relativities often includes adjusting the raw GLM output, the resultant selections are typically not credibility-weighted with any complement of credibility.[10,11] And, selected relativities based on GLM model output may differ from GLM point estimates. Lack of credibility for particular estimates could be discerned if standard errors are large relative to the point estimates and/or if the confidence intervals are broad.

Because of this presumption in credibility, which may or may not be valid in practice, the modeler and the regulator reviewing the model would need to engage in thoughtful consideration when incorporating GLM output into a rating plan to ensure that model predictiveness is not compromised by any lack of actual credibility. Another consideration is the availability of data, both internal and external, that may result in the selection of predictor variables that have spurious correlation with the target variable. Therefore, to mitigate the risk that model credibility or predictiveness is lacking, a complete filing for a rating plan that incorporates GLM output should include validation evidence for the rating plan, not just the statistical model.

IV. DO REGULATORS NEED BEST PRACTICES TO REVIEW PREDICTIVE MODELS?

It might be better to revise the question "Do regulators need best practices to review predictive models?" to "Are best practices in the review of predictive models of value to regulators and insurance companies?" The answer is "yes" to both questions. Regulatory best practices need to be developed that do not unfairly or inordinately create barriers for insurers and ultimately consumers while providing a baseline of analysis for regulators to review the referenced filings. Best practices will aid regulatory reviewers by raising their level of model understanding. Also, with regard to scorecard models and the model algorithm, there is often not sufficient support for relative weight, parameter values, or scores of each variable. Best practices can potentially aid in addressing this problem.

Best practices are not intended to create standards for filings that include predictive models. Rather, best practices will assist the states in identifying the model elements they should be looking for in a filing that will aid the regulator in understanding why the company believes that the filed predictive model improves the company's rating plan, making that rating plan fairer to all consumers in the marketplace. To make this work, both regulators and industry need to recognize that:

- Best practices provide guidance to regulators in their essential and authoritative role over the rating plans in their state.

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[8] Minutes of the Big Data (EX) Working Group, March 9, 2018: https://secure.naic.org/secure/minutes/2018_spring/ex_it_tf.pdf?59 NAIC login required.
[9] All comments received by the end of January were posted to the NAIC website March 12 for review.
[10] Sometimes insurers do review complements of credibility and further weight the GLM output with those complements. While this may not be a standard practice today, new techniques could result in this becoming more standard in the future.
[11] GLMs provide confidence intervals, credibility methods do not. There are techniques such as penalized regression that blend credibility with a GLM and improve a model's ability to generalize."

- All states may have a need to review predictive models whether that occurs with approval of rating plans or in a market conduct exam. Best practices help the regulator identify elements of a model that may influence the regulatory review as to whether modeled rates are appropriately justified, compliant with state laws and regulations, and whether to act on that information.

- Best practices provide a framework for states to share knowledge and resources to facilitate the technical review of predictive models.

- Best practices can lead to improved quality in predictive model reviews across states, aiding speed to market and competitiveness of the state marketplace.

- Best practices aid training of new regulators and/or regulators new to reviewing predictive models. (This is especially useful for those regulators who do not actively participate in NAIC discussions related to the subject of predictive models.)

- Each regulator adopting best practices will be better able to identify the resources needed to assist their state in the review of predictive models.

V. SCOPE

The best practices identified in this paper were derived from a ground-up study and analysis of how GLMs are used in personal automobile and home insurance rating plans. These three components (GLM, PPA, and HO) were selected as the basis to develop best practices for regulatory review of predictive models because many state regulators are very familiar with and have expertise in such filings. In addition, the legal and regulatory constraints (including state variations) are likely to be more evolved, and challenging, for personal automobile and home insurance. It is through review of these personal lines and the knowledge needed to review GLMs[12] used in their rate filings that will provide meaningful best practices for regulators. The identified best practices should be readily transferrable when the review involves other predictive models applied to other lines of business or for an insurance purpose other than rating.

VI. CONFIDENTIALITY

Each state determines the confidentiality of a rate filing and the supplemental material to the filing, when filing information might become public, the procedure to request that filing information be held confidentially, and the procedure by which a public records request is made. Regulatory reviewers are required to protect confidential information in accordance with applicable state law. Regulators should be aware of their state laws on confidentiality when requesting data from insurers that may be proprietary or trade secret. However, insurers should be aware that a rate filing might become part of the public record. It is incumbent on an insurer to be familiar with each state's laws regarding the confidentiality of information submitted with their rate filing.

State authority, regulations and rules governing confidentiality always apply when a regulator reviews a model used in rating. When NAIC or a third party enters into the review process, the confidential, proprietary, and trade secret protections of the state on behalf of which a review is being performed will continue to apply.

VII. BEST PRACTICES FOR REGULATORY REVIEW OF PREDICTIVE MODELS

Best practices will help the regulator understand if a predictive model is cost based, if the predictive model is compliant with state law, and how the model improves a company's rating plan. Best practices can, also, improve the consistency among the regulatory review processes across states and improve the efficiency, of each regulator's review thereby assisting companies in getting their products to market faster. With this in mind, the regulator's review of predictive models should:

1. Ensure that the selected rating factors, based on the model or other analysis, produce rates that are not excessive, inadequate, or unfairly discriminatory.

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[12] See Appendix B.

    a.   Review the overall rate level impact of the proposed revisions to rate level indications provided by the filer.

    b.   Determine that individual input characteristics to a predictive model and their resulting rating factors are related to the expected loss or expense differences in risk.

    c.   Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.

    d.   Review the individual input characteristics to and output factors from the predictive model (and its sub-models), as well as associated selected relativities, to ensure they are compatible with practices allowed in the state and do not reflect prohibited characteristics.

2.   Obtain a clear understanding of the data used to build and validate the model, and thoroughly review all aspects of the model, including assumptions, adjustments, variables, sub-models used as input, and resulting output.

    a.   Obtain a clear understanding of how the selected predictive model was built.

    b.   Determine that the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values and outliers are handled.

    c.   Determine that any adjustments to the raw data are handled appropriately, including but not limited to, trending, development, capping and removal of catastrophes.

    d.   Obtain a clear understanding of how often each risk characteristic, used as input to the model, is updated and whether the model is periodically refreshed, so model output reflects changes to non-static risk characteristics.

3.   Evaluate how the model interacts with and improves the rating plan.

    a.   Obtain a clear understanding of the characteristics that are input to a predictive model (and its sub-models).

    b.   Obtain a clear understanding how the insurer integrates the model into the rating plan and how it improves the rating plan.

    c.   Obtain a clear understanding of how model output interacts with non-modeled characteristics/variables used to calculate a risk's premium.

4.   Enable competition and innovation to promote the growth, financial stability, and efficiency of the insurance marketplace.

    a.   Enable innovation in the pricing of insurance through acceptance of predictive models, provided models are in compliance with state laws, particularly prohibitions on unfair discrimination.

    b.   Protect the confidentiality of filed predictive models and supporting information in accordance with state law.

    c.   Review predictive models in a timely manner to enable reasonable speed to market.

VIII. PROPOSED CHANGES TO THE *PRODUCT FILING REVIEW HANDBOOK*

The Task Force was charged to propose modifications to the 2016 *Product Filing Review Handbook* to reflect best practices for the regulatory review of GLM predictive analytics. The following are the titled sections in Chapter Three "The Basics of Property and Casualty Rate Regulation."

Product Filing Review Handbook, August 2016
CHAPTER THREE
The Basics of Property and Casualty Rate Regulation

No changes are proposed to the following sections at the beginning of Chapter Three: **Introduction; Rating Laws; Rate Standards; Rate Justification and Supporting Data; Number of Years of Historical Data; Segregation of Data; Data Adjustments; Premium Adjustments; Losses and LAE (perhaps just DCC) Adjustments; Catastrophe or Large Loss Provisions; Loss Adjustment Expenses; Data Quality; Rate Justification: Overall Rate Level; Contingency Provision; Credibility; Calculation of Overall Rate Level Need: Methods (Pure Premium and Loss Ratio Methods); Rate Justification: Rating Factors; Calculation of Deductible Rating Factors; Calculation of Increased Limit Factors**; and **Credibility for Rating Factors**.

The following are the proposed changes to the remainder of Chapter Three:

Interaction between Rating Variables (Multivariate Analysis)

If each rating variable is evaluated separately, statistically significant interactions between rating variables may not be identified and, thus, may not be included in the rating plan. Care should be taken to have a multivariate analysis when practical. In some instances, a multivariate analysis is not possible. But, with computing power growing exponentially, insurers believe they have found many ways to improve their operations and competitiveness through use of complex predictive models in all areas of their insurance business.

Approval of Classification Systems

With rate changes, companies sometimes propose revisions to their classification system. Because the changes to classification plans can be significant and have large impacts on the consumers' rates, regulators should focus on these changes.

Some items of proposed classification can sometimes be deemed to be contrary to state law, such as the use of education or occupation. You should be aware of your state's laws and regulations regarding which rating factors are allowed, and you should require definitions of all data elements that can affect the charged premium. Finding rating or underwriting characteristics that may violate law/regulation is becoming more difficult for regulators with the increasing and innovative ways insurers use predictive models.

Rating Tiers – (No change is proposed.)

Rate Justification: New Products – (No change is proposed.)

Predictive Modeling

The ability of computers to process massive amounts of data (referred to as "big data") has led to the expansion of the use of predictive modeling in insurance ratemaking. Predictive models have enabled insurers to build rating, marketing, underwriting, and claim models with significant predictive ability.

Data quality within and communication about models are of key importance with predictive modeling. Depending on definitional boundaries, predictive modeling can sometimes overlap with the field of machine learning. In the modeling space, predictive modeling is often referred to as predictive analytics.

Insurers' use of predictive analytics along with big data has significant potential benefits to both consumers and insurers. Predictive analytics can reveal insights into the relationship between consumer behavior and the cost of insurance, lower the cost of insurance for many, and provide incentives for consumers to better control and mitigate loss. However, predictive

analytic techniques are evolving rapidly and leaving many regulators without the necessary tools to effectively review insurers' use of predictive models in insurance applications. To aid the regulator in the review of predictive models, best practices have been developed.

The term "predictive model" refers to a set of models that use statistics to predict outcomes. When applied to insurance, the model is chosen to estimate the probability or expected value of an outcome given a set amount of input data; for example, models can predict the frequency of loss, the severity of loss, or the pure premium.

To further complicate regulatory review of models in the future, modeling technology and methods are evolving rapidly. Generalized linear models (GLMs) are relatively transparent and their output and consequences are much clearer than many other complex models. But as computing power grows exponentially, it is opening up the modeling world to more sophisticated forms of data acquisition and data analysis. Insurance actuaries and data scientists seek increased predictiveness by using even more complex predictive modeling methods. Examples of these methods are predictive models utilizing logistic regression, K-nearest neighbor classification, random forests, decision trees, neural networks, or combinations of available modeling methods (often referred to as "ensembles"). These evolving techniques will make the regulators' understanding and oversight of filed rating plans even more challenging.

Generalized Linear Models

The GLM is a commonly used predictive model in insurance applications, particularly in building an insurance product's rating plan. Because of this and the fact most Property/Casualty regulators are most concerned about personal lines, NAIC has developed an appendix in its white paper for guidance[13] in reviewing GLMs for personal automobile and home insurance.

What is a "Best Practice"?

A best practice is a form of program evaluation in public policy. At its most basic level, a practice is a "tangible and visible behavior… [based on] an idea about how the actions…will solve a problem or achieve a goal"[14]. Best practices can maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking.[15] Therefore, a best practice represents an effective method of problem solving. The "problem" regulators want to solve is probably better posed as seeking an answer to this question: How can regulators determine that predictive models, as used in rate filings, are compliant with state laws and regulations? However, best practices are not intended to create standards for filings that include predictive models.

Best practices are based on the following principles that promote a comprehensive and coordinated review of predictive models across states:

- State insurance regulators will maintain their current rate regulatory authority and autonomy.
- State insurance regulators will be able to share information to aid companies in getting insurance products to market more quickly across the states.
- State insurance regulators will share expertise and discuss technical issues regarding predictive models to make the review process in any state more effective and efficient.
- State insurance regulators will maintain confidentiality, in accordance with state law, regarding predictive models.

Best Practices for the Regulatory Review of Predictive Models

Best practices will help the regulator understand if a predictive model is cost based, if the predictive model is compliant with state law, and how the model improves the company's rating plan. Best practices can also improve the consistency among the regulatory review processes across states and improve the efficiency of each regulator's review, thereby assisting companies in getting their products to market faster. With this in mind, the regulator's review of predictive models should:

1. Ensure that the selected rating factors, based on the model or other analysis, produce rates that are not excessive, inadequate, or unfairly discriminatory.
   a. Review the overall rate level impact of the proposed revisions to rate level indications provided by the filer.

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[13] Refer to Appendix B in the NAIC's white paper titled *Regulatory Review of Predictive Models* found at the NAIC website.

[14] Bardach, E. and Patashnik, E. (2016.) *A Practical Guide for Policy Analysis, The Eightfold Path to More Effective Problem Solving.* Thousand Oaks, CA: CQ Press. See Appendix A for an overview of Bardach's best-practice analysis.

[15] Bogan, C.E. and English, M.J. (1994). Benchmarking for Best Practices: Winning Through Innovative Adaptation. New York: McGraw-Hill.

       b. Determine that individual input characteristics to a predictive model and their resulting rating factors are related to the expected loss or expense differences in risk.

       c. Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.

       d. Review the individual input characteristics to and output factors from the predictive model (and its sub-models), as well as associated selected relativities, to ensure they are compatible with practices allowed in the state and do not reflect prohibited characteristics.

2. Obtain a clear understanding of the data used to build and validate the model, and thoroughly review all aspects of the model, including assumptions, adjustments, variables, sub-models used as input, and resulting output.

       a. Obtain a clear understanding of how the selected predictive model was built.

       b. Determine that the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values and outliers are handled.

       c. Determine that any adjustments to the raw data are handled appropriately, including but not limited to, trending, development, capping and removal of catastrophes.

       d. Obtain a clear understanding of how often each risk characteristic, used as input to the model, is updated and whether the model is periodically refreshed, so model output reflects changes to non-static risk characteristics.

3. Evaluate how the model interacts with and improves the rating plan.

       a. Obtain a clear understanding of the characteristics that are input to a predictive model (and its sub-models).

       b. Obtain a clear understanding how the insurer integrates the model into the rating plan and how it improves the rating plan.

       c. Obtain a clear understanding of how model output interacts with non-modeled characteristics/variables used to calculate a risk's premium.

4. Enable competition and innovation to promote the growth, financial stability, and efficiency of the insurance marketplace.

       a. Enable innovation in the pricing of insurance through acceptance of predictive models, provided models are in compliance with state laws, particularly prohibitions on unfair discrimination.

       b. Protect the confidentiality of filed predictive models and supporting information in accordance with state law.

       c. Review predictive models in a timely manner to enable reasonable speed to market.

Confidentiality

Each state determines the confidentiality of a rate filing and the supplemental material to the filing, when filing information might become public, the procedure to request that filing information be held confidentially, and the procedure by which a public records request is made. Regulatory reviewers are required to protect confidential information in accordance with applicable state law. Regulators should be aware of their state laws on confidentiality when requesting data from insurers that may be proprietary or trade secret. However, insurers should be aware that a rate filing might become part of the public record. It is incumbent on an insurer to be familiar with each state's laws regarding the confidentiality of information submitted with their rate filing.

State authority, regulations and rules governing confidentiality always apply when a regulator reviews a model used in rating. When NAIC or a third party enters into the review process, the confidential, proprietary, and trade secret protections of the state on behalf of which a review is being performed will continue to apply.

Advisory Organizations – (No change is proposed.)

Workers' Compensation Special Rules – (No change is proposed.)

Premium Selection Decisions – (No change is proposed.)

Installment Plans – (No change is proposed.)

Policy Fees – (No change is proposed.)

Potential Questions to Ask Oneself as a Regulator – (No change is proposed.)

Questions to Ask a Company

If you remain unsatisfied that the company has satisfactorily justified the rate change, then consider asking additional questions of the company. Questions should be asked of the company when they have not satisfied statutory or regulatory requirements in the state or when any current justification is inadequate and could have an impact on the rate change approval or the amount of the approval.

If there are additional items of concern, the company can be notified so they will make appropriate modifications in future filings.

The CASTF white paper, *Regulatory Review of Predictive Models*, documents questions that a regulator may want to ask when reviewing a model. These questions are listed as "information elements" in Appendix B of the paper. Note that although Appendix B focuses on GLMs for personal automobile and home insurance, many of the "information elements" and concepts they represent may be transferable to other types of models, other lines of business, and other applications beyond rating.

Additional Ratemaking Information

The Casualty Actuarial Society (CAS) and the Society of Actuaries (SOA) have extensive examination syllabi that contain a significant amount of ratemaking information, on both the basic topics covered in this chapter and on advanced ratemaking topics. The CAS and SOA websites contain links to many of the papers included in the syllabi. Recommended reading is the *Foundations of Casualty Actuarial Science*, which contains chapters on ratemaking, risk classification, and individual risk rating.

Other Reading

Some additional background reading is recommended:

- *Foundations of Casualty Actuarial Science*, Fourth Edition (2001):
    - Chapter 1: Introduction
    - Chapter 3: Ratemaking
    - Chapter 6: Risk Classification
    - Chapter 9: Investment Issues in Property-Liability Insurance
    - Chapter 10: Only the section on Regulating an Insurance Company, pp. 777–787
- Casualty Actuarial Society (CAS) Statements of Principles, especially regarding property and casualty ratemaking.
- Casualty Actuarial Society (www.casact.org): "Basic Ratemaking."
- American Institute for Chartered Property Casualty Underwriters: "Insurance Operations, Regulation, and Statutory Accounting," Chapter Eight.
- Association of Insurance Compliance Professionals: "Ratemaking—What the State Filer Needs to Know."
- Review of filings and approval of insurance company rates.
- NAIC Casualty Actuarial and Statistical (C) Task Force's white paper: "Regulatory Review of Predictive Models."

Summary

Rate regulation for property/casualty lines of business requires significant knowledge of state rating laws, rating standards, actuarial science, statistical modeling and many data concepts.

- Rating laws vary by state, but the rating laws are usually grouped into prior approval, file and use or use and file (competitive), no file (open competition), and flex rating.
- Rate standards typically included in the state rating laws require that "Rates shall not be inadequate, excessive, or unfairly discriminatory."
- A company will likely determine their indicated rate change by starting with historical years of underwriting data (earned premiums, incurred loss and loss adjustment expenses, general expenses) and adjusting that data to reflect the anticipated ultimate level of costs for the future time period covered by the policies. Numerous adjustments are made to the data. Common premium adjustments are on-level premium, audit, and trend. Common loss adjustments are trend, loss development, Catastrophe/large loss provisions, and an adjusting and other (A&O) loss adjustment expense provision. A profit/contingency provision is also calculated to determine the indicated rate change.
- Once an overall rate level is determined, the rate change gets allocated to the classifications and other rating factors.

- Individual risk rating allows manual rates to be modified by an individual policyholder's own experience.
- Advisory organizations provide the underlying loss costs for companies to be able to add their own expenses and profit provisions (with loss cost multipliers) to calculate their insurance rates.
- Casualty Actuarial Society's *Statement of Principles Regarding Property and Casualty Insurance Ratemaking* provides guidance and guidelines for the numerous actuarial decisions and standards employed during the development of rates.
- NAIC model laws also include special provisions for workers' compensation business, penalties for not complying with laws, and competitive market analysis to determine whether rates should be subject to prior approval provisions.
- Best practices for reviewing predictive models are provided in the CASTF white paper titled *Regulatory Review of Predictive Models*. The best practices and many of the information elements and underlying concepts may be transferrable to other types of models, other lines of insurance, and applications beyond rating.

While this chapter provides an overview of the rate determination/actuarial process and regulatory review, state statutory or administrative rule may require the examiner to adopt different standards or guidelines than the ones described.

No additional changes are proposed to the *Product Filing Review Handbook.*

IX. PROPOSED STATE GUIDANCE

This paper acknowledges that different states will apply the guidance within the paper differently, based on variations in the legal environment pertaining to insurance regulation in those states, as well as the extent of available resources, including staff members with actuarial and/or statistical expertise, the workloads of those staff members, and the time that can be reasonably allocated to predictive-model reviews. States with prior-approval authority over personal-lines rate filings often already require answers in connection with many of the information elements expressed in this paper. However, states – including those with and without prior-approval authority – may also use the guidance in this paper to choose which model elements to focus on in their reviews and/or to train new reviewers, as well as to gain an enhanced understanding of how predictive models are developed, supported, and deployed in their markets. Ultimately, the insurance regulators within each state will decide how best to tailor the guidance within this paper to achieve the most effective and successful implementation, subject to the framework of statutes, regulations, precedents, and processes that comprise the insurance regulatory framework in that state.

X. OTHER CONSIDERATIONS

During the development of state guidance for the review of predictive models used in rate filings, important topics that may impact the review arose that were not within the scope of this paper. These topics are listed here without elaboration, not in any order of importance, and is not an exhaustive list but may need to be addressed during the regulator's review of a predictive model. It may be that one or more of these topics will be addressed by an NAIC committee in the future. These topics are:

- Provide guidance for regulators to identify when a rating variable or rating plan becomes too granular.
- Provide guidance for regulators on the importance of causality vs. correlation when evaluating a rating variable's relationship to risk, in general and in relation to Actuarial Standard of Practice 12 (ASOP 12).
- Provide guidance for regulators on the value and/or concerns of data mining, including how data mining may assist in the model building process, how data mining may conflict with standard scientific principles, how data mining may increase "false positives" during the model building process, and how data mining may result in less accurate models or models that are unfairly discriminatory.
- Provide guidance and/or tools for the regulator to determine how a policy premium is calculated and to identify the most important risk characteristics that underlie the calculated premium.
- Provide guidance for regulators when reviewing consumer-generated data in insurance transactions including disclosure to the consumer, ownership of data, and verification of data procedures.
- Provide guidance, research tools, and techniques for regulators to monitor consumer market outcomes resulting from insurers' use of data analytics underlying rating plans.
- Provide guidance for regulators to expand the best practices and information elements contained in this white paper to non-GLM models and insurance applications other than for personal automobile and home insurance rating plans.

- Provide guidance for regulators to determine that individual input characteristics to a model or a sub-model, as well as associated relativities, are not unfairly discriminatory or a "proxy for a protected class."
- Provide guidance for regulators to identify and minimize unfair discrimination manifested as "disparate impact."
- Provide guidance for regulators that seek a causal or rational explanation why a rating variable is correlated to expected loss or expense, and why that correlation is consistent with the expected direction of the relationship.

APPENDIX A – BEST PRACTICE DEVELOPMENT

Best-practices development is a method for reviewing public policy processes that have been effective in addressing particular issues and could be applied to a current problem. This process relies on the assumptions that top performance is a result of good practices and these practices may be adapted and emulated by others to improve results.[16]

The term "best practice" can be a misleading one due to the slippery nature of the word "best". When proceeding with policy research of this kind, it may be more helpful to frame the project as a way of identifying practices or processes that have worked exceptionally well and the underlying reasons for their success. This allows for a mix-and-match approach for making recommendations that might encompass pieces of many good practices[17].

Researchers have found that successful best-practice analysis projects share five common phases:

Scope

The focus of an effective analysis is narrow, precise and clearly articulated to stakeholders. A project with a broader focus becomes unwieldy and impractical. Furthermore, Bardach urges the importance of realistic expectations in order to avoid improperly attributing results to a best practice without taking into account internal validity problems.

Identify Top Performers

Identify outstanding performers in this area to partner with and learn from. In this phase, it is key to recall that a best practice is a tangible behavior or process designed to solve a problem or achieve a goal (i.e. reviewing predictive models contributes to insurance rates that are not unfairly discriminatory). Therefore, top performers are those who are particularly effective at solving a specific problem or regularly achieve desired results in the area of focus.

Analyze Best Practices

Once successful practices are identified, analysts will begin to observe, gather information and identify the distinctive elements that contribute to their superior performance. Bardach suggests it is important at this stage to distill the successful elements of the process down to their most essential idea. This allows for flexibility once the practice is adapted for a new organization or location.

Adapt

Analyze and adapt the core elements of the practice for application in a new environment. This may require changing some aspects to account for organizational or environmental differences while retaining the foundational concept or idea. This is also the time to identify potential vulnerabilities of the new practice and build in safeguards to minimize risk.

Implementation and Evaluation

The final step is to implement the new process and carefully monitor the results. It may be necessary to make adjustments, so it is likely prudent to allow time and resources for this. Once implementation is complete, continued evaluation is important to ensure the practice remains effective.

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[16] Ammons, D. N. and Roenigk, D. J. 2014. Benchmarking and Interorganizational Learning in Local Government. *Journal of Public Administration Research and Theory,* Volume 25, Issue 1. P 309-335. https://doi.org/10.1093/jopart/muu014
[17] Bardach, E. and Patashnik, E. 2016. *A Practical Guide for Policy Analysis: The Eightfold Path to More Effective Problem Solving.* Thousand Oaks, CA. CQ Press.

APPENDIX B – INFORMATION ELEMENTS AND GUIDANCE FOR A REGULATOR TO MEET BEST PRACTICES' OBJECTIVES (WHEN REVIEWING GLMS)

This appendix identifies the information a regulator may need to review a predictive model used by an insurer to support a personal automobile or home insurance rating plan. The list is lengthy but not exhaustive. It is not intended to limit the authority of a regulator to request additional information in support of the model or filed rating plan. Nor is every item on the list intended to be a requirement for every filing. However, the items listed should help guide a regulator to sufficient information that helps determine if the rating plan meets state specific filing and legal requirements.

Documentation of the design and operational details of the model will ensure business continuity and transparency of models used. Documentation should be sufficiently detailed and complete to enable a qualified third party to form a sound judgment on the suitability of the model for the intended purpose. The theory, assumptions, methodologies, software and empirical bases should be explained, as well as the data used in developing and implementing the model. Relevant testing and ongoing performance testing need to be documented. Key model limitations and overrides need to be pointed out so that stakeholders understand the circumstances under which the model does not work effectively. End-user documentation should be provided and key reports using the model results described. Major changes to the model need to be shared with regulators in a timely manner and documented, and IT controls should be in place, such as a record of versions, change control and access to model.[18]

Many information elements listed below are probably confidential, proprietary or trade secret and should be treated as such according to state law. Regulators should be aware of their state laws on confidentiality when requesting data from insurers that may be proprietary or trade secret. For example, some proprietary models may have contractual terms (with the insurer) that prevent disclosure to the public. Without clear necessity, exposing this data to additional dissemination may compromise the model's protection.[19]

Though the list of information is long, the insurer should already have internal documentation on the model for more than half of the information listed. The remaining items on the list require either minimal analysis (approximately 25%) or deeper analysis to generate for a regulator (approximately 25%).

The "Level of Importance to the Regulator's Review" is a ranking of information a regulator may need to review is based on the following level criteria:

Level 1 - This information is necessary to begin the review of a predictive model. These data elements pertain to basic information about the type and structure of the model, the data and variables used, the assumptions made, and the goodness of fit. Ideally, this information would be included in the filing documentation with the initial submission of a filing made based on a predictive model.

Level 2 - This information is necessary to continue the review of all but the most basic models; such as those based only on the filer`s internal data and only including variables that are in the filed rating plan. These data elements provide more detailed information about the model and address questions arising from review of the information in Level 1. Insurers concerned with speed to market may also want to include this information in the filing documentation.

Level 3 - This information is necessary to continue the review of a model where concerns have been raised and not resolved based on review of the information in Levels 1 and 2. These data elements address even more detailed aspects of the model. This information does not necessarily need to be included with the initial submission, unless specifically requested in a particular state, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws.

Level 4 - This information is necessary to continue the review of a model where concerns have been raised and not resolved based on the information in Levels 1, 2, and 3. This most granular level of detail is addressing the basic building blocks of the model and does not necessarily need to be included by the filer with the initial submission, unless specifically requested in a particular state. It is typically requested only if the reviewer has serious concerns that the model may produce rates or rating factors that are excessive, inadequate, or unfairly discriminatory.

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[18] Model Risk Management: An Overview, the Modeling Section of the Society of Actuaries, Michele, Bourdeau, The Modeling Platform Issue 4, December 2016.

[19] There are some models that are made public by the vendor and would not result in a hindrance of the model's protection.

Lastly, though the best practices presented in this paper will readily be transferrable to review of other predictive models, the information elements presented here might be useful only with deeper adaptations when starting to review different types of predictive models. If the model is not a GLM, some listed items might not apply, for example, not all predictive models generate p-values or F tests. Depending on the model type, other considerations might be important but are not listed here. When information elements presented in this appendix is applied to lines of business other than personal automobile and home insurance or other type of models, unique considerations may arise. Regulators should be aware of the context in which a predictive model is deployed, the uses to which the model is proposed to be put, and the potential consequences the model may have on the insurer, its customers, and its competitors. This paper does not delve into these possible considerations, but regulators should be prepared to address them as they arise.

A. SELECTING MODEL INPUT

Section	Information Element	Level of Importance to the Regulator's Review	Comments
1. Available Data Sources			
A.1.a	Review the details of sources for both insurance and non-insurance data used as input to the model (only need sources for filed input characteristics included in the filed model).	1	Request details of all data sources, whether internal to the company or from external sources. For insurance experience (policy or claim), determine whether data are aggregated by calendar, accident, fiscal or policy year and when it was last evaluated. For each data source, get a list all data elements used as input to the model that came from that source. For insurance data, get a list all companies whose data is included in the datasets. Request details of any non-insurance data used (customer-provided or other), whether the data was collected by use of a questionnaire/checklist, whether data was voluntarily reported by the applicant, and whether any of the data is subject to the Fair Credit Reporting Act. If the data is from an outside source, find out what steps were taken to verify the data was accurate, complete and unbiased in terms of relevant and representative time frame, representative of potential exposures and lacking in obvious correlation to protected classes. Note that reviewing source details should not make a difference when the model is new or refreshed; refreshed models would report the prior version list with the incremental changes due to the refresh.
A.1.b	Reconcile aggregated insurance data underlying the model with available external insurance reports.	4	Accuracy of insurance data should be reviewed. It is assumed that the data in the insurer's data banks is subject to routine internal company audits and reconciliation. "Aggregated data" is straight from the insurer's data banks without further modification (e.g., not scrubbed or transformed for the purposes of modeling). In other words, the data would not have been specifically modified for the purpose of model building. The company should provide some form of reasonability check that the data makes sense when checked against other audited sources.
A.1.c	Review the geographic scope and geographic exposure distribution of the raw data for relevance to the state where the model is filed.	2	The company should explain how the data used to build the model makes sense for a specific state. The regulator should inquire which states were included in the data underlying the model build, testing and validation. The company should provide an explanation where the data came from geographically and that it is a good representation for a state, i.e., the distribution by state should not introduce a geographic

			bias. For example, there could be a bias by peril or wind-resistant building codes. Evaluate whether the data is relevant to the loss potential for which it is being used. For example, verify that hurricane data is only used where hurricanes can occur.

2. Sub-Models

A.2.a	Consider the relevance of (e.g., is there a bias) of overlapping data or variables used in the model and sub-models.	1	Check if the same variables/datasets were used in both the model, a sub-model or as stand-alone rating characteristics. If so, verify there was no double-counting or redundancy.
A.2.b	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	1	If the sub-model was previously approved, that may reduce the extent of the sub-model's review. If approved, verify when and that it was the same model currently under review. However, previous approvals do not necessarily confer a guarantee of ongoing approval, for example when statutes and regulations have changed or if a model's indications have been undermined by subsequent empirical experience. However, knowing whether a model has been previously approved can help focus the regulator's efforts and determine whether or not the prior decision needs to be revisited.
A.2.c	Determine if sub-model output was used as input to the GLM; obtain the vendor name, and the name and version of the sub-model.	1	To accelerate the review of the filing, get the name and contact information for a representative from the vendor. The company should provide the name of the third-party vendor and a contact in the event the regulator has questions. The "contact" can be an intermediary at the insurer, e.g., a filing specialist, who can place the regulator in direct contact with a Subject Matter Expert (SME) at the vendor." Examples of such sub-models include credit/financial scoring algorithms and household composite score models. Sub-models can be evaluated separately and in the same manner as the primary model under evaluation. A sub-model contact for additional information should be provided. SMEs on sub-model may need to be brought into the conversation with regulators (whether in-house or 3rd-party sub-models are used).
A.2.d	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	For example, it is important to know hurricane model settings for storm surge, demand surge, long/short-term views. To accelerate the review of the filing, get contact information for the SME that ran the model and an SME from the vendor. The "SME" can be an intermediary at the insurer, e.g., a filing specialist, who can place the regulator in direct contact with the appropriate SMEs at the insurer or model vendor.
A.2.e	If using catastrophe model output (a sub-model) as input to the GLM under review, verify whether loss associated with the modeled output was removed from the loss experience datasets.	1	If a weather-based sub-model is input to the GLM under review, loss data used to develop the model should not include loss experience associated with the weather-based sub-model. Doing so could cause

			distortions in the modeled results by double counting such losses when determining relativities or loss loads in the filed rating plan. For example, redundant losses in the data may occur when non-hurricane wind losses are included in the data while also using a severe convective storm model in the actuarial indication. Such redundancy may also occur with the inclusion of fluvial or pluvial flood losses when using a flood model, inclusion of freeze losses when using a winter storm model or including demand surge caused by any catastrophic event. Note that, the rating plan or indications underlying the rating plan, may provide special treatment of large losses and non-modeled large loss events. If such treatments exist, the company should provide an explanation how they were handled. These treatments need to be identified and the company/regulator needs to determine whether model data needs to be adjusted. For example, should large BI losses, in the case of personal automobile insurance, be capped or excluded, or should large non-catastrophe wind/hail claims in home insurance be excluded from the model's training, test and validation data?
A.2.f	If using output of any scoring algorithms, obtain a list of the variables used to determine the score and provide the source of the data used to calculate the score.	1	Any sub-model should be reviewed in the same manner as the primary model that uses the sub-model's output as input. Depending on the result of item A.2.b, the importance of this item may be decreased.
3. Adjustments to Data			
A.3.a	Determine if premium, exposure, loss or expense data were adjusted (e.g., developed, trended, adjusted for catastrophe experience or capped) and, if so, how? Do the adjustments vary for different segments of the data and, if so, identify the segments and how was the data adjusted?	2	The rating plan or indications underlying the rating plan may provide special treatment of large losses and non-modeled large loss events. If such treatments exist, the company should provide an explanation how they were handled. These treatments need to be identified and the company/regulator needs to determine whether model data needs to be adjusted. For example, should large bodily injury (BI) liability losses in the case of personal automobile insurance be excluded, or should large non-catastrophe wind/hail claims in home insurance be excluded from the model's training, test and validation data? Look for anomalies in the data that should be addressed. For example, is there an extreme loss event in the data? If other processes were used to load rates for specific loss events, how is the impact of those losses considered? Examples of losses that can contribute to anomalies in the data are large losses or flood, hurricane or severe convective storm losses for personal automobile comprehensive or home insurance.

A.3.b	Identify adjustments that were made to aggregated data, e.g., transformations, binning and/or categorizations. If any, identify the name of the characteristic/variable and obtain a description of the adjustment.	1	
A.3.c	Ask for aggregated data (one data set of pre-adjusted/scrubbed data and one data set of post-adjusted/scrubbed data) that allows the regulator to focus on the univariate distributions and compare raw data to adjusted/binned/transformed/etc. data.	4	This is most relevant for variables that have been "scrubbed" or adjusted. Though most regulators may never ask for aggregated data and do not plan to rebuild any models, a regulator may ask for this aggregated data or subsets of it. It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category were provided. This data can be displayed in either graphical or tabular formats.
A.3.d	Determine how missing data was handled.	1	This is most relevant for variables that have been "scrubbed" or adjusted. The regulator should be aware of assumptions the modeler made in handling missing, null or "not available" values in the data. For example, it would be helpful to the reviewer if the modeler were to provide a statement as to whether there is any systemic reason for missing data. If adjustments or re-coding of values were made, they should be explained. It may also be useful to the regulator if the percentage of exposures and premium for missing information from the model data were provided. This data can be displayed in either graphical or tabular formats.
A.3.e	If duplicate records exist, determine how they were handled.	1	
A.3.f	Determine if there were any material outliers identified and subsequently adjusted during the scrubbing process.	3	Look for a discussion of how outliers were handled. If necessary, the regulator may want to investigate further by getting a list (with description) of the outliers and determine what adjustments were made to each outlier. To understand the filer's response, the regulator should ask for the filer's materiality standard.

4. Data Organization

A.4.a	Obtain documentation on the methods used to compile and organize data, including procedures to merge data from different sources or filter data based on particular characteristics and a description of any preliminary analyses, data checks, and logical tests performed on the data and the results of those tests.	2	This should explain how data from separate sources was merged or how subsets of policies, based on selected characteristics, are filtered to be included in the data underlying the model and the rationale for that filtering.

A.4.b	Obtain documentation on the insurer's process for reviewing the appropriateness, reasonableness, consistency and comprehensiveness of the data, including a discussion of the rational relationship the data has to the predicted variable.	2	An example is when by-peril or by-coverage modeling is performed; the documentation should be for each peril/coverage and make rational sense. For example, if "murder" or "theft" data are used to predict the wind peril, provide support and a rational explanation for their use.
A.4.c	Identify material findings the company had during their data review and obtain an explanation of any potential material limitations, defects, bias or unresolved concerns found or believed to exist in the data. If issues or limitations in the data influenced modeling analysis and/or results, obtain a description of those concerns and an explanation how modeling analysis was adjusted and/or results were impacted.	1	A response of "none" or "n/a" may be an appropriate response.

B. BUILDING THE MODEL

Section	Information Element	Level of Importance to Regulator's Review	Comments
1. High-Level Narrative for Building the Model			
B.1.a	Identify the type of model underlying the rate filing (e.g. Generalized Linear Model – GLM, decision tree, Bayesian Generalized Linear Model, Gradient-Boosting Machine, neural network, etc.). Understand the model's role in the rating system and provide the reasons why that type of model is an appropriate choice for that role.	1	It is important to understand if the model in question is a GLM, and therefore these information elements are applicable or, if it is some other model type, in which case other reasonable review approaches may be considered. There should be an explanation of why the model (using the variables included in it) is appropriate for the line of business. If by-peril or by-coverage modeling is used, the explanation should be by-peril/coverage. Note, if the model is not a GLM, the information elements in this white paper may not apply in their entirety.
B.1.b	Identify the software used for model development. Obtain the name of the software vender/developer, software product and a software version reference used in model development.	3	Changes in software from one model version to the next may explain if such changes, over time, contribute to changes in the modeled results. The company should provide the name of the third-party vendor and a "contact" in the event the regulator has questions. The "contact" can be an intermediary at the insurer who can place the regulator in direct contact with appropriate SMEs. Open-source software/programs used in model development should be identified by name and version the same as if from a vendor.
B.1.c	Obtain a description how the available data was divided between model training, test and/or validation datasets. The description should include an explanation why the selected approach was deemed most appropriate, whether the company made any further subdivisions of available data and reasons for the subdivisions (e.g., a portion separated from training data to support testing of components during model building). Determine if the validation data was accessed before model training was completed and, if so, obtain an explanation why that came to occur. Obtain a discussion of whether the model was rebuilt using all of the data or if it was only based on the training data.	1	The reviewer should be aware that modelers may break their data into three or just two datasets. Although the term "training" is used with little ambiguity, "test" and "validation" are terms that are sometimes interchanged, or the word "validation" may not be used at all. It would be unexpected if validation and/or test data were used for any purpose other than validation and/or test, prior to the selection of the final model.
B.1.d	Obtain a brief description of the development process, from initial concept to final model and filed rating plan.	1	The narrative should have the same scope as the filing.

B.1.e	Obtain a narrative on whether loss ratio, pure premium or frequency/severity analyses were performed and, if separate frequency/severity modeling was performed, how pure premiums were determined.	1	
B.1.f	Identify the model's target variable.	1	A clear description of the target variable is key to understanding the purpose of the model. It may also prove useful to obtain a sample calculation of the target variable in Excel format, starting with the "raw" data for a policy, or a small sample of policies, depending on the complexity of the target variable calculation.
B.1.g	Obtain a description of the variable selection process.	1	The narrative regarding the variable selection process may address matters such as the criteria upon which variables were selected or omitted, identification of the number of preliminary variables considered in developing the model versus the number of variables that remained, and any statutory or regulatory limitations that were taken into account when making the decisions regarding variable selection. The modeler should comment if any form of data mining to identify selected variables was performed and explain how the modeler addressed "false positives" which often arise from data mining techniques.
B.1.h	In conjunction with variable selection, obtain a narrative on how the company determine the granularity of the rating variables during model development.	3	This discussion should include discussion of how credibility was considered in the process of determining the level of granularity of the variables selected.
B.1.i	Determine if model input data was segmented in any way. For example, was modeling performed on a by-coverage, by-peril, or by-form basis? If so, obtain a description of data segmentation and the reasons for data segmentation.	1	The regulator would use this to follow the logic of the modeling process.
B.1.j	If adjustments to the model were made based on credibility considerations, obtain an explanation of the credibility considerations and how the adjustments were applied.	2	Adjustments may be needed given models do not explicitly consider the credibility of the input data or the model's resulting output; models take input data at face value and assume 100% credibility when producing modeled output.
2. Medium-Level Narrative for Building the Model			
B.2.a	At crucial points in model development, if selections were made among alternatives regarding model assumptions or techniques, obtain a narrative on the judgment used to make those selections.	3	

B.2.b	If post-model adjustments were made to the data and the model was rerun, obtain an explanation on the details and the rationale for those adjustments.	2	Evaluate the addition or removal of variables and the model fitting. It is not necessary for the company to discuss each iteration of adding and subtracting variables, but the regulator should gain a general understanding how these adjustments were done, including any statistical improvement measures relied upon.
B.2.c	Obtain a description of the testing that was performed during the model-building process and a discussion of why interaction terms were included (or not included).	3	There should be a description of testing that was performed during the model-building process. Examples of tests that may have been performed include univariate testing and review of a correlation matrix.
B.2.d	For the GLM, identify the link function used. Identify which distribution was used for the model (e.g., Poisson, Gaussian, log-normal, Tweedie). Obtain an explanation why the link function and distribution were chosen. Obtain the formulas for the distribution and link functions, including specific numerical parameters of the distribution. Obtain a discussion of applicable convergence criterion.	1	Solving the GLM is iterative and the modeler can check to see if fit is improving. At some point convergence occurs, though when it occurs can be subjective or based on threshold criteria. The convergence criterion should be documented with a brief explanation of why it was selected. If the software's default convergence criteria were relied upon, the regulator should look for a description of the default convergence criterion and an explanation of any deviation from it.
B.2.e	Obtain a narrative on the formula relationship between the data and the model outputs, with a definition of each model input and output. The narrative should include all coefficients necessary to evaluate the predicted pure premium, relativity or other value, for any real or hypothetical set of inputs.	2	
B.2.f	If there were data situations in which GLM weights were used, obtain an explanation of how and why they were used.	3	Investigate whether identical records were combined to build the model.

3. Predictor Variables

B.3.a	Obtain a complete data dictionary, including the names, types, definitions and uses of each predictor variable, offset variable, control variable, proxy variable, geographic variable, geodemographic variable and all other variables in the model used on their own or as an interaction with other variables (including sub-models and external models).	1	Types of variables might be continuous, discrete, Boolean, etc. Definitions should not use programming language or code. For any variable(s) intended to function as a control or offset, obtain an explanation of its purpose and impact. Also, for any use of interaction between variables, obtain an explanation of its rationale and impact.
B.3.b	Obtain a list of predictor variables considered but not used in the final model, and the rationale for their removal.	4	The purpose of this requirement is to identify variables that the company finds to be predictive but ultimately may reject for reasons other than loss-cost considerations (e.g., price optimization). Also, look for variables the company tested and then rejected. This item could help address concerns about data dredging. The reasonableness of including a variable with given significance level could depend greatly on the other variables the company evaluated for inclusion in the model and the criteria for inclusion or omission. For instance, if the company tested 1,000 similar variables

			and selected the one with the lowest p-value of 0.001, this would be a far, far weaker case for statistical significance than if that variable was the only one the company evaluated. Note, context matters.
B.3.c	Obtain a correlation matrix for all predictor variables included in the model and sub-model(s).	3	While GLMs accommodate collinearity, the correlation matrix provides more information about the magnitude of correlation between variables. The company should indicate what statistic was used (e.g., Pearson, Cramer's V). The regulatory reviewer should understand what statistic was used to produce the matrix but should not prescribe the statistic.
B.3.d	Obtain a rational explanation for why an increase in each predictor variable should increase or decrease frequency, severity, loss costs, expenses, or any element or characteristic being predicted.	3	The explanation should go beyond demonstrating correlation. Considering possible causation may be relevant, but proving causation is neither practical nor expected. If no rational explanation can be provided, greater scrutiny may be appropriate. For example, the regulator should look for unfamiliar predictor variables and, if found, the regulator should seek to understand the connection that variable has to increasing or decreasing the target variable.
B.3.e	If the modeler made use of one or more dimensionality reduction techniques, such as a Principal Component Analysis (PCA), obtain a narrative about that process, an explanation why that technique was chosen, and a description of the step-by-step process used to transform observations (usually correlated) into a set of linearly uncorrelated variables. In each instance, obtain a list of the pre-transformation and post-transformation variable names, and an explanation how the results of the dimensionality reduction technique was used within the model.	2	

4. Adjusting Data, Model Validation and Goodness-of-Fit Measures

B.4.a	Obtain a description of the methods used to assess the statistical significance/goodness of the fit of the model to validation data, such as lift charts and statistical tests. Compare the model's projected results to historical actual results and verify that modeled results are reasonably similar to actual results from validation data.	1	For models that are built using multi-state data, validation data for some segments of risk is likely to have low credibility in individual states. Nevertheless, some regulators require model validation on State-only data, especially when analysis using state-only data contradicts the countrywide results. State-only data might be more applicable but could also be impacted by low credibility for some segments of risk.

Look for geographic stability measures, e.g., across states or territories within state. |

B.4.b	For all variables (discrete or continuous), review the appropriate parameter values, confidence intervals, chi-square tests, p-values and any other relevant and material tests. Determine if model development data, validation data, test data or other data was used for these tests.	1	Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model. For example, the threshold might be lower when many candidate variables were evaluated for inclusion in the model. Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.
B.4.c	Identify the threshold for statistical significance and explain why it was selected. Obtain a reasonable and appropriately supported explanation for keeping the variable for each discrete variable level where the p-values were not less than the chosen threshold.	1	The explanation should clearly identify the thresholds for statistical significance used by the modeler. Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model. For example, the threshold might be lower when many candidate variables were evaluated for inclusion in the model. Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests.

B.4.d	For overall discrete variables, review type 3 chi-square tests, p-values, F tests and any other relevant and material test. Determine if model development data, validation data, test data or other data was used for these tests.	2	Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model. Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.
B.4.e	Obtain evidence that the model fits the training data well, for individual variables, for any relevant combinations of variables and for, the overall model.	2	For a GLM, such evidence may be available using chi-square tests, p-values, F tests and/or other means. The steps taken during modeling to achieve goodness-of-fit are likely to be numerous and laborious to describe, but they contribute much of what is generalized about GLM. We should not assume we know what they did and ask "how?" Instead, we should ask what they did and be prepared to ask follow-up questions.
B.4.f	For continuous variables, provide confidence intervals, chi-square tests, p-values and any other relevant and material test. Determine if model development data, validation data, test data or other data was used for these tests.	2	Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model. Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.

B.4.g	Obtain a description how the model was tested for stability over time.	2	Evaluate the build/test/validation datasets for potential time-sensitive model distortions (e.g., a winter storm in year 3 of 5 can distort the model in both the testing and validation datasets). Obsolescence over time is a model risk (e.g., old data for a variable or a variable itself may no longer be relevant). If a model being introduced now is based on losses from years ago, the reviewer should be interested in knowing whether that model would be predictive in the proposed context. Validation using recent data from the proposed context might be requested. Obsolescence is a risk even for a new model based on recent and relevant loss data. The reviewer may want to inquire as to the following: What steps, if any, were taken during modeling to prevent or delay obsolescence? What controls will exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model? The reviewer should also consider that as newer technologies enter the market (e.g., personal automobile) their impact may change claim activity over time (e.g., lower frequency of loss). So, it is not necessarily a bad thing that the results are not stable over time.
B.4.h	Obtain a narrative on how potential concerns with overfitting were addressed.	2	
B.4.i	Obtain support demonstrating that the GLM assumptions are appropriate.	3	Visual review of plots of actual errors is usually sufficient. The reviewer should look for a conceptual narrative covering these topics: How does this particular GLM work? Why did the rate filer do what it did? Why employ this design instead of alternatives? Why choose this particular distribution function and this particular link function? A company response may be at a fairly high level and reference industry practices. If the reviewer determines that the model makes no assumptions that are considered to be unreasonable, the importance of this item may be reduced.
B.4.j	Obtain 5-10 sample records with corresponding output from the model for those records.	4	

5. "Old Model" Versus "New Model"

B.5.a	Obtain an explanation why this model is an improvement to the current rating plan. If it replaces a previous model, find out why it is better than the one it is replacing; determine how the company reached that conclusion and identify metrics relied on in reaching that conclusion. Look for an explanation of any changes in calculations, assumptions, parameters, and data used to build this model from the previous model.	2	Regulators should expect to see improvement in the new class plan's predictive ability or other sufficient reason for the change.
B.5.b	Determine if two Gini coefficients were compared and obtain a narrative on the conclusion drawn from this comparison.	3	One example of a comparison might be sufficient. This is relevant when one model is being updated or replaced. Regulators should expect to see improvement in the new class plan's predictive ability. This information element requests a comparison of Gini coefficient from the prior model to the Gini coefficient of proposed model. It is expected that there should be improvement in the Gini coefficient. A higher Gini coefficient indicates greater differentiation produced by the model and how well the model fits that data. This comparison is not applicable to initial model introduction. Reviewer can look to CAS monograph for information on Gini coefficients.
B.5.c	Determine if double lift charts were analyzed and obtain a narrative on the conclusion drawn from this analysis.	2	One example of a comparison might be sufficient. Note that "not applicable" is an acceptable response.
B.5.d	If replacing an existing model, obtain a list of any predictor variables used in the old model that are not used in the new model. Obtain an explanation why these variables were dropped from the new model. Obtain a list of all new predictor variables in the new model that were not in the prior old model.	2	Useful to differentiate between old and new variables so the regulator can prioritize more time on variables not yet reviewed.

6. Modeler Software

B.6.a	Request access to SMEs (e.g., modelers) who led the project, compiled the data, built the model, and/or performed peer review.	3	The filing should contain a contact that can put the regulator in touch with appropriate SMEs and key contributors to the model development to discuss the model.

C. THE FILED RATING PLAN

Section	Information Element	Level of Importance to Regulator's Review	Comments
1. General Impact of Model on Rating Algorithm			
C.1.a	In the actuarial memorandum or explanatory memorandum, for each model and sub-model (including external models), look for a narrative that explains each model and its role (how it was used) in the rating system.	1	The "role of the model" relates to how the model integrates into the rating plan as a whole and where the effects of the model are manifested within the various components of the rating plan. This is not intended as an overarching statement of the model's goal, but rather a description of how specifically the model is used. This item is particularly important, if the role of the model cannot be immediately discerned by the reviewer from a quick review of the rate and/or rule pages. (Importance is dependent on state requirements and ease of identification by the first layer of review and escalation to the appropriate review staff.)
C.1.b	Obtain an explanation of how the model was used to adjust the rating algorithm.	1	Models are often used to produce factor-based indications, which are then used as the basis for the selected changes to the rating plan. It is the changes to the rating plan that create impacts. Consider asking for an explanation of how the model was used to adjust the rating algorithm.
C.1.c	Obtain a complete list of characteristics/variables used in the proposed rating plan, including those used as input to the model (including sub-models and composite variables) and all other characteristics/variables (not input to the model) used to calculate a premium. For each characteristic/variable, determine if it is only input to the model, whether it is only a separate univariate rating characteristic, or whether it is both input to the model and a separate univariate rating characteristic. The list should include transparent descriptions (in plain language) of each listed characteristic/variable.	1	Examples of variables used as inputs to the model and used as separate univariate rating characteristics might be criteria used to determine a rating tier or household composite characteristic.

2. Relevance of Variables and Relationship to Risk of Loss

C.2.a	Obtain a narrative regarding how the characteristics/rating variables included in the filed rating plan relate to the risk of insurance loss (or expense) for the type of insurance product being priced.	2	The narrative should include a discussion of the relevance each characteristic/rating variable has on consumer behavior that would lead to a difference in risk of loss (or expense). The narrative should include a rational relationship to cost, and model results should be consistent with the expected direction of the relationship. This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.

3. Comparison of Model Outputs to Current and Selected Rating Factors

C.3.a	Compare relativities indicated by the model to both current relativities and the insurer's selected relativities for each risk characteristic/variable in the rating plan.	1	"Significant difference" may vary based on the risk characteristic/variable and context. However, the movement of a selected relativity should be in the direction of the indicated relativity; if not, an explanation is necessary as to why the movement is logical.
C.3.b	Obtain documentation and support for all calculations, judgments, or adjustments that connect the model's indicated values to the selected values.	1	The documentation should include explanations for the necessity of any such adjustments and explain each significant difference between the model's indicated values and the selected values. This applies even to models that produce scores, tiers, or ranges of values for which indications can be derived. This information is especially important if differences between model indicated values and selected values are material and/or impact one consumer population more than another.
C.3.c	For each characteristic/variable used as both input to the model (including sub-models and composite variables) and as a separate univariate rating characteristic, obtain a narrative how each characteristic/variable was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	Modeling loss ratio with these characteristics/ variables as control variables would account for possible overlap. The insurer should address this possibility or other considerations, e.g., tier placement models often use risk characteristics/ variables that are also used elsewhere in the rating plan. One way to do this would be to model the loss ratios resulting from a process that already uses univariate rating variables. Then the model/composite variables would be attempting to explain the residuals.

4. Responses to Data, Credibility and Granularity Issues			
C.4.a	Determine what, if any, consideration was given to the credibility of the output data.	2	At what level of granularity is credibility applied. If modeling was by-coverage, by-form or by-peril, explain how these were handled when there was not enough credible data by coverage, form or peril to model.
C.4.b	If the rating plan is less granular than the model, obtain an explanation why.	2	This is applicable if the insurer had to combine modeled output in order to reduce the granularity of the rating plan.
C.4.c	If the rating plan is more granular than the model, obtain an explanation why.	2	A more granular rating plan implies that the insurer had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications.
5. Definitions of Rating Variables			
C.5.a	Obtain a narrative on adjustments made to model output, e.g., transformations, binning and/or categorizations. If adjustments were made, obtain the name of the characteristic/variable and a description of the adjustment.	2	If rating tiers or other intermediate rating categories are created from model output, the rate and/or rule pages should present these rating tiers or categories. The company should provide an explanation how model output was translated into these rating tiers or intermediate rating categories.
6. Supporting Data			
C.6.a	Obtain aggregated state-specific, book-of-business-specific univariate historical experience data, separately for each year included in the model, consisting of loss ratio or pure premium relativities and the data underlying those calculations for each category of model output(s) proposed to be used within the rating plan. For each data element, obtain an explanation whether it is raw or adjusted and, if the latter, obtain a detailed explanation for the adjustments.	4	For example, were losses developed/undeveloped, trended/untrended, capped/uncapped, etc.? Univariate indications should not necessarily be used to override more sophisticated multivariate indications. However, they do provide additional context and may serve as a useful reference.

C.6.b	Obtain an explanation of any material (especially directional) differences between model indications and state-specific univariate indications.	4	Multivariate indications may be reasonable as refinements to univariate indications, but possibly not for bringing about significant reversals of those indications. For instance, if the univariate indicated relativity for an attribute is 1.5 and the multivariate indicated relativity is 1.25, this is potentially a plausible application of the multivariate techniques. If, however, the univariate indicated relativity is 0.7 and the multivariate indicated relativity is 1.25, a regulator may question whether the attribute in question is negatively correlated with other determinants of risk. Credibility of state data should be considered when state indications differ from modeled results based on a broader data set. However, the relevance of the broader data set to the risks being priced should also be considered. Borderline reversals are not of as much concern.

7. Consumer Impacts

C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in premium, both as increases and decreases.	4	These rating variables may represent changes to rating factors, be newly introduced to the rating plan, or have been removed from the rating plan.
C.7.b	Determine if the insurer performed sensitivity testing to identify significant changes in premium due to small or incremental change in a single risk characteristic. If such testing was performed, obtain a narrative that discusses the testing and provides the results of that testing.	3	One way to see sensitivity is to analyze a graph of each risk characteristic's/variable's possible relativities. Look for significant variation between adjacent relativities and evaluate if such variation is reasonable and credible.
C.7.c	For the proposed filing, obtain the impacts on expiring policies and describe the process used by management, if any, to mitigate those impacts.	2	Some mitigation efforts may substantially weaken the connection between premium and expected loss and expense, and hence may be viewed as unfairly discriminatory by some states.

C.7.d	Obtain a rate disruption/dislocation analysis, demonstrating the distribution of percentage and/or dollar impacts on renewal business (created by rerating the current book of business), and sufficient information to explain the disruptions to individual consumers.	2	The analysis should include the largest dollar and percentage impacts arising from the filing, including the impacts arising specifically from the adoption of the model or changes to the model as they translate into the proposed rating plan. While the default request would typically be for the distribution/dislocation of impacts at the overall filing level, the regulator may need to delve into the more granular variable-specific effects of rate changes if there is concern about particular variables having extreme or disproportionate impacts, or significant impacts that have otherwise yet to be substantiated. See Appendix C for an example of a disruption analysis.
C.7.e	Obtain exposure distributions for the model's output variables and show the effects of rate changes at granular and summary levels, including the overall impact on the book of business.	3	See Appendix C for an example of an exposure distribution.
C.7.f	Identify policy characteristics, used as input to a model or sub-model, that remain "static" over a policy's lifetime versus those that will be updated periodically. Obtain a narrative on how the company handles policy characteristics that are listed as "static," yet change over time.	3	Some examples of "static" policy characteristics are prior carrier tenure, prior carrier type, prior liability limits, claim history over past X years, or lapse of coverage. These are specific policy characteristics usually set at the time new business is written, used to create an insurance score or to place the business in a rating/underwriting tier, and often fixed for the life of the policy. The reviewer should be aware, and possibly concerned, how the company treats an insured over time when the insured's risk profile based on "static" variables changes over time but the rate charged, based on a new business insurance score or tier assignment, no longer reflect the insured's true and current risk profile. A few examples of "non-static" policy characteristics are age of driver, driving record and credit information (FCRA related). These are updated automatically by the company on a periodic basis, usually at renewal, with or without the policyholder explicitly informing the company.

C.7.g	Obtain a means to calculate the rate charged a consumer.	3	The filed rating plan should contain enough information for a regulator to be able to validate policy premium. However, for a complex model or rating plan, a score or premium calculator via Excel or similar means would be ideal, but this could be elicited on a case-by-case basis. Ability to calculate the rate charged could allow the regulator to perform sensitivity testing when there are small changes to a risk characteristic/variable. Note that this information may be proprietary.
C.7.h	In the filed rating plan, be aware of any non-insurance data used as input to the model (customer-provided or other). In order to respond to consumer inquiries, it may be necessary to inquire as to how consumers can verify their data and correct errors.	1	If the data is from a third-party source, the company should provide information on the source. Depending on the nature of the data, data may need to be documented with an overview of who owns it and the topic of consumer verification may need to be addressed, including how consumers can verify their data and correct errors.

8. Accurate Translation of Model into a Rating Plan

C.8.a	Obtain sufficient information to understand how the model outputs are used within the rating system and to verify that the rating plan's manual, in fact, reflects the model output and any adjustments made to the model output.	1	The regulator can review the rating plan's manual to see that modeled output is properly reflected in the manual's rules, rates, factors, etc.

9. Efficient and Effective Review of Rate Filing

C.9.a	Establish procedures to efficiently review rate filings and models contained therein.	1	"Speed to market" is an important competitive concept for insurers. Though regulators need to understand the rate filing before accepting the rate filing, the regulator should not request information which does not increase their understanding of the rate filing. Regulators should review their state's rate filing review process and procedures to ensure that they are fair and efficient. Regulators need to be aware that requesting information that is not necessary for a decision to be made on a rate filing's compliance with state laws and regulations.
C.9.b	Be knowledgeable of state laws and regulations in order to determine if the proposed rating plan (and models) are compliant with state law.	1	This is a primary duty of regulators. The regulator should be knowledgeable of their state laws and regulations and apply them to a rate filing fairly and efficiently. The regulator should pay special attention to prohibitions of unfair discrimination.

C.9.c	Be knowledgeable of state laws and regulations in order to determine if any information contained in the rate filing (and models) should be treated as confidential.	1	The regulator should be knowledgeable of their state laws and regulations regarding confidentiality of rate filing information and apply them to a rate filing fairly and efficiently. Confidentiality of proprietary information is key to innovation and competitive markets.

Appendix B (cont.)

Mapping BPs to IEs and IEs to BPs

Table 1 maps the best practices to each GLM information element. Table 2 maps the GLM information elements to each best practice. With this mapping a regulator interested in how to meet the objective of a best practice can consider the information elements associated with the best practice in the table.

Appendix B: Table 1 Best Practices Mapped to Information Element	
Information Element	**Selected Best Practices Mapped to Info Element**
A. Selecting Model Input	
A.1. Available Data Sources	
A.1.a	1.b, 1.d, 2.b, 3.a
A.1.b	2.b, 2.c
A.1.c	1.b
A.2. Sub-Models	
A.2.a	1.b, 1.d, 3.a, 3.c
A.2.b	4.c
A.2.c	2.a, 2.d, 3.a, 4.c
A.2.d	2.a, 2.d, 3.a, 4.c
A.2.e	2.c, 1.d, 2.a, 3.a
A.2.f	1.b, 1.d, 2.a, 3.a
A.3. Adjustments to Data	
A.3.a	1.b, 2.a, 2.b, 2.c
A.3.b	2.a, 2.c
A.3.c	2.b, 2.c
A.3.d	2.b, 2.c
A.3.e	2.b, 2.c
A.3.f	2.b, 2.c
A.4. Data Organization	
A.4.a	2.a, 2.b, 2.c, 3.a
A.4.b	1.b, 1.d, 2.b, 2.c
A.4.c	1.d, 2.a, 2.b, 2.c
B. Building the Model	
B.1. High-Level Narrative for Building the Model	
B.1.a	2.a
B.1.b	2.a
B.1.c	2.a
B.1.d	2.a, 3.b
B.1.e	2.a
B.1.f	1.b, 2.a

B.1.g	1.b, 1.d, 2.a, 3.a
B.1.h	2.a, 2.b
B.1.i	1.b, 2.a
B.1.j	2.a, 2.c
B.2. Medium-Level Narrative for Building the Model	
B.2.a	2.a
B.2.b	2.a, 2.c
B.2.c	2.a, 3.b
B.2.d	2.a
B.2.e	2.a, 3.a, 3.b
B.2.f	2.a, 2.c
B.3. Predictor Variables	
B.3.a	1.b, 1.d, 2.a, 3.a
B.3.b	2.a
B.3.c	1.d, 2.a, 3.a
B.3.d	1.b, 1.d, 3.a
B.3.e	2.a, 3.a
B.4. Adjusting Data, Model Validation and Goodness-of-Fit Measures	
B.4.a	2.a, 3.b
B.4.b	2.a, 3.b
B.4.c	1.b, 2.a
B.4.d	1.b, 2.a, 2.b, 3.b
B.4.e	1.b, 2.a
B.4.f	1.b, 2.a, 3.b
B.4.g	2.a, 2.d, 3.b
B.4.h	2.a
B.4.i	1.b, 2.a
B.4.j	1.d, 2.a, 3.c
B.5. "Old Model" Versus "New Model"	
B.5.a	3.b
B.5.b	3.b
B.5.c	3.b
B.5.d	2.d, 3.a, 3.b
B.6. Modeler Software	
B.6.a	2.a
C. The Filed Rating Plan	
C.1. General Impact of Model on Rating Algorithm	
C.1.a	3.b
C.1.b	3.b, 3.c

C.1.c	1.b, 1.d, 3.a, 3.c
C.2. Relevance of Variables and Relationship to Risk of Loss	
C.2.a	1.b, 1.d, 3.a
C.3. Comparison of Model Outputs to Current and Selected Rating Factors	
C.3.a	1.a, 1.c, 3.b
C.3.b	1.a, 1.c, 3.b
C.3.c	3.a, 3.b, 3.c
C.4. Responses to Data, Credibility and Granularity Issues	
C.4.a	3.b
C.4.b	3.b
C.4.c	3.b
C.5. Definitions of Rating Variables	
C.5.a	2.c, 3.b, 3.c
C.6. Supporting Data	
C.6.a	2.c
C.6.b	1.b, 3.b
C.7. Consumer Impacts	
C.7.a	1.a, 1.c
C.7.b	1.a, 1.c
C.7.c	1.a, 1.c, 3.b
C.7.d	1.a, 1.c
C.7.e	1.a, 1.c
C.7.f	2.d
C.7.g	1.c, 3.b
C.7.h	1.d, 2.b, 2.d, 3.b
C.8. Accurate Translation of Model into a Rating Plan	
C.8.a	3.b, 3.c
C.9. Efficient and Effective Review of a Rate Filing	
C.9.a	4.a
C.9.b	4.a
C.9.c	4.a, 4.b

<table>
<tr><td colspan="3" align="center">Appendix B: Table 2
Information Element Mapped to Best Practices</td></tr>
<tr><td align="center">Best Practice</td><td align="center">Best Practice Code</td><td align="center">Information Element (for GLMs)</td></tr>
<tr><td>1.   Ensure that the factors developed based on the model produce rates that are not excessive, inadequate, or unfairly discriminatory.</td><td></td><td></td></tr>
<tr><td>a.   Review the overall rate level impact of the proposed revisions to rate level indications provided by the filer.</td><td align="center">1.a</td><td>C.3.a, C.7.a, C.7.b, C.7.c, C.7.d, C.7.e, C.7.d</td></tr>
<tr><td>b.   Determine that individual input characteristics to a predictive model and their resulting rating factors are related to the expected loss or expense differences in risk.</td><td align="center">1.b</td><td>A.1.a, A.1.c, A.2.a, A.2.f, A.3.a, A.4.b, B.1.f, B.1.g, B.1.i, B.3.a, B.3.d, B.4.c, B.4.d, B.4.e, B.4.f, B.4.i, C.1.c, C.2.a, C.6.b</td></tr>
<tr><td>c.   Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.</td><td align="center">1.c</td><td>C.3.a, C.3.b, C.7.a, C.7.b, C.7.c, C.7.d, C.7.e, C.7.g</td></tr>
<tr><td>d.   Review the individual input characteristics to and output factors from the predictive model (and its sub-models), as well as, associated selected relativities to ensure they are compatible with practices allowed in the state and do not reflect prohibited characteristics.</td><td align="center">1.d</td><td>A.1.a, A.2.a, A.2.e, A.2.f, A.4.b, A.4.c, B.1.g, B.3.a, B.3.c, B.3.d, B.4.j, C.1.c, C.2.a, C.7.h</td></tr>
<tr><td>2.   Obtain a clear understanding of the data used to build and validate the model, and thoroughly review all aspects of the model, including assumptions, adjustments, variables, sub-models used as input, and resulting output.</td><td></td><td></td></tr>
<tr><td>a.   Obtain a clear understanding of how the selected predictive model was built.</td><td align="center">2.a</td><td>A.1.a, A.2.c, A.2.d, A.2.e, A.2.f, A.3.a, A.3.b, A.4.a, A.4.c, B.1.a, B.1.b, B.1.c, B.1.d, B.1.e, B.1.f, B.1.g, B.1.h, B.1.i, B.1.j, B.2.a, B.2.b, B.2.c, B.2.d, B.2.e, B.2.f, B.3.a, B.3.b, B.3.c, B.3.e, B.4.a, B.4.b, B.4.c, B.4.d, B.4.e, B.4.f, B.4.g, B.4.h, B.4.i, B.4.j, B.5.b, B.5.c, B.6.a, C.1.a, C.4.b, C.4.c, C.5.a</td></tr>
<tr><td>b.   Determine that the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values and outliers are handled.</td><td align="center">2.b</td><td>A.1.a, A.1.b, A.3.a, A.3.b, A.3.c, A.3.d, A.3.e, A.3.f, A.4.a, A.4.b, A.4.c, B.1.h, B.4.d, C.6.a, C.7.h</td></tr>
</table>

	c. Determine that any adjustments to the raw data are handled appropriately, including but not limited to trending, development, capping, and removal of catastrophes.	2.c	A.1.b, A.2.e, A.3.a, A.3.b, A.3.c, A.3.d, A.3.e, A.3.f, A.4.a, A.4.b, A.4.c, B.1.j, B.2.b, B.2.f, C.5.a, C.6.a
	d. Obtain a clear understanding of how often each risk characteristic, used as input to the model, is updated and whether the model is periodically refreshed, so model output reflects changes to non-static risk characteristics.	2.d	A.2.c, A.2.d, B.4.g, B.5.d, C.7.f, C.7.h
3. Evaluate how the model interacts with and improves the rating plan.			
	a. Obtain a clear understanding of the characteristics that are input to a predictive model (and its sub-models).	3.a	A.1.a, A.2.a, A.2.c, A.2.d, A.2.e, A.2.f, A.4.a, B.1.g, B.2.e, B.3.a, B.3.c, B.3.d, B.3.e, B.5.d, C.1.c, C.2.a, C.3.c, C.7.h
	b. Obtain a clear understanding how the insurer integrates the model into the rating plan and how it improves the rating plan.	3.b	B.1.d, B.2.c, B.2.e, B.4.a, B.4.b, B.4.d, B.4.f, B.4.g, B.5.a, B.5.b, B.5.c, B.5.d, C.1.a, C.1.b, C.3.a, C.3.b, C.3.c, C.4.a, C.4.b, C.4.c, C.5.a, C.6.b, C.7.c, C.7.g, C.7.h, C.8.a
	c. Obtain a clear understanding of how model output interacts with non-modeled characteristics/variables used to calculate a risk's premium.	3.c	A.2.a, B.4.j, C.1.b, C.1.c, C.3.c, C.5.a, C.8.a
4. Enable competition and innovation to promote the growth, financial stability, and efficiency of the insurance marketplace.			
	a. Enable innovation in the pricing of insurance through acceptance of predictive models, provided they are in compliance with state laws, particularly prohibitions on unfair discrimination.	4.a	C.9.b, C.9.c
	b. Protect the confidentiality of filed predictive models and supporting information in accordance with state law.	4.b	C.9.a, C.9.b, C.9.c
	c. Review predictive models in a timely manner to enable reasonable speed to market.	4.c	C.9.a, C.9.b, C.9.c

APPENDIX C – GLOSSARY OF TERMS

Adjusting Data – Adjusting data refers to any changes made when the modeler makes any to the raw data. For example, capping losses, on-leveling, binning, transformation of the data, etc. This includes scrubbing of the data.

Aggregated Data - Data summarized or compiled in a manner that is meaningful to the intended user of the data. Aggregation involves segmenting and combining individual data entries into categories based on common features within the data. For example, aggregated raw data requested for a predictive model would be categorized in the same manner as the categories of variables which receive specific treatments within the model outputs.

Big Data – "Big Data" refers to extremely large data sets analyzed computationally to infer laws (regressions, nonlinear relationships, and causal effects) to reveal relationships and dependencies or to perform predictions of outcomes and behaviors.

Composite Characteristic - A composite characteristic is the combination of two or more individual risk characteristics. Composite characteristics are used to create composite variables.

Composite Score - A composite score is a number derived by combining multiple variables by means of a sequence of mathematical steps - for example, a credit-based insurance scoring model.

Composite Variable - A composite variable is a variable created by incorporating two or more individual risk characteristics of the insured into a single variable.

Continuous Variable - A continuous variable is a numeric variable that represents a measurement on a continuous scale. Examples include age, amount of insurance (in dollars), and population density.[20]

Control Variable - Control variables are variables whose relativities are not used in the final rating algorithm but are included when building the model. They are included in the model so that other correlated variables do not pick up their signal. For example, state and year are frequently included in countrywide models as control variables so that the different experiences and distributions between states and across time do not influence the rating factors used in the final rating algorithm.[21]

Correlation Matrix - A correlation matrix is a table showing correlation coefficients between sets of variables. Each random variable (X_i) in the table is correlated with each of the other variables in the table (X_j). Using the correlation matrix, one can determine which pairs of variables have the highest correlation. Below is a sample correlation matrix showing correlation coefficients for combinations of 5 variables B1:B5. The table shows that variables B2 and B4 have the highest correlation coefficient (0.96) in this example. The diagonal of the table is always set to one, because the correlation coefficient between a variable and itself is always 1. The upper-right triangle would be a mirror image of the lower-left triangle (because correlation between B1 andB2 is the same as between B2 and B1). In other words, a correlation matrix is also a symmetric matrix.[22]

	B1	B2	B3	B4	B5
B1	1				
B2	0.53	1			
B3	0.73	0.44	1		
B4	0.87	0.96	0.41	1	
B5	0.43	0.71	0.72	0.56	1

Data Dredging - Data dredging is also referred to as data fishing, data snooping, data butchery, and p-hacking. It is the misuse of data analysis to find patterns in data that can be presented as statistically significant when, in fact, there is no real underlying effect. Data dredging is done by performing many statistical tests on the data and focusing only on those that produce significant results. Data dredging is in conflict with hypothesis testing, which entails performing at most a handful of tests to determine the validity of the hypothesis about an underlying effect.[23]

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[20] https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf
[21] www.casact.org/cms/pdf/Practical_Guide_for_Evaluating_Predictive_Models_Closter_Carmean.pdf
[22] https://www.statisticshowto.datasciencecentral.com/correlation-matrix
[23] Davey Smith, G.; Ebrahim, S. (2002). "Data dredging, bias, or confounding". BMJ. 325 (7378): 1437–1438. doi:10.1136/bmj.325.7378.1437. PMC 1124898. PMID 12493654.

Data Source - A data source is the original repository of the information used to build the model. For example, information from internal insurance data, an application, a vendor, credit bureaus, government websites, a sub-model, verbal information provided to agents, external sources, consumer information databases, etc.

Discrete Variable - A discrete variable is a variable that can only take on a countable number of values/categories. Examples include number of claims, marital status, and gender.

Discrete Variable Level - Discrete variables are generally referred to as "factors" (not to be confused with rating factors), with values that each factor can take being referred to as "levels."[24]

Double-Lift Chart - Double lift charts are similar to simple quantile plots, but rather than sorting based on the predicted loss cost of each model, the double lift chart sorts based on the ratio of the two models' predicted loss costs. Double lift charts directly compare the results of two models.[25]

Exponential Family - The exponential family is a class of distributions that share the same general density form and have certain properties that are used in fitting GLMs. It includes many well-known distributions, such as the Normal, Poisson, Gamma, Tweedie, and Binomial, to name a few.[26]

Fair Credit Reporting Act – The Fair Credit Reporting Act (FCRA), 15 U.S.C. § 1681 (FCRA) is U.S. Federal Government legislation enacted to promote the accuracy, fairness and privacy of consumer information contained in the files of consumer reporting agencies. It was intended to protect consumers from the willful and/or negligent inclusion of inaccurate information in their credit reports. To that end, the FCRA regulates the collection, dissemination and use of consumer information, including consumer credit information.[27] Together with the Fair Debt Collection Practices Act (FDCPA), the FCRA forms the foundation of consumer rights law in the United States. It was originally passed in 1970 and is enforced by the US Federal Trade Commission, the Consumer Financial Protection Bureau and private litigants.

Generalized Linear Model - Generalized linear models (GLMs) are a means of modeling the relationship between a variable whose outcome we wish to predict and one or more explanatory variables. The predicted variable is called the target variable and is denoted y. In property/casualty insurance ratemaking applications, the target variable is typically one of the following:

- Claim count (or claims per exposure)
- Claim severity (i.e., dollars of loss per claim or occurrence)
- Pure premium (i.e., dollars of loss per exposure)
- Loss ratio (i.e., dollars of loss per dollar of premium)

For quantitative target variables such as those above, the GLM will produce an estimate of the expected value of the outcome. For other applications, the target variable may be the occurrence or non-occurrence of a certain event. Examples include:

- Whether or not a policyholder will renew his/her policy.
- Whether a submitted claim contains fraud.

For such variables, a GLM can be applied to estimate the probability that the event will occur.

The explanatory variables, or predictors, are denoted $x_1 \ldots x_p$, where p is the number of predictors in the model. Potential predictors are typically any policy term or policyholder characteristic that an insurer may wish to include in a rating plan.

Some examples are:
- Type of vehicle, age, or marital status for personal auto insurance.
- Construction type, building age, or amount of insurance (AOI) for home insurance.[28]

[24] https://www.casact.org/pubs/dpp/dpp04/04dpp1.pdf
[25] "Exploring Model Lift: Is Your Model Worth Implementing?," Actuarial Review, volume 40, number 2, May 2013, Dan Trevet, https://www.casact.org/newsletter/index.cfm?fa=viewart&id=6540.
[26] Generalized Linear Models for Insurance Rating, CAS Monograph Series, Number 5, Second Edition, Mark Goldburd, et al, www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf
[27] Dlabay, Les R.; Burrow, James L.; Brad, Brad (2009). Intro to Business. Mason, Ohio: South-Western Cengage Learning. p. 471. ISBN 978-0-538-44561-0.
[28] Generalized Linear Models for Insurance Rating, CAS Monograph Series, Number 5, Second Edition, Mark Goldburd, et al, www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf

Geodemographic - Geodemographics is the study of the population and its characteristics, divided according to regions on a geographical basis. This involves application of clustering techniques to group statistically similar neighborhoods and areas with the assumption that the differences within any group should be less than the difference between groups. While the main source of data for a geodemographic study is the census data, the use of other sources of relevant data is also prevalent. Geodemographic segmentation is based on two principles:

1. People who live in the same neighborhood are more likely to have similar characteristics than are two people chosen at random.
2. Neighborhoods can be categorized in terms of the characteristics of the population that they contain. Any two neighborhoods can be placed in the same category, i.e., they contain similar types of people, even though they are widely separated.

Granularity of Data - Granularity of data is the level of segmentation at which the data is grouped or summarized. It reflects the level of detail used to slice and dice the data.[29]

For example, a postal address can be recorded, with coarse granularity, as:
- Country

Or, with finer granularity, as multiple fields:
- Country
- State

Or, with much finer granularity, as multiple fields:
- Country
- State
- County
- ZIP Code
- Property Geo Code

Home Insurance – Home insurance covers damage to the property, contents, and outstanding structures (if applicable), as well as loss of use, liability and medical coverage. The perils covered, the amount of insurance provided, and other policy characteristics are detailed in the policy contract.[30]

Insurance Data - Data collected by the insurance company. For example, data obtained from the consumer through communications with an agent or on an insurance application would be "insurance data." However, data obtained from a credit bureau or census would not be considered "insurance data" but would be considered "non-insurance data" instead."

Interaction Term - Two predictor variables are said to interact if the effect of one of the predictors on the target variable depends on the level of the other. Suppose that predictor variables X_1 and X_2 interact. A GLM modeler could account for this interaction by including an interaction term of the form X_1X_2 in the formula for the linear predictor. For instance, rather than defining the linear predictor as $\eta = \beta_0 + \beta_1X_1 + \beta_2X_2$, they could set $\eta = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_1X_2$.[31]

The following two plots of modeled personal auto bodily injury pure premium by age and gender illustrate this effect. The plots are based on two otherwise identical log-link GLMs, built using the same fictional dataset, with the only difference between the two being that the second model includes the Age∗Gender interaction term while the first does not. Notice that the male curve in the first plot is a constant multiple of the female curve, while in the second plot the ratios of the male to female values differ from age to age.

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[29] Granularity (also called graininess), https://en.wikipedia.org/wiki/Granularity#Data_granularity
[30] Basic Ratemaking, Fifth Edition, May 2016, Geoff Werner, et al, www.casact.org/library/studynotes/Werner_Modlin_Ratemaking.pdf
[31] To see that this second definition accounts for the interaction, note that it is equivalent to $\eta = \beta0 + \beta1'X1 + \beta2X2$ and to $\eta = \beta0 + \beta1X1 + \beta2'X2$, with $\beta1'$ = $\beta1 + \beta3X2$ and $\beta2' = \beta2 + \beta3X1$. Since $\beta1'$ is a function of X2 and $\beta2'$ is a function of X1, these two equivalences say that the effect of X1 depends on the level of X2 and vice versa.
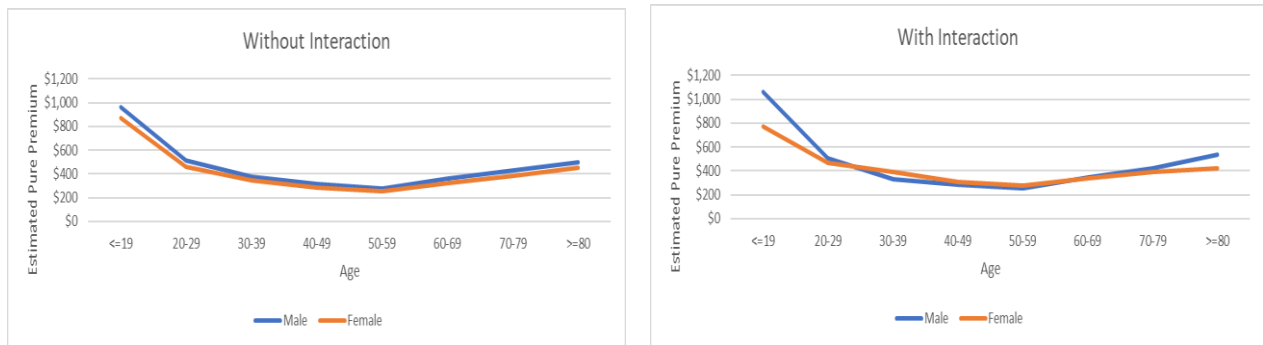
Lift Chart - See definition of quantile plot.

Linear Predictor - A linear predictor is the linear combination of explanatory variables $(X_1, X_2, ... X_k)$ in the model... e.g., $\beta_0 + \beta_1 X_1 + \beta_2 X_2$.[32]

Link Function - The link function, η or $g(\mu)$, specifies how the expected value of the response relates to the linear predictor of explanatory variables; e.g., $\eta = g(E(Y_i)) = E(Y_i)$ for linear regression, or $\eta = \text{logit}(\pi)$ for logistic regression.[33]

Missing data - Missing data occurs when some records contain blanks or "Not Available" or "Null" where variable values would normally be available.

Non-Insurance Data - Non-insurance data is data provided by another party other than the insurance company. For example, data obtained from a credit bureau or census would be considered "non-insurance data." However, data obtained from the consumer through communications with an agent or on an insurance application would not be considered "non-insurance data" but would be "insurance data" instead."

Offset Variable – Offset variables (or factors) are model variables with a known or pre-specified coefficient. Their relativities are included in the model and the final rating algorithm, but they are generated from other studies outside the multivariate analysis and are fixed (not allowed to change) in the model when it is run. The model does not estimate any coefficients for the offset variables, and they are included in the model, so that the estimated coefficients for other variables in the model would be optimal in their presence. Examples of offset variables include limit and deductible relativities that are more appropriately derived via loss elimination analysis. The resulting relativities are then included in the multivariate model as offsets. Another example is using an offset factor to account for the exposure in the records; this does not get included in the final rating algorithm.[34]

Overfitting – Overfitting is the production of an analysis that corresponds too closely or exactly to a particular set of data and may, therefore, fail to fit additional data or predict future observations reliably.[35]

PCA Approach (Principal Component Analysis) – The PCA method creates multiple new variables from correlated groups of predictors. Those new variables exhibit little or no correlation between them—thereby making them potentially more useful in a GLM. A PCA in a filing can be described as "a GLM within a GLM." One of the more common applications of PCA is geodemographic analysis, where many attributes are used to modify territorial differentials on, for example, a census block level.

Personal Automobile Insurance – Personal automobile insurance is insurance for privately owned motor vehicles and trailers for use on public roads not owned or used for commercial purposes. This includes personal auto combinations of private passenger auto, motorcycle, financial responsibility bonds, recreational vehicles and/or other personal auto. Policies

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[32] Generalized Linear Models for Insurance Rating, CAS Monograph Series, Number 5, Second Edition, Mark Goldburd, et al, www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf
[33] https://online.stat.psu.edu/stat504/node/216
[34] Predictive Models: A Practical Guide for Practitioners and Regulators, Don Closter ACAS, MAAA, ASA and Caryn Carmean ACAS, MAAA, www.casact.org/cms/pdf/Practical_Guide_for_Evaluating_Predictive_Models_Closter_Carmean.pdf
[35] Wikipedia, https://en.wikipedia.org/wiki/Overfitting

include any combination of coverage such as the following: auto liability, personal injury protection (PIP), medical payments (MP), uninsured/underinsured motorist (UM/UIM); specified causes of loss, comprehensive, and collision.[36]

Post-model Adjustment - Post-model adjustment is any adjustment made to the output of the model including but not limited to adjusting rating factors or removal of variables.

Probability Distribution – A probability distribution is a statistical function that describes all the possible values and likelihoods that a random variable can take within a given range. The chosen probability distribution is supposed to best represent the likely outcomes.

Proxy Variable - A proxy variable is any variable that indirectly captures the characteristics of another variable, whether or not that other variable is used in the insurer's rating plan.

Quantile Plot - A quantile plot is a visual representation of a model's ability to accurately differentiate between the best and the worst risks. Data is sorted by predicted value from smallest to largest, and the data is then bucketed into quantiles with the same volume of exposures. Within each bucket the average predicted value and the average actual value are calculated and for each quantile the actual and the predicted values are plotted. The first quantile contains the risks that the model predicts have the best experience and the last quantile contains the risks predicted to have the worst experience. The plot shows two things: how well the model predicts actual values by quantile, and the lift of the model, the difference between the first and last quantile, which is a reflection of the model's ability to distinguish between the best and worst risks. By definition, the average predicted values would be monotonically increasing, but the average actual values may show reversals.[37] An example follows:
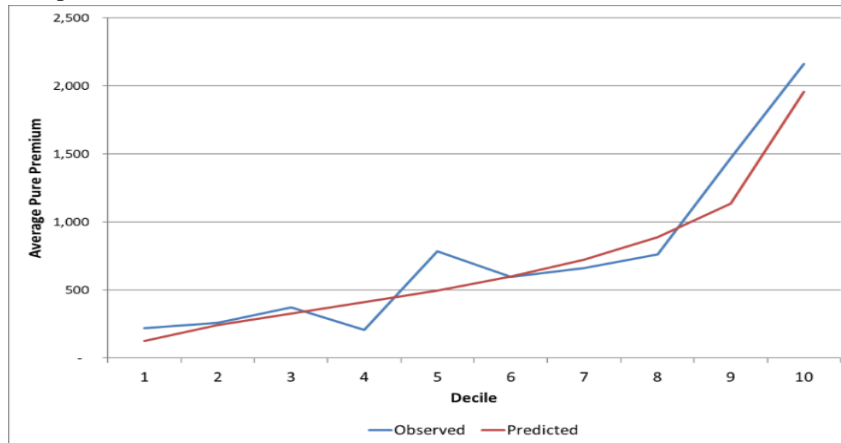
Rating Algorithm – A rating algorithm is the mathematical or computational component of the rating plan used to calculate an insured's premium.

Rating Category - A rating category is the same as a rating characteristic and can be quantitative or qualitative.

Rating Characteristic - A rating characteristic is a specific risk criterion of the insured used to define the level of the rating variable that applies to the insured. Ex. Rating variable- Driver age, Rating characteristic- Age 42

Rating Factor – A rating factor is the numerical component included in the rate pages of the rating plan's manual. Rating factors are used together with the rating algorithm to calculate the insured's premium.

Rating Plan – The rating plan describes in detail how to combine the various components in the rules and rate pages to calculate the overall premium charged for any risk. The rating plan is very specific and includes explicit instructions, such as:
- the order in which rating variables should be considered,
- how the effect of rating variables is applied in the calculation of premium (e.g., multiplicative, additive, or some unique mathematical expression),

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[36] NAIC, https://content.naic.org/cipr_topics/topic_auto_insurance.htm
[37] Generalized Linear Models for Insurance Rating, CAS Monograph Series, Number 5, Second Edition, Mark Goldburd, et al, https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf

- the existence of maximum and minimum premiums (or in some cases the maximum discount or surcharge that can be applied), and
- specifics associated with any rounding that takes place.

If the insurance product contains multiple coverages, then separate rating plans by coverage may apply.[38]

Rating System - The rating system is the insurance company's IT infrastructure that produces the rates derived from the rating algorithm.

Rating Tier - A rating tier is rating based on a combination of rating characteristics rather than a single rating characteristic resulting in a separation of groups of insureds into different rate levels within the same or separate companies. Often, rating tiers are used to differentiate quality of risk, e.g., substandard, standard, or preferred.

Rating Treatment - Rating treatment is the manner in which an aspect of the rating affects an insured's premium.

Rating Variable - A rating variable is a risk criterion of the insured used to modify the base rate in a rating algorithm.[39]

Rational Explanation – A "rational explanation" refers to a plausible narrative connecting the variable and/or treatment in question with real-world circumstances or behaviors that contribute to the risk of insurance loss in a manner that is readily understandable to a consumer or other educated layperson. A "rational explanation" does not require strict proof of causality but should establish a sufficient degree of confidence that the variable and/or treatment selected are not obscure, irrelevant, or arbitrary.

A "rational explanation" can assist the regulator in explaining an approved rating treatment if challenged by a consumer, legislator, or the media. Furthermore, a "rational explanation" can increase the regulator's confidence that a statistical correlation identified by the insurer is not spurious, temporary, or limited to the specific data sets analyzed by the insurer.

Raw Data - Data originating straight from the insurer's data banks without modification (e.g., not scrubbed, transformed). Raw data may occur with or without aggregation. Aggregated raw datasets are those summarized or compiled prior to data selection and model building.

Sample Record - A sample record is one line of data from a data source including all variables. For example:

Record	ZIP	Garage Type	Lot Size	Roof	Square Feet	Replacement Cost	Heating	Living Area SqFt	Num Stories	Style	Num Bedrooms
1	04254	garage, basement	25700	asphalt shingle	1680	213000	FORCED HOT WATER	1680	1	Ranch	3

Scrubbed Data - Scrubbed data is data reviewed for errors, where "N/A" has been replaced with a value, and where most transformations have been performed. Data that has been "scrubbed" is now in a useable format to begin building the model.

Scrubbing Data - Scrubbing is the process of editing, amending, or removing data in a dataset that is incorrect, incomplete, improperly formatted, or duplicated.

SME - Subject Matter Expert.

Sub-Model - A sub-model is any model that provides input into another model.

Variable Transformation - A variable transformation is a change to a variable by taking a function of that variable, for example, when age's value is replaced by the value (age)^2. The result is called a **transformation variable**.

Voluntarily Reported Data - Voluntarily reported data is data directly obtained by a company from a consumer. Examples would be data taken directly from an application for insurance or obtained verbally by a company representative.

Univariate Model – A univariate model is a model that only has one independent variable.
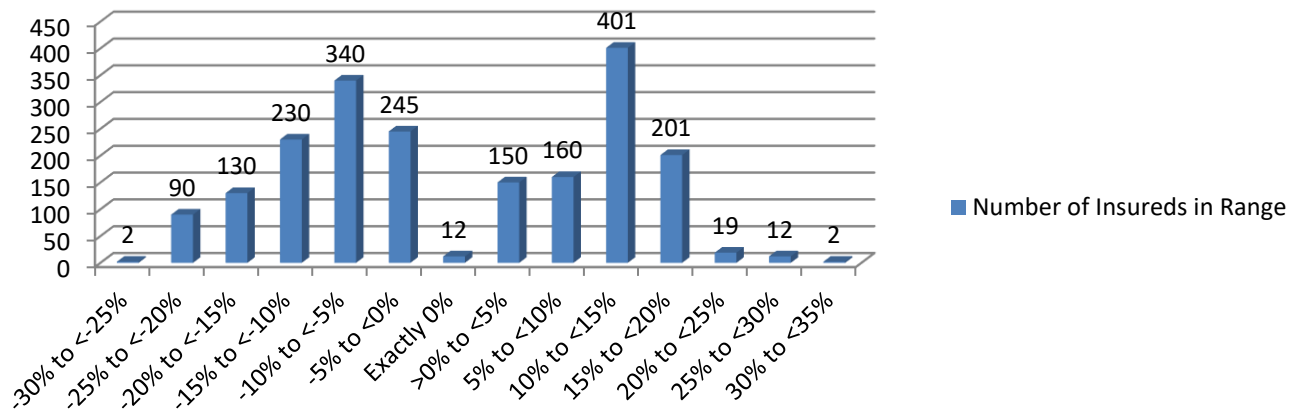
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[38] Basic Ratemaking, Fifth Edition, May 2016, Geoff Werner, et al, https://www.casact.org/library/studynotes/Werner_Modlin_Ratemaking.pdf
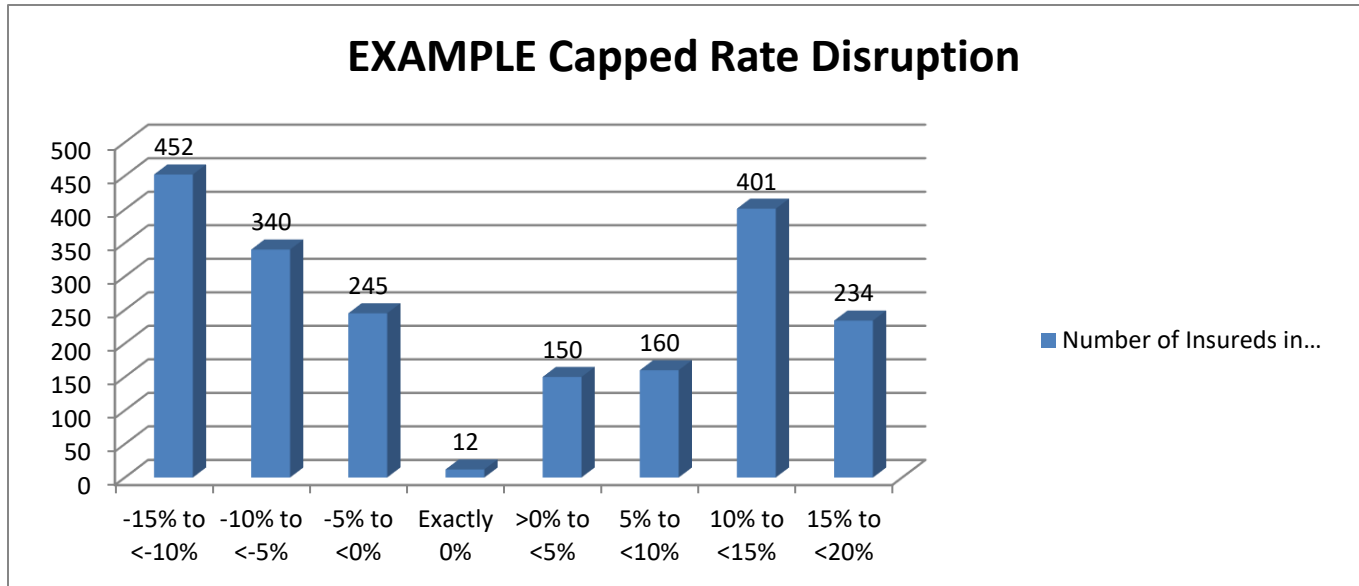[39] Basic Ratemaking, Fifth Edition, May 2016, Geoff Werner, et al, https://www.casact.org/library/studynotes/werner_modlin_ratemaking.pdf

APPENDIX D – SAMPLE RATE-DISRUPTION TEMPLATE

State Division of Insurance - EXAMPLE for Rate Disruption		*Template Updated October 2018*	
● First, fill in the boxes for minimum and maximum individual impacts, shaded in light blue. Default values in the cells are examples only.			
● The appropriate percent-change ranges will then be generated based on the maximum/minimum changes.			
● For every box shaded in light green, replace "ENTER VALUE" with the number of affected insureds within the corresponding change range.			
● Once all values are filled in, use the "Charts" feature in Excel to generate a histogram to visually display the spread of impacts.			
NOTE: Values of Minimum % Change, Maximum % Change, and Total Number of Insureds must reconcile to the Rate/Rule Schedule in SERFF.			

	Uncapped		*Capped (If Applicable)*
Minimum % Change	-30.000%	**Minimum % Change**	-15.000%
Maxmium % Change	30.000%	**Maxmium % Change**	15.000%
Total Number of Insureds (Auto-Calculated)	1994	**Total Number of Insureds (Auto-Calculated)**	1994

Uncapped Rate Disruption		*Capped Rate Disruption (If Applicable)*	
Percent-Change Range	**Number of Insureds in Range**	**Percent-Change Range**	**Number of Insureds in Range**
-30% to <-25%	2	-15% to <-10%	452
-25% to <-20%	90	-10% to <-5%	340
-20% to <-15%	130	-5% to <0%	245
-15% to <-10%	230	Exactly 0%	12
-10% to <-5%	340	>0% to <5%	150
-5% to <0%	245	5% to <10%	160
Exactly 0%	12	10% to <15%	401
>0% to <5%	150	15% to <20%	234
5% to <10%	160		
10% to <15%	401		
15% to <20%	201		
20% to <25%	19		
25% to <30%	12		
30% to <35%	2		

EXAMPLE Uncapped Rate Disruption

EXAMPLE Capped Rate Disruption

Bar chart showing Number of Insureds by percentage change bracket:
- -15% to <-10%: 452
- -10% to <-5%: 340
- -5% to <0%: 245
- Exactly 0%: 12
- >0% to <5%: 150
- 5% to <10%: 160
- 10% to <15%: 401
- 15% to <20%: 234

Legend: ■ Number of Insureds in...

State Division of Insurance - EXAMPLE for Largest Percentage Increase			*Template Updated October 2018*	
● Fill in fields highlighted in light green. Fields highlighted in red are imported from the Template for Rate Disruption.				

Largest Percentage Increase		*Corresponding Dollar Increase (for Insured Receiving Largest Percentage Increase)*			
Uncapped Change	30.00%	**Uncapped Dollar Change**	$165.00	**Current Premium**	$550.00
Capped Change (If Applicable)	15.00%	**Capped $ Change (If Applicable)**	$82.50	**Proposed Premium**	$632.50
Characteristics of Policy (Fill in Below)					

● **For Auto Insurance:** At minimum, identify the age and gender of each named insured, limits by coverage, territory, make / model of vehicle(s), prior accident / violation history, and any other key attributes whose treatments are affected by this filing.

● **For Home Insurance:** At minimum, identify age and gender of each named insured, amount of insurance, territory, construction type, protection class, any prior loss history, and any other key attributes whose treatments are affected by this filing.

Automobile policy: Three insureds - Male (Age 54), Female (Age 49), and Male (Age 25). **Territory:** Las Vegas, ZIP Code 89105.					
Vehicle:	**BI Limits:**	**PD Limits:**	**UM/UIM Limits:**	**MED Limits:**	**COMP Deductible:**	**COLL Deductible:**
2009 Ford Focus	$50,000 / $100,000	$25,000	$50,000 / $100,000	$5,000	$500	$1,000
2003 Honda Accord	$25,000 / $50,000	$10,000	$25,000 / $50,000	$1,000	$500	$1,000

No prior accidents, 1 prior speeding conviction for 25-year-old male. Policy receives EFT discount and loyalty discount.

Primary impacts are the increases to the relativities for the age of insured, ZIP Code 89105, COLL Deductible of $1,000, and symbol for 2003 Honda Accord.

Most Significant Impacts to This Policy (Identify attributes - e.g., base-rate change or changes to individual rating variables)

NOTE: If capping is proposed to apply for this policy, include the impact of capping at the end, after displaying uncapped impacts by attribute. Add rows as needed. Total percent and dollar impacts should reconcile to the values presented above in this exhibit.

Attribute	% Impact (Uncapped)	Dollar Impact (Uncapped)	What lengths of policy terms does the insurer offer in this book of business?
Insured Age (M/25)	12.00%	$66.00	Check all options that apply below.
COLL Deductible ($1,000)	10.00%	$61.60	
Territory (89105)	4.00%	$27.10	☐ 12-Month Policies
Vehicle Symbol (2003 Honda Accord)	1.46%	$10.29	☑ 6-Month Policies
			☐ 3-Month Policies
Effect of Capping	-11.54%	-$82.50	☐ Other (SPECIFY)
TOTAL	**15.00%**	**$82.50**	

Draft: 6/12/2020
As adopted by the Casualty Actuarial and Statistical (C) Task Force on XX/XX/XX

State Division of Insurance - EXAMPLE for Largest Dollar Increase				*Template Updated October 2018*		
● Fill in fields highlighted in light green.						
Largest Dollar Increase			*Corresponding Percentage Increase (for Insured Receiving Largest Dollar Increase)*			
Uncapped Change		$306.60	**Current Premium**	$2,555.00	**Uncapped Percent Change**	12.00%
Capped Change (If Applicable)		$306.60	**Proposed Premium**	$2,861.60	**Capped % Change (If Applicable)**	12.00%

Characteristics of Policy (Fill in Below)

● **For Auto Insurance:** At minimum, identify the age and gender of each named insured, limits by coverage, territory, make / model of vehicle(s), prior accident / violation history, and any other key attributes whose treatments are affected by this filing.

● **For Home Insurance:** At minimum, identify age and gender of each named insured, amount of insurance, territory, construction type, protection class, any prior loss history, and any other key attributes whose treatments are affected by this filing.

Automobile policy: Two insureds - Male (Age 33), Female (Age 32). **Territory:** Reno, ZIP Code 89504.

Vehicle:	BI Limits:	PD Limits:	UM/UIM Limits:	MED Limits:	COMP Deductible:	COLL Deductible:
2016 Tesla Model S	$200,000 / $600,000	$50,000	$200,000 / $600,000	$10,000	$2,500	$2,500
2015 Mercedes-Benz C-Class (W205)	$200,000 / $600,000	$50,000	$200,000 / $600,000	$10,000	$2,500	$2,500

1 prior at-fault accident for 32-year-old female. Policy receives EFT discount and loyalty discount.

Primary impacts are the increases to the relativities for the age of insured, symbol for 2015 Mercedes-Benz C-Class, and increased-limit factors for Property Damage and Medical Payments coverages.

Most Significant Impacts to This Policy (Identify attributes - e.g., base-rate change or changes to individual rating variables)

NOTE: If capping is proposed to apply for this policy, include the impact of capping at the end, after displaying uncapped impacts by attribute. Add rows as needed. Total percent and dollar impacts should reconcile to the values presented above in this exhibit.

Attribute	% Impact (Uncapped)	Dollar Impact (Uncapped)					
Insured Age (M/33)	3.15%	$80.48					
Insured Age (F/32)	3.23%	$85.13					
Vehicle Symbol (2015 Mercedes-Benz C-Class)	2.45%	$66.65					
Increased-Limit Factor for PD	1.55%	$43.20					
Increased-Limit Factor for MED	1.10%	$31.14					
TOTAL	**12.00%**	**$306.60**					