

CASUALTY ACTUARIAL AND STATISTICAL (C) TASK FORCE

Casualty Actuarial and Statistical (C) Task Force August 11, 2025, Minutes

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Draft Pending Adoption

Draft: 8/26/25

Casualty Actuarial and Statistical (C) Task Force
Minneapolis, Minnesota
August 11, 2025

The Casualty Actuarial and Statistical (C) Task Force met in Minneapolis, MN, Aug. 11, 2025. The following Task Force members participated: D.J. Bettencourt, Chair, represented by Christian Citarella (NH); Angela L. Nelson, Vice Chair, Jo A. LeDuc, and Julie Lederer (MO); Mark Fowler represented by Charles Hale (AL); Ricardo Lara represented by Mitra Sanandajifar (CA); Andrew N. Mais represented by Wanchin Chou and Kristin Fabian (CT); Trinidad Navarro represented by Tom Hudson (DE); Michael Yaworsky represented by Richie Frederick (FL); Doug Ommen represented by Travis Grassel (IA); Vicki Schmidt represented by Nicole Boyd (KS); Timothy J. Temple represented by Stephan Kowalski (LA); Robert L. Carey represented by Sandra Darby (ME); Anita G. Fox represented by Kevin Dyke (MI); Grace Arnold represented by Phil Vigliaturo (MN); Eric Dunning represented by Michael Muldoon and Margaret Otto (NE); Ned Gaines represented by Gennady Stolyarov (NV); Judith L. French represented by Tom Botsko (OH); Glen Mulready represented by Eli Snowbarger (OK); TK Keen represented by John Haworth (OR); Michael Humphreys represented by Michael McKenney (PA); Michael Wise represented by Will Davis (SC); Cassie Brown, Nicole Elliott, Miriam Fisk, and Eric Hintikka (TX); Patty Kuderer represented by William Wilder (WA); and Allan L. McVey (WV). Also participating was: Tom Zuppan (AZ); Jason Lapham (CO); and Tomasz Serbinowski (UT).

1. Adopted its June 10, June 6, May 15, April 25, April 1, and Spring National Meeting Minutes

Citarella said the Task Force met June 10 and conducted e-votes that ended June 6, May 15, April 25, and April 1. During its June 10 meeting, the Task Force took the following action: 1) adopted the reports of its working groups; 2) exposed the *NAIC Rate Model Review Manual*; 3) heard a report on the data collection/rates and models project; and 4) heard reports from liaisons. The June 6 e-vote included adoption of the *2023 Auto Insurance Database Average Premium Supplement*. The May 15 e-vote included adoption of *2023 Competition Database Report* (Competition Report). The April 25 e-vote included adoption of *2022 Dwelling, Fire, and Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report* (Homeowners Report). The April 1 e-vote included adoption of the *2023 Report on Profitability by Line by State* (Profitability Report).

The Task Force also met July 15, June 17, May 20, May 6, and April 15 in regulator-to-regulator session, pursuant to paragraph 3 (specific companies, entities, or individuals) of the NAIC Policy Statement on Open Meetings, to discuss rate filing issues.

Additionally, the Task Force held Predictive Analytics Book Club meetings July 29, June 24, May 27, and April 22. The Book Club meetings included presentations from Mallika Bender of the Casualty Actuarial Society (CAS) on "Balancing Risk Assessment and Social Fairness: An Auto Telematics Case Study"; Matt Moore of Highway Loss Data Institute (HLDI) on "The Evolution of Advanced Driver Assistance Systems (ADAS) and Automated Driving"; Dr. Huai ren Ye on "Wildfire Model Updates and New Geospatial Rating Approach"; and Thomas Holmes of Akur8 on "Comparison of Penalized Modeling Techniques."

Botsko made a motion, seconded by Dyke, to adopt the Task Force's June 10 (Attachment One), June 6 (Attachment Two), May 15 (Attachment Three), April 25 (Attachment Four), April 1 (Attachment Five), and March 24 (see *NAIC Proceedings – Spring 2025, Casualty Actuarial and Statistical (C) Task Force*) minutes. The motion passed unanimously.

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2. Adopted the Report of the Actuarial Opinion (C) Working Group

Fisk said the Actuarial Opinion (C) Working Group met July 23, June 18, and April 3. During its July 23 meeting, the Working Group reviewed proposed edits to the 2026 property/casualty (P/C) Statement of Actuarial Opinion (SAO) Instructions and the 2025 Regulatory Guidance. Changes included adding language from the 2024 guidance on handling immaterial but non-zero long-duration P/C unearned premium and incorporating previously delayed 2025 edits into the 2026 instructions. During its June 18 meeting, the Working Group discussed proposed updates to the definition of accepted actuarial designation in the P/C SAO Instructions, reflecting Society of Actuaries (SOA) pathway changes and new general insurance exams. The Working Group reviewed implications for candidates transitioning from the old system and made edits for clarity and consistency. The revised definition was exposed for public comment until August 8. No comments were received during the public comment period. At the April 3 meeting, the Working Group continued discussions on items disclosed in the P/C Statement of Actuarial Opinion that are not reported elsewhere in the annual statement. The Working Group met in regulator-to-regulator session on July 16 and June 4, pursuant to paragraph 3 (specific companies, entities, or individuals) of the NAIC Policy Statement on Open Meetings, to discuss issues in the educational assessments.

The Working Group conducted e-votes ending May 27, May 20, April 7, and April 2. During its May 27 and April 7 e-votes, the Working Group adopted the initial 2025 Casualty Actuarial Society (CAS) educational assessment and the final decision that the CAS property/casualty (P/C) educational materials meet the NAIC's educational standards. During its May 20 and April 2 e-votes included adoption of the initial 2025 Society of Actuaries (SOA) educational assessment and the final decision that the SOA property/casualty (P/C) educational materials meet the NAIC's educational standards.

Fisk said both organizations revised certain materials based on the Working Group's preliminary feedback, and the revisions were subsequently acceptable to the Working Group. The group concluded that the CAS's Associate of the Casualty Actuarial Society (ACAS) and Fellow of the Casualty Actuarial Society (FCAS) designations and the SOA's Fellow of the Society of Actuaries (FSA) designation under the new pathway meet the minimum educational standards for an actuary signing a P/C SAO if certain exams are completed. This will be documented in the 2026 opinion instruction's definition of accepted actuarial designation.

The Working Group met in regulator-to-regulator session July 16, pursuant to paragraph 3 (specific companies, entities, or individuals) of the NAIC Policy Statement on Open Meetings, for its annual discussion of observations and concerns from the regulators' review of 2024 SAOs. The Working Group will meet Aug. 20, to discuss proposed edits to the instructions and regulatory guidance document, working toward a draft of the regulatory guidance document that can be exposed for a comment period before being adopted by the Working Group in time to be included in the American Academy of Actuaries' (Academy's) Committee on Property and Liability Financial Reporting (COPLFR) practice note.

Fisk made a motion, seconded by McKenney, to adopt the report of the Actuarial Opinion (C) Working Group, including its July 23 (Attachment Six), June 18 (Attachment Seven), May 27 (Attachment Eight), May 20 (Attachment Nine), April 7 (Attachment Ten), April 3 (Attachment Eleven), and April 2 minutes (Attachment Twelve). The motion passed unanimously.

Citarella thanked the Working Group and volunteers for participating in the educational assessment, noting that it was an extensive amount of work.

3. Adopted the Report of the Statistical Data (C) Working Group

Darby said the Statistical Data (C) Working Group met July 16, June 4, May 14, April 30, April 9, and March 19 to discuss changes to the *Statistical Handbook of Data Available to Insurance Regulators*. The Working Group started

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discussing comments received on the Homeowners and Dwelling Fire sections of the handbook and proceeded to the Personal Auto section. The Working Group will continue to meet regularly, working through each section of the handbook.

The Working Group adopted the *Auto Insurance Database Average Premium Supplement* and will soon be reviewing the 2023 Homeowners Data.

Darby made a motion, seconded by Vigliaturo, to adopt the report of the Statistical Data (C) Working Group, including its July 16 (Attachment Thirteen), June 4 (Attachment Fourteen), May 14 (Attachment Fifteen), April 30 (Attachment Sixteen), April 9 (Attachment Seventeen), and March 19 (Attachment Eighteen) minutes. The motion passed unanimously.

4. Received an Update on the Data Collection/Rates and Models Project

Hintikka provided an update on the data collection, rates, and models project. The plan is for the Task Force to improve the usefulness of System for Electronic Rates & Forms Filing (SERFF) data. Currently, a small group of regulators is discussing how to develop rate indices to track, over time and in detail, the cumulative magnitude of the rate changes that impact each state's P/C insurance markets.

Some states currently have their own methods and have identified their limitations. A survey was sent to Task Force members, and 21 responses were received. Equipped with that information, the project is in the very early stages of collaborating with the SERFF modernization team to help guide the new platform in a direction that hopes to make these types of indices more granular, reliable, and useful. The group heard from S&P Global about the rate tracking product they produce. Other parties are welcome to provide input.

In the future, the group plans to expand regulators' ability to readily track and compare across filings some of the many inputs that feed into insurers' rate change indications.

The group will draft a proposal for discussion by the Task Force, exposure, and potential adoption.

5. Heard From Commenters and Discussed Comments Received on the NAIC Model Review Manual

Zuppan said a small group of Task Force regulators met on June 2 and April 29 to edit the draft *NAIC Model Review Manual*. The Task Force released the manual (as revised) for a 45-day public comment period that ended July 25. Numerous comments were received. (Attachment Nineteen)

Erica Weyhenmeyer (National Association of Mutual Insurance Companies—NAMIC) said NAMIC appreciates the intent of the model review team to create an opportunity for efficient reviews and multi-state approval of model filings. NAMIC emphasized maintaining inherent state-specific laws and procedures, including a list of participating states, identifying statutory authority to enhance protection of insurer data and precise confidentiality provisions, and being transparent regarding information sharing agreements and safeguards for sensitive information in NAIC's databases.

6. Discussed Unknown Risk Characteristics

Citarella said the Task Force has been discussing unknown risk characteristics for several months. As rating algorithms and predictive models in auto and home insurance become increasingly complex and the number of rating characteristics grows, there is a greater likelihood of data fields being missing or incorrect.

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Roosevelt Mosley (Pinnacle Actuarial Resources) was asked by the American Property Casualty Insurance Association (APCIA) to present his views on missing data (Attachment Twenty). Mosley said missing and unknown data issues are contended with throughout the entire ratemaking process: model development, rating factor development, and policy rating. He said his presentation would focus on policy rating. Actuaries want complete and accurate data, but recognize that it will not often be fulfilled, so actuaries must address inconsistencies and incomplete data to be predictive and accurate but also practical.

Mosley said the rating factor development process varies by company. He said “unknown/missing” could be a distinct category, could be a weighted average of non-missing categories, could be a judgmentally selected factor, or something else. Treating missing data as a distinct category can be useful when the missingness is not a random occurrence, such as when data on old vehicles is not available; in this case, using a weighted average of non-missing categories may not be appropriate. Using a weighted average of non-missing categories is a common approach when the missingness is random. When there is a systematic concern about the unknown category, a judgmentally selected factor may be used. Mosley said they do not see this case often, but actuarial standards would require support for that kind of treatment.

In production, there are several different reasons for missing data. The applicant may not have provided the information, the third-party data provider may not have information on the person, or the data may not exist for that person at all. If the missing data is critical, such as the VIN, the policy may be unable to be rated. In certain situations, it makes sense to provide the policyholder the most favorable rating factor if the data is missing; for example, if information on prior violations is missing, it may make sense to assign the policyholder the “no violations” rating factor. In other situations, the insurer may assign the policyholder to the missing or unknown category of the rating variable if the data is missing.

Requesting missing data from a policyholder may sound like a reasonable solution on its face but may not be practical or lead to the outcomes one might expect. The cost of sending notices to policyholders, making sure that the information received gets to the right place, and updating the system may mean that the insurer concludes that it’s not efficient to use that variable. In addition, asking the policyholder doesn’t mean that the information will be more accurate because the policyholder may not know the information. Finally, there are cases in which there’s an advantageous answer, such as for miles driven, and asking the policyholder may yield the advantageous answer; this can make the rating algorithm less predictive or the data going into the rating less accurate.

He said companies are attempting to obtain the most accurate rate for the individual policyholder. If they have information about a policyholder, they want to use that information.

McKenney asked if a variable with a high rate of missing data, such as one out of four, could be a valid variable when there are numerous other rating points in the plan. Mosley said he looks at that as three out of four get a more accurate rate if this variable is included. If the variable was removed, then three out of four would not be rated accurately. McKenney said he sees that one out of four is not rated accurately in this example.

McKenney asked if policyholders could get large rate increases from one renewal to the next just because the third party adds the policyholder to its database. Mosley said then the policyholder would be rated more accurately. McKenney said a lower rate upon initial writing, followed by a greatly increased rate, is a concern. Mosley said there are other solutions, such as rate capping.

McKenney asked if 1.00 is a neutral rating factor for the missing category if the variable has two categories: 0.97 (if the policyholder gets the discount) and 1.00 (if the policyholder does not get the discount). Mosley said he prefers a weighted average of the non-missing factors (0.985 in this case, assuming even exposure). He said 1.00 is neutral in that it does not impact the rate, but it is not neutral “if neutral means average.” McKenney said with

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a discount and assignment of “missing” to a 1.00 factor, the 1.00 is not just that one is not considering that variable for someone with missing data; it is the same factor as not qualifying for the discount.

McKenney asked if there is a significant amount of missing rating data for age, marital status, where they live, number of car doors, number of bathrooms, the floor of an apartment, etc., and said the “missing” category exists for every rating variable. Mosley said a number of customers would know this information, but that does not mean the data will become more accurate. He said it is costly to verify the accuracy. There is a balance between more accurate rates and efficiency. If the expense of verification becomes greater than the lift associated with a variable, the company may decide that the variable is not worth adopting.

McKenney said in the Pennsylvania draft regulation, there is no limitation to being able to ask for verification of the rating variables. For example, if a customer tells the insurer their mileage, an insurer can require a picture of the odometer.

Commissioner Nelson said that, similar to the mileage example, two policyholders were smoking in the agent’s office and were told they qualified for a smoke-free discount. Data has not always been accurate. She said this is a value of having insurance agents do good insurance check-ups. Much of the data under discussion comes from the application, and people miss things on an application. She is concerned that the request for more information will delay the binding of coverage. Commissioner Nelson said McKenney’s questions are all good to ask when the rate filing is made.

Frederick said asking every consumer about all these data elements is not workable and is nonsensical. He said Florida will push back on individual filings. McKenney said the Pennsylvania draft regulation does not delay binding; the requirement is to ask consumers about their missing data, and the insurer can rate as “missing” until or unless the consumer responds. He said there is also a safe harbor of 2.5% of missing data for a variable. The idea is that there would be a step beyond the query of a third-party vendor, which is to try to rate someone properly. He added that there are many cases where the rate of “missing” applies because “the system is down.”

Commissioner Nelson said when credit scoring first came out, there were issues with people who did not have a credit score, and they were put into a “no hit” category. She reiterated that rate filing reviewers need to tease out the issues with rating variables in their reviews. McKenney added that with credit scoring, consumers are notified in every case when they do not qualify for the best rate.

Consumer advocates submitted two comment letters (Attachment Twenty-One). Michael DeLong (Consumer Federation of America—CFA) also presented on behalf of the Center for Insurance Policy and Research (CIPR). He urged the Task Force to issue recommendations on appropriate disclosures for unknown risk characteristics and to establish processes to fix this rapidly developing crisis. He said the use of unknown risk characteristics is especially important in property insurance and for risk mitigation. Right now, property insurance availability is plummeting across America, and the cost of coverage is going up. Increased costs are rising because of the use of broader risk scoring systems, complex models, aerial images, and other data, and a lot of this is received from third parties that are not subject to any meaningful oversight. Right now, consumers are left in the dark. They do not have access to the data and determinations that are needed to correct misinformation.

DeLong said consumers are faced with losing coverage or affordable coverage, and unlike other areas, consumers generally have no protections. They have the right to get a copy of their credit reports. They can see what actions have impacted their credit score, and that allows them to improve and mitigate their credit risks. There are also financial credit scores that provide mechanisms for correcting false and outdated information. There are problems with this, but at least there are some resources for consumers. DeLong said insurance consumers do not have any of that for other variables. Consumers have no access to which features or factors are used in risk scores and,

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therefore, have no way to correct misinformation. He said in wildfire rating models, there are numerous variables, and insurers do not explain these scoring mechanisms or how consumers can lower their risk.

He summarized that the Task Force should require 1) strong and reasonable disclosures; 2) insurers provide a clear avenue for consumers to challenge inaccurate conclusions about their risk profile; and 3) insurers explain what steps consumers can take to mitigate property risks. DeLong said these should apply to each rating variable used in pricing and underwriting, especially if a customer will be rejected or nonrenewed. He added that California's regulation on the consideration of mitigation factors is an example that could be followed.

Chou suggested attending the Third-Party Data and Models (H) Working Group meetings and for the Task Force to work with that group about third-party issues.

Erica Eversman (Automotive Education and Policy Institute—AEPI) said there are similar issues with auto insurance. Prices are skyrocketing, and there is very little transparency so that a consumer can make changes to decrease risk and obtain a lower premium. She asked regulators to think broadly about the disclosures needed.

Citarella said that when insurers collect more information from a consumer, they sometimes want proof, like a transcript, to get a good student discount. Other times, they do not ask for proof, such as when his child went to college without a car. Citarella expressed concern that policyholders are not always told about discounts they might receive.

Stolyarov said one of his first experiences with credit score rating involved a company with three categories concerning the presence of foreclosures. "No" was a factor of .95; "yes" was 1.10; the "missing factor" was 5.0. He questioned this treatment because there is either a foreclosure or not. If there is missing information, there is either a foreclosure or there is not. Insurers have the responsibility to think logically and realistically about how to treat these rates.

Citarella said the Task Force will continue discussion to gain a better understanding of the issues and will coordinate with the Third-Party Data and Models (H) Working Group. He said it is not a complete hand-off of the topic to the Working Group, but there is some overlap. Lapham said that as Chair of the Third-Party Data and Models (H) Working Group, he agrees that a partnership would be beneficial.

Citarella said there is a suggestion that this issue become a distinct charge for the Task Force in 2026. Two members said that, at this time, a charge would be premature. The Task Force agreed to continue discussing this topic.

Serbinowski said other businesses require the distribution of Buyer's Guides. He said the guides seem to, at the very least, let the consumer know what was used in rating. The consumer can ignore it or choose to evaluate it.

7. Heard Updates on Activities and Research from Professional Actuarial Associations

The Academy, Actuarial Standards Board (ASB), SOA, and CAS provided reports on current activities and research.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

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Draft: 7/8/25

Casualty Actuarial and Statistical (C) Task Force
Virtual Meeting
June 10, 2025

The Casualty Actuarial and Statistical (C) Task Force met June 10, 2025. The following Task Force members participated: D.J. Bettencourt, Chair, represented by Christian Citarella (NH); Angela L. Nelson, Vice Chair, represented by Julie Lederer (MO); Lori K. Wing-Heier represented by Sian Ng-Ashcraft (AK); Mark Fowler represented by Charles Hale and Ken Williamson (AL); Ricardo Lara represented by Tina Shaw, Mitra Sanandajifar, and Sarah Ye (CA); Andrew N. Mais represented by Wanchin Chou (CT); Karima M. Woods represented by David A. Christhlf (DC); Michael Yaworsky represented by Peshala Disanayaka (FL); Doug Ommen represented by Travis Grassel and Jordan Esbrook (IA); Holly W. Lambert represented by Larry Steinert (IN); Vicki Schmidt represented by Nicole Boyd (KS); Timothy J. Temple represented by Nichole Torblaa (LA); Marie Grant represented by Walter Dabrowski (MD); Robert L. Carey represented by Sandra Darby (ME); Anita G. Fox represented by Kevin Dyke (MI); Grace Arnold represented by Phil Vigliaturo (MN); Eric Dunning represented by Nguyen Thai and Connie Van Slyke (NE); Scott Kipper represented by Gennady Stolyarov (NV); Judith L. French represented by Stewart Trego (OH); TK Keen represented by Brian Fjeldheim (OR); Michael Humphreys represented by Michael Stoner (PA); Michael Wise represented by Will Davis (SC); Cassie Brown represented by J'ne Elizabeth Byckovski, Rebecca Armon, and Eric Hintikka (TX); Sandy Bigglestone represented by Zoie Y. Swaim (VT); Patty Kuderer represented by William Wilder (WA); and Allan L. McVey represented by Juanita Wimmer (WV).

1. Adopted the Report of the Actuarial Opinion (C) Working Group

Lederer reported that the Actuarial Opinion (C) Working Group met April 3 to continue discussions on items disclosed in the Property/Casualty (P/C) Statement of Actuarial Opinion that are also not reported elsewhere in the annual statement. The Working Group will continue this discussion in the coming months.

The Casualty Actuarial Society/Society of Actuaries (CAS/SOA) Educational Assessment project is nearing completion. The Working Group sent letters to the CAS and SOA on May 27 and May 16, respectively, summarizing the results of the assessment. Both organizations revised some of their educational materials based on the results of the Working Group's preliminary assessments, and the Working Group found these revisions acceptable. The Working Group concluded that the CAS' Associate of the CAS (ACAS) and Fellow of the CAS (FCAS) pathways and the SOA's Fellow of the SOA (FSA) pathway meet the minimum educational standards for an actuary signing a P/C Statement of Actuarial Opinion if certain exams are completed. The Working Group will document acceptance of the organizations' designations, with the caveat of which exams must be completed, in the *2026 Statement of Actuarial Opinion's* definition of a Qualified Actuary.

Lederer mentioned that the SOA is introducing a revised fellowship pathway this fall. The Working Group met in regulator-to-regulator session on June 4 to discuss the circumstances under which a candidate who has passed combinations of old exams or modules and new exams would meet the minimum educational standards for signing a P/C opinion. These discussions are ongoing.

Lederer made a motion, seconded by Darby, to adopt the report of the Actuarial Opinion (C) Working Group. The motion passed unanimously.

2. Adopted the Report of the Statistical Data (C) Working Group

Darby reported that the Statistical Data (C) Working Group has been meeting regularly to discuss changes to the *Statistical Handbook of Data Available to Insurance Regulators*. The Working Group met June 4, May 14, April 30, and April 9 to discuss comments received on the homeowners and dwelling fire sections of the handbook. The Working Group plans to meet July 16 to discuss comments regarding the personal auto section. The Working Group will continue to meet regularly, working through each section of the handbook. Darby mentioned that the *Auto Database Average Premium Supplement* was adopted by the Working Group and sent to the Task Force for adoption.

Darby made a motion, seconded by Chou, to adopt the report of the Statistical Data (C) Working Group. The motion passed unanimously.

3. Exposed the NAIC Rate Model Review Manual

Citarella introduced the *NAIC Rate Model Review Manual* and explained that the manual is intended to guide NAIC staff in assisting insurance regulators in a state's review of predictive models. The aim is to provide a consistent and documented review of complex predictive models used in insurance products while providing appropriate speed to market. To the extent possible, the manual is intended to add uniformity when NAIC staff produce reports applicable to all states. Compliance with a state's laws and regulations will be performed by the state insurance regulator.

Citarella said the *NAIC Rate Model Review Manual* will be exposed for a 45-day public comment period ending July 25. If there are no substantive comments requiring significant re-drafting, the aim is to consider adopting it at the Summer National Meeting.

4. Heard a Report on Data Collection/Rates and Models Project

Hintikka reported that the project subgroup met May 22 and May 6 and is currently in the information-gathering stage. The Subgroup is primarily focused on understanding the methods states currently use to analyze rate changes for their markets, as well as the limitations of those methods and possibilities for future improvement. The Subgroup also discussed four secondary but related focuses regarding data collection through System for Electronic Rates & Forms Filing (SERFF). Hintikka said the Subgroup plans to meet July 3 to receive a presentation from S&P Global representatives explaining how they use SERFF data to analyze rate changes. Later in July, the Subgroup also plans to have a discussion with SERFF team members to determine what data may be available and what SERFF improvements could potentially help to obtain accurate calculations.

5. Heard Reports from Liaisons

Citarella said the Innovation, Cybersecurity, and Technology (H) Committee is currently receiving feedback on the potential development of an artificial intelligence/machine learning (AI/ML) model law, which could result in a robust conversation among commissioners. As previously discussed, there is interest in using AI/ML in ratings, but there are also questions on how AI/ML will be used in a reserve setting, actuarial opinions/statements, financials, and other areas of insurance.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

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Draft: 6/11/25

Casualty Actuarial and Statistical (C) Task Force
E-Vote
June 6, 2025

The Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded June 6, 2025. The following Task Force members participated: Lori K. Wing-Heier represented by Sian Ng-Ashcraft (AK); Mark Fowler (AL); Ricardo Lara represented by Tina Shaw (CA); Andrew N. Mais represented by Wanchin Chou (CT); Karima M. Woods represented by David A. Christhlf (DC); Michael Yaworsky represented by Stephanie Avello (FL); Doug Ommen represented by Travis Grassel (IA); Holly W. Lambert represented by Larry Steinert (IN); Timothy J. Temple represented by Nichole Torblaa (LA); Marie Grant (MD); Robert L. Carey represented by Sandra Darby (ME); Grace Arnold represented by Phil Vigliaturo (MN); Scott Kipper represented by Gennady Stolyarov (NV); Judith L. French represented by Tom Botsko (OH); Glen Mulready represented by Andy Schallhorn (OK); Andrew R. Stolfi represented by David Dahl (OR); Michael Humphreys represented by Michael McKenney (PA); Michael Wise represented by Will Davis (SC); Cassie Brown represented by J'ne Elizabeth Byckovski (TX); Kaj Samsom represented by Rosemary Raszka (VT); Patty Kuderer represented by William Wilder (WA); and Allan L. McVey (WV).

1. Adopted the 2023 Auto Insurance Database Average Premium Supplement

The Task Force conducted an e-vote to consider adoption of the *2023 Auto Insurance Database Average Premium Supplement*. The motion passed unanimously.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/060625 Minutes evote 2023 Auto Database Avg Premium Supplement.docx

Draft: 5/20/25

Casualty Actuarial and Statistical (C) Task Force
E-Vote
May 15, 2025

The Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded May 15, 2025. The following Task Force members participated: D.J. Bettencourt, Chair, represented by Christian Citarella (NH); Lori K. Wing-Heier represented by Sian Ng-Ashcraft (AK); Mark Fowler represented by Charles Hale (AL); Andrew N. Mais represented by Wanchin Chou (CT); Karima M. Woods represented by David A. Christhlf and Angela King (DC); Michael Yaworsky represented by Stephanie Avello (FL); Doug Ommen represented by Travis Grassel (IA); Holly W. Lambert represented by Larry Steinert (IN); Marie Grant represented by Aaron Levine (MD); Robert L. Carey represented by Sandra Darby (ME); Grace Arnold represented by Phil Vigliaturo (MN); Judith L. French represented by Tom Botsko (OH); Glen Mulready represented by Andy Schallhorn (OK); Andrew R. Stolfi represented by David Dahl (OR); Michael Wise represented by Will Davis (SC); Cassie Brown represented by J'ne Elizabeth Byckovski (TX); and Allan L. McVey (WV).

1. Adopted the 2023 Competition Report

The Task Force conducted an e-vote to consider adoption of the *2023 Competition Database Report* (Competition Report). The motion passed unanimously.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

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Draft: 5/5/25

Casualty Actuarial and Statistical (C) Task Force
E-Vote
April 25, 2025

The Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded April 25, 2025. The following Task Force members participated: Lori K. Wing-Heier represented by Sian Ng-Ashcraft (AK); Ricardo Lara represented by Tina Shaw (CA); Andrew N. Mais represented by Wanchin Chou (CT); Karima M. Woods represented by David A. Christhilf and Angela King (DC); Michael Yaworsky (FL); Holly W. Lambert represented by Larry Steinert (IN); Marie Grant represented by Aaron Levine (MD); Robert L. Carey represented by Sandra Darby (ME); Grace Arnold represented by Phil Vigliaturo (MN); Remedio C. Mafnas (MP); Scott Kipper represented by Gennady Stolyarov (NV); Judith L. French represented by Tom Botsko (OH); Glen Mulready represented by Andy Schallhorn (OK); Andrew R. Stolfi represented by David Dahl (OR); Michael Humphreys represented by Michael McKenney (PA); Michael Wise represented by Will Davis (SC); Cassie Brown represented by J'ne Elizabeth Byckovski and Nicole Elliott (TX); Kaj Samsom represented by Rosemary Raszka (VT); Patty Kuderer represented by William Wilder (WA); and Allan L. McVey (WV).

1. Adopted the 2022 Homeowners Report

The Task Force conducted an e-vote to consider adoption of the *2022 Dwelling, Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report* (Homeowners Report). The motion passed unanimously.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/042525 2022 Homeowners Report evote min.docx

Draft: 4/8/25

Casualty Actuarial and Statistical (C) Task Force
E-Vote
April 1, 2025

The Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded April 1, 2025. The following Task Force members participated: Lori K. Wing-Heier represented by Chad Bennett (AK); Andrew N. Mais represented by Wanchin Chou (CT); Karima M. Woods represented by Angela King (DC); Doug Ommen represented by Travis Grassel (IA); Holly W. Lambert represented by Larry Steinart (IN); Vicki Schmidt represented by Nicole Boyd (KS); Timothy J. Temple represented by Nichole Torblaa (LA); Marie Grant represented by Aaron Levine (MD); Robert L. Carey represented by Sandra Darby (ME); Grace Arnold represented by Phil Vigliaturo (MN); Judith L. French represented by Tom Botsko (OH); Andrew R. Stolfi represented by David Dahl (OR); Michael Wise represented by Will Davis (SC); Sandy Bigglestone represented by Rosemary Raszka (VT); Patty Kuderer represented by William Wilder (WA); and Allan L. McVey (WV).

1. Adopted the 2023 Profitability Report

The Task Force conducted an e-vote to consider adoption of the 2023 *Report on Profitability by Line by State* (Profitability Report). The motion passed unanimously.

Having no further business, the Casualty Actuarial and Statistical (C) Task Force adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/040125 Profitability evote min.docx

Draft: 8/5/25

Actuarial Opinion (C) Working Group
Virtual Meeting
July 23, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met July 23, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); Susan Gozzo Andrews (CT); Chantel Long (IL); Sandra Darby (ME); Tom Botsko (OH); Andy Schallhorn (OK); and Kevin Clark (PA).

1. Discussed Proposed Edits to the 2026 P/C SAO Instructions and Regulatory Guidance Documents

Fisk discussed proposed edits to the 2026 Statement of Actuarial Opinion (SAO) instructions. The edits discussed include: 1) clarification of when qualification documents for an appointed actuary need to be provided to the board of directors; 2) adding an item stating that, as required by *Statement of Statutory Accounting Principle (SSAP) No. 65—Property and Casualty Contracts*, Exhibit A, should also include the reserve for direct and assumed unearned premiums for property/casualty (P/C) long-duration contracts and the reserve for net unearned premiums for P/C long-duration contracts regardless of whether the amounts are material; 3) language clarifying that if the unearned premium reserves for P/C long-duration contracts reported on Lines 7 or 8 of Exhibit A are immaterial but non-zero, and the appointed actuary is not issuing an opinion on the amounts, clarifying comments should be included in the scope, opinion, and/or relevant comment sections of the opinion; 4) removal of line 10 from Exhibit B; and 5) removal of the general insurance track qualifier for the Fellow of Society of Actuaries (FSA) credential in the appointed actuary's accepted actuarial designations list.

Fisk also discussed amounts disclosed in the SAO that are not reported elsewhere in the annual statement, including: 1) the unearned premium reserves for P/C long-duration contracts on Exhibit A, Lines 7 and 8; 2) the total claims made extended loss and loss-adjustment expense (LAE) and unearned premium reserves on Exhibit B, Line 12; and 3) the net reserves for the accident and health (A&H) long-duration contracts on Exhibit B, Line 13. Fisk noted that Exhibit A, Line 7, is not reported elsewhere, while Line 8 is similar to the Underwriting and Investment Exhibit, Part 1A, Column 2.

Fisk proposed removing Exhibit B, Line 10, due to inconsistent reporting and limited usefulness. Botsko asked whether the data supported the removal. Fisk responded that while some companies report amounts, the data is inconsistent and not widely relied upon. Lederer also raised concerns about the clarity of Exhibit B, Line 12, and asked whether it refers to issued or not-yet-issued policies. Fisk agreed to review SSAP No. 65 and propose revised language in future meetings.

Stephen Koca (Committee on Property and Liability Financial Reporting—COPLFR) confirmed that the line is intended for policies not yet issued, but for which the company may be obligated to provide coverage. Koca recommended aligning the wording with SSAP No. 65.

Fisk transitioned the discussion to the regulatory guidance document. Fisk proposed several edits to ensure the document is up to date and internally consistent. Fisk also discussed incorporating guidance on net versus gross reserve opinions into the instructions.

Lederer noted that Exhibit B already includes a clarifying note, but additional reinforcement may be beneficial. Fisk also raised the idea of enhancing guidance on company-specific risk factors and requested volunteers to help draft language. Koca offered to provide feedback from COPLFR.

Fisk concluded by noting that an updated draft of the guidance document should be ready for the Working Group's next meeting.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/AOWG 07_23_2025 min.docx

Draft: 6/18/25

Actuarial Opinion (C) Working Group
Virtual Meeting
June 18, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met June 18, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); Susan Gozzo Andrews (CT); David A. Christhlf (DC); Tom Botsko (OH); and Kevin Clark and James Di Santo (PA).

1. Received an Update on 2025 Statement of Actuarial Opinion (SAO) Instructions Changes

Fisk explained that while the Working Group adopted the 2025 P/C SAO instructions changes proposal on January 27, these changes were not sent to the Blanks Working Group in time for adoption this year. As an alternative, the Blanks Working Group will add an editorial note to the 2025 instructions, clarifying that the FSA designation is considered an accepted actuarial designation only if it was earned under the requirements in effect through May 2025. This editorial note was adopted by the Blanks working group during their May 29 meeting. The blanks working group will consider making all the other outstanding changes in the new proposal to modify 2026 SAO instructions.

2. Discussed Proposed Edits to the Accepted Actuarial Designation Definition in the P/C Statement of Actuarial Opinion instructions

Fisk led a discussion on proposed edits to the definition of accepted actuarial designation in the P/C opinion instructions. The changes reflect updates to the Society of Actuaries (SOA) educational pathways, including the elimination of specific tracks and the introduction of new general insurance exams. The Working Group reviewed the draft and discussed the implications of the transition period for candidates who partially completed the old system. Weber (SOA) confirmed the draft language aligns with their expectations. Additional edits were proposed to ensure clarity and consistency. The group agreed to expose the revised definition for public comment for 30 days, pending final review by the SOA and Casualty Actuarial Society (CAS).

Fisk said the Working Group plans to continue meeting monthly to discuss changes to the 2026 SAO instructions.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/AOWG 06_18_2025 min.docx

Draft: 5/27/25

Actuarial Opinion (C) Working Group
E-Vote
May 27, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded May 27, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); David A. Christhilf (DC); Chantel Long (IL); Tom Botsko (OH); and Andy Schallhorn (OK).

1. Adopted the Decision Recognizing CAS P/C Educational Materials as Meeting the NAIC's Educational Standards

The Working Group conducted an e-vote to consider adoption of the decision that the Casualty Actuarial Society (CAS) property/casualty (P/C) educational materials meet the NAIC's educational standards. The motion passed unanimously.

The final assessment results will be reflected in the 2026 Statement of Actuarial Opinion instructions.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/052725 CAS assessment final evote min.docx

Draft: 5/26/25

Actuarial Opinion (C) Working Group
E-Vote
May 20, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded May 20, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); Susan Gozzo Andrews (CT); Chantel Long (IL); Sandra Darby (ME); Andy Schallhorn (OK); and James Di Santo (PA).

1. Adopted the Decision Recognizing SOA P/C Educational Materials as Meeting the NAIC's Educational Standards

The Working Group conducted an e-vote to consider adoption of the decision that the Society of Actuaries' (SOA's) property/casualty (P/C) educational materials meet the NAIC's educational standards. The motion passed unanimously.

The final assessment results will be reflected in the 2026 Statement of Actuarial Opinion instructions.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/052325 SOA assessment final evote min.docx

Draft: 5/26/25

Actuarial Opinion (C) Working Group
E-Vote
April 7, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded April 7, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer (MO); David Christhlf (DC); Sandra Darby (ME); Andy Schallhorn (OK); and James Di Santo (PA).

1. Adopted the CAS Educational Assessment

The Working Group conducted an e-vote to consider adoption of the 2025 Casualty Actuarial Society (CAS) educational assessment. The motion passed unanimously. A letter will be sent to the CAS. Any revised or new materials will be requested by April 30 and then reviewed by the Working Group, with an answer produced by May 31.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/040725 CAS assessment evote min.docx

Draft: 4/3/25

Actuarial Opinion (C) Working Group
Virtual Meeting
April 3, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met April 3, 2025. The following Working Group members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); Susan Gozzo Andrews (CT); David A. Christhlf (DC); Chantel Long (IL); Sandra Darby (ME); Tom Botsko (OH); and Kevin Clark and James Di Santo (PA).

1. Discussed Instructions for the Actuarial Opinion

Fisk gave a presentation covering what is being reported in Statements of Actuarial Opinions (SAOs), which included:

1. Categories of amounts required to be disclosed in an SAO
2. Quantification of reported amounts for P/C long duration unearned premium reserves
3. Pooled reserves on Exhibit B, Line 10

Fisk highlighted that the focus of the conversation should be on the amounts that are not reported elsewhere in the annual statement to determine if they should be included in the annual statement or removed from the SAO. These include the pool reserves on Exhibit B, Line 10, and the unearned premium reserves for property/casualty (P/C) long-duration contracts on Exhibit A, Lines 7 and 8.

Fisk emphasized that while Exhibit A, Line 7 is not included anywhere else in the annual statement, Exhibit A, Line B is similar to Underwriting and Investment Exhibit, Part 1A, column 2. The group discussed practical uses for these reported amounts and suggested additional analysis to better understand their reporting in the SAO. Regarding the pooled reserves on Exhibit B, Line 10, the group discussed the need to better define the item or remove the item.

Fisk said the Working Group plans to continue meeting monthly to continue its discussion of these issues, including claims made extended loss and loss adjustment expense and unearned premium reserves.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/AOWG 04_03_2025 min.docx

Draft: 4/8/25

Actuarial Opinion (C) Working Group
E-Vote
April 2, 2025

The Actuarial Opinion (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force conducted an e-vote that concluded April 2, 2025. The following Task Force members participated: Miriam Fisk, Chair (TX); Julie Lederer, Vice Chair (MO); David A. Christhlf (DC); Sandra Darby (ME); Andy Schallhorn (OK); and James Di Santo (PA).

1. Adopted the SOA Educational Assessment

The Working Group conducted an e-vote to consider adoption of the 2025 Society of Actuaries (SOA) educational assessment. The motion passed unanimously. A letter will be sent to the SOA. Any revised or new materials will be requested by April 30, and then the Working Group will review them and produce an answer by May 31.

Having no further business, the Actuarial Opinion (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/AOWG/040225 SOA assessment evote min.docx

Draft: 8/7/25

Statistical Data (C) Working Group
Virtual Meeting
July 16, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met July 16, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair (MO); Kyle Ogden (AL); Qing He and Kristin Fabian (CT); David A. Christhlf (DC); Christian Citarella (NH); Alexander Vajda (NY); Tom Botsko (OH); Andy Schallhorn (OK); David Dahl (OR); and Nicole Elliot (TX). Also participating were: Borwen Lee and Daniel Zhong (FL); Julie Rachford (IL); John Sobhanian and Nichole Torblaa (LA); Arthur Schwartz (MD); Chris Slovinski (MI); Mari Kindberg and Ashley Perez (MT); Nicholas Vogl (NC); Kelly Christensen (UT); and William Wilder and Richelle Geiger (WA).

1. Discussed Comments on Statistical Handbook Sections 1, 2, 3, 5, 7, and 8

Darby said that during the Working Group's last meeting, Gerling introduced language for the exposure section for both homeowners and dwelling fires in the *Statistical Handbook of Data Available to Insurance Regulators* (Statistical Handbook). She said the new definition outlined that exposures will be reported as written house months, netted for cancellations, with an example included. The Working Group agreed with this change.

Darby said that the NAIC sent questions to participating statistical agents as a follow-up to the discussion during the Working Group's last meeting. She said the statistical agents were asked the following questions:

- Can you provide an example of how you are currently receiving data for endorsements for both homeowners and dwelling fire policies?
- Do you collect year of construction/renovation as outlined in the Statistical Handbook of Data Available to Regulators (Statistical Handbook)?
- Do you collect the split of owner-occupied versus non-owner-occupied policies for both homeowners and dwelling fire?

Darby said the National Independent Statistical Service (NISS) responded that for homeowners, mobilehome, and dwelling fire policies, it collects the following data elements: ZIP code, amount of insurance, line of business, written exposure, written premium, paid losses, paid claims, outstanding losses, and outstanding claims. Darby said the NISS collects daycare liability endorsements in the personal liability section of its general liability data call. Darby said the NISS collects the four-digit year of construction on the dwelling, and companies do have the option to report 1901 for dwellings built prior to 1960. Darby said the NISS collects the split of owner-occupied and non-owner-occupied policies.

Andy Regis (American Association of Insurance Services—AAIS) said the AAIS collects miscellaneous endorsements via major peril codes for dwelling fire and policy forms for homeowners. He said the AAIS collects the year of construction but does not collect the year of renovation. He said the AAIS does collect the split of owner-occupied and non-owner-occupied policies.

Laura Panesso (Insurance Services Office—ISO) said the ISO collects endorsement information in a variety of ways, and it would be too much information to provide the group information for every endorsement. She said if the Working Group could narrow down the type of endorsements it is looking into, the ISO could provide specific information for those endorsements. Panesso said the ISO collects the year of construction but does not consider

or define the year of renovation. She said the ISO does differentiate between owner-occupied and non-owner-occupied for both dwelling fire and homeowners.

Rick Bushur (Independent Statistical Service—ISS) said the ISS receives endorsements in different ways. He said most endorsements are reported with an identifying code and a more limited amount of reporting fields than full policies. These can be identified as endorsements, but the exact endorsement is not always captured. In some cases, a second code is used to more specifically identify the endorsement. Bushur said the year of construction is captured for homes built after 1959. He said the ISS collects the split of owner-occupied and non-owner-occupied for dwelling fire policies, but not for homeowners policies.

Darby asked Working Group members to think about what other endorsements would be useful to include in the Statistical Handbook. She said she would be interested in collecting private flood information. Panesso said the ISO collects that information as a separate program and not as an endorsement to homeowners policies. Gerling said if it is not provided as an endorsement, the Working Group should look at adding private flood as a line of business that is collected. Gerling said he did not see a need to collect further endorsement information for dwelling fire policies.

Darby said the definition of “year of construction” should be updated to reflect that statistical agents do not usually collect the year of renovation. Panesso agreed that the year of renovation should be removed. Darby asked how it was decided that homes built before 1960 did not need to be reported separately. Steve Clarke (ISO) said this date could be due to universal residential building codes being put into place around this time. Gerling said Missouri would like to see the individual collection year go back further than 1960. He said a recent tornado hit one of the oldest neighborhoods in St. Louis, MO, and it would be nice to know the year of construction for those homes. Darby said a change here would not be to the data field, only the instructions to the carrier to report the year of construction for homes built in 1901 and after. Jenny Tornquist (AAIS) asked if this would only apply to policies effective after the change to the Statistical Handbook has been implemented. Darby said companies should already have this information if the age of the home is already one of their rating elements. Citarella said once a change is implemented, the statistical agents should provide the requested information, not just on new policies, but on renewal policies effective after the change.

Darby said most of the statistical agents reported that they currently split owner-occupied and non-owner-occupied policies. Gerling asked how these categorizations are defined and where seasonal and rental homes fit into these categories. Darby said the Working Group would look to clarify and define these terms during its next meeting.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/SDWG/StatDataWGmin_716

Draft: 7/21/25

Statistical Data (C) Working Group
Virtual Meeting
June 4, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met June 4, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair, (MO); Ken Williamson (AL); Lori Dreaver Munn (AZ); Qing He, George Bradner, and Wanchin Chou (CT); Mike Andring (ND); Christian Citarella (NH); Alexander Vajda (NY); Andy Schallhorn and Landon Hubbard (OK); and David Dahl and Ying Liu (OR). Also participating were: Luciano Gobbo and Susan Wu (CA); Borwen Lee and Sun Min (FL); Julie Rachford (IL); Kristina Shelley (IN); John Sobhanian and Nichole Torblaa (LA); Phillip Glasovatz, Robyn Lowes, and Chris Slovinski (MI); Mari Kindberg and Ashley Perez (MT); Nicholas Vogl (NC); Will Davis (SC); Kelly Christensen (UT); James Young (VA); and William Wilder (WA).

1. Discussed Comments on Statistical Handbook Sections 1, 2, 3, 7, and 8

Darby said NAIC staff had compiled a side-by-side list of data elements found in Sections 7 and 8 of the *Statistical Handbook of Data Available to Regulators* (Statistical Handbook).

Darby said the Dwelling Fire section has a data element called “Transaction Identifier and Amounts,” which includes premiums and losses. These are separate from the data elements in the Homeowners section. Darby asked if Working Group members had a preference on which format the data should be collected. Gerling said he generally prefers longer tables, and the data works better in programs like Tableau when laid out longer versus wider. Laura Panesso (Insurance Services Office—ISO) said ISO collects the data for both sections in a format more similar to the Dwelling Fire section. Jenny Tornquist (American Association of Insurance Services—AAIS) confirmed AAIS collects the data similarly. Darby said it makes sense to format both sections the same way and to do that in a way that makes sense for how the data is already being collected by statistical agents.

Darby said the Working Group should consider whether to add endorsement information into the Dwelling Fire section. Munn said for consistency, an endorsement section should be added. She said regulators would want to see things like wildfire endorsements here. Gerling asked if it is only the exposure count being collected for endorsements. Panesso said exposure information is not reported here because you would not want to double-count exposures. Gerling said it is likely that this column is only descriptive of the type of endorsement, and the other data elements contain the actual data relating to this endorsement.

Darby asked if statistical agents are receiving endorsement information in the same way for both homeowners and dwelling fire policies. Panesso said it would depend on the type of endorsement, as some are premium credits and some require additional premium. Darby said she would like the Working Group to think further about this endorsement section and its place in Section 8—Dwelling Fire. Panesso said the Working Group should also consider whether every type of endorsement is appropriate to report in both sections. Munn said she would like to know what perils are being excluded in these policies. Darby agreed and said that the way the endorsement information is currently collected, you would not get a count of exclusion endorsements. Darby asked participating statistical agents to provide information on how their endorsement data is currently collected.

Gerling asked how the year of construction is reported in an aggregate data set. Mike Puchner (AAIS) said the Statistical Handbook indicated grouping the years into ranges when the data is reported out to regulators. Gerling said there are very few elements that are numeric in this data set. He said there are many fields that would change

what a row would indicate. He said if the Working Group is considering expanding the data that is collected, they should be collecting more numeric fields that would not increase the number of rows.

Darby said the definition for year of construction is vague and could be confusing for construction versus renovation. She said the Working Group should consider updating this definition for clarity.

Darby said Section 8—Dwelling Fire includes a section on occupancy, separating seasonal and non-seasonal policy. She asked if the same section should be included in Section 7—Homeowners. Panesso said its homeowners policy definition requires the home to be owner-occupied and, therefore, would not allow for seasonal occupancy. Darby asked if collecting non-owner-occupied homeowners policies should be considered. She said she would like the participating statistical agents to clarify how they currently collect the occupancy information, and if the season and other-than-seasonal data are further split into owner-occupied and non-owner-occupied.

Gerling submitted language to update the exposure definition in Sections 7 and 8. He said the definition is similar to what Missouri uses in its data call. The definition says written dwelling months are reported in the year the policy is effective, and cancellations are netted out. The definition includes an example of how to report the written dwelling months.

Darby said the Working Group would continue discussing comments on Sections 1, 2, 3, 7, and 8 during its next meeting and opened Section 5—Private Passenger Auto for comment.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/SDWG/StatDataWGmin_604

Draft: 7/21/25

Statistical Data (C) Working Group
Virtual Meeting
May 14, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met May 14, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair, and Jo A. LeDuc (MO); Charles Hale, Kyle Ogden, and Ken Williamson (AL); Qing He (CT); Colton Schulz (ND); Alexander Vajda (NY); Tom Botsko (OH); Andy Schallhorn and Landon Hubbard (OK); David Dahl (OR); and Nicole Elliott (TX). Also participating were: Luciano Gobbo (CA); Julie Rachford (IL); Borwen Lee (FL); John Sobhanian and Nichole Torblaa (LA); Phillip Glasovatz and Robyn Lowes (MI); Mari Kindberg (MT); and William Wilder (WA).

1. Discussed Comments on Statistical Handbook Sections 1, 2, 3, 7, and 8

Darby said the Working Group has been discussing comments submitted on Sections 1, 2, 3, and 7 of the *Statistical Handbook of Data Available to Regulators* (Statistical Handbook), and during the previous meeting, Section 8 was opened for comment.

Darby said during the last meeting, the Working Group discussed how the definition of “exposure” is not very descriptive and could be enhanced. Laura Panesso (Insurance Service Office—ISO) said the ISO does not collect the exposure months, but it calculates the exposure based on the effective month and year and the expiration month and year. Becky Konkle (National Independent Statistical Service—NISS) said the NISS collects exposure months, which are calculated by the companies. Jenny Tornquist (American Association of Insurance Services—AAIS) said an example would help to clarify this definition. Gerling agreed that the definition should include a mention of cancelled house months and provide an example.

Darby said the Working Group had discussed breaking out “fire caused by lightning” as a separate type of loss. Gerling said he would like to see this broken out so that states can use it to assess actual storm-related losses. Tornquist said AAIS has a category for lightning that would include fire caused by lightning and any other damage caused by lightning. Panesso questioned whether companies capture fire caused by lightning as a cause of loss instead of just fire. Darby clarified that the proposed change is to collect fire and removal, lightning, and fire caused by lightning as separate types of loss elements.

Tornquist asked if any other statistical agents are collecting smoke damage as a type of loss. Darby said smoke damage likely falls under “all other.”

Darby said the proposed buckets for the Amount of Insurance section would collect this data point at a much more granular level than what is currently collected for the *Dwelling, Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner’s Insurance Report* (Homeowners Report). Panesso said the ISO proposal reflects what it is already collecting and expands the Statistical Handbook standards to reflect the rising cost of home value and rebuilding costs.

Darby said the Working Group had previously discussed updating the Deductible section to collect both the total policy deductible and a wind/hail deductible. Vajda said he would like to see both deductibles. Albert Burton (Independent Statistical Service—ISS) said ISS is already collecting both deductible types. Representatives from ISO and AAIS stated they also collect these deductibles separately. Darby said she would like to bring this item up again during a future meeting.

Panesso said ISO submitted comments for Section 8—Dwelling Fire and Allied Lines, and these comments are in line with the suggestions made for Section 7—Homeowners. Gerling said it makes sense to adopt similar changes in both sections.

Darby said she would like to review Section 8's Policy Form section to ensure it currently includes everything regulators want to collect.

Gerling said Section 8.7—Specific Report Features states that exposures and premium are shown on an earned basis. He said that elsewhere within Section 8, exposures are defined as written dwelling months. Darby said that throughout the Statistical Handbook, there are discrepancies between what is being collected by statistical agents and what is required to be provided to regulators. Participating statistical agents confirmed that they are calculating earned premium from inception and cancellation dates.

Gerling said Section 8 is structured differently from Section 7. He suggested the Working Group look at each section's structure and try to align it to be more consistent in reporting. Darby asked NAIC staff to put together a side-by-side view of the listed data elements for both sections.

Darby said the Working Group would continue discussing comments on Sections 1, 2, 3, 7, and 8 during its next meeting.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Summer/CASTF/SDWG/StatDataWGmin_514

Draft: 6/11/25

Statistical Data (C) Working Group
Virtual Meeting
April 30, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met April 30, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair (MO); Charles Hale, Kyle Ogden, and Ken Williamson (AL); Lori Dreaver Munn (AZ); Qing He, George Bradner, and Wanchin Chou (CT); Colton Schulz and Mike Andring (ND); Alexander Vajda (NY); Tom Botsko (OH); David Dahl and Ying Liu (OR); and Nicole Elliott (TX). Also participating were: Luciano Gobbo (CA); Julie Rachford (IL); Borwen Lee and Daniel Zhong (FL); John Sobhanian and Nichole Torblaa (LA); Gregory Ricci (MD); Phillip Glasovatz and Robyn Lowes (MI); Mari Kindberg and Ashley Perez (MT); Will Davis (SC); and William Wilder (WA).

1. Discussed Comments on the Statistical Handbook Sections 1, 2, 3, and 7

Darby said the Working Group has been discussing comments submitted on Sections 1, 2, 3, and 7 of the *Statistical Handbook of Data Available to Regulators* (Statistical Handbook).

Darby said the Insurance Services Office (ISO) made a comment that Section 7.6.11 should be updated to reflect higher deductible options, as well as collecting percentage deductibles. Vajda asked if the deductible amounts need to be restricted to only certain amounts. Darby said they do not need to be restricted, and the amounts provided by the ISO in its comment likely reflect its current offerings.

Birny Birnbaum (Center for Economic Justice—CEJ) said if the Statistical Handbook dictates summary reporting, then deductible amounts would have to be defined and restricted to certain categories. He said if the Statistical Handbook dictated transaction reporting, then actual deductible amounts would be reported for each policy. He said transaction-level reporting would avoid having to readjust deductible bucket amounts in the future. Becky Konkle (National Independent Statistical Service—NISS) said the NISS has a very low number of percentage deductibles. Darby said the Working Group should work with the statistical agents to figure out how they are currently receiving the deductible information and the best way to get that information reported to regulators.

Bradner said the Working Group should collect and report both the standard deductible and any additional peril deductibles. Darby agreed and said that currently, the Statistical Handbook only dictates to report a wind/hail deductible if it is separate from the standard deductible. Darby said the Working Group will need to work on suggested language to clarify that both a standard deductible and a peril deductible should be reported.

Darby said the ISO commented to increase the reported amount of insurance in Section 7.6.12 from reporting to the nearest thousandth up to \$998,500 to reporting to the nearest thousandth up to \$9,998,500. Darby suggested the Working Group examine the current amount of insurance buckets collected for the *Dwelling, Fire, Homeowners Owner-Occupied, and Homeowners Tenant and Condominium/Cooperative Unit Owner's Insurance Report* (Homeowners Report).

Gerling said the definition of exposure basis in Section 7.6.13 should be expanded and clarified. He said the definition should include an example of how a company should report cancelled policies. Munn said the Working Group should review definitions from other data collection efforts and align the definitions for clarity. Darby said this section relates to Section 7.6.3, and the Working Group should align both definitions within the Statistical Handbook.

Darby said the ISO commented that Section 7.6.14 should include paid allocated loss adjustment expense and case-basis outstanding allocated loss adjustment expense. Botsko said this section should include the option to report as a defense and cost containment expense.

Darby said the ISO commented that Section 7.6.16 should be updated to include wildfire as a type of loss. The Working Group agreed. Gerling suggested separating fire caused by lightning from the fire, fire caused by lightning, and the removal line. He said this would help inform storm-related losses. Jenny Tornquist (American Association of Insurance Services—AAIS) said the AAIS has lightning as a separate cause of loss and would be able to report this way.

Darby said the ISO's comment suggested adding the number closed without payment to Section 7.6.16—Claim Count. Nancy Clark (ISO) said this data element is requested in other data calls, and it makes sense to include it in the statistical data reporting. Vajda said companies count and report claims differently, and the Working Group should take that into consideration when defining claim counts in the Statistical Handbook.

Darby said the Working Group would continue discussing comments on Sections 1, 2, 3, and 7 during its next meeting.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Spring/CASTF/SDWG/StatDataWGmin_430

Draft: 6/10/25

Statistical Data (C) Working Group
Virtual Meeting
April 9, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met April 9, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair, and Cynthia Amann (MO); Charles Hale (AL); Lori Dreaver Munn and Tom Zuppan (AZ); Qing He and George Bradner (CT); David A. Christhlf (DC); Christian Citarella (NH); Alexander Vajda (NY); Maureen A. Motter (OH); Landon Hubbard (OK); David Dahl and Ying Liu (OR); and J'ne Elizabeth Byckovski (TX). Also participating were: Luciano Gobbo (CA); Borwen Lee and Daniel Zhong (FL); John Sobhanian (LA); Phillip Glasovatz, Robyn Lowes, and Chris Slovinski (MI); Mari Kindberg and Ashley Perez (MT); Mike Andring (ND); and William Wilder (WA).

1. Discussed Comments on the Statistical Handbook Sections 1, 2, 3, and 7

Darby said that during the last meeting, the Working Group voted to remove Section 13—Glass Reports from the *Statistical Handbook of Data Available to Insurance Regulators* (Statistical Handbook), as there is very little data reported.

Qing He said in Section 7.3, which discusses additional coverages such as credit card and debris removal, the Working Group should consider adding other coverages, including identity theft.

Darby said in Section 7.3, the Working Group should consider including the HO-7 form in the mobile home section. Al Burton (Independent Statistical Service—ISS) said ISS does not collect mobile home data on an HO-7 form, but it does have other ways of identifying if a policy is covering a mobile home. Bradner said the Statistical Handbook should make mobile home reporting clear and consistent.

Darby said the Insurance Services Office (ISO) recommended removing the sentence in Section 7.5 that states, “Where no notation is made, the item applies to both.” Darby said removing this sentence and the asterisks next to certain data items would require all data items to be reported for both homeowners and mobile home owners.

Darby said the ISO commented to delete “territory” from the ZIP code or territory data item and change “Year of Loss” to “Date of Loss.” The Working Group agreed to both of these changes.

Darby said the Working Group needs to review the list of data items listed in Section 7.5 and determine if there is anything else that should be added. Gerling said the Working Group should consider adding data items for the count of policies and coverage limits. He said it should consider the types of data being collected by the NAIC Homeowners Market Data Call. Bradner said it does not want to replicate the data call, and there are two ways of getting the same information. Darby said that since statistical data collection has been around for a long time, it could mean it could expand what is collected here, and other data calls would not be necessary.

Darby said in Section 7.6, the ISO commented that “HO Only” should be removed from the “Type of Business” line so that this information is collected for both homeowners and mobile home owners. The Working Group agreed.

Darby asked statistical agents to clarify whether they are receiving written premium and earned premium or using a calculation to estimate earned premium. Rob Curry (ISO), Mike Puchner (American Association of Insurance Services—AAIS), and Burton said their companies receive written premium and calculate earned premium based on the policy period.

Darby said the ISO commented to remove “policy form not applicable” under “mobile home” in Section 7.6.6 and to add policy forms HO-7 and Other. Darby suggested that this section be changed so that all policy types are available to report for either line of business. Bradner agreed, saying that mobile home policies can be written on a number of different homeowners policy forms.

Darby said the ISO commented on adding manufactured homes as a construction type in Section 7.6.7 and to add a new section to collect information on property mitigation designation. Darby suggested allowing this section to be updated as needed since this is an evolving space. ISO also commented to add manufactured homes to the definition of “Year of Construction.” The Working Group agreed to these changes.

Darby suggested the Working Group consider breaking out the protection codes and collecting the actual code number instead of collecting Protected (1-8) and Unprotected (9-10). Becky Konkle (National Independent Statistical Service—NISS) said it does not collect the individual codes and only collects as the Statistical Handbook currently indicates.

Darby said the ISO commented on removing the note on only collecting statewide totals under Section 7.6.10—Miscellaneous Endorsements. The ISO suggested adding actual cash value (ACV) roof settlement, wind exclusion, wildfire exclusion, and other peril-specific exclusions to this section. Darby asked the statistical agents to make sure that they would be able to provide endorsement information on the ZIP code level.

Darby said the Working Group would continue discussing comments on Sections 1, 2, 3, and 7 during the next meeting.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Spring/CASTF/SDWG/StatDataWGmin_409

Draft: 4/22/25

Statistical Data (C) Working Group
Virtual Meeting
March 19, 2025

The Statistical Data (C) Working Group of the Casualty Actuarial and Statistical (C) Task Force met March 19, 2025. The following Working Group members participated: Sandra Darby, Chair (ME); Brad Gerling, Vice Chair, and Cynthia Amann (MO); Charles Hale (AL); Lori Dreaver Munn and Tom Zuppan (AZ); Qing He and George Bradner (CT); David A. Christhlf (DC); Christian Citarella (NH); Alexander Vajda (NY); Maureen A. Motter (OH); Landon Hubbard (OK); David Dahl and Ying Liu (OR); and J'ne Elizabeth Byckovski (TX). Also participating were: Luciano Gobbo (CA); Lee Borwen and Daniel Zhong (FL); John Sobhanian (LA); Phillip Glasovatz, Robyn Lowes, and Chris Slovinski (MI); Mari Kindberg and Ashley Perez (MT); Mike Andring (ND); and William Wilder (WA).

1. Discussed Comments on Statistical Handbook Sections 1, 2, 3, 7, and 13

Darby said that during the Working Group's last meeting, Sections 1—Introduction to the Handbook and to Statistical Reporting; 2—Data Quality for Insurers and Statistical Agents; 3—Reports Available from Statistical Agents: Summary; 7—Homeowners and Mobilehome Reports; and 13—Glass Reports of the *Statistical Handbook of Data Available to Regulators* (Statistical Handbook) were opened for comment. She said comments were received from the Center for Economic Justice (CEJ) and the Insurance Services Office (ISO).

Birny Birnbaum (CEJ) said Section 1 describes the purpose of statistical data collection as for rate review, but as seen with recent data calls, regulators need to collect data for various purposes, including analysis of availability and affordability. He said the current data does not allow regulators to use it for its intended purpose. He said data collected by regulators is collected in silos and that the way to reduce silos is to start collecting more granular data that can be used for a variety of purposes.

Birnbaum said Section 1.5—The Statutory Foundation for Statistical Reporting should be updated to reflect the variety of data sources not subject to regulatory oversight. He added that Section 1.5 should discuss advisory organizations.

Birnbaum said Section 1.7—Relation of the Statistical Handbook to the Model Regulation to Require Reporting of Statistical Data by Property and Casualty Insurance Companies refers to a model law, but the framework should include the commissioner's authority to: 1) collect data from insurers; 2) collect the data pursuant to a promulgated statistical plan; and 3) designate a statistical agent to collect data from insurers on behalf of the commissioner.

Birnbaum said Section 1.8—Confidentiality of Statistical Data should specify certain data as public because it cannot implicate any trade secret exemption from a state's public information law, including industry aggregate data at any level of geographic detail and insurer-specific data at the state level. These examples should not be interpreted as other data compilations are non-public information, but the public reporting of the examples should not be controversial.

Birnbaum said Sections 1.9—Scope and 1.10—Role and Responsibility of the Statistical Data (C) Working Group would need to be updated based on changes to the Statistical Handbook's structure and content. He added that the Statistical Handbook needs to be updated to reflect a different type of data collection. He said collecting anything other than transaction-level data will not improve the data or timeliness that regulators aim to achieve.

Munn said the Working Group should look at developing a data dictionary in addition to making updates to the Statistical Handbook. Bradner agreed that the NAIC should have a data dictionary for consistency in the data being requested, and insurers can be consistent with the data they submit. Birnbaum said the data dictionary should be incorporated into a statistical plan. Jenny Tornquist (American Association of Insurance Services—AAIS) said the AAIS has been working on an open-source insurance data standard and will soon release a white paper on the topic. Nancy Clark (ISO) said the ISO is working on a regulatory data repository that will be available for regulators to preview soon. Amann said the Cybersecurity (H) Working Group is working on a cyber dictionary and has a workstream looking at other NAIC data calls to put together a master dictionary for all NAIC data calls.

Birnbaum said another issue to address is the timing and access of data. He said that reporting is currently about two years behind the data year due to the need to wait for losses to develop. He said there are other reasons to collect statistical data beyond analyzing losses, and the data should not have to wait for those losses. He said regulators should be able to access data on an ongoing basis.

Clark said the ISO looked at what data was requested in the Statistical Handbook and what data is requested elsewhere in order to avoid duplicate data collections. She said that for Section 7, the ISO suggests making ZIP code a mandatory field, adding data elements on mitigation, expanding deductible and amount of insurance information, and adding date of loss in place of year of loss. Birnbaum said this could all be achieved by transaction-level reporting.

Darby said the ISO submitted comments on Section 13, which stated that the section should be eliminated, given the low volume of data submitted.

Munn made a motion, seconded by Gerling, to eliminate Section 13 from the Statistical Handbook, with a footnote explaining the removal. The motion passed unanimously.

Birnbaum said that just because data elements are reported elsewhere within regulatory data collection does not mean they should not be included in the statistical plans. He said if the statistical plan included transactional data, it could eliminate the need for the other data collection projects. He said other data collection avenues have proved to be too slow for what regulators need. Darby noted that the NAIC is creating a group to look at the various data collection projects and how they align with each other.

Darby said the Working Group should look at the timing of reporting with input from statistical agents. Birnbaum suggested at least quarterly reporting. He said the Statistical Handbook should also address regulators' need for ad hoc reporting. Munn said the timing issue should be addressed after all the sections have been updated.

Having no further business, the Statistical Data (C) Working Group adjourned.

SharePoint/NAIC Support Staff Hub/Member Meetings/C CMTE/2025_Spring/CASTF/SDWG/StatDataWGmin_319



06/05/2025

NAIC Model Review Manual

As of __month/day__, 2025

This *NAIC Model Review Manual (Manual)* provides a narrative description of the NAIC Model Review Team's ("NAIC Staff") processes and procedures as well as guidance regarding responsibilities.

The Casualty Actuarial and Statistical (C) Task Force ("Task Force") initially adopted the *Manual* in __[month]__ 2025. This guidance is subject to revision by the Task Force.

If you have questions regarding the *Manual* please contact NAIC staff:

Kris DeFrain
Director, Research and Actuarial Services
816-783-8229
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BACKGROUND

The NAIC model review project officially began in April 2018 when the Executive Committee adopted the recommendation of the Big Data (EX) Working Group to direct NAIC management to “conduct research on the appropriate skills and potential number of resources for the organization to help NAIC members in coordinating their reviews of predictive models.” NAIC senior management conducted the research and recommended gradual build-up of expertise at the NAIC to aid regulators’ review of P/C rate models.

In 2019 with existing actuarial, legal, and IT staff, the NAIC did 3 things:

- 1) Drafted a contractual agreement called the Rate Review Support Services Agreement (Appendix A) to be used so a state can gain access to the model database and can request a rate model technical review from the NAIC.
- 2) The NAIC developed the initial NAIC rate model technical review process with a consulting Actuary, and
- 3) the NAIC created a model database for confidential regulatory communication.

The NAIC does not do the following actions:

- Assume any regulatory authority,
- Create objections (“compliance issues”) to be sent to the company,
- Recommend acceptance or rejection of the model or any specific rating variable and,
- Separate analysis to determine any correlation with unlawful characteristics or to assess disparate impact.

Model reviews conducted by NAIC Staff were initially guided by the NAIC white paper *Regulatory Review of Predictive Models* (Attachment 2). This includes the initial paper and Appendices for different types of models adopted by the Task Force over time.

INTRODUCTION

This *Manual* is intended to guide NAIC Staff to assist insurance regulators in the state’s review of predictive models. The aim is to provide a consistent and documented review of complex predictive models used in insurance products while providing appropriate speed to market. To the extent possible, the *Manual* is intended to add uniformity when NAIC Staff produce reports applicable to all states. Compliance with a state’s laws and regulations will be performed by the state insurance regulator.

RATE REVIEW SUPPORT SERVICES AGREEMENT

This Rate Review Support Services Agreement (Agreement) identifies the NAIC services that can be requested and utilized:

- 1) Rate Model Reviews: Develop reports so state insurance regulators can review and decide if the insurer’s rate model support is in compliance with state law and regulations.

- 2) **Model Database:** Once reports are written, those reports are uploaded to the shared model database. All regulators in states with the Agreement may have access to the database and can also upload the state's own model reviews or communication to the database. There are no limits to the number of regulators in a state that can receive access.

The Agreement provides confidentiality protection. As required by the SERFF contract, all information from SERFF is held confidential by NAIC Staff and is only available to staff assigned to work in model review services. NAIC reports are confidential and for regulator use only.

The template for the Agreement is attached as Appendix A and can be requested from NAIC Staff or the NAIC Legal Department. Once the Agreement is agreed and signed, NAIC Staff meets with the state to explain model services and how to request them.

The Agreement includes no charges to conduct a model review or to provide access to the database. A state is not obligated by the Agreement to ask for reviews or use the database. In such a case, the Agreement is often signed as a contingency measure (e.g., resignation of a state expert on models).

A monthly e-mail is distributed to update all database members and contacts from states that have signed the Agreement regarding reports that were added to the database and other important information.

States with Signed Rate Review Support Services Agreement

The NAIC does not distribute the list of states who have signed a Rate Review Support Services Agreement. States are allowed to share they have signed the Agreement.

SERFF Access

The System for Electronic Rate and Form Filing (SERFF) allows insurers, advisory organizations, and third-party filers to submit insurance product filings (typically rate, rule, and form filings) electronically to state insurance regulators. This is a multi-state electronic filing system (licensed in all jurisdictions), but SERFF access is limited to a regulator's individual state. NAIC Staff will request access to every state with a signed Rate Review Support Services Agreement.

Access to NAIC and State Reports

Access to the Model Database and NAIC or state reports is restricted to regulators only.

REVIEW SUBMISSIONS AND DUE DATES

Before submission of a review request, the regulator will check the model database to see if the model has already been reviewed. Upon receipt of a regulator's request to review model support and/or objections (compliance issues), NAIC Staff will review the model complexity and the current state of the filing's supporting documentation. NAIC Staff will reply within 2 business days to share their availability and a date of when they can complete a review. The regulator will respond whether that date is acceptable, or they wish to withdraw the model review request.

Review submissions should include any specific instructions. The Task Force can also request that specific policy questions be answered with each NAIC model review.

After a model is reviewed in one state, Comparison Reports were completed to compare an insurer's model in one state with the model reviewed in another state. At this time with limited NAIC resources, NAIC Staff will only create Comparison Reports if there are current resources available in the 30 days following the request. A Comparison Report template is maintained by NAIC staff.

STATE, INSURER, AND MODEL-TYPE PRIORITIES

1. Data Gathered before Submission to the NAIC

- **Objective:** Ensure complete support documentation is received from the insurer prior to asking for an initial report from the NAIC. This should facilitate a smooth and more efficient review process. Insisting that companies provide complete information will reduce the review time of a model and will effectively reduce the number of NAIC reports per filing by one.
- **Process:**
 - States will be responsible for collecting and compiling relevant model support information prior to NAIC review.
 - The NAIC Model Checklist (Appendix C) provides information that must be submitted by regulators to the NAIC. The current Appendix C contains only GLM information. The Task Force will add the following to the GLM information in Appendix C: 1) checklists for non-GLM models, 2) modifications to support information when a model is a refresh to a previously filed model, and 3) guidance for any other special circumstances (e.g., specific components of a telematics filing to be reviewed).
 - States are encouraged to continually update their model filing requirements in SERFF upon adoption of new guidance from the Task Force.
 - Regularly review and adjust model support requirements to maintain efficiency and relevance.

2. Focus on Nationally Significant Companies and Licensed Third Parties

- **Objective:** Prioritize NAIC efforts on entities with the greatest impact.
- **Process:**
 - Limit NAIC review work to top 20 insurance groups (by market size) and third-party vendors licensed or operating in 10 or more states.
 - Exceptions may arise; as in the case of an innovative modeling approach initiated by a smaller company or a new product.

3. Scheduling with Priorities -- Limiting the Number of Reports by State

- **Objective:** Ensure fairness in each state's ability to receive assistance from the NAIC Staff in a timely manner, while recognizing that every state benefits from the Model Database regardless of which state requests the review.
- **Process:**
 - Give priority to states that have had fewer requests in the previous six months.
 - Implement measures to limit the number of reports from any state for fairness.
 - Limit the number of initial model reviews from one state to two (2) filed models in a calendar month.
 - Should resources become available at the NAIC during a week, scheduled review request(s) will be moved up in the queue to an earlier open date.

5. Scheduling with Priorities – Maintain Open Spots for 30-day Response States

- **Objective:** For those states that must respond to a rate filing within a limited number of days (often 30 days) by law or regulation, ensure fairness in each state's ability to receive assistance from the NAIC Staff in a timely manner.
- **Process:**
 - Maintain at least 4 open spots a month for those states that need a review within a limited amount of time.

6. Scheduling with Priorities – Objection (Compliance Issues) Reviews

- **Objective:** Ensure a rate model is reviewed through all stages of a filing review process and provide faster speed-to-market.
- **Process:**
 - Upon scheduling the initial review, the NAIC will also set aside two additional review slots for expected objection (compliance issues) reviews.
 - The "set aside" review slots will be postponed if the insurer's responses do not arrive in the expected time period.
 - The aim will be to review objection responses within 30 days of receipt from the regulator.

7. Follow-Up Calls with State and Insurer for Unresolved High- and Medium-Priority Questions

- **Objective:** Address unresolved high-priority and medium-priority questions in an efficient manner to aid speed-to-market of rate models.
- **Process:**
 - NAIC Staff will conduct a second assessment of insurer compliance issues to identify any remaining high-priority or medium-priority questions.
 - If these questions are not fully answered, or if additional discussion is needed, the state will schedule a follow-up call with the company.
 - Use these calls to clarify outstanding issues and ensure all critical points are addressed in the next insurer submission of responses to compliance issues.

NAIC STAFF RESOURCES

The Task Force will quarterly evaluate the queue of filings and the NAIC model review staff/resources. If the Task Force and/or Task Force leadership determine regulatory needs are not being met, the Task Force will first attempt to find efficiencies or suggest using other resources. If the Task Force wishes the needs to be met by NAIC Staff, the Task Force chair will discuss NAIC resources with the chair of the Property and Casualty Insurance (C) Committee.

MANUAL REVISIONS

NAIC will evaluate the prioritization and utilization of NAIC resources to ensure that they are meeting the needs of those states participating in this process. Suggestions for improving or correcting information contained in the *Manual* may be made via written proposal to the Task Force. The Task Force will determine if changes should be made. Substantive changes made will be discussed in open session, while mechanical corrections (e.g., editorial or typographical changes) will be made without announcement or discussion.

APPENDIX

- A. Rate Review Support Services Agreement Template
- B. The Task Force's white paper and all adopted appendices
- C. NAIC Model Checklists

Appendix A: Rate Review Support Services Agreement Template

RATE REVIEW SUPPORT SERVICES AGREEMENT **BETWEEN THE INSURANCE DEPARTMENT AND** **THE NATIONAL ASSOCIATION OF INSURANCE COMMISSIONERS**

This Rate Review Support Services Agreement (“Agreement”) is entered into on this [REDACTED] day of [REDACTED], 2020 by and between the National Association of Insurance Commissioners (“NAIC”) and the [REDACTED] Insurance Department (“DOI”).

PURPOSE

The DOI is a member of the NAIC, a non-profit organization whose mission is to assist state insurance regulators in serving the public interest and achieving fundamental insurance regulatory goals. This Agreement is intended to allow DOI to utilize the services of the NAIC in connection with its rate review process. The DOI is the recipient of rate review documents, materials and other information pursuant to its authority under [INSERT CITATION].

[INSERT CITATION] provides that certain documents, materials or other information, in the possession or control of the DOI that are obtained by, created by or disclosed to the Commissioner or any other person acting under the authority of the commissioner, shall be confidential by law and privileged, shall be recognized as being proprietary and to contain trade secrets, shall not be subject to disclosure under [INSERT STATE FOIA CITATION], shall not be subject to subpoena, shall not be subject to discovery or admissible in evidence in any civil action in this state, and shall be otherwise protected as provided by [INSERT CITATION].

[INSERT CITATION] specifically authorizes the disclosure to other state regulatory authorities and the NAIC of such confidential and exempt information. Disclosure of such confidential and exempt information pursuant to [INSERT CITATION] requires the receiving party to maintain the confidential and exempt status of the information disclosed. [INSERT CITATION] requires [NAME OF STATE] to maintain the confidentiality of information received from other state regulatory authorities and the NAIC when [NAME OF STATE] is the receiving party.

Upon request, the NAIC will provide the DOI with review, analysis, documentation, and such other services as may be requested by the DOI in connection with its rate review process (“Support Services”), including, but not limited to, a rate review report (“the Report”). The NAIC will use rate review documents, materials, and other information shared by the DOI pursuant to applicable state law (“rate review Materials”) in order to produce the Report. Upon such a request being made, NAIC will use its best efforts to provide the Report within a reasonable amount of time. Should the NAIC be prevented from complying with a request and/or meeting a deadline, it will communicate same with the DOI at its earliest opportunity.

In order to facilitate the implementation and effectiveness of the Support Services to be delivered to DOI staff, the DOI and the NAIC enter into the following Agreement.

AGREEMENT

1. This Agreement applies to rate review Materials owned and/or controlled by DOI pursuant to applicable state law and disclosed to the NAIC.

2. Upon mutual consent, the DOI will provide the rate review Materials to the NAIC and the DOI hereby grants the NAIC access to the state's System for Electronic Rates & Forms Filing (SERFF) data for the sole purpose of providing the Support Services described herein.
3. The DOI authorizes the NAIC to facilitate the sharing of rate review Materials with other state insurance departments who have executed the Rate Review Support Services Agreement, or a substantially similar agreement, when permitted to do so by the DOI. Such sharing of information shall take place pursuant to the terms of master Information Sharing and Confidentiality Agreement when permitted to do so by the DOI.
4. The NAIC shall not facilitate the sharing of rate review Materials with any other party unless directed in writing to do so by the DOI. These rate review Materials may not be used for any other purpose.
5. The NAIC agrees to protect from disclosure the rate review Materials provided by the DOI under this Agreement and determined by the DOI to be confidential and exempt from public disclosure ("Confidential Information"). The NAIC further agrees to take all actions reasonably necessary to preserve, protect, and maintain all privileges or other protections from disclosure related to the Confidential Information.
6. The DOI acknowledges it may be expedient to receive rate review Materials submitted by regulatory authorities from other states and/or territories from time to time. The DOI authorizes the NAIC to facilitate such information sharing when directed to do so by the DOI. In its capacity as a receiving party, the DOI agrees to protect from disclosure, rate review Materials produced by regulatory authorities of another state or territory pursuant to the master Information Sharing and Confidentiality Agreement. The DOI further agrees to take all actions reasonably necessary to preserve, protect, and maintain all privileges or other protections from disclosure related to the Confidential Information.
7. The term "Confidential Information" shall not include any information that is in the public domain, is developed independently by or on behalf of the DOI or the NAIC as shown by documentary evidence, or becomes disclosed to DOI or the NAIC by a third party not having an obligation of confidence to either party.
8. The NAIC agrees that the Confidential Information disclosed by the DOI remains the property of the DOI and agrees that it will take no action the effect of which would be to limit, waive or jeopardize any privilege or claim of confidentiality related to the Confidential Information.
9. The DOI agrees and acknowledges that the rate review Report contains technical analyses that may assist DOI in its review of rates under applicable state law, and that the Report is not intended to substitute or otherwise supersede the judgment of DOI regarding rate review. The DOI may provide the Report to other state Departments of Insurance with permission from the NAIC.
10. With the exception of the Report described herein, the NAIC retains any and all rights, title and interest in any work papers, methodologies, models, standards, and any other type of material whatsoever ("Proprietary Materials"), which it may have developed or employed in the performance of the Support Services under this Agreement, and neither the DOI nor the State of [state] shall have any right, title or interest in or to the Proprietary Materials

for any purpose. The DOI agrees to take no action adverse to the rights of the NAIC as owner of the Proprietary Materials.

11. To the extent the DOI intends to produce the Report or use the Report in the course of any administrative hearing, or in the furtherance of any other regulatory action, the DOI will notify the NAIC as soon as possible. The NAIC shall use its best efforts to provide guidance and assistance as needed, provided that adequate notice is provided to the NAIC, and that all reasonable fees and expenses incurred by the NAIC are reimbursed by the DOI.
12. The NAIC has MADE NO WARRANTY OR PROMISE, EITHER EXPRESS OR IMPLIED, with respect to the Report or the Support Services covered by this Agreement. OTHER THAN AS EXPRESSLY PROVIDED HEREIN, THE REPORT AND SUPPORT SERVICES ARE PROVIDED "AS IS" WITHOUT WARRANTY OF ANY KIND AND THE NAIC EXPRESSLY DISCLAIMS **THE IMPLIED WARRANTY OF MERCHANTABILITY AND FITNESS FOR ANY PARTICULAR PURPOSE**. THERE ARE NO WARRANTIES, EITHER EXPRESS OR IMPLIED, WHICH EXTEND BEYOND THE DESCRIPTION OF THE REPORT AND SUPPORT SERVICES SET FORTH IN THIS AGREEMENT. THE NAIC SHALL NOT BE LIABLE FOR AND THE DOI EXPRESSLY WAIVES ANY CLAIM FOR ANY LOSS, COST, OR INJURY, DIRECT OR INDIRECT (INCLUDING, BUT NOT LIMITED TO, LOST SALES, LOST PROFIT, BUSINESS INTERRUPTION, OR THIRD PARTY CLAIMS), SUFFERED BY THE DOI AS A RESULT OF RELIANCE ON OR USE OF THE REPORT OR SUPPORT SERVICES.
13. In the event that the NAIC receives a third-party request for Confidential Information furnished by regulatory officials of another state or territory pursuant to a substantially similar version of this Agreement, or in the event that the NAIC is served with a subpoena, motion, order, or other process requiring production of such information or testimony related thereto, the NAIC shall:
 - (i) Immediately notify the DOI whose Confidential Information is subject to the request that such production is being sought and afford DOI the opportunity to take whatever action it deems appropriate to protect the confidential or privileged nature of the Confidential Information;
 - (ii) Notify the party seeking production of the Confidential Information that it is the property of the DOI;
 - (iii) Use its best efforts to resist production of the Confidential Information to the third party except to the extent that the DOI has consented to such production; and
 - (iv) Consent to any application by DOI or by an insurer that has submitted documents subject to this agreement to intervene in any action for the purpose of asserting and preserving any privileges, confidentiality rights or other protection from disclosure with respect to the Confidential Information.
14. It is expressly agreed and understood that if a court of competent jurisdiction issues an order to compel the NAIC to produce Confidential Information covered by this Agreement, they may comply with such an order. No compulsory disclosure to third parties of Confidential Information disclosed under the Agreement shall be deemed a waiver of any privilege, protection from disclosure or other claim of confidentiality.

15. Nothing in this Agreement shall be construed as a delegation of regulatory or rulemaking authority nor shall it be construed to restrict the regulatory prerogatives of the DOI in any way.
16. The NAIC is an independent contractor and not an employee of the DOI.
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NATIONAL ASSOCIATION OF INSURANCE COMMISSIONERS

Signature

Printed Name

Title

Date

INSURANCE DEPARTMENT

Signature

Printed Name

Title

Date

Appendix B: Regulatory Review of Predictive Models White Paper and Approved Appendices

Adopted by the Casualty Actuarial and Statistical (C) Task Force, 9/15/20
Adopted by the Property and Casualty Insurance (C) Committee, 12/8/20
Adopted by the Executive (EX) Committee and Plenary, 4/14/21

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 state insurance 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 white 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 has been charged with identifying best practices to serve as a guide to state insurance departments in their review of the predictive models¹ underlying rating plans. There were two charges given to Task Force 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 white 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 the review of rate filings based on predictive models. Upon adoption of this white paper by the Executive (EX) Committee and Plenary, the Task Force 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.

As discussed further in the body of the white paper, this document is intended as guidance for state insurance regulators as they review predictive models. Nothing in this document is intended to, or could, change the applicable legal and regulatory standards for approval of rating plans. This guidance is intended only to assist state insurance regulators as they review models to determine whether modeled rates are compliant with existing state laws and/or regulations. To the extent these best practices are incorporated into the *Product Filing Review Handbook*, the handbook provides that it is intended to “add uniformity and consistency of regulatory processes, while maintaining the benefits of the application of unique laws and regulations that address the state-specific needs of the nation’s insurance consumers.”

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 whether predictive models, as used in rate filings, are compliant with state laws and/or regulations?

Key Regulatory Principles

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

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

¹ In this white 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, NY: McGraw-Hill.

2. State insurance regulators will be able to share information to aid companies in getting insurance products to market more quickly across the states.⁴
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.
4. State insurance regulators will maintain confidentiality, in accordance with state law, regarding predictive models.

Best practices are presented to state insurance regulators for the review of predictive models and to insurance companies as a consideration in filing rating plans that incorporate predictive models. As a byproduct 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 the 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 white paper are glossary terms (see Appendix C) and references (contained in the footnotes) that can expand a state insurance 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.⁵ 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 GLM⁶ 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 because 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.⁷ 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 state insurance regulator when model results are difficult to explain to someone (e.g., a consumer) who has little to no expertise in modeling techniques.

Generalized Linear Models

A GLM consists of three elements:⁸

- A target variable, Y , which is a random variable that is independent and is assumed to follow 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 $E(Y) = \mu = g^{-1}(\eta)$.

⁴ The states can share information if they can maintain confidentiality and legally share such information. Information about a classification plan documented in one state could be shared with another state.

⁵ A more thorough exploration of different predictive models will be found in many books on statistics, including:

- Geisser, S., 2016. *Predictive Inference: An Introduction*, New York, NY: Chapman & Hall.
- James, G., et al., 2017. *An Introduction to Statistical Learning: with Applications in R*, New York, NY: Springer Science+Business Media, pp. 87–90. Accessed online at <http://faculty.marshall.usc.edu/gareth-james/ISL/ISLR%20Seventh%20Printing.pdf>.

⁶ The GLM is a flexible family of models that are unified under a single method. Types of GLMs include logistic regression, Poisson regression, gamma regression, and multinomial regression.

⁷ Goldburd, M., et al., 2016. "Generalized Linear Models for Insurance Rating," CAS Monograph Series, Number 5, Second Edition, pp. 52–58. Accessed online at www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

⁸ Information on model elements can be found in most books on statistics.

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 a GLM's output than that of a univariate model.

To further complicate the regulatory review of models in the future, modeling methods are evolving rapidly and are not limited just to GLMs. As computing power grows exponentially, it is opening 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 include predictive models utilizing random forests, decision trees, neural networks, or combinations of available modeling methods (often referred to as “ensembles”). These evolving techniques will make a state insurance regulator's understanding and oversight of filed rating plans that incorporate 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 the use of predictive models. The Big Data (EX) Working Group identified the need to provide the states with guidance and assistance when reviewing predictive models underlying filed rating plans.⁹ 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 Working Group members and interested parties on Dec. 19, 2017, for a public comment period ending Jan. 12, 2018.¹⁰ The Working Group's effort resulted in new charges for the Casualty Actuarial and Statistical (C) Task Force (see Section I—Introduction) to identify best practices that provide guidance to the states in their 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.^{11,12} 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 state insurance 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 of “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 state insurance regulators to review the referenced filings. Best practices will aid regulatory reviewers by raising their level of model understanding. Also, with regard to scorecard

⁹ Big Data (EX) Working Group March 24, 2018, minutes (see *NAIC Proceedings – Spring 2018, Innovation and Technology (EX) Task Force, Attachment Two*). Accessed online at https://www.naic.org/prod_serv/PRC-ZS-18-01.pdf.

¹⁰ All comments received by the end of January 2018 were posted to the NAIC website March 12, 2018, for review.

¹¹ 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.

¹² 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.

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 and, therefore, makes that rating plan fairer to all consumers in the marketplace. To make this work, state insurance regulators and the industry need to recognize that:

- Best practices provide guidance to state insurance regulators in their essential and authoritative role over the rating plans in their respective state.
- Every state may have a need to review predictive models, whether that occurs during the approval process of a rating plan or during a market conduct exam. Best practices help the state insurance 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/or regulations, and whether to act on that information.
- Best practices provide a framework for the 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 the states, aiding speed to market and competitiveness of the state's insurance marketplace.
- Best practices aid training of new state insurance 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 state insurance 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 white 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 the regulatory review of predictive models because many state insurance regulators are 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 a review of these personal lines and the knowledge needed to review GLMs¹³ used in their rate filings that will provide meaningful best practices for state insurance 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. State insurance regulators should be aware of their state laws on confidentiality when requesting data from insurers that may be proprietary or a 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 its rate filing.

State authority, regulations and/or rules governing confidentiality always apply when a state insurance regulator reviews a model used in rating. When the NAIC or a third party enters 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.

¹³ See Appendix B.

VII. BEST PRACTICES FOR THE REGULATORY REVIEW OF PREDICTIVE MODELS

Best practices will help the state insurance 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 the states and improve the efficiency of each regulator's review, thereby helping companies get 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.
 - b. Determine whether 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 whether 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 whether 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, to help determine whether the 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 the predictive model (and its sub-models).
 - b. Obtain a clear understanding of how the insurer integrates the model into the rating plan and how it improves the rating plan.
 - c. Obtain a clear understanding of how the 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 the acceptance of predictive models, provided such models are in compliance with state laws and/or regulations, particularly prohibitions on unfair discrimination.
 - b. Protect the confidentiality of filed predictive models and supporting information in accordance with state laws and/or regulations.
 - 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 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 laws and/or regulations, 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 state laws and/or regulations 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 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 state insurance 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 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, the NAIC has developed an appendix in its white paper for guidance¹⁴ 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.”¹⁵ Best practices can maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking.¹⁶ 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 whether predictive models, as used in rate filings, are compliant with state laws and/or 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 the 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 laws and/or regulations, 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 laws and/or regulations, and how the model improves the company's rating plan. Best practices can also improve the consistency among the regulatory review processes across the 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:

¹⁴ Refer to Appendix B in the NAIC white paper, *Regulatory Review of Predictive Models*.

¹⁵ 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. Refer to Appendix A in the NAIC white paper, *Regulatory Review of Predictive Models*, for an overview of Bardach's best-practice analysis.

¹⁶ Bogan, C.E., and English, M.J., 1994. *Benchmarking for Best Practices: Winning Through Innovative Adaptation*. New York, NY: McGraw-Hill.

Appendix B: Casualty Actuarial and Statistical (C) Task White Paper and Appendices

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.
 - b. Determine whether 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 whether 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 whether 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 such models are in compliance with state laws and/or regulations, particularly prohibitions on unfair discrimination.
 - b. Protect the confidentiality of filed predictive models and supporting information in accordance with state laws and/or regulations.
 - 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 laws and/or regulations. State insurance Regulators should be aware of their state laws and/or regulations 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 and/or regulations 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 the 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 it has 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 it can make appropriate modifications in future filings.

The NAIC white paper, *Regulatory Review of Predictive Models*, documents questions that a state insurance regulator may want to ask when reviewing a model. These questions are listed as “information elements” in Appendix B of the white paper. **Note:** 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 (<https://www.casact.org> and <https://www.soa.org>, respectively) 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

Additional background reading is recommended:

- CAS: *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
- CAS: Statements of Principles, especially regarding property/casualty ratemaking.
- CAS: “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 its indicated rate change by starting with historical years of underwriting data (earned premiums, incurred loss and loss adjustment expenses, and 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.
- The CAS’ *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 and regulations include special provisions for workers’ compensation business, penalties for not complying with state laws and/or regulations, 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 NAIC white paper, *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 employ different standards or guidelines than the ones described.

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

IX. PROPOSED STATE GUIDANCE

This white paper acknowledges that different states will apply the guidance within this white 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. The 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 white paper. However, the states—including those with and without prior-approval authority—may also use the guidance in this white 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 white paper to achieve the most effective and successful implementation, subject to the framework of statutes, regulations, precedents, and/or 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 white paper. The topics are listed below without elaboration and not in any order of importance. **Note:** This not an exhaustive list. These topics may need to be addressed during the regulator’s review of a predictive model. It may be that one or more of the following topics will be addressed by an NAIC committee in the future:

- Provide guidance for state insurance regulators to identify when a rating variable or rating plan becomes too granular.
- Provide guidance for state insurance regulators on the importance of causality versus correlation when evaluating a rating variable’s relationship to risk, in general and in relation to Actuarial Standard of Practice (ASOP) No. 12, *Risk Classification (for All Practice Areas)*.
- Provide guidance for state insurance regulators on the value and/or concerns of data mining, including how data mining may assist in the model building process, how data dredging may conflict with standard scientific principles, how data dredging may increase “false positives” during the model building process, and how data dredging may result in less accurate models and/or models that are unfairly discriminatory.
- Provide guidance and/or tools for state insurance regulators to determine how a policy premium is calculated and to identify the most important risk characteristics that underlie the calculated premium.
- Provide guidance for state insurance 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 state insurance regulators to monitor consumer market outcomes resulting from insurers’ use of data analytics underlying rating plans.
- Provide guidance for state insurance 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 state insurance regulators to determine whether 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 state insurance regulators to identify and minimize unfair discrimination manifested as “disparate impact.”
- Provide guidance for state insurance 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 PRACTICES DEVELOPMENT

The development of best practices 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.¹⁷

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 and/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.¹⁸

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

1. Define 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.

2. 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.

3. 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.

4. 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.

5. Implement and Evaluate

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 help ensure the practice remains effective.

¹⁷ 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, pp. 309–335. Accessed online at <https://doi.org/10.1093/jopart/muu014>.

¹⁸ 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 state insurance 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 help ensure the business continuity and transparency of the 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 documented and shared with regulators in a timely and appropriate manner. Information technology (IT) controls should be in place, such as a record of versions, change control, and access to the model.¹⁹

Many information elements listed below are probably confidential, proprietary, or trade secret and should be treated as such, in accordance with state laws and/or regulations. Regulators should be aware of their state laws and/or regulations 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.²⁰

Although 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 which 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 Level 1 and Level 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 by a particular state, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws and/or regulations.

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 Level 1, Level 2, and Level 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 by 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, and/or unfairly discriminatory.

¹⁹ Bourdeau, M., 2016. “Model Risk Management: An Overview,” *The Modeling Platform*, Issue 4, December. Accessed online at <https://www.soa.org/globalassets/assets/library/newsletters/the-modeling-platform/2016/december/mp-2016-iss4.pdf>.

²⁰ There are some models that are made public by the vendor and would not result in a hindrance of the model’s protection.

Lastly, although the best practices presented in this white 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; e.g., 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 are applied to lines of business other than personal automobile and home insurance or other type of models, unique considerations may arise. In particular, data volume and credibility may be lower for other lines of business. 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 white 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	<p>Request details of 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 of 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.</p> <p>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 federal Fair Credit Reporting Act (FCRA). 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.</p> <p>Note: 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.</p>
A.1.b	Reconcile aggregated insurance data underlying the model with available external insurance reports.	4	<p>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 (i.e., 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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	Many models are developed using a countrywide or a regional dataset. 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. However, 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 (i.e., whether there is bias) of overlapping data or variables used in the model and sub-models.	1	Check if the same variables/datasets were used in the model, a sub-model, or as stand-alone rating characteristics. If so, verify the insurance company has processes and procedures in place to assess and address double-counting or redundancy.
A.2.b	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	1	<p>If the sub-model was previously approved/accepted, that may reduce the extent of the sub-model's review. If approved, obtain the tracking number(s) (e.g., state, SERFF) and verify when and if it was the same model currently under review.</p> <p>Note: A previous approval does not necessarily confer a guarantee of ongoing approval; e.g., when statutes and/or 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 the prior decision needs to be revisited. In some circumstances, direct dialogue with the vendor could be quicker and more useful.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.2.c	Determine if the sub-model output was used as input to the GLM; obtain the vendor name, as well as the name and version of the sub-model.	1	<p>To accelerate the review of the filing, it may be desirable to request (from the company), the name and contact information for a vendor representative. 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.</p> <p>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. Sub-model SMEs may need to be brought into the conversation with regulators (whether in-house or third-party sub-models are used).</p>
A.2.d	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	<p>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.</p> <p>For example, it is important to know hurricane model settings for storm surge, demand surge, and long-term/short-term views.</p>
A.2.e	Obtain an explanation of how catastrophe models are integrated into the model to ensure no double-counting.	1	<p>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.</p> <p>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 or inclusion of freeze losses when using a winter storm model.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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). If so, how? Do the adjustments vary for different segments of the data? If so, identify the segments and how the data was adjusted.	2	<p>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.</p> <p>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?</p> <p>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.</p>
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 dataset of pre-adjusted/scrubbed data and one dataset 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	<p>This is most relevant for variables that have been "scrubbed" or adjusted.</p> <p>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.</p> <p>It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category are provided. This data can be displayed in either graphical or tabular formats.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.3.d	Determine how missing data was handled.	1	<p>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.</p> <p>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 recoding 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 are provided. This data can be displayed in either graphical or tabular formats.</p>
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	<p>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 types of outliers and determine what adjustments were made to each type of outlier. To understand the filer's response, the regulator should ask for the filer's materiality standard.</p>
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	<p>This should explain how data from separate sources was merged and/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.</p>
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	<p>An example is when by-peril or by-coverage modeling is performed; the documentation should be for each peril/coverage and make rational sense.</p> <p>For example, if “murder” or “theft” data are used to predict the wind peril, the company should provide support and a rational explanation for their use.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.4.c	Identify material findings the company had during its 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	“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., GLM, decision tree, Bayesian GLM, 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	<p>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/by-coverage.</p> <p>Note: If the model is not a GLM, the information elements in this white paper may not apply in their entirety.</p>
B.1.b	Identify the software used for model development. Obtain the name of the software vendor/developer, software product, and a software version reference used in model development.	3	<p>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 (e.g., a filing specialist) who can place the regulator in direct contact with the appropriate SME at the vendor.</p> <p>Open-source software/programs used in model development should be identified by name and version the same as if from a vendor.</p>
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 of why that came to occur. Obtain a discussion of whether the model was rebuilt using all the data or if it was only based on the training data.	1	<p>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.</p> <p>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. However, according to the CAS monograph, "Generalized Linear Models for Insurance Rating": "Once a final model is chosen, ... we would then go back and rebuild it using all of the data, so that the parameter estimates would be at their most credible."</p> <p>The reviewer should note whether a company employed cross-validation techniques instead of a training/test/validation dataset approach. If cross-validation techniques were used, the reviewer should request a description of how cross-validation was done and confirm that the final model was not built on any particular subset of the data, but rather the full dataset.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
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 on the use of automated feature selection algorithms to choose predictor variables and explain how potential overfitting that can arise from these techniques was addressed.
B.1.h	In conjunction with variable selection, obtain a narrative on how the company determined the granularity of the rating variables during model development.	3	The narrative 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 (e.g., 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 that 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	

Section	Information Element	Level of Importance to Regulator's Review	Comments
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 of 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, including an explanation of the decision-making process to determine which interactions were included and which were not.	3	<p>There should be a description of the 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.</p> <p>The number of interaction terms that could potentially be included in a model increases far more quickly than the number of “main effect” variables (i.e., the basic predictor variables that can be interacted together). Analyzing each possible interaction term individually can be unwieldy. It is typical for interaction terms to be excluded from the model by default, and only included where they can be shown to be particularly important. So, as a rule of thumb, the regulator’s emphasis should be on understanding why the insurer included the interaction terms it did, rather than on why other candidate interactions were excluded.</p> <p>In some cases, however, it could be reasonable to inquire about why a particular interaction term was excluded from a model—for example, if that interaction term was ubiquitous in similar filings and was known to be highly predictive, or if the regulator had reason to believe that the interaction term would help differentiate dissimilar risks within an excessively heterogenous rating segment.</p>
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 of why the link function and distribution were chosen. Obtain the formulas for the distribution and link functions, including specific numerical parameters of the distribution. If changed from the default, 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; however, when it occurs can be subjective or based on threshold criteria. If the software’s default convergence criteria were not relied upon, an explanation of any deviation should be provided.
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	

Section	Information Element	Level of Importance to Regulator's Review	Comments
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 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 a 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.

Section	Information Element	Level of Importance to Regulator's Review	Comments
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, as well as an explanation of 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-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 multistate 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. Note: It may be useful to consider geographic stability measures for territories within the state.
B.4.b	For all variables (discrete or continuous), review the appropriate parameter values and relevant tests of significance, such as confidence intervals, chi-square tests, p-values, or F 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; 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; e.g., confidence intervals around each level of an AOI curve might be more than what is needed.

Section	Information Element	Level of Importance to Regulator's Review	Comments
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	<p>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; e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>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.</p>
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	<p>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.</p> <p>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.</p> <p>For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; e.g., confidence intervals around each level of an AOI curve might be more than what is needed.</p>
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	<p>For a GLM, such evidence may be available using chi-square tests, p-values, F tests and/or other means.</p> <p>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 a GLM.</p> <p>The regulator should not assume to know what the company did and ask, "How?" Instead, the regulator should ask what the company did and be prepared to ask follow-up questions.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
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	<p>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.</p> <p>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.</p> <p>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.</p>
B.4.g	Obtain a description how the model was tested for stability over time.	2	<p>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).</p> <p>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.</p> <p>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 exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model?</p> <p>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.</p>
B.4.h	Obtain a narrative on how potential concerns with overfitting were addressed.	2	

Section	Information Element	Level of Importance to Regulator's Review	Comments
B.4.i	Obtain support demonstrating that the GLM assumptions are appropriate.	3	<p>A visual review of plots of actual errors is usually sufficient.</p> <p>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.</p> <p>If the reviewer determines that the model makes no assumptions that are considered to be unreasonable, the importance of this item may be reduced.</p>
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	<p>Obtain an explanation of why this model is an improvement to the current rating plan.</p> <p>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.</p>	2	The regulator 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	<p>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.</p> <p>This is relevant when one model is being updated or replaced. The regulator should expect to see improvement in the new class plan's predictive ability. One example of a comparison might be sufficient.</p> <p>Note: This comparison is not applicable to initial model introduction. Reviewer can look to CAS monograph, “Generalized Linear Models for Insurance Rating.”</p>
B.5.c	Determine if double-lift charts were analyzed and obtain a narrative on the conclusion drawn from this analysis.	3	<p>One example of a comparison might be sufficient.</p> <p>Note: “Not applicable” is an acceptable response.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
B.5.d	<p>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 of why these variables were dropped from the new model.</p> <p>Obtain a list of all new predictor variables in the new model that were not in the prior old model.</p>	2	It is 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, and/or built the model.	4	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 (i.e., how it was used) in the rating system.	1	<p>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.</p> <p>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.)</p>
C.1.b	Obtain an explanation of how the model was used to adjust the filed rating algorithm.	1	<p>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.</p> <p>The regulator should consider asking for an explanation of how the model was used to adjust the rating algorithm.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
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	<p>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.</p> <p>Note: This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.</p>
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	<p>"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.</p>
C.3.b	Obtain documentation and support for all calculations, judgments, or adjustments that connect the model's indicated values to the selected relativities filed in the rating plan.	1	<p>The documentation should include explanations for the necessity of any such adjustments and 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.</p> <p>Note: 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.</p>
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 regarding how each characteristic/variable was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	<p>Modeling loss ratios 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.</p> <p>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.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
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	The regulator should determine at what level of granularity credibility is applied. If modeling was by-coverage, by-form, or by-peril, the company should 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 of why.	2	This is applicable if the company 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 of why.	2	A more granular rating plan may imply that the company had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications. It may be necessary to extrapolate due to data availability or other considerations.
5. Definitions of Rating Variables			
C.5.a	Obtain a narrative regarding 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 of 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 of 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.

Section	Information Element	Level of Importance to Regulator's Review	Comments
C.6.b	Obtain an explanation of any material (especially directional) differences between model indications and state-specific univariate indications.	4	<p>Multivariate indications may be reasonable as refinements to univariate indications, but possibly not for bringing about significant reversals of those indications.</p> <p>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.</p> <p>Credibility of state-level data should be considered when state indications differ from modeled results based on a broader dataset. However, the relevance of the broader dataset to the risks being priced should also be considered. Borderline reversals are not of as much concern. If multivariate indications perform well against the state-level data, this should suffice. However, credibility considerations need to be taken into account as state-level segmentation comparisons may not have enough credibility.</p>
7. Consumer Impacts			
C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in renewal premium, both as increases and decreases, as well as the top five rating variables with the largest spread of impact for both new and renewal business.	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 company 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 renewal business 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.

Section	Information Element	Level of Importance to Regulator's Review	Comments
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	<p>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.</p> <p>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.</p> <p>See Appendix D for an example of a disruption analysis.</p>
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 D 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	<p>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.</p> <p>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.</p> <p>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.</p>

Section	Information Element	Level of Importance to Regulator's Review	Comments
C.7.g	Obtain a means to calculate the rate charged a consumer.	3	<p>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. The 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: This information may be proprietary.</p> <p>For the rating plan, the rate order of calculation rule may be sufficient. However, it may not be feasible for a regulator to get all the input data necessary to reproduce a model's output. Credit and telematics models are examples of model types where model output would be readily available, but the input data would not be readily available to the regulator.</p>
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	<p>If the data is from a third-party source, the company should provide information on the source. Depending on the nature of the data, it may need to be documented with an overview of who owns it.</p> <p>The topic of consumer verification may also need to be addressed, including how consumers can verify their data and correct errors.</p>
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.

Section	Information Element	Level of Importance to Regulator's Review	Comments
9. Efficient and Effective Review of Rate Filing			
C.9.a	Establish procedures to efficiently review rate filings and models contained therein.	1	<p>“Speed to market” is an important competitive concept for insurers. Although the regulator needs to understand the rate filing before accepting the rate filing, the regulator should not request information that does not increase his/her understanding of the rate filing.</p> <p>The regulator should review the state’s rate filing review process and procedures to ensure that they are fair and efficient.</p>
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 laws and/or regulations.	1	<p>This is a primary duty of state insurance regulators. The regulator should be knowledgeable of 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.</p>
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	<p>The regulator should be knowledgeable of 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.</p>

APPENDIX B (Continued)**Mapping Best Practices to Information Elements and Information Elements to Best Practices**

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 state insurance 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 Information Element
A. Selecting Model Input	
A.1. Available Data Sources	
A.1.a	1.b, 1.d, 2.a, 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.b, 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

Appendix B: Table 1 Best Practices Mapped to Information Element	
Information Element	Selected Best Practices Mapped to Information Element
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	2.a, 3.b

Appendix B: Table 1	
Best Practices Mapped to Information Element	
Information Element	Selected Best Practices Mapped to Information Element
B.5.c	2.a, 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	2.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.a, 2.c, 3.b, 3.c
C.6. Supporting Data	
C.6.a	2.b, 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

Appendix B: Table 1 Best Practices Mapped to Information Element	
Information Element	Selected Best Practices Mapped to Information Element
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, 4.b, 4.c
C.9.b	4.a, 4.b, 4.c
C.9.c	4.a, 4.b, 4.c

Appendix B: Table 2 Information Element Mapped to Best Practices			
Best Practice		Best Practice Code	Information Element (for GLMs)
1. Ensure that the factors developed based on the model 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.	1.a	C.3.a, C.3.b, C.7.a, C.7.b, C.7.c, C.7.d, C.7.e, C.7.d
	b. Determine whether individual input characteristics to a predictive model and their resulting rating factors are related to the expected loss or expense differences in risk.	1.b	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
	c. Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.	1.c	C.3.a, C.3.b, C.7.a, C.7.b, C.7.c, C.7.d, C.7.e, C.7.g
	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.	1.d	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
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.	2.a	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
	b. Determine whether the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values, and outliers are handled.	2.b	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
	c. Determine whether 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

Appendix B: Table 2 Information Element Mapped to Best Practices			
Best Practice		Best Practice Code	Information Element (for GLMs)
	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 of 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 the 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 and/or regulations, particularly prohibitions on unfair discrimination.	4.a	C.9.a, C.9.b, C.9.c
	b. Protect the confidentiality of filed predictive models and supporting information in accordance with state laws and/or regulations.	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	A.2.b, A.2.c, A.2.d, 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 datasets 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; e.g., 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.²¹

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 the states and across time do not influence the rating factors used in the final rating algorithm.²²

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 five 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 and B2 is the same as between B2 and B1). In other words, a correlation matrix is also a symmetric matrix.²³

	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.²⁴

²¹ Goldburd, M., et al., 2016. “Generalized Linear Models for Insurance Rating,” CAS Monograph Series, Number 5, Second Edition. Accessed online at <https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf>.

²² Closter, D., and Carmean, C., 2019. “Predictive Models: A Practical Guide for Practitioners and Regulators,” CAS Ratemaking Committee. Accessed online at www.casact.org/cms/pdf/Practical_Guide_for_Evaluating_Predictive_Models_Closter_Carmean.pdf.

²³ <https://www.statisticshowto.datasciencecentral.com/correlation-matrix>.

²⁴ Davey Smith, G., and 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 Mining – Data mining is a process used to extract usable data from a larger set of any raw data. It implies analyzing data patterns in large batches of data using one or more software programs. As an application of data mining, businesses can learn more about their customers and develop strategies related to various business functions. One application of data mining for insurance companies is analyzing large datasets to charge different groups of insureds different amounts of premium corresponding to their level of risk. Data mining involves substantial data collection and warehousing, as well as computer processing. For segmenting the data and evaluating the probability of future events, data mining uses sophisticated mathematical algorithms.²⁵

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.”²⁶ For example, “one driver” and “more than one driver” may be levels within a “number of drivers” rating variable.

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.²⁷

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.²⁸

Fair Credit Reporting Act – The federal 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 consumers’ credit reports. To that end, the FCRA regulates the collection, dissemination, and use of consumer information, including consumer credit information.²⁹ Together with the federal Fair Debt Collection Practices Act (FDCPA), the FCRA forms the foundation of consumer rights law in the U.S. Originally enacted in 1970, the FCRA is enforced by the Federal Trade Commission, the Consumer Financial Protection Bureau, and private litigants.

²⁵ <https://economictimes.indiatimes.com/definition/data-mining>.

²⁶ <https://www.casact.org/pubs/dpp/dpp04/04dpp1.pdf>.

²⁷ Trevet, D., 2013. “Exploring Model Lift: Is Your Model Worth Implementing?,” *Actuarial Review*, Volume 40, Number 2, May. Accessed online at <https://www.casact.org/newsletter/index.cfm?fa=viewart&id=6540>.

²⁸ Goldburd, M., et al., 2016. “Generalized Linear Models for Insurance Rating,” CAS Monograph Series, Number 5, Second Edition. Accessed online at www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

²⁹ Dlabay, L.R., Burrow, J.L., and Brad, B., 2009. *Intro to Business*. Mason, Ohio: South-Western Cengage Learning, p. 471, ISBN 978-0-538-44561-0.

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 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 $x_1 \dots x_p$, 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.³⁰

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 U.S. Census Bureau 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.³¹

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

³⁰ Goldburd, M., et al., 2016. “Generalized Linear Models for Insurance Rating,” CAS Monograph Series, Number 5, Second Edition. Accessed online at www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

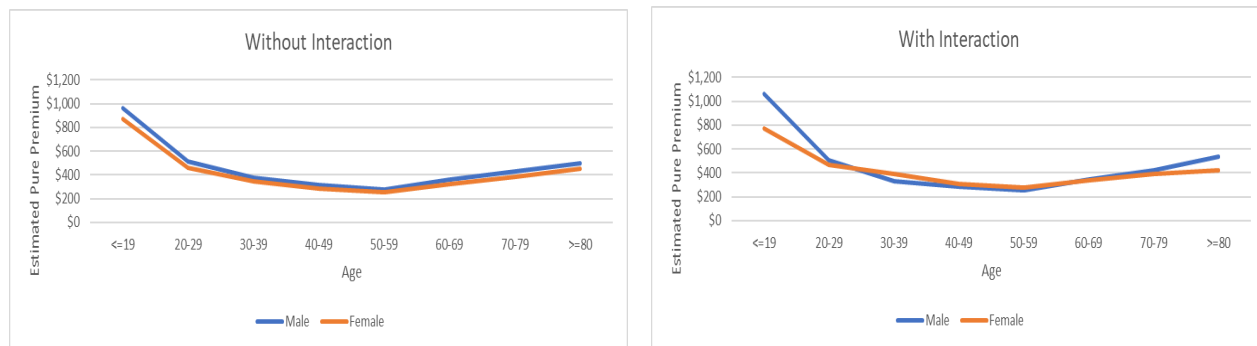
³¹ <https://en.wikipedia.org/wiki/Granularity>.

Home Insurance – Home insurance may cover, depending on the specific product, damage to the property, contents, and outstanding structures of a residential dwelling, 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.³² Common examples of home insurance policy forms are homeowners insurance (HO3 or HO5), renter’s insurance (HO4), and condominium insurance (HO6).

Insurance Data – Data collected by the insurance company directly from the consumer or through direct interactions with the consumer (e.g., claims). This is often referred to as “internal data.” 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 $\eta = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_1X_2$.³³

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.



Lift Chart – See definition of “quantile plot.”

Linear Predictor – A linear predictor is the linear combination of explanatory variables (X_1, X_2, \dots, X_k) in the model; e.g., $\beta_0 + \beta_1X_1 + \beta_2X_2$.³⁴

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.³⁵

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 any data not defined as “insurance data.” Non-insurance data includes data provided by another party other than the insurance company and is often referred to as “external data.” 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.

³² Werner, G., and Modlin, C., 2016. “Basic Ratemaking, Fifth Edition,” CAS. Accessed online at www.casact.org/library/studynotes/Werner_Modlin_Ratemaking.pdf.

³³ To see that this second definition accounts for the interaction, note that it is equivalent to $\eta = \beta_0 + \beta_1'X_1 + \beta_2'X_2$ and to $\eta = \beta_0 + \beta_1X_1 + \beta_2'X_2$, with $\beta_1' = \beta_1 + \beta_3X_2$ and $\beta_2' = \beta_2 + \beta_3X_1$. Since β_1' is a function of X_2 and β_2' is a function of X_1 , these two equivalences say that the effect of X_1 depends on the level of X_2 and vice versa.

³⁴ Goldburd, M., et al., 2016. “Generalized Linear Models for Insurance Rating,” CAS Monograph Series, Number 5, Second Edition. Accessed online at www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf.

³⁵ <https://online.stat.psu.edu/stat504/node/216>.

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.³⁶

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.³⁷

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 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.³⁸

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.

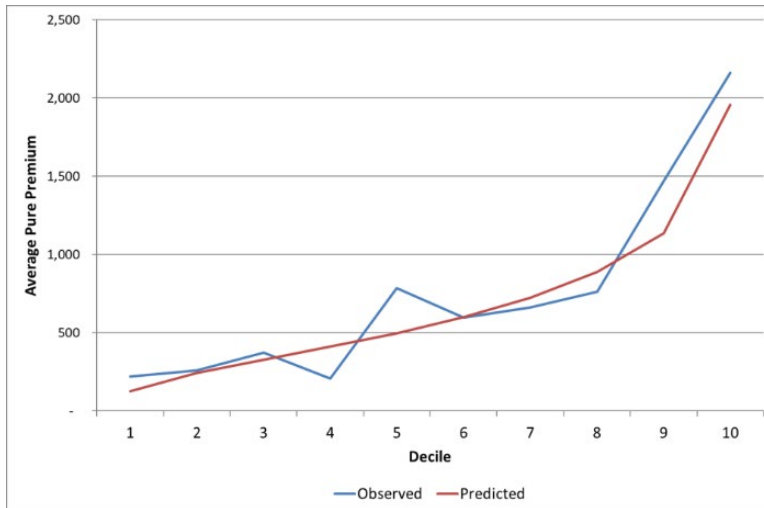
Proxy Variable – A proxy variable is any variable that indirectly captures the characteristics of another variable, regardless of whether that other variable is used in the insurer’s rating plan.

³⁶ Closter, D., and Carmean, C., 2019. “Predictive Models: A Practical Guide for Practitioners and Regulators,” CAS Ratemaking Committee. Accessed online at www.casact.org/cms/pdf/Practical_Guide_for_Evaluating_Predictive_Models_Closter_Carmean.pdf.

³⁷ <https://en.wikipedia.org/wiki/Overfitting>.

³⁸ https://content.naic.org/cipr_topics/topic_auto_insurance.htm.

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 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: 1) how well the model predicts actual values by quantile; and 2) the lift of the model (i.e., 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.³⁹ 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; e.g., 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 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).
- The existence of maximum and minimum premiums (or, in some cases, the maximum discount or surcharge that can be applied).
- Specifics associated with any rounding that takes place.

If the insurance product contains multiple coverages, then separate rating plans by coverage may apply.⁴⁰

Rating System – The rating system is the insurance company’s information technology (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.

³⁹ Goldburd, M., et al., 2016. “Generalized Linear Models for Insurance Rating,” CAS Monograph Series, Number 5, Second Edition. Accessed online at <https://www.casact.org/pubs/monographs/papers/05-Goldburd-Khare-Tevet.pdf>.

⁴⁰ Werner, G., and Modlin, C., 2016. “Basic Ratemaking, Fifth Edition,” CAS. Accessed online at https://www.casact.org/library/studynotes/Werner_Modlin_Ratemaking.pdf.

Rating Variable – A rating variable is a risk criterion of the insured used to modify the base rate in a rating algorithm.⁴¹

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 datasets analyzed by the insurer.

Raw Data – Data originating straight from the insurer’s data banks without modification (e.g., not scrubbed or 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.

⁴¹ Ibid.

APPENDIX D – SAMPLE RATE-DISRUPTION TEMPLATE

State Division of Insurance - EXAMPLE for Rate Disruption

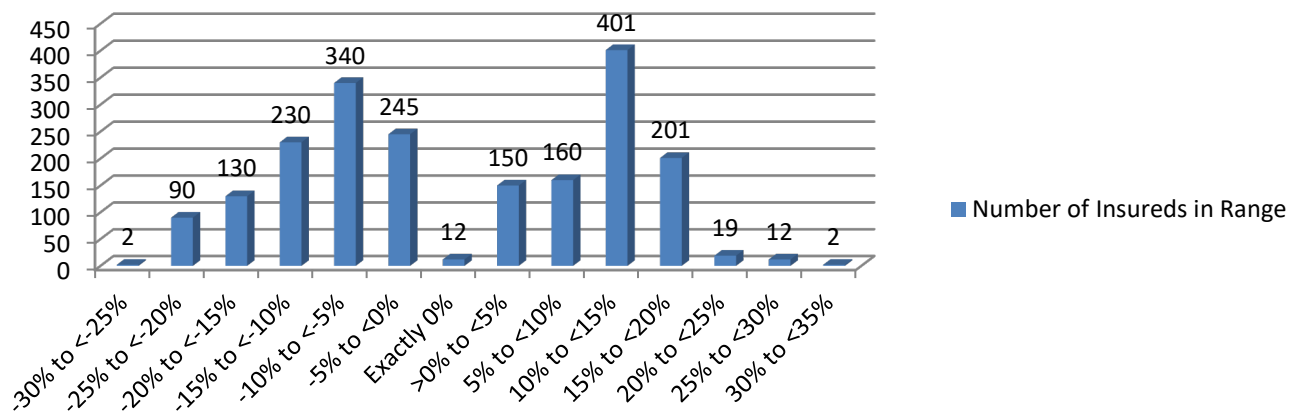
Template Updated October 2018

- 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.

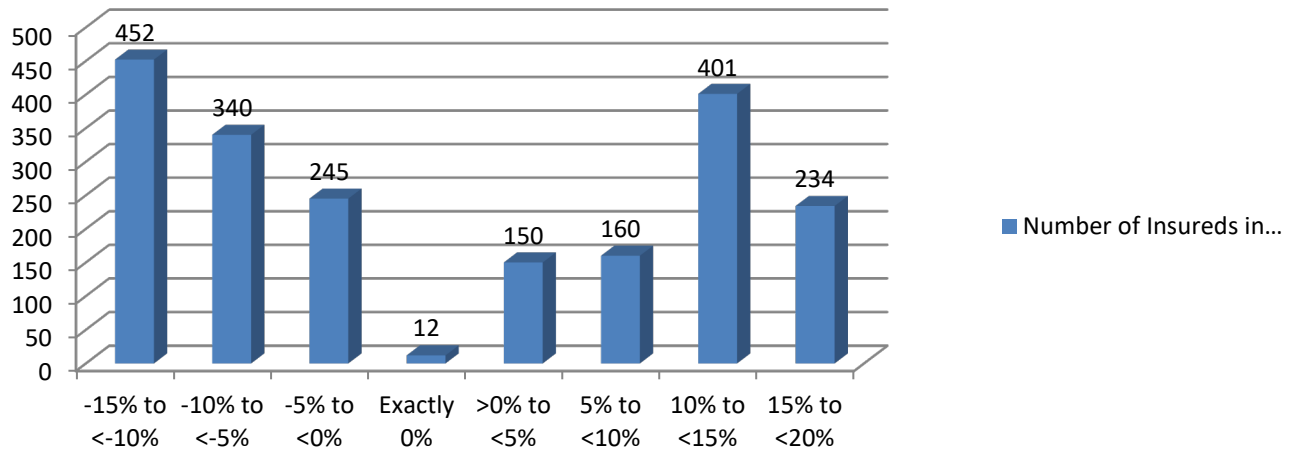
NOTE: Values of Minimum % Change, Maximum % Change, and Total Number of Insureds must reconcile to the Rate/Rule Schedule in SERFF.

	<u>Uncapped</u>		<u>Capped (If Applicable)</u>
Minimum % Change	-30.000%	Minimum % Change	-15.000%
Maximum % Change	30.000%	Maximum % Change	15.000%
Total Number of Insureds (Auto-Calculated)	1994	Total Number of Insureds (Auto-Calculated)	1994
	<u>Uncapped Rate Disruption</u>		<u>Capped Rate Disruption (If Applicable)</u>
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



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.						
<u>Largest Percentage Increase</u>		<u>Corresponding Dollar Increase (for Insured Receiving Largest Percentage Increase)</u>				
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)						
<ul style="list-style-type: none"> • 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	<input type="checkbox"/> 12-Month Policies <input checked="" type="checkbox"/> 6-Month Policies <input type="checkbox"/> 3-Month Policies <input type="checkbox"/> Other (SPECIFY)			
Vehicle Symbol (2003 Honda Accord)	1.46%	\$10.29				
Effect of Capping	-11.54%	-\$82.50				
TOTAL	15.00%	\$82.50				

Appendix B: Casualty Actuarial and Statistical (C) Task White Paper and Appendices

State Division of Insurance - EXAMPLE for Largest Dollar Increase				<i>Template Updated October 2018</i>			
• Fill in fields highlighted in light green.							
<u>Largest Dollar Increase</u>		<u>Corresponding Percentage Increase (for Insured Receiving Largest Dollar Increase)</u>					
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					

APPENDIX B-RGLM – INFORMATION ELEMENTS AND GUIDANCE FOR A REGULATOR TO MEET BEST PRACTICES’ OBJECTIVES (WHEN REVIEWING REGULARIZED GENERALIZED LINEAR MODELS)

This appendix identifies the information that a state insurance regulator may need to review a regularized generalized linear model (GLM) used by an insurer to support a personal automobile or home insurance rating plan. Regularized GLMs include lasso, derivative lasso, lasso credibility, ridge, elastic net, and accurate generalized linear models (AGLMs). Other modeling approaches may fall within the category of regularized GLMs. The main distinguishing feature of regularized GLMs is that they have complexity penalty hyper parameters (also known as shrinkage factors), which put constraints on the model such that the coefficients are tempered from what they would be in a standard (unpenalized) GLM. Generally, if the complexity penalties in a regularized GLM are set to zero, the model indications will be identical to those achieved from a standard GLM. The list of information elements below 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 help ensure the business continuity and transparency of the 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 documented and shared with regulators in a timely and appropriate manner. Information technology (IT) controls should be in place, such as a record of versions, change control, and access to the model.¹

Many information elements listed below are probably confidential, proprietary, or trade secret and should be treated as such, in accordance with state laws and/or regulations. Regulators should be aware of their state laws and/or regulations 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.²

Although 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, which 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 Level 1 and Level 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 by a particular state, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws and/or regulations.

¹ Bourdeau, M. (2016). Model risk management: An overview. *The Modeling Platform*, (4).

<https://www.soa.org/globalassets/assets/library/newsletters/the-modeling-platform/2016/december/mp-2016-iss4.pdf>.

² There are some models that are made public by the vendor and would not result in a hindrance of the model’s protection.

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 Level 1, Level 2, and Level 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 by 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, and/or unfairly discriminatory.

Appendix B-RGLM is focused on regularized GLMs, including lasso, derivative lasso, lasso credibility, ridge, elastic net, and AGLMs. This appendix should not be referenced in the review of other model types. Appendix B-RGLM is intended to provide state guidance for the review of rate filings based on regularized GLMs.

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, ensuring that only necessary sources for filed input characteristics are included in the filed model.	1	<p>Request details of data sources, whether internal to the company or from external sources. For insurance experience (policy or claim), determine whether data is aggregated by calendar, accident, fiscal, or policy year and when it was last evaluated. For each data source, get a list of 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.</p> <p>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 federal Fair Credit Reporting Act (FCRA). 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.</p> <p>Note: 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.</p>
A.1.b	Reconcile aggregated insurance data underlying the model with available external insurance reports.	4	<p>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 (i.e., 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 conduct a reasonability check to ensure that the data aligns with other audited sources.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	Many models are developed using a countrywide or a regional dataset. 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 explain why any states were excluded from the countrywide data. 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. However, 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. The company should provide a demonstration that the model fits well on the specific state or surrounding region.
2. Sub-Models			
A.2.a	Consider the relevance of (i.e., whether there is bias) of overlapping data or variables used in the model and sub-models.	1	Check if the same variables/datasets were used in the model, a sub-model, or as stand-alone rating characteristics. If so, verify the insurance company has processes and procedures in place to assess and address double-counting or redundancy.
A.2.b	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	1	<p>If the sub-model was previously approved/accepted, that may reduce the extent of the sub-model's review. If approved, obtain the tracking number(s) (e.g., state, System for Electronic Rates & Forms Filing [SERFF]), and verify when and if it was the same model currently under review.</p> <p>Note: A previous approval does not necessarily confer a guarantee of ongoing approval (e.g., when statutes and/or 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 the prior decision needs to be revisited. In some circumstances, direct dialogue with the vendor could be quicker and more useful.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.2.c	Determine if the sub-model output was used as input to the regularized GLM; obtain the vendor name, as well as the name and version of the sub-model.	1	<p>To accelerate the review of the filing, it may be desirable to request (from the company), the name and contact information for a vendor representative. 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.</p> <p>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. Sub-model SMEs may need to be brought into the conversation with regulators (whether in-house or third-party sub-models are used).</p>
A.2.d	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	<p>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.</p> <p>For example, it is important to know hurricane model settings for storm surge, demand surge, and long-term/short-term views.</p>
A.2.e	Obtain an explanation of how catastrophe models are integrated into the model to ensure no double-counting.	1	<p>If a weather-based sub-model is input to the regularized 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.</p> <p>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 or inclusion of freeze losses when using a winter storm model.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
3. Adjustments to Data			
A.3.a	Determine if premium, exposure, loss, or expense data was adjusted (e.g., on-leveled, developed, trended, adjusted for catastrophe experience, or capped). If so, how? Do the adjustments vary for different segments of the data? If so, identify the segments and how the data was adjusted.	2	<p>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 of how they were handled. These treatments need to be identified, and the company/regulator needs to determine whether model data needs to be adjusted.</p> <p>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?</p> <p>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.</p> <p>Premium should be brought to current rate level if the target variable is calculated with a premium metric, such as loss ratio. Premium can be brought to current rate level with the extension of exposures method or the parallelogram method. Note that the premium must be on-leveled at a granular variable level for each variable included in the new model if the parallelogram method is used. Statewide on-level factors by coverage are typically sufficient for statewide rate indication development but not sufficient for models that determine rates by variable level.</p>
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	<p>Pre-modeling binning may be unnecessary for ordinal variables in a lasso derivative or lasso credibility model, as the model will automatically set bins. Other regularized GLM approaches often group some variable levels with a base level during model fitting. However, if the insurer does bin variables or group levels before modeling, the reason should be understood.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.3.c	Ask for aggregated data (one dataset of pre-adjusted/scrubbed data and one dataset 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	<p>This is most relevant for variables that have been “scrubbed” or adjusted.</p> <p>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.</p> <p>It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category are provided. This data can be displayed in either graphical or tabular formats.</p>
A.3.d	Determine how missing data was handled.	1	<p>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.</p> <p>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 recoding 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 are provided. This data can be displayed in either graphical or tabular formats.</p>
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	<p>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 types of outliers and determine what adjustments were made to each type of outlier. To understand the filer’s response, the regulator should ask for the filer’s materiality standard.</p>
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	<p>This should explain how data from separate sources was merged and/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.</p>
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	<p>An example is when by-peril or by-coverage modeling is performed; the documentation should be for each peril/coverage and make rational sense.</p> <p>For example, if “murder” or “theft” data is used to predict the wind peril, the company should provide support and a rational explanation for their use.</p>
A.4.c	Identify material findings the company had during its data review, and obtain an explanation of any	1	<p>“None” or “N/A” may be an appropriate response.</p>

Section	Information Element	Level of Importance to the Regulator’s Review	Comments
	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 of how modeling analysis was adjusted and/or results were impacted.		

B. BUILDING THE MODEL

Section	Information Element	Level of Importance to the 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., lasso regression, ridge regression, elastic net regression, 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. Understand why a regularized GLM is preferable to a standard GLM for the specific modeling exercise.	1	<p>A main drawback of GLMs is assigning full credibility to the data, and a main benefit of penalized regression is the assignment of partial credibility to the data. The ability of regularized GLMs to help avoid overfitting through the assignment of partial credibility is expected to be a core reason for their adoption.</p> <p>It is important to understand if the model in question is a regularized 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/by-coverage. When a company is using a regularized GLM, it is helpful to understand why a penalized model is preferable to a standard GLM (without penalties for model complexity).</p> <p>Note: If the model is not a regularized GLM, the information elements in this white paper may not apply in their entirety.</p>
B.1.b	Identify the credibility complement used (if applicable). Lasso credibility is an example of a regularized GLM that contains a credibility complement. Discuss why the selected complement is reasonable.	1	<p>Many regularized GLMs are analogous in concept to a credibility weighted approach. Predictor variable values with low data volume will often result in coefficients that are closer to the credibility complement. For many regularized linear models, the implied credibility complement for each parameter is 0. However, in lasso credibility, an alternate complement of credibility can be set. The alternate complement of credibility might be based on something like the currently approved rating factors. The regulator should determine if the complement of credibility is reasonable for use since it is not driven by the latest data.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.1.c	Identify the software used for model development. Obtain the name of the software vendor/developer, software product, and a software version reference used in model development.	3	<p>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 (e.g., a filing specialist) who can place the regulator in direct contact with the appropriate SME at the vendor.</p> <p>Open-source software/programs used in model development should be identified by name and version the same as if from a vendor.</p>
B.1.d	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 components during model building). Determine if the validation data was accessed before model training was completed; if so, obtain an explanation of why that came to occur. Obtain a discussion of whether the model was rebuilt using all the data or if it was only based on the training data.	1	<p>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.</p> <p>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. However, according to the Casualty Actuarial Society (CAS) monograph, <i>Generalized Linear Models for Insurance Rating</i>: “Once a final model is chosen, ... we would then go back and rebuild it using all of the data, so that the parameter estimates would be at their most credible.”</p> <p>The reviewer should note whether a company employed cross-validation techniques instead of a training/test/validation dataset approach. If cross-validation techniques were used, the reviewer should request a description of how cross-validation was done and confirm that the final model was not built on any particular subset of the data but rather the full dataset.</p>
B.1.e	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.f	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.g	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.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.1.h	Obtain a description of the variable selection process.	1	<p>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 considered when making the decisions regarding variable selection.</p> <p>The modeler should comment on the use of automated feature selection algorithms to choose predictor variables and explain how potential overfitting that can arise from these techniques was addressed.</p> <p>Certain variables may not end up used in the final model as some regularized GLM models (lasso, elastic net, etc.) will remove less significant variables.</p>
B.1.i	In conjunction with variable selection, obtain a narrative on how the company determined the granularity of the rating variables during model development.	3	<p>The narrative should include discussion of how credibility was considered in the process of determining the level of granularity of the variables selected. In derivative lasso, AGLM, and similar techniques, the granularity of ordinal variables should avoid “pre-binning,” which removes the algorithm’s ability to define a breakpoint where there should be one. The bin width should consider the amount of exposures in each bin in order to obtain credible bins. The number of bins may need to be constrained since an extremely large number of bins may be too computationally intensive.</p>
B.1.j	Determine if model input data was segmented in any way (e.g., by-coverage, by-peril, or by-form basis). If so, obtain a description of data segmentation and the reasons for data segmentation.	1	<p>The regulator would use this to follow the logic of the modeling process.</p>
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	<p>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 of how these adjustments were done, including any statistical improvement measures relied upon.</p>
B.2.c	Obtain a description of the testing that was performed during the model-building process, including an explanation of the decision-making	3	<p>There should be a description of the testing that was performed during the model-building process. Examples of tests that may have been performed</p>

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	process to determine which interactions were included and which were not.		<p>include univariate testing and review of a correlation matrix.</p> <p>The number of interaction terms that could potentially be included in a model increases far more quickly than the number of “main effect” variables (i.e., the basic predictor variables that can be interacted together). Analyzing each possible interaction term individually can be unwieldy. It is typical for interaction terms to be excluded from the model by default and only included where they can be shown to be particularly important. So, as a rule of thumb, the regulator’s emphasis should be on understanding why the insurer included the interaction terms it did, rather than on why other candidate interactions were excluded.</p> <p>In some cases, however, it could be reasonable to inquire about why a particular interaction term was excluded from a model (e.g., if that interaction term was ubiquitous in similar filings and was known to be highly predictive, or if the regulator had reason to believe that the interaction term would help differentiate dissimilar risks within an excessively heterogeneous rating segment).</p>
B.2.d	For the regularized GLM, identify the link function used. Identify which distribution was used for the model (e.g., Poisson, Gaussian, log-normal, Tweedie). Obtain an explanation of why the link function and distribution were chosen. Certain distribution assumptions will involve numerical parameters. For example, a Tweedie assumed distribution will have a p power value. Obtain the specific numerical parameters associated with the distribution. If changed from the default, obtain a discussion of applicable convergence criterion.	1	Solving the regularized GLM is iterative, and the modeler can check to see if fit is improving. At some point, convergence occurs. However, when it occurs can be subjective or based on threshold criteria. If the software’s default convergence criteria were not relied upon, an explanation of any deviation should be provided. If the regularized GLM did not reach convergence, an explanation should be provided.
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 weights were used, obtain an explanation of how and why they were used.	3	Investigate whether identical records were combined to build the model.
B.2.g	Obtain the value of any additional relevant model hyperparameter(s) other than the complexity parameter. Obtain an explanation on how they were chosen.	2	The complexity hyperparameter(s) are discussed in Information Element B.2.h. Some regularized GLMs will have additional hyperparameters needed to fit the model. For example, certain smoothed terms in a generalized additive model (GAM) may require

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			selecting a number of knots.
B.2.h	Obtain the value of the applicable model complexity hyperparameter(s) and an explanation on how it was chosen.	4	Regularized GLMs have model complexity hyperparameters, which can materially impact the final model parameters. The value of the model complexity hyperparameter determines whether the model is close to a standard GLM or is significantly tempered. For most regularized GLMs, tuning the hyperparameter to maximize GINI on test data or minimize deviance on test data would be appropriate methods. For the derivative lasso method, it may be useful to review the plots of coefficients to determine if there is enough grouping of variable levels to remove reversals between adjacent variable levels. The exact value of the penalty parameter holds no meaning without context. The reviewer should focus less on the value selected but instead confirm that the process of selecting a value is sound.
B.2.i	Understand how the model would differ if different hyperparameter(s) were selected. Obtain a sensitivity analysis showing the coefficient output with higher and lower complexity hyperparameters or a plot showing coefficients by penalty value.	4	If the process for selecting a complexity hyperparameter(s) is sound, it is generally unnecessary to provide documentation on model results using alternative complexity hyperparameters. However, the regulator may want to scrutinize the hyperparameter more if the process for selecting a value does not seem sound. A regulator may decide they need more assurance that a reasonable value of complexity hyperparameter was selected. The regulator could ask for a sensitivity analysis showing how output model coefficients would differ if other hyperparameter values are used.
3. Predictor Variables			
B.3.a	Obtain a complete data dictionary, including the names, data 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	Data types of variables might be continuous, discrete, ordinal, 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 a 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

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			variables and selected the one with the greatest reduction in mean square error on test data, this would be a far weaker case for statistical significance than if that variable was the only one that 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 regularized 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 (usually linearly uncorrelated) transformed variables. In each instance, obtain a list of the pre-transformation and post-transformation variable names, as well as an explanation of how the results of the dimensionality reduction technique were 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-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 multistate 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. Note: It may be useful to consider geographic stability measures for territories within the state.

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B.4.b	For all variables, review the appropriate parameter values and relevant demonstrations of stability. Relevant demonstrations of stability may be provided as either plots by variable of indicated factors, which also show upper bound and lower bound values (95 th percentile and 5 th percentile) on bootstrapped datasets, coefficient ranges across dataset folds, or p-values from a comparable standard GLM.	3	<p>Statistical confidence intervals and p-values are often not available for regularized GLMs. However, there are other ways to demonstrate model stability. The regulator should not prescribe one of these methods specifically, as they may be not applicable for some forms of regularized GLMs.</p> <p>The model could be run 100+ times on bootstrapped datasets to determine the stability of model parameters. If the bootstrapped models produce a narrow range of coefficient values, this implies the model is stable. Extra scrutiny should apply if the range of coefficient values includes negative and positive values. If the bootstrapped models produce a wide range of coefficient values, this implies the model is less stable. The range could be represented visually for each predictor variable by showing a plot with predictor variable values on the X-axis and three separate lines representing mean indicated factors, the 95th percentile factors, and the 5th percentile factors. If the model was built with k-fold cross validation, the range of coefficients could be reviewed in a similar fashion.</p> <p>Narrower ranges represent a more stable model. The results may be less meaningful if more than 20 folds were used since each model run would be based on significantly similar datasets. Coefficient ranges could also be reviewed by year or by other dataset segments to assess model stability. Variable stability can also be approximated by looking at the p-values from a comparable standard GLM, which contains the same predictor variables as the regularized GLM in question.</p>

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B.4.c	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	<p>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 a regularized GLM.</p> <p>The regulator should not assume to know what the company did and ask, "How?" Instead, the regulator should ask what the company did and be prepared to ask follow-up questions.</p> <p>For a regularized GLM, such evidence may be available using observed versus predicted average plots by variable and overall model lift charts.</p> <p>The regulator should ask the company to provide exhibits or plots that show how the fitted average makes sense when compared to the observed average for variables of interest. Regulators would ideally review this comparison for every variable, but time constraints may limit the focus to just variables of interest. Variables of interest should include variables with high potential impacts on consumers (steep discounts or surcharges), variables without an intuitive relationship to loss, or variables that may be proxies for a protected class attribute. It is expected that the fit relativity will be different from the observed relativity for regularized GLMs as the fit relativity will be penalized towards the prior assumption or null relativity. These differences can be evaluated through the lens of credibility; items with lower exposure are expected to differ more than levels with high exposure. Low credibility datasets may see less alignment between these values in general. This credibility view is most easily applied to ordinal and categorical variables and less easily applied to continuous variables as continuous variables may extrapolate to areas with low credibility.</p> <p>Lift charts such as quantile plots demonstrate the overall model fit. The risks in the modeling data are bucketed into quantiles with equal volume representing different levels of predicted risk. Quantile plots graph the predicted averages versus the observed averages by quantile. The quantile plots should have at least 10 quantiles to demonstrate predictive accuracy across different risk levels. Decile plots may look less stable for small books of business. In these cases, it may be helpful to obtain additional lift charts with less than 10 quantiles.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.d	Obtain a description of how the model was tested for stability over time.	2	<p>Evaluate the build/test/validation datasets for potential time-sensitive model distortions. For example, a winter storm in year 3 of 5 can distort the model in both the testing and validation datasets.</p> <p>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.</p> <p>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 exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model?</p> <p>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.</p>
B.4.e	Obtain a narrative on how potential concerns with overfitting were addressed.	2	
B.4.f	Obtain support demonstrating that the overall regularized GLM assumptions are appropriate.	3	<p>A visual review of plots of actual errors is usually sufficient.</p> <p>The reviewer should look for a conceptual narrative covering these topics: How does this particular regularized 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.</p> <p>If the reviewer determines that the model makes no assumptions that are considered to be unreasonable, the importance of this item may be reduced.</p>
B.4.g	Obtain five to ten sample records with corresponding output from the model for those records.	4	
5. "Old Model" Versus "New Model"			
B.5.a	Obtain an explanation of why this model is an improvement to the current rating plan. If it replaces a previous model, find out why it is	2	The regulator should expect to see improvement in the new class plan's predictive ability or other sufficient reason for the change.

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	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.		
B.5.b	Determine if two Lorenz curves or Gini coefficients were compared, and obtain a narrative on the conclusion drawn from this comparison.	3	<p>This information element requests a comparison of the Lorenz curve and 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.</p> <p>This is relevant when one model is being updated or replaced. The regulator should expect to see improvement in the new class plan's predictive ability. One example of a comparison might be sufficient.</p> <p>Note: This comparison is not applicable to initial model introduction. The reviewer can look to the CAS monograph <i>Generalized Linear Models for Insurance Rating</i>.</p>
B.5.c	Determine if double-lift charts were analyzed, and obtain a narrative on the conclusion drawn from this analysis.	3	<p>One example of a comparison might be sufficient.</p> <p>Note: "Not applicable" is an acceptable response.</p>
B.5.d	<p>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 of why these variables were dropped from the new model.</p> <p>Obtain a list of all new predictor variables in the new model that were not in the prior old model.</p>	2	<p>It is useful to differentiate between old and new variables so that the regulator can prioritize more time on variables not yet reviewed.</p>
B.5.e	If using a credibility complement, obtain variable plots that visualize the credibility complement and the model indicated as separate lines. Lasso credibility is an example of a regularized GLM that contains a credibility complement.	2	<p>It is useful to see the coefficients as originally specified in the credibility complement, and how the model indicates these initially set coefficients should change based on the modeling data. These changes can be visualized as relativity plots that show complement relativity (initially set coefficients), indicated relativity (complement of credibility combined with modeled relativity), target relativity, and data volume (shown on a secondary axis). The combination of these four elements makes relativity plots a helpful tool for review of regularized GLMs, which have a credibility complement. The regulator should determine if the change from complement relativity to indicated relativity appears directionally appropriate based on the model target relativities and if the magnitude of the change appears reasonable.</p>

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6. Modeler Software			
B.6.a	Request access to SMEs (e.g., modelers) who led the project, compiled the data, and/or built the model.	4	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 the 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 (i.e., how it was used) in the rating system.	1	<p>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.</p> <p>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.)</p>
C.1.b	Obtain an explanation of how the model was used to adjust the filed rating algorithm.	1	<p>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.</p> <p>The regulator should consider asking for an explanation of how the model was used to adjust the rating algorithm.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	<p>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.</p> <p>Note: This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.</p>
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 relativities filed in the rating plan.	1	<p>The documentation should include explanations for the necessity of any such adjustments and 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.</p> <p>Note: 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.</p>
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 regarding how each characteristic/variable was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	<p>Modeling loss ratios with these characteristics/variables as control variables would account for possible overlap. The insurer should address this possibility or other considerations. For example, tier placement models often use risk characteristics/variables that are also used elsewhere in the rating plan.</p> <p>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.</p>
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	The regulator should determine at what level of granularity credibility is applied. If modeling was by-coverage, by-form, or by-peril, the company should explain how these were handled when there was not enough credible data by coverage, form, or peril to model.

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C.4.b	If the rating plan is less granular than the model, obtain an explanation of why.	2	This is applicable if the company 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 of why.	2	A more granular rating plan may imply that the company had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications. It may be necessary to extrapolate due to data availability or other considerations.
5. Definitions of Rating Variables			
C.5.a	Obtain a narrative regarding 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 of 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. This data should include 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 of 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.

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C.6.b	Obtain an explanation of any material (especially directional) differences between model indications and state-specific univariate indications.	4	<p>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.</p> <p>Credibility of state-level data should be considered when state indications differ from modeled results based on a broader dataset. However, the relevance of the broader dataset to the risks being priced should also be considered. Borderline reversals are not a major concern. If multivariate indications perform well against the state-level data, this should suffice. However, credibility considerations need to be taken into account as state-level segmentation comparisons may not have enough credibility.</p>
7. Consumer Impacts			
C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in renewal premium, both as increases and decreases, as well as the top five rating variables with the largest spread of impact for both new and renewal business.	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 company 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 renewal business, 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	<p>This analysis is typically done at the state level. 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.</p> <p>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</p>

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			there is concern about particular variables having extreme or disproportionate impacts, or significant impacts that have otherwise yet to be substantiated. See Appendix D 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	This analysis is typically done at the state level. See Appendix D 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 reflects 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 (Fair Credit Reporting Act [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. The 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: This information may be proprietary. For the rating plan, the rate order of calculation rule may be sufficient. However, it may not be feasible for a regulator to get all the input data necessary to reproduce a model's output. Credit and telematics models are examples of model types where model output would be readily available, but the input data would not be readily available to the regulator.
C.7.h	In the filed rating plan, be aware of any non-insurance data used as input to the model	1	If the data is from a third-party source, the company should provide information on the source. Depending

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	(customer-provided or other). In order to respond to consumer inquiries, it may be necessary to inquire how consumers can verify their data and correct errors.		on the nature of the data, it may need to be documented with an overview of who owns it. The topic of consumer verification may also 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. Although the regulator needs to understand the rate filing before accepting the rate filing, the regulator should not request information that does not increase their understanding of the rate filing. The regulator should review the state's rate filing review process and procedures to ensure that they are fair and efficient.
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 laws and/or regulations.	1	This is a primary duty of state insurance regulators. The regulator should be knowledgeable of 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 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-GAM – INFORMATION ELEMENTS AND GUIDANCE FOR A REGULATOR TO MEET BEST PRACTICES’ OBJECTIVES (WHEN REVIEWING GENERALIZED ADDITIVE MODELS)

This appendix identifies the information a state insurance regulator may need to review a Generalized Additive Model (GAM) used by an insurer to support a personal automobile or home insurance rating plan. GAM models are similar to Generalized Linear Models (GLMs) but feature smoothed terms in addition to traditional parametric terms. 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 help ensure the business continuity and transparency of the 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 documented and shared with regulators in a timely and appropriate manner. Information technology (IT) controls should be in place, such as a record of versions, change control, and access to the model.¹

Many information elements listed below are probably confidential, proprietary, or trade secret and should be treated as such, in accordance with state laws and/or regulations. Regulators should be aware of their state laws and/or regulations 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.²

Although 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 definition of GAM is quite broad and the available information elements will differ depending on the basis functions used in the GAM as well as the method of penalization. This broad definition of a GAM means that a reviewer should be looking for analogous information in the case where certain necessary information elements are not available. For example, p-values will not be produced for some varieties of GAM. If p-values are being evaluated to confirm the significance of variables included in the model, the reviewer may start a dialogue on how variable significance was evaluated in this particular GAM to obtain the information necessary to satisfy this area of review. In this way, a reviewer can use the information elements below to review wide varieties of GAM.

The “Level of Importance to the Regulator’s Review” is a ranking of information a regulator may need to review which 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 Level 1 and Level 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 by a particular state, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws and/or regulations.

¹ Bourdeau, M., 2016. “Model Risk Management: An Overview,” The Modeling Platform, Issue 4, December. Accessed online at <https://www.soa.org/globalassets/assets/library/newsletters/the-modeling-platform/2016/december/mp-2016-iss4.pdf>.

² There are some models that are made public by the vendor and would not result in a hindrance of the model’s protection.

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 Level 1, Level 2, and Level 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 by 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, and/or unfairly discriminatory.

Appendix B-GAM is focused on Generalized Additive Models (GAMs). This appendix should not be referenced in the review of other model types. GAMs have significant differences from GLMs. This Appendix B-GAM is intended to provide state guidance for the review of rate filings based on Generalized Additive Models.

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	<p>Request details of 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 of 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.</p> <p>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 federal Fair Credit Reporting Act (FCRA). 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.</p> <p>Note: 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.</p>
A.1.b	Reconcile aggregated insurance data underlying the model with available external insurance reports.	4	<p>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 (i.e., 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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	Many models are developed using a countrywide or a regional dataset. 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. However, 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 (i.e., whether there is bias) of overlapping data or variables used in the model and sub-models.	1	Check if the same variables/datasets were used in the model, a sub-model, or as stand-alone rating characteristics. If so, verify the insurance company has processes and procedures in place to assess and address double-counting or redundancy.
A.2.b	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	1	<p>If the sub-model was previously approved/accepted, that may reduce the extent of the sub-model's review. If approved, obtain the tracking number(s) (e.g., state, SERFF) and verify when and if it was the same model currently under review.</p> <p>Note: A previous approval does not necessarily confer a guarantee of ongoing approval; e.g., when statutes and/or 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 the prior decision needs to be revisited. In some circumstances, direct dialogue with the vendor could be quicker and more useful.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.2.c	Determine if the sub-model output was used as input to the GAM; obtain the vendor name, as well as the name and version of the sub-model.	1	<p>To accelerate the review of the filing, it may be desirable to request (from the company), the name and contact information for a vendor representative. 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.</p> <p>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. Sub-model SMEs may need to be brought into the conversation with regulators (whether in-house or third-party sub-models are used).</p>
A.2.d	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	<p>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.</p> <p>For example, it is important to know hurricane model settings for storm surge, demand surge, and long-term/short-term views.</p>
A.2.e	Obtain an explanation of how catastrophe models are integrated into the model to ensure no double-counting.	1	<p>If a weather-based sub-model is input to the GAM 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.</p> <p>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 or inclusion of freeze losses when using a winter storm model.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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). If so, how? Do the adjustments vary for different segments of the data? If so, identify the segments and how the data was adjusted.	2	<p>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.</p> <p>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?</p> <p>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.</p>
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 dataset of pre-adjusted/scrubbed data and one dataset of post-adjusted/scrubbed data) that allows the regulator to focus on the univariate distributions and compare raw data to adjusted/binning/transformed/etc. data.	4	<p>This is most relevant for variables that have been "scrubbed" or adjusted.</p> <p>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.</p> <p>It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category are provided. This data can be displayed in either graphical or tabular formats.</p>
A.3.d	Determine how missing data was handled.	1	<p>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.</p> <p>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 recoding 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 are provided. This data can be displayed in either graphical or tabular formats.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 types of outliers and determine what adjustments were made to each type of 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 and/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, the company should provide support and a rational explanation for their use.
A.4.c	Identify material findings the company had during its 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 of how modeling analysis was adjusted and/or results were impacted.	1	"None" or "N/A" may be an appropriate response.

B. BUILDING THE MODEL

Section	Information Element	Level of Importance to the 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., GAM, GLM, decision tree, Bayesian GLM, 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	<p>It is important to understand if the model in question is a GAM 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/by-coverage.</p> <p>Note: If the model is not a GAM, the information elements in this white paper may not apply in their entirety.</p>
B.1.b	Identify the software used for model development. Obtain the name of the software vendor/developer, software product, and a software version reference used in model development.	3	<p>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 (e.g., a filing specialist) who can place the regulator in direct contact with the appropriate SME at the vendor.</p> <p>Open-source software/programs used in model development should be identified by name and version the same as if from a vendor.</p>
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 of why that came to occur. Obtain a discussion of whether the model was rebuilt using all the data or if it was only based on the training data.	1	<p>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.</p> <p>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. However, according to the CAS monograph, "Generalized Linear Models for Insurance Rating": "Once a final model is chosen, ... we would then go back and rebuild it using all of the data, so that the parameter estimates would be at their most credible."</p> <p>The reviewer should note whether a company employed cross-validation techniques instead of a training/test/validation dataset approach. If cross-validation techniques were used, the reviewer should request a description of how cross-validation was done and confirm that the final model was not built on any particular subset of the data, but rather the full dataset.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 on the use of automated feature selection algorithms to choose predictor variables and explain how potential overfitting that can arise from these techniques was addressed.
B.1.h	In conjunction with variable selection, obtain a narrative on how the company determined the granularity of the rating variables during model development.	3	The narrative 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 anyway (e.g., 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 that 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	

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 of 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, including an explanation of the decision-making process to determine which interactions were included and which were not.	3	<p>There should be a description of the 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.</p> <p>The number of interaction terms that could potentially be included in a model increases far more quickly than the number of “main effect” variables (i.e., the basic predictor variables that can be interacted together). Analyzing each possible interaction term individually can be unwieldy. It is typical for interaction terms to be excluded from the model by default, and only included where they can be shown to be particularly important. So, as a rule of thumb, the regulator’s emphasis should be on understanding why the insurer included the interaction terms it did, rather than on why other candidate interactions were excluded.</p> <p>In some cases, however, it could be reasonable to inquire about why a particular interaction term was excluded from a model—for example, if that interaction term was ubiquitous in similar filings and was known to be highly predictive, or if the regulator had reason to believe that the interaction term would help differentiate dissimilar risks within an excessively heterogeneous rating segment.</p>
B.2.d	For the GAM, identify the link function used. Identify which distribution was used for the model (e.g., Poisson, Gaussian, log-normal, Tweedie). Obtain an explanation of why the link function and distribution were chosen. Obtain the formulas for the distribution and link functions, including specific numerical parameters of the distribution. If changed from the default, obtain a discussion of applicable convergence criterion.	1	Solving the GAM is iterative and the modeler can check to see if fit is improving. At some point, convergence occurs; however, when it occurs can be subjective or based on threshold criteria. If the software’s default convergence criteria were not relied upon, an explanation of any deviation should be provided. If the GAM did not reach convergence, an explanation should be provided.
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 describe all parametric (non-smoothed terms represented as coefficients) and smoothed terms necessary to evaluate the predicted pure premium, relativity, or other value, for any real or hypothetical set of inputs.	2	GAMs can have both parametric terms similar to those available in GLMs (e.g., those terms associated with coefficients) and smoothed terms. The smoothed terms are the sum of multiple basis functions which can take on a variety of types. The narrative should describe the relationships captured between the terms in the model (parametric and non-parametric) and the model output.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.2.f	If there were data situations in which GAM 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, data types, variable fit 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	Data types of variables might be continuous, discrete, Boolean, etc. Definitions should not use programming language or code. Variable fit types include parametric (non-smoothed) and smoothed. 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 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 a 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). The variables used as parametric terms and the variables used as inputs to the smooth functions should all be included.	3	While GAMs 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 concurvity metrics for all smoothed predictor variables included in the model and sub-models.	3	GAMs can suffer from high concurvity in addition to high collinearity. Concurvity is the degree to which the smoothed terms move together. The company should indicate what concurvity metrics were used. The regulatory reviewer should understand what metric was used to produce the concurvity metrics but should not prescribe the type of metrics. The review of multiple concurvity metrics may be beneficial.*

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.3.e	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	<p>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.</p> <p>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.</p>
B.3.f	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 (usually linearly uncorrelated) transformed variables. In each instance, obtain a list of the pre-transformation and post-transformation variable names, as well as an explanation of 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-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	<p>For models that are built using multistate 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.</p> <p>Note: It may be useful to consider geographic stability measures for territories within the state.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.b	For all parametric (non-smoothed) variables, review the appropriate parameter values and relevant tests of significance, such as confidence intervals, chi-square tests, p-values, or F tests. Determine if model development data, validation data, test data, or other data was used for these tests.	1	<p>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.</p> <p>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.</p> <p>For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; e.g., confidence intervals around each level of an AOI curve might be more than what is needed.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.c	For all smoothed variables, including interactions between smoothed variables, review plots representing the smooths and relevant tests of significance, such as approximate confidence intervals, chi-square tests, approximate p-values, or F tests. Determine if model development data, validation data, test data, or other data was used for these tests.	1	<p>Smoothed terms in a GAM can have many coefficients based on the number of basis functions. It is difficult to interpret the impact of the smoothed term based on the coefficients. Instead, regulators can review plots representing the cumulative effect of smoothed terms. The company could provide variable value on the x-axis and partial effects on the y-axis. The company could alternatively provide variable value on the x-axis and model prediction for the base risk on the y-axis. A base risk is a specific rating class and is often defined as the risk where each predictor variable is set at the base level (where the indicated factor is 1.000). The company should provide confidence interval lines regardless of the type of plot. The regulatory reviewer should assess whether the plot has an intuitive shape and whether the curve extrapolates well, especially to areas of the curve representing thinner data. The regulatory reviewer should review whether the plot passes the “horizontal line test”. The “horizontal line test” checks whether a horizontal line could be drawn in the plot through the confidence intervals. If so, this implies that the smoothed variable is not measuring significant differences across the target variable.</p> <p>Smoothed interaction terms should also be expressed as plots. Heat map contour plots or 3D perspective plots may be useful.</p> <p>GAMs are a form of penalized regression which complicates the calculation of p-values. The p-values for the smoothed terms output by the modeling software are generally approximate p-values for GAMs. Approximate p-values should be reviewed at the smoothed variable level. The regulatory reviewer may want to select a smaller threshold for smoothed terms than they used for the parametric term p-value threshold. For example, if a regulator typically applies a 0.05 threshold to a GLM, they may want to consider applying a 0.03 threshold to the smoothed terms within a GAM.*</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.d	For all smoothed variables, request details about the basis functions comprising each smoothed function.	4 or 2	<p>Smooth functions are based on a sum of basis functions. The company should provide the number of basis functions for each smooth and discuss how the number was chosen.</p> <p>There are many types of smooth functions that can be applied. Examples include thin plate splines, cubic splines, and cyclic splines. The company should provide the type of each smooth and a narrative on why that type of smooth is appropriate for the variable.</p> <p>If the GAM is built using a basis function significantly different from those available in the MGCV package in R, this information element may have a higher level of significance (2). The goal of requesting details of the basis function would be to help identify any metrics that may be interpreted similarly to the MGCV package's concurvity metrics and gain a better understanding of the GAM building process.</p> <p>In these cases, it is not necessary that a reviewer request the exact mathematical formula for the basis function. Instead, a written or visual example of how the basis function creates a final factor curve for a variable may be requested to aid model review.</p>
B.4.e	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	<p>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; e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>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 values for parametric terms, plots representing smoothed terms, confidence intervals, chi-square tests, p-values, and any other relevant and material tests.*</p>
B.4.f	For overall discrete variables, review type 3 chi-square tests, p-values for parametric terms, approximate p-values for non-parametric terms, 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	<p>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.</p> <p>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</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
			<p>variables, the reviewer may obtain, for each discrete variable level, the parameter values for parametric terms, plots representing smoothed terms, confidence intervals, chi-square tests, p-values, and any other relevant and material tests.</p> <p>For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; e.g., confidence intervals around each level of an AOI curve might be more than what is needed.*</p>
B.4.g	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	<p>For a GAM, such evidence may be available using chi-square tests, approximate p-values, F tests and/or other means.</p> <p>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 a GAM.</p> <p>The regulator should not assume to know what the company did and ask, "How?" Instead, the regulator should ask what the company did and be prepared to ask follow-up questions.</p>
B.4.h	For continuous variables, provide confidence intervals, chi-square tests, p-values for parametric terms, approximate p-values for non-parametric terms, 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	<p>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.</p> <p>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 values for parametric terms, plots representing smoothed terms confidence intervals, chi-square tests, approximate p-values and any other relevant and material tests.</p> <p>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.*</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.i	Obtain a description how the model was tested for stability over time.	2	<p>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).</p> <p>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.</p> <p>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 exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model?</p> <p>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.</p>
B.4.j	Obtain a narrative on how potential concerns with overfitting were addressed.	2	
B.4.k	Obtain the value of the model complexity parameter λ and a discussion of how it was chosen.	4	<p>GAMs are a form of penalized regression. Smaller values of λ allow the model to increase complexity and fit “wigglier” data. Larger values of λ constricts the model and increases smoothness. Multiple automated approaches exist for tuning λ including predictive approaches that optimize AIC or Bayesian approaches such as Restricted Maximum Likelihood.</p>
B.4.l	Obtain support demonstrating that the overall GAM assumptions are appropriate.	3	<p>A visual review of plots of actual errors is usually sufficient.</p> <p>The reviewer should look for a conceptual narrative covering these topics: How does this particular GAM 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.</p> <p>If the reviewer determines that the model makes no assumptions that are considered to be unreasonable, the importance of this item may be reduced.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.m	Obtain support demonstrating that the assumptions for each smoothed term are appropriate.	3	<p>The reviewer should look for a narrative on how the fit of the smoothed terms was checked for reasonableness.</p> <p>It may be useful to ask for each plot of the smoothed terms to include residuals to ensure that the smoothed line runs through the middle of the residuals.</p> <p>It may be useful for the company to provide tests that each smoothed term is not predictive of residual values (similar to tests achieved in the gam.check() function of the mcgv R package). These tests would ideally demonstrate that the residuals are randomly distributed across all parts of the smoothed term.*</p>
B.4.n	Obtain 5-10 sample records with corresponding output from the model for those records.	4	
<p>*Please note that certain statistics such as p-values, confidence intervals, and concavity may not be available or relevant for all varieties of GAM. In these cases, requests should focus on satisfying the purpose of this information element through methodology or metrics supplied by this type of GAM.</p>			
5. “Old Model” Versus “New Model”			
B.5.a	Obtain an explanation of 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, changes in smoothed variable plots, and data used to build this model from the previous model.	2	The regulator 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	<p>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.</p> <p>This is relevant when one model is being updated or replaced. The regulator should expect to see improvement in the new class plan's predictive ability. One example of a comparison might be sufficient.</p> <p>Note: This comparison is not applicable to initial model introduction. Reviewer can look to CAS monograph, “Generalized Linear Models for Insurance Rating.”</p>
B.5.c	Determine if double-lift charts were analyzed and obtain a narrative on the conclusion drawn from this analysis.	3	<p>One example of a comparison might be sufficient.</p> <p>Note: “Not applicable” is an acceptable response.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.5.d	<p>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 of why these variables were dropped from the new model.</p> <p>Obtain a list of all new predictor variables in the new model that were not in the prior old model.</p>	2	It is 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, and/or built the model.	4	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 the 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 (i.e., how it was used) in the rating system.	1	<p>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.</p> <p>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.)</p>
C.1.b	Obtain an explanation of how the model was used to adjust the filed rating algorithm.	1	<p>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.</p> <p>The regulator should consider asking how the smoothed terms of the GAM will be implemented. The regulator should consider asking for an explanation of how the model was used to adjust the rating algorithm.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 productbeing priced.	2	<p>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.</p> <p>Note: This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.</p>
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	<p>"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.</p>
C.3.b	Obtain documentation and support for all calculations, judgments, or adjustments that connect the model's indicated values to the selected relativities filed in the rating plan.	1	<p>The documentation should include explanations for the necessity of any such adjustments and each significantdifference 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.</p> <p>Note: 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.</p>
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 regarding how each characteristic/variable was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	<p>Modeling loss ratios 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 inthe rating plan.</p> <p>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.</p>
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	<p>The regulator should determine at what level of granularity credibility is applied. If modeling was by-coverage, by-form, or by-peril, the company should explain how these were handled when there was not enough credible data by coverage, form, or peril to model.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
C.4.b	If the rating plan is less granular than the model, obtain an explanation of why.	2	This is applicable if the company 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 of why.	2	A more granular rating plan may imply that the company had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications. It may be necessary to extrapolate due to data availability or other considerations.
5. Definitions of Rating Variables			
C.5.a	Obtain a narrative regarding 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 of 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 of whether it is raw or adjusted and, if the latter, obtain a detailed explanation for the adjustments.		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-level data should be considered when state indications differ from modeled results based on a broader dataset. However, the relevance of the broader dataset to the risks being priced should also be considered. Borderline reversals are not of as much concern. If multivariate indications perform well against the state-level data, this should suffice. However, credibility considerations need to be taken into account as state-level segmentation comparisons may not have enough credibility.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
7. Consumer Impacts			
C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in renewal premium, both as increases and decreases, as well as the top five rating variables with the largest spread of impact for both new and renewal business.	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 company 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 renewal business 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 D 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 D for an example of an exposure distribution.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	<p>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.</p> <p>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.</p> <p>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.</p>
C.7.g	Obtain a means to calculate the rate charged a consumer.	3	<p>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. The 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: This information may be proprietary.</p> <p>For the rating plan, the rate order of calculation rule may be sufficient. However, it may not be feasible for a regulator to get all the input data necessary to reproduce a model’s output. Credit and telematics models are examples of model types where model output would be readily available, but the input data would not be readily available to the regulator.</p>
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	<p>If the data is from a third-party source, the company should provide information on the source. Depending on the nature of the data, it may need to be documented with an overview of who owns it.</p> <p>The topic of consumer verification may also need to be addressed, including how consumers can verify their data and correct errors.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	<p>"Speed to market" is an important competitive concept for insurers. Although the regulator needs to understand the rate filing before accepting the rate filing, the regulator should not request information that does not increase his/her understanding of the rate filing.</p> <p>The regulator should review the state's rate filing review process and procedures to ensure that they are fair and efficient.</p>
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 laws and/or regulations.	1	This is a primary duty of state insurance regulators. The regulator should be knowledgeable of 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 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-TREES – INFORMATION ELEMENTS AND GUIDANCE FOR A REGULATOR TO MEET BEST PRACTICES’ OBJECTIVES (WHEN REVIEWING TREE-BASED MODELS)

This appendix identifies the information a state insurance regulator may need to review a Tree-based predictive model used by an insurer to support a personal automobile or home insurance rating plan. Tree-based predictive models include Random Forest (RF) and Gradient Boosting Machines (GBM). The list of information elements below 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 help ensure the business continuity and transparency of the 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 documented and shared with regulators in a timely and appropriate manner. Information technology (IT) controls should be in place, such as a record of versions, change control, and access to the model.¹

Many information elements listed below are probably confidential, proprietary, or trade secret and should be treated as such, in accordance with state laws and/or regulations. Regulators should be aware of their state laws and/or regulations 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.² Although 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, which 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 Level 1 and Level 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 by a particular state, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws and/or regulations.

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 Level 1, Level 2, and Level 3. This most granular level of detail is addressing the

¹ Bourdeau, M., 2016. “Model Risk Management: An Overview,” The Modeling Platform, Issue 4, December. Accessed online at <https://www.soa.org/globalassets/assets/library/newsletters/the-modeling-platform/2016/december/mp-2016-iss4.pdf>

² There are some models that are made public by the vendor and would not result in a hindrance of the model’s protection.

basic building blocks of the model and does not necessarily need to be included by the filer with the initial submission, unless specifically requested by 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, and/or unfairly discriminatory.

Appendix B-TREES is focused on Tree-based models including RFs and GBMs. This appendix should not be referenced in the review of other model types. Tree-based approaches have many significant differences from GLMs. This Appendix B-TREES is intended to provide state guidance for the review of rate filings based on Tree-based models.

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	<p>Request details of data sources, whether internal to the company or from external sources. For insurance experience (policy or claim), determine whether data is aggregated by calendar, accident, fiscal, or policy year and when it was last evaluated. For each data source, get a list of 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.</p> <p>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 federal Fair Credit Reporting Act (FCRA). 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 a relevant and representative time frame, representative of potential exposures, and lacking in obvious correlation to protected classes.</p> <p>Note: 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.</p>
A.1.b	Reconcile aggregated insurance data underlying the model with available external insurance reports.	4	<p>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 (i.e., 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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	Many models are developed using a countrywide or a regional dataset. 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 explain why any states were excluded from the countrywide data. 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. However, 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. The company should provide a demonstration that the model fits well on the specific state or surrounding region.
2. Sub-Models			
A.2.a	Consider the relevance of (i.e., whether there is bias) of overlapping data or variables used in the model and sub-models.	3	Check if the same variables/datasets were used in the model, a sub-model, or as stand-alone rating characteristics. Tree-based models handle redundant variables by splitting on only one of the variables within each component tree. By contrast, generalized linear models (GLMs) struggle with redundant variables as they try to include redundant variables simultaneously. However, best actuarial practice is to keep models as parsimonious as possible and only include additional variables that contribute significant additional predictive power.
A.2.b	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	1	<p>If the sub-model was previously approved/accepted, that may reduce the extent of the sub-model's review. If approved, obtain the tracking number(s) (e.g., state, System for Electronic Rates & Forms Filing [SERFF]) and verify when and if it was the same model currently under review.</p> <p>Note: A previous approval does not necessarily confer a guarantee of ongoing approval; e.g., when statutes and/or 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 the prior decision needs to be revisited. In some circumstances, direct dialogue with the vendor could be quicker and more useful.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.2.c	Determine if the sub-model output was used as input to the Tree-based Model; obtain the vendor name, as well as the name and version of the sub-model.	1	<p>To accelerate the review of the filing, it may be desirable to request (from the company) the name and contact information for a vendor representative. 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.</p> <p>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. Sub-model SMEs may need to be brought into the conversation with regulators (whether in-house or third-party sub-models are used).</p>
A.2.d	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	<p>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.</p> <p>For example, it is important to know hurricane model settings for storm surge, demand surge, and long-term/short-term views.</p>
A.2.e	Obtain an explanation of how catastrophe models are integrated into the model to ensure no double-counting.	1	<p>If a weather-based sub-model is input to the Tree-based model 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.</p> <p>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 or inclusion of freeze losses when using a winter storm model.</p>
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	<p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
3. Adjustments to Data			
A.3.a	Determine if premium, exposure, loss, or expense data were adjusted (e.g., on-leveled, developed, trended, adjusted for catastrophe experience, or capped). If so, how? Do the adjustments vary for different segments of the data? If so, identify the segments and how the data was adjusted.	2	<p>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 of how they were handled. These treatments need to be identified, and the company/regulator needs to determine whether model data needs to be adjusted.</p> <p>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?</p> <p>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.</p> <p>Premium should be brought to current rate level if the target variable is calculated with a premium metric, such as loss ratio. Premium can be brought to current rate level with the extension of exposures method or the parallelogram method. Note that the premium must be on-leveled at a granular variable level for each variable included in the new model if the parallelogram method is used. Statewide on-level factors by coverage are typically sufficient for statewide rate indication development but not sufficient for models that determine rates by variable level.</p>
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	<p>Pre-modeling binning may be unnecessary in a Tree-based model. The tree model will naturally segment numerical values in the splitting process of the trees. However, if the insurer does bin variables before modeling, the reason should be understood.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
A.3.c	Ask for aggregated data (one dataset of pre-adjusted/scrubbed data and one dataset 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	<p>This is most relevant for variables that have been “scrubbed” or adjusted.</p> <p>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.</p> <p>It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category are provided. This data can be displayed in either graphical or tabular formats.</p>
A.3.d	Determine how missing data was handled.	1	<p>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.</p> <p>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 recoding 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 are provided. This data can be displayed in either graphical or tabular formats.</p> <p>The modeler should describe the way the tree fitting process handled missing values. The modeler should specify if missing values are treated before running the Tree-based model or if they are allowed to be handled by the Tree-based model.</p> <p>When creating predictions on new datasets (such as hold out datasets), tree-based models may have different approaches for handling missing data or categorical levels not encountered in the training data for a predictor variable. The modeler should specify the process utilized when this occurs.</p>
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	<p>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 types of outliers, and determine what adjustments were made to each type of outlier. To understand the filer's response, the regulator should ask for the filer's materiality standard.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 and/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 is used to predict the wind peril, the company should provide support and a rational explanation for their use.
A.4.c	Identify material findings the company had during its 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	"None" or "N/A" may be an appropriate response.

B. BUILDING THE MODEL

Section	Information Element	Level of Importance to the 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., Random Forest, GLM, decision tree, Bayesian GLM, 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	<p>It is important to understand if the model in question is a Tree-based model 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/by-coverage.</p> <p>Note: If the model is not a Tree-based model, the information elements in this appendix may not apply in their entirety.</p>
B.1.b	Identify the software used for model development. Obtain the name of the software vendor/developer, software product, and a software version reference used in model development.	3	<p>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 (e.g., a filing specialist) who can place the regulator in direct contact with the appropriate SME at the vendor.</p> <p>Open-source software/programs used in model development should be identified by name and version the same as if from a vendor.</p>
B.1.c	Obtain a description of 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 of why that came to occur. Obtain a discussion of whether the model was rebuilt using all the data or if it was only based on the training data.	1	<p>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.</p> <p>The reviewer should note whether a company employed cross-validation techniques instead of a training/test/validation dataset approach. If cross-validation techniques were used, the reviewer should request a description of how cross-validation was done and confirm that the final model was not built on any particular subset of the data, but rather the full dataset.</p> <p>The discussion of training, test, and/or validation datasets is a separate discussion from the percentage of observations (rows of data) or percentage of features (columns of data) used within each tree. These splits are based on hyperparameters and are commented on in other sections.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 candidate variable selection process prior to the model building.	1	<p>Candidate variables are the variables used as input to the modeling process. Certain variables may not end up used in the final model if none of the component trees of the model split on the variable. The narrative regarding the candidate 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 candidate variable selection.</p> <p>The modeler should comment on the use of automated feature selection algorithms to choose candidate predictor variables and explain how potential overfitting that can arise from these techniques was addressed.</p>
B.1.h	In conjunction with variable selection, obtain a narrative on how the company determined the granularity of the rating variables during model development.	3	The narrative 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 (e.g., 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.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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, techniques, or hyperparameters, obtain a narrative on the judgment used to make those selections.	2	
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 of how these adjustments were done, including any statistical improvement measures relied upon.
B.2.c	Identify which distribution was used for the model (e.g., Regression based on Poisson, Gamma, Logistic, or Tweedie are common choices). Obtain an explanation of why the distribution was chosen. Certain distribution assumptions will involve numerical parameters; i.e., regression with a Tweedie assumed distribution will have a p power value. Obtain the specific numerical parameters associated with the distribution.	1	
B.2.d	Obtain a narrative on how the predictions from the component trees are combined to arrive at a final model prediction.	2	Tree-based methods combine predictions from multiple component trees and aggregate them into a final prediction for each observation. Common methods for combining Random Forest model predictions include the arithmetic or geometric mean of all the component trees. Boosting algorithms further refine the model iteratively in each tree, with a focus on records where predictions were off in prior iterations. Gradient Boosting Machines similarly aggregate predictions from all trees. Producing predictions sometimes involve summing all applicable terminal node values and applying the inverse of a link function.
B.2.e	If there were data situations in which weights were used, obtain an explanation of how and why they were used.	3	Investigate whether identical records were combined to build the model.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.2.f	Obtain the number of component trees comprising the Tree-based model. Obtain a narrative on how this number was chosen.	1	<p>Tree-based models should contain enough trees to reduce error to an acceptable level. They should also balance this with the concept of parsimony. A model with fewer trees that achieves relatively similar reduction in error is preferable to a model with more trees. Checking the error on a test dataset or out of bag error for different numbers of trees can reveal at what value the error on test data starts to level off.</p> <p>Modelers might rely on early stopping rules within modeling software to arrive at the final number of trees. The narrative on the number of trees should discuss the stopping criterion, which defines what condition is met when the model stopped adding more trees.</p>
B.2.g	Obtain the sampling parameters that apply to both the percent of observations used in each component tree and the number of features tested for each split within each tree. Obtain a narrative on how the sampling parameters were selected.	1	<p>Tree-based models often sample both the observations (typically rows of modeling data) with replacement and sample the features (typically columns of modeling data) This means that each tree has a bootstrapped dataset.</p> <p>The company should discuss the bagging fraction (sample size) applied to observations (typically rows of data). This is often expressed as a percent. For example: perhaps each tree is based on a bootstrapped sample that is 50% of the original dataset.</p> <p>The company should discuss the number of features considered at each split. This is often expressed as an integer. A common choice for the number of features is equal to roughly the square root of the total number of candidate variables. For example: perhaps each split is based on 10 randomly selected features (typically columns of data) when there are 100 candidate variables.</p>
B.2.h	Obtain the maximum depth that applies to the component trees in the model. Obtain a narrative on how this number was chosen.	1	<p>The depth of a tree is the number of splits that are allowed to occur between the root node and the terminal nodes. This number can be set explicitly in modeling software or may be implicitly set if the company applies a splitting constraint, such as a minimum observations per node. Maximum tree depths of eight or higher are considered extremely high.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.2.i	Obtain parameters that determined the volume of data in each tree node and a narrative of how parameters were chosen.	1	<p>Minimum data volume constraints can be applied to a tree-based model, such that the trees will not create a split that would result in terminal nodes with volume below a set amount. The modeler should comment on how the threshold was chosen.</p> <p>If there was no minimum data volume threshold applied to the trees, or if the threshold was exceedingly small, obtain an explanation of any post-modeling adjustments the modeler made to address the credibility considerations and how the adjustments were applied.</p>
B.2.j	Obtain the learning rate aka “shrinkage” if the model is a Gradient Boosting Machine	1	<p>Learning rate is a hyperparameter that applies to Gradient Boosting Machines but not to random forest models. The hyperparameter controls how far towards indicated each tree is allowed to move. The number is typically set to a low value, to reflect that GBM is intended to be a collection of “weak learners”, whose accuracy comes after ensembling a large number of trees. As a rule of thumb, values less than or equal to 0.20 are common.</p>
B.2.k	Obtain a narrative of the process to select all hyperparameters for the Tree-based model. Detail how this process addressed potential overfitting in the model.	2	<p>The narrative should include a description of each hyperparameter, document the values of the hyperparameters, specify the implication of using a higher or lower value for each hyperparameter, and discuss any sensitivity testing completed on the hyperparameters and observations from the sensitivity analysis. Hyperparameter tuning can be done in a variety of ways. The rigor of the tuning process should reflect the risk of overfitting on the specific dataset.</p>
3. Predictor Variables			
B.3.a	Obtain a complete data dictionary, including the names, types, definitions, and rationales for each variable.	1	<p>Types of variables might be continuous, discrete, Boolean, etc. Identify any variable used as an offset or control in the Tree-based model and the offset factor that was applied for each level of the offset variable.</p> <p>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.</p>
B.3.b	Obtain a list of predictor variables considered but not used in the final model and the rationale for their removal.	4	<p>The purpose of this requirement is to identify variables 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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.3.c	Obtain a correlation matrix for all predictor variables included in the model and sub-model(s).	3	High correlation is less of an issue for tree-based models than it is for GLMs. Tree-based models naturally only use one variable at a time during each split in each tree. However, a correlation matrix still helps the reviewer understand relationships in the data being modeled better. The company should indicate what statistic was used (e.g., Pearson, Cramer's V, etc.) in the correlation matrix. The regulatory reviewer should understand what statistic was used to produce the matrix but should not prescribe the statistic.
B.3.d	Obtain plots describing the relationship between each predictor variable and the target variable. Obtain a rational explanation for the observed relationship between each predictor variable and the target variable (frequency, severity, loss costs, expenses, or any element or characteristic being predicted).	1	<p>Partial dependence plots (PDPs), accumulated local effects (ALE) plots, or Shapley plots will help improve model interpretability. There should be at least one plot for every variable used in the model. The plots should be accompanied by commentary on why the visualized relationship is reasonable for variables of concern. 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.</p> <p>For example, the regulator should look for unfamiliar predictor variables and, if found, the regulator should seek to understand the relationship that variable has to the target variable.</p> <p>The regulator should also consider that interpretability plots for tree-based models need to be reviewed with other considerations in mind. For example, partial dependence calculations assume independence with other variables in the model.</p>
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, as well as an explanation of how the results of the dimensionality reduction technique was used within the model.	2	

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.3.f	Obtain variable importance plots. Obtain a description of how variable importance was calculated.	1	<p>Variable Importance Plots for tree-based methods highlight which variables contributed most to the model. There are multiple ways to calculate variable importance.</p> <p>Variables with the lowest importance measures should be prioritized when identifying variables that may not be contributing significantly to the model. Variables may have a low importance measure due to high correlation with other variables but may still prove useful if they interact with other variables to identify unique subsets of risks.</p> <p>Variables with the highest importance measures should be prioritized when determining which variables have the largest impact on predictions.</p>
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-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	<p>For models that are built using multistate 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 it could also be impacted by low credibility for some segments of risk.</p> <p>Note: It may be useful to consider geographic stability measures for territories within the state.</p>
B.4.b	Obtain evidence that the model fits the training data well by variable and for the overall model.	2	<p>The regulator should ask for the company to provide exhibits or plots that show the fitted average makes sense when compared to the observed average for variables of interest. Regulators would ideally review this comparison for every variable, but time constraints may limit the focus to just variables of interest. Variables of interest should include those with a high importance measure (which will have the most material impact on rates), those with a low importance measure (which may not be contributing significantly to the model), variables without an intuitive relationship to loss, or variables that may be proxies for a protected class attribute.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.c	Obtain a description how the model was tested for stability over time.	2	<p>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).</p> <p>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.</p> <p>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 exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model?</p> <p>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.</p>
B.4.d	Obtain a narrative on how potential concerns with overfitting were addressed.	2	<p>Tree-based models are notorious for overfitting. The company should provide a narrative on how overfitting was addressed. The company should provide a lift chart on training data used to fit the model and a lift chart on testing data that was not used to fit the model. If pruning was used to address overfitting, the narrative should provide commentary on the pruning process.</p>
B.4.e	Obtain support demonstrating that the model assumptions are appropriate.	3	<p>A visual review of plots of actual errors is usually sufficient.</p> <p>The reviewer should look for a conceptual narrative covering these topics: How does this particular Tree-based model work? Why did the rate filer do what they 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.</p> <p>If the reviewer determines that the model makes no assumptions that are considered to be unreasonable, the importance of this item may be reduced.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.4.f	Obtain 5-10 sample records with corresponding output from the model for those records.	2	The company should provide comprehensive documentation of the rating algorithm such that a rate can be reproduced for any theoretical risk. The company should demonstrate the comprehensiveness of the documentation by providing 5-10 sample records with corresponding input variable values and the final model prediction. The company should describe how the final model prediction aggregates the individual tree model predictions. The company should describe how to use other filing exhibits to reproduce the final model prediction for each sample record.
B.4.g	Obtain a deviance analysis by number of trees.	2	The company should provide a plot showing that the deviance of the overall model decreases after each iteration (each additional tree). Plots which show negative log-likelihood would also be sufficient as models which minimize negative log-likelihood also minimize deviance. If the company chooses an error metric other than deviance or log-likelihood, the company should describe why they chose a different metric and explain how it is calculated.
5. "Old Model" Versus "New Model"			
B.5.a	Obtain an explanation of 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	The regulator 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	This information element requests a comparison of the Lorenz curve and 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 is relevant when one model is being updated or replaced. The regulator should expect to see improvement in the new class plan's predictive ability. One example of a comparison might be sufficient. Note: This comparison is not applicable to initial model introduction. The reviewer can look to CAS monograph, "Generalized Linear Models for Insurance Rating."

Section	Information Element	Level of Importance to the Regulator's Review	Comments
B.5.c	Determine if double-lift charts were analyzed and obtain a narrative on the conclusion drawn from this analysis.	3	One example of a comparison might be sufficient. Note: "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 as candidate variables. Obtain an explanation of 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	It is 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, and/or built the model.	4	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 the 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 (i.e., how it was used) in the rating system.	1	<p>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.</p> <p>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.)</p>
C.1.b	Obtain an explanation of how the model was used to adjust the filed rating algorithm.	1	The regulator should 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	<p>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 visualization plots (such as partial dependence plots, accumulated local effects plots, or Shapley plots) should be consistent with the expected direction of the relationship.</p> <p>Note: This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
3. Comparison of Model Outputs to Current and Selected Rating Factors			
C.3.a	Obtain documentation and support for all calculations, judgments, or adjustments that connect the model's indicated values to the selected rates filed in the rating plan.	1	<p>The documentation should include explanations for the necessity of any such adjustments and 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.</p> <p>Note: 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.</p>
C.3.b	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 regarding how each characteristic/variable was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	<p>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.</p> <p>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.</p>
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	The regulator should determine at what level of granularity credibility is applied. If modeling was by coverage, by form, or by peril, the company should 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 of why.	2	This is applicable if the company 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 of why.	2	A more granular rating plan may imply that the company had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications. It may be necessary to extrapolate due to data availability or other considerations.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
5. Definitions of Rating Variables			
C.5.a	Obtain a narrative regarding 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 of 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 of 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.
7. Consumer Impacts			
C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in renewal premium, both as increases and decreases, as well as the top five rating variables with the largest spread of impact for both new and renewal business.	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 company 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 average fitted model prediction. Look for significant variation between the average fitted model predictions for adjacent rating variable levels and evaluate if such variation is reasonable and credible.
C.7.c	For the proposed filing, obtain the impacts on renewal business, 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.

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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	<p>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.</p> <p>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.</p> <p>See Appendix D for an example of a disruption analysis.</p>
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 D 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	<p>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.</p> <p>The reviewer should be aware of, and possibly concerned about, 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.</p> <p>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.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
C.7.g	Obtain a means to calculate the rate charged a consumer.	3	<p>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. The 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: This information may be proprietary.</p> <p>For the rating plan, the rate order of calculation rule may be sufficient. However, it may not be feasible for a regulator to get all the input data necessary to reproduce a model's output. Credit and telematics models are examples of model types where model output would be readily available, but the input would not be readily available to the regulator.</p>
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	<p>If the data is from a third-party source, the company should provide information on the source. Depending on the nature of the data, it may need to be documented with an overview of who owns it.</p> <p>The topic of consumer verification may also need to be addressed, including how consumers can verify their data and correct errors.</p>
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	<p>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.</p>
9. Efficient and Effective Review of Rate Filing			
C.9.a	Establish procedures to efficiently review rate filings and models contained therein.	1	<p>"Speed to market" is an important competitive concept for insurers. Although the regulator needs to understand the rate filing before accepting the rate filing, the regulator should not request information that does not increase his/her understanding of the rate filing.</p> <p>The regulator should review the state's rate filing review process and procedures to ensure that they are fair and efficient.</p>

Section	Information Element	Level of Importance to the Regulator's Review	Comments
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 laws and/or regulations.	1	This is a primary duty of state insurance regulators. The regulator should be knowledgeable of 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 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.
C.9.d	Obtain complete documentation that would allow future audits of model predictions.	1	The company should provide comprehensive documentation of the rating algorithm such that a rate can be reproduced for any theoretical risk. Comprehensive documentation could be provided as one of the following: a complete set of tree diagrams, a set of if-else logic statements that represents the trees, or a table showing every possible combination of risk characteristics and the final prediction.

TREE-BASED MODELS GLOSSARY OF TERMS

Accumulated Local Effects Plots: A type of interpretability plot. Accumulated local effects (ALE) plots calculate smaller, incremental changes in the feature effects. ALE shows the expected and centered effects of a variable.

Bagged Trees: An ensemble of trees where each tree is based on a “bootstrap aggregated” sample.

Branch: A connection on a decision tree between a parent node and a child node. A relationship based on a predictor variable is checked at each node, determining which branch applies.

Candidate Variables: The variables specified by the modeler to be used within the full model. The variable selection process performed by a Tree-based model means that component trees might only use a subset of these variables in each tree.

Child Node: The node below a parent node. The child node is the result of a split that occurs based on a predictor variable. The node above the child node, which is where the split occurred resulting in the creation of the child nodes, is called the parent node. There is one parent node for every child node. The root node is the only node that is not a child node.

Component Tree: An individual tree within an approach based on an ensemble of trees, such as Random Forest or gradient boosting machine.

Deviance: A measure of model fit. Deviance is based on the difference between the log-likelihood of the saturated model and the log-likelihood of the proposed model being evaluated. Smaller values of deviance demonstrate that a model’s predictions fit closer to actual. Deviance on training data will always decrease as model complexity increases.

Gradient Boosting Machine: An ensemble of trees model made up a series of “weak learner” trees which iteratively focus more on the residuals of the model at each iterative tree.

Hyperparameter: A model hyperparameter is a model setting specified by the modeler that is external to the model and whose value cannot be estimated from data.

Node: A point on a decision tree. Nodes are either root nodes (the top node), leaf nodes (a terminal node at which point no further splitting occurs), or an internal node that appears in the middle of the tree while splitting is still taking place.

Out-of-Bag Error: Error calculated for observations based on the trees that did not include them in the set of training observations. Out-of-Bag Error is calculable when bootstrapping is used to generate different datasets for each component tree in an ensemble tree method.

Parent Node: The node above a child node. The parent node is where a split occurs based on a predictor variable. The nodes below the parent node, which are a direct result of the parent node’s split, are called child nodes. There are typically two child nodes for every parent node. Terminal nodes cannot be parent nodes.

Partial Dependence Plots: A type of interpretability plot. The partial dependence plot computes the marginal effect of a given variable on the prediction.

Pruning: The process of scaling back a tree to reduce its complexity. This results in trees with fewer branches and terminal nodes appearing higher on the tree. Pruning is more common on models built on a single decision tree rather than on ensemble models such as Random Forests or gradient boosting machines.

Random Forest: An ensemble of trees where each tree is based on a bootstrap aggregated sample, and each split is based on a random sample of the candidate variables.

Root Node: The first (top) node in a decision tree. This node contains the entire set of data used by the tree as no splits have occurred yet.

Shapley Additive Explanation Plots: A type of interpretability plot. Shapley plots investigate the effect of including a variable in the model by the order in which it is added. The Shapley value represents the amount the variable of interest contributes to the prediction.

Splitting: The process of dividing a node into two or more sub-nodes, starting from the root node. Splitting occurs at every node up until the terminal (leaf) nodes when the stopping criterion is met.

Stopping Criterion: A criterion applied to the splitting process that informs the node when it is ineligible to split any further. Volume of data is often used as a stopping criterion, such that each leaf node is based on at least a pre-determined amount of data.

Terminal Node: An end node containing no child nodes because the node has met the stopping criterion. The terminal node is associated with a prediction for one of the component trees. The terminal node is also known as a “leaf” node, the resulting endpoint of a decision tree.

Tree-based Model: A model that can be represented as a decision tree or a collection of decision trees.

Tree Depth: The maximum number of splits between the root node and a leaf node for a tree.

Variable Importance: A measure of how the variables (a.k.a. features) contribute to the overall model. There are multiple ways to measure variable importance.

Appendix C: NAIC Rate Model Checklists

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Predictive Model Checklists Introduction

Regulators frequently using the NAIC rate model review service asked the NAIC rate model review team to create a list of rate filing documentation needed for the NAIC to complete a full-scope rate model review. The goals of such lists are to make the NAIC review process more efficient and expeditious. Regulators may evaluate these lists and determine the state's needs. Regulators can share this list with insurers, revise the state's rate filing checklists, or communicate with insurers through rate filing objections, when needed.

The lists below are divided by "Essential Information" and "Sometimes Needed Information." These terms are defined in this table:

Category	Description
Essential Information	Information that the NAIC rate model review team requests before writing a full-scope initial assessment of a model.
Sometimes Needed Information	Information that the NAIC model review team finds useful for model reviews but may only be needed if something appears non-standard about the modeling approach. Regulators may want to wait to request such information from insurers only when requested in the initial NAIC report.

This document is meant to address multiple model types. There are some differences in model documentation available for different model types. The sections below are divided by model type. Today, the majority of predictive models used in personal automobile and home insurance rating plans are GLMs. According to many in the insurance industry, GLMs introduce significant improvements over univariate-based rating plans by automatically adjusting for correlations among input variables. Tree-based models, including random forests and gradient boosting machines, can capture complex non-linear relationships between predictor variables and the target variable. Tree-based models can account for deep interactions between predictor variables. Penalized regression methods can mitigate the risk of overfitting and multi-collinearity in a multi-variate model. Some penalized regression methods (such as lasso regression) also offer automatic variable selection. This checklist document details the rate filing documentation requested by the NAIC Model Review Team for efficient review of standard GLMs, Tree-based models, and penalized regression models.

Generalized Linear Model (GLM) List

GLM Introduction

Essential Information

- A narrative discussing what the company is trying to accomplish with the model, including the following details:
 - Is this a new model or refresh? What is the prior model's SERFF number (if applicable)?
 - Does the filing impact existing renewals?
 - Who is the target consumer?
 - What is the target variable of the model? (Frequency, Severity, Loss Ratios, Pure Premium, etc.) How is it defined?
 - What is being optimized? Does the model consider anything other than differences in loss cost?
- A narrative discussing the specifications and high-level assumptions of the model, including the following details:
 - Number of GLMs
 - Split of the data into models (by coverage, by peril, etc.)
 - Split of the data into datasets (training, test, holdout)
 - How models were combined to derive the final rating algorithm

Sometimes Needed Information

- A narrative discussing the credentials of the modeling team, including the following details:
 - Name of each individual
 - Relevant educational experience
 - Relevant credentials and designations
 - Years of experience building predictive models
 - Years of experience in the insurance industry
- Discuss how Actuarial Standards of Practice (ASOPs) 12, 23, 41, and 56 were considered in building the models.
- Describe the software (including packages and libraries if applicable) used to build the models.
- Provide copies of or links to academic references for their modeling techniques.
- A table listing the states where the model has been filed for review, the SERFF tracking number, and an indicator showing whether the filing has been approved.

GLM Data

Essential Information

- A narrative providing the description of each data source including the following:
 - Informational materials or website links for each 3rd party
 - Commentary on how the company reviewed the veracity of the data source
 - Why the company believes the data source is useful for the model's intended purpose
 - Disclosure of known data errors
 - SERFF filing numbers where the use of the data was previously approved (if applicable)
- A description of the relevance of the data
 - The lines of business and companies included should be identified
 - Description of any considerations or adjustments made to make the data more applicable for its intended use
- A data dictionary provided as a table with the following columns:
 - Data Source (Vendor name or "Internal")
 - Variable name
 - Alternate names appearing in other filing documents
 - Data types (discrete, continuous, logical, categorical)
 - Treatment Type (Model, Control, Offset, Target)
 - Possible values (Empirical min and max for numerical variables, all categories for categorical variables)
- Tables showing summary metrics for each dataset by year (training, testing, holdout)
 - Year
 - Losses
 - Exposures (or Policy Count)
 - Claim Count (if applicable)
- A narrative on how the company determined the variables to include in the final model
- A narrative on the data accuracy and data reconciliation process
 - Description of the methods used to compile, filter, and/or merge data from different sources
 - How the data was reconciled to other sources
- A listing of the rational explanation for each modeled variable that discusses why it would plausibly impact insurance risk as discussed in the CASTF white paper.
- A guarantee that the modeling dataset will be retained for at least 7 years.
- A description of any dimensionality reduction techniques (PCA, clustering, etc.) that were applied to the data.
- An Excel file with 100 anonymized sample modeling records including all predictor variables and target variables.

Sometimes Needed Information

- A description of steps taken to meet state requirements regarding unfair discrimination (if applicable).
- A listing of variables which are subject to the fair credit reporting act (if applicable).
- A table showing the data volume distribution by state for each dataset (training, testing, holdout)
- A listing of variables initially considered but later removed from the model.

GLM Modeling

Essential Information

- A narrative discussing the specifications and assumptions of the model, including the following details:
 - Form of the regression equation
 - Distribution assumed for the error term
 - The link function
 - Weights used in regression (if applicable)
- A description of how the model differs from prior versions of the model (if applicable).
- A description for each control or offset variable of why it was necessary to treat them as control/offset variables.
- A description of how the variables with null or missing values will be treated, including the following:
 - A table showing the rate of null or missing values for each variable
 - A description of the scenarios which generated null or missing values
 - A description of how each null or missing value is treated (might include imputation method or simply left in as a control)
 - A description of what happens to null and/or missing values when generated in production. (Is there a rating factor applied for null/missing or is the data populated before policy issuance?)
- A description of any large loss capping applicable to the dataset
 - Identify the size of the large loss cap
 - Identify the percentile of claim severity represented by large loss cap
- A description of adjustments and modifications to the data including trending, loss development, capping at minimums or maximums, and removal of outliers.
- A description of variable transformations applied to the data. The description should include the name of each transformation technique used, and an example transformation complete with a sample unadjusted value and a final transformed value.
- A description of each feature engineered variables. The description should include the rationale behind the feature engineered variable and a sample calculation including unadjusted original variable values and the final feature engineered variable value.
- A description of how binning was applied to numeric variables and how categorical variable values were grouped together.

Sometimes Needed Information

- Deviance residual plots for each model demonstrating the appropriateness of the model assumptions.

GLM Validation

Essential Information

- A narrative on how the model was validated and assessed for model stability
- A narrative on how the model was assessed for improvement over the prior version of the model (if applicable)
- An Excel file containing model output in this format:
 - Each model is a separate worksheet
 - Column A is Variable Name
 - Column B is Variable Level Name
 - Column C is the coefficient
 - Column D is the p-value (if applicable)
 - Column E is the 95th confidence interval lower bound (if applicable)
 - Column F is the 95th confidence interval upper bound (if applicable)
- Ventile plots (quantile plots with at least 20 buckets) for both state specific data and countrywide data, built on data not used for model training. Each plot should include lines for both predicted averages and actual average.
- Lorenz curve for each model built on countrywide data. The plot should include the Lorenz curve and the equality reference line. The plot should also include the Gini value for the model.
- An Excel file containing correlation matrices in this format:
 - Each model's correlation matrix is a separate worksheet
 - Row 1 and Column 1 include variable names
 - The rest of the table displays the correlation metrics
- Commentary on which correlation metric (Pearson's, Cramer's V, etc.) was provided in the correlation matrix Excel file

Sometimes Needed Information

- A description of how often the model will be validated against new data in the future.
- A double lift chart comparing the newly proposed model and the current model (if applicable)
- Actual vs. Expected plots by model and variable (aka "Univariate Plots") which show the closeness between actual averages and predicted averages.
- Akaike Information Criterion (AIC) analysis showing AIC for the full model and each subset model excluding one variable at a time to demonstrate the potential impact on AIC of removing each variable.
- F-nested model tests comparing the full model to subset models excluding one variable at a time to demonstrate the significance of each term. Each test should include the following:
 - F-statistic
 - F-test critical values
 - Numerator degrees of freedom
 - Denominator degrees of freedom
- Variance Inflation Factors (VIFs) for each variable

GLM Implementation

Essential Information

- A description of how the models being filed are ultimately integrated into the company's final rating algorithm
- A narrative about all post modeling adjustments, such as smoothing, mapping to scores, and tempering of factors
- A narrative identifying the variables where deviations from indicated were made and commentary on the reason for the deviations
- A dislocation analysis, including the following:
 - Histograms showing percentage premium change on uncapped and capped basis (if applicable), using buckets of 5%
 - Descriptions of the scenarios with the highest increases
 - Descriptions of the scenarios with the biggest decreases
- Commentary on the differences between rating new and existing policyholders
- An Excel file which documents deviations between indicated and selected in this format:
 - Each model is a separate worksheet
 - Column A is Variable Name
 - Column B is Variable Level Name
 - Column C is the Current Factor (if applicable)
 - Column D is the Indicated Factor
 - Column E is the Proposed Factor
 - Column F is the percentage difference between indicated and proposed. If the absolute value of the percentage difference is > 10%, the cell should be highlighted.
- Sample rating/scoring exhibits for 10 risks in Excel, which show risk characteristics, all intermediate adjustments, and the final algorithm output considering the company's final selections.

Sometimes Needed Information

None are listed at this time.

Tree-based Model (Random Forest, GBM, etc.) Checklist

Tree-based Model Introduction

Essential Information

- A narrative discussing what the company is trying to accomplish with the model, including the following details:
 - Is this a new model or refresh? What is the prior model's SERFF number (if applicable)?
 - Does the filing impact existing renewals?
 - Who is the target consumer?
 - What is the target variable of the model? (Frequency, Severity, Loss Ratios, Pure Premium, etc.) How is it defined?
 - What is being optimized? Does the model consider anything other than differences in loss cost?
- A narrative discussing the specifications and high-level assumptions of the model, including the following details:
 - Number and Type of models (GBM, Random Forest, etc.)
 - Split of the data into models (by coverage, by peril, etc.)
 - Split of the data into datasets (training, test, holdout)
 - How models were combined to derive the final rating algorithm

Sometimes Needed Information

- A narrative discussing the credentials of the modeling team, including the following details:
 - Name of each individual
 - Relevant educational experience
 - Relevant credentials and designations
 - Years of experience building predictive models
 - Years of experience in the insurance industry
- Discuss how Actuarial Standards of Practice (ASOPs) 12, 23, 41, and 56 were considered in building the models.
- Describe the software (including packages and libraries if applicable) used to build the models.
- Provide copies of or links to academic references for their modeling techniques.
- A table listing the states where the model has been filed for review, the SERFF tracking number, and an indicator showing whether the filing has been approved.

Tree-based Model Data

Essential Information

- A narrative providing the description of each data source including the following:
 - Informational materials or website links for each 3rd party
 - Commentary on how the company reviewed the veracity of the data source
 - Why the company believes the data source is useful for the model's intended purpose
 - Disclosure of known data errors
 - SERFF filing numbers where the use of the data was previously approved (if applicable)
- A description of the relevance of the data
 - The lines of business and companies included should be identified
 - Description of any considerations or adjustments made to make the data more applicable for its intended use
- A data dictionary provided as a table with the following columns:
 - Data Source (Vendor name or "Internal")
 - Variable name
 - Alternate names appearing in other filing documents
 - Data types (discrete, continuous, logical, categorical)
 - Treatment Type (Model, Control, Offset, Target)
 - Possible values (Empirical min and max for numerical variables, all categories for categorical variables)
- Tables showing summary metrics for each dataset by year (training, testing, holdout)
 - Year
 - Losses
 - Exposures (or Policy Count)
 - Claim Count (if applicable)
- A narrative on the candidate variable selection process prior to the model building.
- A narrative on the data accuracy and data reconciliation process
 - Description of the methods used to compile, filter, and/or merge data from different sources
 - How the data was reconciled to other sources
- A listing of the rational explanation for each modeled variable that discusses why it would plausibly impact insurance risk as discussed in the CASTF white paper.
- A guarantee that the modeling dataset will be retained for at least 7 years
- A description of any dimensionality reduction techniques (PCA, clustering, etc.) that were applied to the data.
- An Excel file with 100 anonymized sample modeling records including all predictor variables and target variables.

Sometimes Needed Information

- A description of steps taken to meet state requirements regarding unfair discrimination (if applicable).
- A listing of variables which are subject to the fair credit reporting act (if applicable).
- A table showing the data volume distribution by state for each dataset (training, testing, holdout)
- A listing of variables initially considered but later removed from the model.

Tree-based Modeling

Essential Information

- A narrative discussing the specifications and assumptions of the model, including the following details:
 - Form of the regression equation (if applicable)
 - Distribution assumed for the error term (if applicable)
 - The link function (if applicable)
 - Weights used in regression (if applicable)
 - Description of the tuning procedure for all hyperparameters
 - Description of how the component trees are combined to arrive at final predictions
- A description of all hyperparameters, including the following:
 - Number of component trees
 - Number of features considered at each split in the trees
 - Sampling size (number of rows)
 - Maximum tree depth
 - Minimum volume of data per node
 - “Shrinkage” or learning rate (applicable to GBMs)
- A description of how the model differs from prior versions of the model (if applicable).
- A description for each control or offset variable of why it was necessary to treat them as control/offset variables.
- A description of how the variables with null or missing values will be treated, including the following:
 - A table showing the rate of null or missing values for each variable
 - A description of the scenarios which generated null or missing values
 - A description of how each null or missing value is treated (might include imputation method or simply left in as a control)
 - A description of what happens to null and/or missing values when generated in production. (Is there a rating factor applied for null/missing or is the data populated before policy issuance?)
 - A description of how the Tree-based model treats null or missing values.
- A description of any large loss capping applicable to the dataset
 - Identify the size of the large loss cap
 - Identify the percentile of claim severity represented by large loss cap
- A description of adjustments and modifications to the data including trending, loss development, capping at minimums or maximums, and removal of outliers.
- A description of variable transformations applied to the data. The description should include the name of each transformation technique used and an example transformation complete with a sample unadjusted value and a final transformed value.
- A description of each feature engineered variables. The description should include the rationale behind the feature engineered variable and a sample calculation including unadjusted original variable values and the final feature engineered variable value.
- A description of how binning was applied to numeric variables and how categorical variable values were grouped together (if binning or grouping were applied before running the Tree-based model).

Sometimes Needed Information

- Deviance residual plots for each model demonstrating the appropriateness of the model assumptions.

Tree-based Model Validation

Essential Information

- A narrative on how the model was validated and assessed for model stability
- A narrative on how the model was assessed for improvement over the prior version of the model (if applicable)
- Ventile plots (quantile plots with at least 20 buckets) for both state specific data and countrywide data, built on data not used for model training. Each plot should include lines for both predicted averages and actual average.
- Lorenz curve for each model built on countrywide data. The plot should include the Lorenz curve and the equality reference line. The plot should also include the Gini value for the model.
- Plots useful for understanding the model
 - Plots showing model performance by number of trees. The company should provide a plot showing that an error metric (deviance, negative log-likelihood, etc.) decreases after each iteration (each additional tree). If the company chooses an error metric other than deviance or log-likelihood, the company should describe why they chose a different metric and explain how it is calculated.
 - Variable Importance Plots highlighting which variables contributed most to the model. Provide commentary why variables with relatively lower importance are still included in the proposed model.
 - Interpretability plots visualizing the relationship between each predictor variable and the target variable such as partial dependence plots (PDPs), accumulated local effects (ALE) plots, or Shapley plots. There should be at least one plot for every variable used in the model. The plots should be accompanied by commentary on why the visualized relationships are reasonable.
- An Excel file containing correlation matrices in this format:
 - Each model's correlation matrix is a separate worksheet
 - Row 1 and Column 1 include variable names
 - The rest of the table displays the correlation metrics
- Commentary on which correlation metric (Pearson's, Cramer's V, etc.) was provided in the correlation matrix Excel file

Sometimes Needed Information

- A description of how often the model will be validated against new data in the future
- A double lift chart comparing the newly proposed model and the current model (if applicable)
- Actual vs. Expected plots by model and variable (aka "Univariate Plots") which show the closeness between actual averages and predicted averages.

Tree-based Model Implementation

Essential Information

- A description of how the models being filed are ultimately integrated into the company's final rating algorithm
- A narrative about all post modeling adjustments, such as smoothing, mapping to scores, and tempering of factors
- A narrative identifying the variables where deviations from indicated were made and commentary on the reason for the deviations
- Tree diagrams for the first tree in each model, demonstrating how the splitting works.
- A dislocation analysis, including the following:
 - Histograms showing percentage premium change on uncapped and capped basis (if applicable), using buckets of 5%
 - Descriptions of the scenarios with the highest increases
 - Descriptions of the scenarios with the biggest decreases
- Commentary on the differences between rating new and existing policyholders
- An Excel file which documents deviations between indicated and selected in this format:
 - Each model is a separate worksheet
 - Column A is Variable Name
 - Column B is Variable Level Name
 - Column C is the Current Factor (if applicable)
 - Column D is the Indicated Factor
 - Column E is the Proposed Factor
 - Column F is the percentage difference between indicated and proposed. If the absolute value of the percentage difference is > 10%, the cell should be highlighted.
- Sample rating/scoring exhibits for 10 risks in Excel, which show risk characteristics, all intermediate adjustments, and the final algorithm output considering the company's final selections.

Sometimes Needed Information

- Complete documentation that would allow future audits of model predictions. This could be satisfied by one of the following:
 - Comprehensive Tree diagrams for every tree
 - Comprehensive splitting rules that reproduce the tree logic
 - Tables showing every possible combination of risk characteristics and the final model prediction.

Penalized Regression Model (GAM, Elastic Net, Lasso, Ridge, Derivative Lasso, Lasso Credibility, etc.) Checklist

Penalized Regression Model Introduction

Essential Information

- A narrative discussing what the company is trying to accomplish with the model, including the following details:
 - Is this a new model or refresh? What is the prior model's SERFF number (if applicable)?
 - Does the filing impact existing renewals?
 - Who is the target consumer?
 - What is the target variable of the model? (Frequency, Severity, Loss Ratios, Pure Premium, etc.) How is it defined?
 - What is being optimized? Does the model consider anything other than differences in loss cost?
- A narrative discussing the specifications and high-level assumptions of the model, including the following details:
 - Number and Type of models (GAM, Elastic Net, Lasso, Ridge, Derivative Lasso, Lasso Credibility, etc.)
 - Split of the data into models (by coverage, by peril, etc.)
 - Split of the data into datasets (training, test, holdout)
 - How models were combined to derive the final rating algorithm

Sometimes Needed Information

- A narrative discussing the credentials of the modeling team, including the following details:
 - Name of each individual
 - Relevant educational experience
 - Relevant credentials and designations
 - Years of experience building predictive models
 - Years of experience in the insurance industry
- Discuss how Actuarial Standards of Practice (ASOPs) 12, 23, 41, and 56 were considered in building the models.
- Describe the software (including packages and libraries if applicable) used to build the models.
- Provide copies of or links to academic references for their modeling techniques.
- A table listing the states where the model has been filed for review, the SERFF tracking number, and an indicator showing whether the filing has been approved.

Penalized Regression Model Data

Essential Information

- A narrative providing the description of each data source including the following:
 - Informational materials or website links for each 3rd party
 - Commentary on how the company reviewed the veracity of the data source
 - Why the company believes the data source is useful for the model's intended purpose
 - Disclosure of known data errors
 - SERFF filing numbers where the use of the data was previously approved (if applicable)
- A description of the relevance of the data
 - The lines of business and companies included should be identified
 - Description of any considerations or adjustments made to make the data more applicable for its intended use
- A data dictionary provided as a table with the following columns:
 - Data Source (Vendor name or "Internal")
 - Variable name
 - Alternate names appearing in other filing documents
 - Data types (discrete, continuous, logical, categorical)
 - Treatment Type (Model, Control, Offset, Target)
 - Possible values (Empirical min and max for numerical variables, all categories for categorical variables)
- Tables showing summary metrics for each dataset by year (training, testing, holdout)
 - Year
 - Losses
 - Exposures (or Policy Count)
 - Claim Count (if applicable)
- A narrative on how the company determined the variables to include in the final model
- A narrative on the data accuracy and data reconciliation process
 - Description of the methods used to compile, filter, and/or merge data from different sources
 - How the data was reconciled to other sources
- A listing of the rational explanation for each modeled variable that discusses why it would plausibly impact insurance risk as discussed in the CASTF white paper.
- A guarantee that the modeling dataset will be retained for at least 7 years
- A description of any dimensionality reduction techniques (PCA, clustering, etc.) that were applied to the data.
- An Excel file with 100 anonymized sample modeling records including all predictor variables and target variables.

Sometimes Needed Information

- A description of steps taken to meet state requirements regarding unfair discrimination (if applicable).
- A listing of variables which are subject to the fair credit reporting act (if applicable).
- A table showing the data volume distribution by state for each dataset (training, testing, holdout)
- A listing of variables initially considered but later removed from the model.

Penalized Regression Modeling

Essential Information

- A narrative discussing the specifications and assumptions of the model, including the following details:
 - Form of the regression equation
 - Description of the penalty term used in fitting the model
 - Distribution assumed for the error term
 - The link function (if applicable)
 - Weights used in regression (if applicable)
- A description of the following hyperparameters
 - The penalty parameter value and how it was chosen.
 - Any other hyperparameters used in model fitting if applicable (example: number of knots for a smoothed term in a GAM). Describe how they were chosen.
- A description of how the model differs from prior versions of the model (if applicable).
- A description for each control or offset variable of why it was necessary to treat them as control/offset variables.
- A description of how the variables with null or missing values will be treated, including the following:
 - A table showing the rate of null or missing values for each variable
 - A description of the scenarios which generated null or missing values
 - A description of how each null or missing value is treated (might include imputation method or simply left in as a control)
 - A description of what happens to null and/or missing values when generated in production. (Is there a rating factor applied for null/missing or is the data populated before policy issuance?)
- A description of any large loss capping applicable to the dataset
 - Identify the size of the large loss cap
 - Identify the percentile of claim severity represented by large loss cap
- A description of adjustments and modifications to the data including trending, loss development, capping at minimums or maximums, and removal of outliers.
- A description of variable transformations applied to the data. The description should include the name of each transformation technique used and an example transformation complete with a sample unadjusted value and a final transformed value.
- A description of each feature engineered variables. The description should include the rationale behind the feature engineered variable and a sample calculation including unadjusted original variable values and the final feature engineered variable value.
- A description of how binning was applied to numeric variables and how categorical variable values were grouped together.

Sometimes Needed Information

- Deviance residual plots for each model demonstrating the appropriateness of the model assumptions.
- Demonstration of how the mode would differ if different hyperparameters were selected. This could take one of the following forms:
 - Sensitivity showing coefficient outputs side-by-side for higher and lower complexity hyperparameters
 - Plots showing coefficients by penalty value

Penalized Regression Model Validation

Essential Information

- A narrative on how the model was validated and assessed for model stability
- A narrative on how the model was assessed for improvement over the prior version of the model (if applicable)
- An Excel file containing model output in this format:
 - Each model is a separate worksheet
 - Column A is Variable Name
 - Column B is Variable Level Name
 - Column C is the coefficient
- A demonstration of parameter stability via one of the following methods
 - Confidence intervals (5th to 95th percentile) of coefficients based on 100+ bootstrap samples
 - Range of coefficients from 10 or 20 cross validation folds
 - Range of coefficients across at least 5 different time periods
 - P-values from a reference GLM with the same selected variables
- Ventile plots (quantile plots with at least 20 buckets) for both state specific data and countrywide data, built on data not used for model training. Each plot should include lines for both predicted averages and actual average.
- Lorenz curve for each model built on countrywide data. The plot should include the Lorenz curve and the equality reference line. The plot should also include the Gini value for the model.
- Models with a complement of credibility (example: lasso credibility) should provide plots by variable that visualize the credibility complement and the model indicated as separate lines.
- An Excel file containing correlation matrices in this format:
 - Each model's correlation matrix is a separate worksheet
 - Row 1 and Column 1 include variable names
 - The rest of the table displays the correlation metrics
- Commentary on which correlation metric (Pearson's, Cramer's V, etc.) was provided in the correlation matrix Excel file
- Tables showing concavity metrics (applicable to GAMs)

Sometimes Needed Information

- A description of how often the model will be validated against new data in the future
- A double lift chart comparing the newly proposed model and the current model (if applicable)
- Actual vs. Expected plots by model and variable (aka "Univariate Plots") which show the closeness between actual averages and predicted averages.

Penalized Regression Model Implementation

Essential Information

- A description of how the models being filed are ultimately integrated into the company's final rating algorithm
- A narrative about all post modeling adjustments, such as smoothing, mapping to scores, and tempering of factors
- A narrative identifying the variables where deviations from indicated were made and commentary on the reason for the deviations
- A dislocation analysis, including the following:
 - Histograms showing percentage premium change on uncapped and capped basis (if applicable), using buckets of 5%
 - Descriptions of the scenarios with the highest increases
 - Descriptions of the scenarios with the biggest decreases
- Commentary on the differences between rating new and existing policyholders
- An Excel file which documents deviations between indicated and selected in this format:
 - Each model is a separate worksheet
 - Column A is Variable Name
 - Column B is Variable Level Name
 - Column C is the Current Factor (if applicable)
 - Column D is the Indicated Factor
 - Column E is the Proposed Factor
 - Column F is the percentage difference between indicated and proposed. If the absolute value of the percentage difference is > 10%, the cell should be highlighted.
- Sample rating/scoring exhibits for 10 risks in Excel, which show risk characteristics, all intermediate adjustments, and the final algorithm output considering the company's final selections.

Sometimes Needed Information

None are listed at this time.

Neural Network Checklist

Neural Network Model Introduction

Essential Information

- A narrative discussing what the company is trying to accomplish with the model, including the following details:
 - Is this a new model or refresh? What is the prior model's SERFF number (if applicable)?
 - Does the filing impact existing renewals?
 - Who is the target consumer?
 - What is the target variable of the model? How is it defined?
 - What is being optimized? Does the model consider anything other than differences in loss cost?
- A narrative discussing the specifications and high-level assumptions of the model, including the following details:
 - Number and Type of models (Neural Network, etc.)
 - Split of the data into models (by coverage, by peril, etc.)
 - Split of the data into datasets (training, test, holdout)
 - How models were combined to derive the final rating algorithm

Sometimes Needed Information

- A narrative discussing the credentials of the modeling team, including the following details:
 - Name of each individual
 - Relevant educational experience
 - Relevant credentials and designations
 - Years of experience building predictive models
 - Years of experience in the insurance industry
- Discuss how Actuarial Standards of Practice (ASOPs) 12, 23, 41, and 56 were considered in building the models.
- Describe the software (including packages and libraries if applicable) used to build the models.
- Provide copies of or links to academic references for their modeling techniques.
- A table listing the states where the model has been filed for review, the SERFF tracking number, and an indicator showing whether the filing has been approved.

Neural Network Model Data

Essential Information

- A narrative providing a description of each data source including the following:
 - Informational materials or website links for each 3rd party
 - Commentary on how the company reviewed the veracity of the data source
 - Why the company believes the data source is useful for the model's intended purpose
 - Disclosure of known data errors
 - SERFF filing numbers where the use of the data was previously approved (if applicable)
- A description of the relevance of the data
 - The lines of business and companies included should be identified
 - Description of any considerations or adjustments made to make the data more applicable for its intended use
- Tables showing summary metrics for each dataset by year (training, testing, holdout)
 - Year
 - Losses
 - Exposures (or Policy Count)
 - Claim Count (if applicable)
- A narrative on the data accuracy and data reconciliation process
 - Description of the methods used to compile, filter, and/or merge data from different sources
 - How the data was reconciled to other sources
- A guarantee that the modeling dataset will be retained for at least 7 years
- A description of any dimensionality reduction techniques (PCA, clustering, etc.) that were applied to the data.
- If the neural network is trained on image data
 - Describe the team creating the initial labels, how they determined the labels, the number of people labeling each image, and what their rate of consensus was (interrater reliability).
 - Explain what season(s) of the year the images are captured
 - Explain what percent of US properties have an image in the current database
 - Explain how the images are captured
 - Describe how frequently the images are refreshed
 - Describe what image quality criteria is placed on images
 - Provide a distribution of images by state for each dataset (training, testing, holdout).
 - Provide a histogram showing the age of the latest image for each dwelling in the database

Sometimes Needed Information

- A description of steps taken to meet state requirements regarding unfair discrimination (if applicable).
- A listing of variables which are subject to the fair credit reporting act (if applicable).
- A table showing the data volume distribution by state for each dataset (training, testing, holdout)

Neural Network Modeling

Essential Information

- A narrative discussing the specifications and assumptions of the model, including how the hyperparameters of the neural networks were tuned.
- Provide the hyperparameters selected for the neural network, including the following:
 - Learning Rate
 - Number of Epochs
 - Batch Size
 - Activation Function
 - Number of hidden layers and units
 - Weight initialization
- A description of how the model differs from prior versions of the model (if applicable).
- Commentary on how the risk of overfitting was mitigated including whether these common methods were applied:
 - Early Stopping
 - Regularization
 - Dropout
- Provide plots that help demonstrate how the models work
 - For Artificial Neural Networks (ANN), provide Shapley plots by variable
 - For Artificial Neural Networks (ANN), provide waterfall plots for:
 - 10 records with the worst score and commentary on what is driving the score
 - 10 records of false positives (if applicable) and commentary on what is driving misclassification
 - 10 records of false negatives (if applicable) and commentary on what is driving misclassification
 - For Convolutional Neural Networks (CNN), provide Grad-CAM images for:
 - 10 images with the worst score and commentary on what is driving the score
 - 10 images of false positives (if applicable) and commentary on what is driving misclassification
 - 10 images of false negatives (if applicable) and commentary on what is driving misclassification

Sometimes Needed Information

- A description of any preprocessing (resizing, normalization, etc.) applied to the images before running the model.

Neural Network Model Validation

Essential Information

- A narrative on how the model was validated and assessed for model stability
- A narrative on how the model was assessed for improvement over the prior version of the model (if applicable)
- A confusion matrix arranged as follows:
 - Predicted Class in the row names
 - Actual Class in the column names
 - Test Dataset count in the table
- A summary of performance metrics (precision, recall, accuracy) on the test dataset.
- 10 sample images including model predictions and actual values.
- A description whether the model predictions were compared to an independent report (example: roof image classification versus findings from an actual roof inspection)

Neural Network Model Implementation

Essential Information

- A description of how the models being filed are ultimately utilized by the company
- An explanation regarding whether the data source used to train the model is the same data source that will be used in production. If not, what adjustments will be made to address differences between data sources.
- An explanation regarding whether the neural network prediction can be reproduced by a person using an objective criteria checklist
- A description regarding how consumers can appeal determinations made by the neural network
- A description of how often the data will be refreshed, whether scores will be updated automatically, and whether consumers can request an update to the score
- If the neural network is trained on image data
 - Explain whether an insured can personally submit an updated image if there have been updates to their property



Use of Missing Data in Actuarial Analyses and Rating

CASTF Meeting – 2025 NAIC Summer National Meeting

August 11, 2025

Roosevelt C. Mosley, Jr., FCAS, MAAA, CSPA

Managing Principal

Use of Missing Data in Actuarial Analyses and Rating

Attachment Twenty
Casualty Actuarial and Statistical (C) Task Force
8/11/2025



Model
Development

Rating Factor
Development

Policy Rating

The use of missing/unknown data in model development is an accepted and reasonable actuarial practice

- ASOP 12 – Risk Classification
 - Section 3.2.7: *“When selecting risk characteristics, the actuary should consider limitations created by business practices related to the financial or personal security system as known to the actuary and consider whether such limitations are likely to have a significant impact on the risk classification system.”*
 - Section 3.4.4.c., which encourages the actuary to consider quantitative analysis of the impact of *“significant limitations created by business practices of the financial or personal security system.”*
- ASOP 23 – Data Quality, Section 3.5: *“In most situations, the data are provided to the actuary by others. The accuracy and completeness of data supplied by others are the responsibility of those who supply the data. The actuary may rely on data supplied by others, subject to the guidance in section 3.3 and 3.4. The actuary should disclose reliance on data supplied by others in an appropriate actuarial communication, in accordance with section 4.1 (h).”*
- CASTF White Paper – Regulatory Review of Predictive Models emphasizes the importance of transparency, data quality evaluation and sensitivity testing

Rating Factor Development

- Options for developing rating factors for missing/unknown categories
 - Distinct category
 - Weighted average of non-missing categories
 - Judgmentally selected factor

Policy Rating

- Causes of missing data in production
 - Information not provided as part of application
 - Data not returned from third party vendor
- How missing data is handled in production
 - Policy is unable to be rated
 - Assign most favorable category
 - Assign a missing or unknown category
- Proposed solution: requesting data from policyholder

Concerns with Proposed Solution

- **Efficiency**: reaching out to every policyholder or every applicant about each missing or unknown risk characteristic may not be practical, depending on how many applicants or current policyholders have missing factors, and the number of missing characteristics. **Therefore, introducing this requirement will make balancing the accuracy and efficiency of rating factor determination more challenging.**
- **Accuracy**: it may be unlikely that the policyholder is able to provide accurate information.
- **Increase in excessive and inadequate rates**: The potential implication of the proposed regulation is that if a company is unable to comply with the proposed requirements, or if use of the rating factor is inefficient, the rating factor will not be used. In the case where the unknown or missing category was being rated based on the indication, every policyholder would move from their indicated rate to an average rate, which again would result in a significant increase in the percentage of policyholders whose rates would be inadequate, excessive or unfairly discriminatory.

Example – Increase in Excessive and Inadequate Rates

Base Rate	100				
Rating		Rating		Revised	Percent
Factor 1	Distribution	Factor	Premium	Premium	Difference
Good	25%	0.75	75.00	101.25	35.0%
Neutral	25%	1.00	100.00	101.25	1.3%
Bad	25%	1.25	125.00	101.25	-19.0%
Missing	25%	1.05	105.00	101.25	-3.6%
Total	100%		101.25		

Questions?

Attachment Twenty
Casualty Actuarial and Statistical (C) Task Force
8/11/2025

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Comments from the Consumer Federation of America to the Casualty Actuarial and Statistical Task Force on Unknown Risk Characteristics in Property and Casualty Insurance

August 4th, 2025

Kris DeFrain

kdefrain@naic.org

Casualty Actuarial and Statistical (C) Task Force
National Association of Insurance Commissioners

Dear Kris,

The Consumer Federation of America (CFA) and Center for Insurance Research (CIR) appreciate this opportunity to offer comments on unknown and undisclosed risk characteristics in property and casualty insurance. The Task Force should issue recommendations on appropriate disclosures and processes to remedy this rapidly developing crisis. Such recommendations are a critical first step in addressing the problems that occur when consumers are scored without any ability to understand the insurance risk scores, address any problems with them, or correct errors that have affected these scores. The use of unknown and undisclosed risk characteristics further undermines a critical component of the insurance system – voluntary risk mitigation.

This issue increasingly impacts the consumers that we advocate for - because it affects the accuracy of the data components insurers use to determine both eligibility for coverage *and* the premiums to be charged.¹ Our comments support and endorse the earlier comments by our colleague United Policyholders, and we are available for further dialogue.

While relevant to all insurance coverages, the use of unknown risk characteristics is particularly important in property insurance – a product currently in crisis. Currently property insurance availability is plummeting across the country, while the cost of coverage is soaring. Driving these rising costs is the increased use of broader risk scoring systems, complex models, aerial images and other data (often obtained from third parties not subject to any meaningful oversight) flooding and overwhelming traditional underwriting standards. Yet consumers have been left in the dark and lack access to the data and determinations needed to permit the correction of misinformation, and often face losing their insurance coverage or affordable protection for their property.

Consumers have the right to get a copy of their financial credit reports and their credit score, and can see what actions have impacted their score (allowing them to improve and mitigate their credit risk). Financial credit scores also provide a mechanism for correcting false or

¹ As the numerous proposals and model laws being developed that would give consumers access to aerial images of their properties demonstrate.

outdated information about their financial strength. In contrast, insurance consumers typically cannot access the risk score associated with their property, which features or factors went into that score, or a means for correcting misinformation in their insurance score. Consumers also lack access to aerial images of their property that insurers increasingly use as a basis for rating, for both eligibility decisions, and renewals. Furthermore, consumers lack a means to correct erroneous conclusions about property conditions derived from those aerial images.

In the homeowners marketplace in particular, the use of wildfire risk models is particularly concerning. These models assign risk scores to homes based upon a set of considerations that typically include the distance from a fire station, degree of slope on which the property is located, and distance to significant wildfire fuel loads such as forest or brush. There has been very little effort by insurers to explain these scoring mechanisms or how consumers can improve these factors to lower their risk.

This lack of a clear explanation of this and other critical determinants in the property insurance underwriting and rating process is leading to increased frustration and anger by consumers, media and public policymakers outside the typical insurance regulatory community. Consumers are organizing and making their voices heard in public meetings, the media, and online, often accusing insurers of being greedy and arbitrary and regulators of being negligent in their responsibilities to the detriment of the insurance marketplace as a whole.

We urge the Task Force to provide strong and reasonable disclosure requirements for insurers to increase transparency and provide an avenue for consumers to challenge inaccurate conclusions about their risk profile, give consumers more detail about how their wildfire rating score was determined and where their score falls in the range of possible scores, and what steps they might take to mitigate their property risks.

One good example to follow is California's regulation on the Consideration of Mitigation Factors; Wildfire Risk Models at 10 CA Code of Regs 2644.9, which provides as follows:

“(h) Provision of wildfire risk score or other wildfire risk classification to policyholder or applicant.

An insurer utilizing a Wildfire Risk Model, or rating factor, to segment, create a rate differential, or surcharge the premium based upon the policyholder or applicant's wildfire risk shall, within one hundred eighty (180) days after the date this section is filed with the Secretary of State, implement a written procedure to provide, in writing, to each such policyholder or applicant for property insurance the wildfire risk score or other wildfire risk classification used by the insurer to segment, create a rate differential, or surcharge the premium based upon the policyholder or applicant's wildfire risk. The insurer shall provide to the policyholder or applicant such wildfire risk score or classification at the following times:

- (1) No later than fifteen (15) days following the submission to the insurer of the applicant's completed application;
- (2) At least forty-five (45) days prior to each renewal;

- (3) At least seventy-five (75) days prior to any nonrenewal; and
- (4) In the event that the policyholder or applicant has completed a mitigation measure on the subject property since the time of the last application to or renewal by the insurer, no later than thirty (30) days following the submission to the insurer of the policyholder or applicant's request that the insurer provide a revised wildfire risk score or wildfire risk classification.

(i) Policyholder or applicant's right to appeal.

The procedure described in subdivision (h) of this section shall permit a policyholder under, or applicant for, a policy of property insurance who disagrees with the assignment of the wildfire risk score, or other wildfire risk classification, provided to the policyholder or applicant pursuant to that subdivision the right to appeal orally or in writing that assignment directly to the insurer. The insurer shall notify the policyholder or applicant in writing of this right to appeal the wildfire risk score or other wildfire risk classification whenever such score or classification is provided to the policyholder or applicant as set forth in subdivision (h) of this section. If the policyholder or applicant appeals the wildfire risk score or other wildfire risk classification, the insurer shall acknowledge receipt of the appeal in writing within ten (10) calendar days of receipt of the appeal. The insurer shall respond to the appeal in writing with a reconsideration and decision within thirty (30) calendar days after receiving the appeal. In the event that an appeal is denied, the insurer shall, upon request by the Department, forward a copy of the appeal, and the insurer's response, to the Department."

A similar approach should be required for insurance policies and for each rating factor used by the insurer to determine premiums, as well as underwriting classifications that determine if a consumer will be rejected for coverage or nonrenewed.

Policyholders must be given the opportunity to object or correct any erroneous datapoints and at the very least understand the reasoning behind the coverage denials or premium increases.

We thank you for considering our input. Please contact us at mdelong@consumerfed.org with any questions.

Sincerely,

Michael DeLong
Research and Advocacy Associate
Consumer Federation of America
1620 I Street NW, Suite 200
Washington, DC 20006
mdelong@consumerfed.org

Brendan Bridgeland
Director
Center for Insurance Research
145 South Main Street
Haverhill, MA 01835
insuranceresearch@comcast.net

July 29, 2025

To: Kris DeFrain (NAIC)
Cc: Tim Mullen (NAIC)
Joel Laucher (United Policyholders)
From: Amy Bach (United Policyholders)
Subject: CASTF

Dear Kris,

United Policyholders appreciates this opportunity to address an issue that is becoming increasingly important to the consumers our non-profit organization serves; the accuracy of the data components insurers use to determine both eligibility for coverage *and* premiums to be charged. Thank you for soliciting our input. The following comments were prepared by Joel Laucher (a former regulator) and myself, and we're both available for further dialogue. For reference, the National Council of Insurance Legislators is currently working to [adopt a model law](#) that would give consumers access to aerial images of their properties that are being used by insurers for underwriting.

This topic is of course relevant to all insurance coverages but particularly in the property insurance context where the availability of coverage is currently plummeting across the country, while the cost of coverage for many consumers is soaring. One driver is that insurance companies are now using risk scoring systems, complex models, aerial images and mined data in place of or in addition to traditional underwriting. Yet consumers are in the dark and don't currently have access to information and processes that would allow them to correct misinformation, avoid losing their insurance and/or pay a more reasonable premium for their property coverage. We urge the Task Force to issue recommendations on appropriate disclosures and processes to remedy this developing situation.

Consumers currently have the right to get a copy of their credit report and score and see what transactions/factors are impacting their score. There is transparency and processes in place to allow a consumer to challenge a credit score that's based on incorrect or outdated information about their financial strength. By contrast, insurance consumers don't currently have access to the risk score associated with their property or what features/factors went into that score or a process for correcting misinformation, nor do consumers have access to aerial images of their property that an insurer is using as a basis for rating and/or offering them a new policy or renewing or non-renewing their existing policy or a process for correcting erroneous conclusions about conditions at their property that were derived from those images.

In the homeowners marketplace in particular, one particularly challenging concern is the use of wildfire risk models that assign scores to home based upon a set of considerations that typically include distance from a fire station, degree of slope on which the property is located, and distance to significant wildfire fuel loads such as forest or brush. We have seen very little effort by insurers to explain these scoring mechanisms.

The lack of a clear explanation of this critical determinant in the property underwriting and rating process has led to frustration and anger. Consumers are making their voices heard in the media and

online, accusing insurers of being greedy and arbitrary and regulators to be negligent in their responsibilities.

We urge the Task Force to recommend a set of reasonable requirements on insurers to be more transparent and provide a process for consumers to challenge inaccurate conclusions about their risk profile, give consumers more detail about how their wildfire rating score was determined and where their score falls in the range of possible scores.

An example or starting point can be California's regulation on the Consideration of Mitigation Factors; Wildfire Risk Models at 10 CA Code of Regs 2644.9, which provides as follows:

(h) Provision of wildfire risk score or other wildfire risk classification to policyholder or applicant.

An insurer utilizing a Wildfire Risk Model, or rating factor, to segment, create a rate differential, or surcharge the premium based upon the policyholder or applicant's wildfire risk shall, within one hundred eighty (180) days after the date this section is filed with the Secretary of State, implement a written procedure to provide, in writing, to each such policyholder or applicant for property insurance the wildfire risk score or other wildfire risk classification used by the insurer to segment, create a rate differential, or surcharge the premium based upon the policyholder or applicant's wildfire risk. The insurer shall provide to the policyholder or applicant such wildfire risk score or classification at the following times:

(1) No later than fifteen (15) days following the submission to the insurer of the applicant's completed application;

(2) At least forty-five (45) days prior to each renewal;

(3) At least seventy-five (75) days prior to any nonrenewal; and

(4) In the event that the policyholder or applicant has completed a mitigation measure on the subject property since the time of the last application to or renewal by the insurer, no later than thirty (30) days following the submission to the insurer of the policyholder or applicant's request that the insurer provide a revised wildfire risk score or wildfire risk classification.

(i) Policyholder or applicant's right to appeal.

The procedure described in subdivision (h) of this section shall permit a policyholder under, or applicant for, a policy of property insurance who disagrees with the assignment of the wildfire risk score, or other wildfire risk classification, provided to the policyholder or applicant pursuant to that subdivision the right to appeal orally or in writing that assignment directly to the insurer. The insurer shall notify the policyholder or applicant in writing of this right to appeal the wildfire risk score or other wildfire risk classification whenever such score or classification is provided to the policyholder or applicant as set forth in subdivision (h) of this section. If the policyholder or applicant appeals the wildfire risk score or other wildfire risk classification, the insurer shall acknowledge receipt of the appeal in writing within ten (10) calendar days of receipt of the appeal. The insurer shall respond to the appeal in writing with a reconsideration and decision within thirty (30) calendar days after receiving the appeal. In the event that

an appeal is denied, the insurer shall, upon request by the Department, forward a copy of the appeal, and the insurer's response, to the Department.

A similar approach should be used for every coverage and for each rating factor used by the insurer to determine the final premium and for any underwriting consideration used by the insurer that resulted in a consumer being rejected for coverage or nonrenewed.

As pointed out by Ms. DeFrain, this way, the insured would at least have the opportunity to object or correct the datapoint when the insurer has it wrong or at the very least understand the reasoning behind the increasing premium or the rejection of coverage.

Thank you for considering our input.



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