

OUR MEETING WILL BEGIN SHORTLY

WELCOME TO THE BIG DATA AND ARTIFICIAL INTELLIGENCE (H) WORKING GROUP MEETING

August 10, 2022

IN-PERSON ATTENDEES

Wi-Fi Network: NAIC2022; Password (case sensitive): Summer2022

VIRTUAL ATTENDEES

- Audio will be muted upon entry
- If virtual attendees would like to speak, please use the "Raise Hand" feature and we will let the Chair know you'd like to speak
- Enter with video on or off (your choice)
- Use the "Chat" feature for questions, comments, or assistance
- If you have joined by phone, to mute and unmute your line, press *6
- For additional help, please contact NAIC Technical Support team at MeetingTechHelp@naic.org or call (866) 874-4905

NAI 
**NATIONAL
MEETING
SUMMER 2022
PORTLAND**

**Big Data and Artificial
Intelligence (H)
Working Group**

Welcome and Call to Order
**Superintendent Elizabeth
Kelleher Dwyer (RI), Chair**

Aug. 10, 2022

Roll Call of Working Group Members

| | | | |
|---|----------------------|--------------------------------------|----------------|
| Elizabeth Kelleher Dwyer, Chair | Rhode Island | Matthew Vatter/ Phil Vigliaturo | Minnesota |
| Amy L. Beard, Co-Vice Chair | Indiana | Cynthia Amann | Missouri |
| Doug Ommen, Co-Vice Chair | Iowa | Barbara D. Richardson | Nevada |
| Adrienne A. Harris, Co-Vice Chair | New York | Christian Citarella | New Hampshire |
| Kevin Gaffney, Co-Vice Chair | Vermont | Marlene Caride | New Jersey |
| Daniel Davis/Jimmy Gunn | Alabama | Kathy Shortt | North Carolina |
| Lori K. Wing-Heier/ Katie Hegland/Sian Ng-Ashcraft | Alaska | Jon Godfread/ Chris Aufenthie | North Dakota |
| Evan G. Daniels | Arizona | Judith L. French/Lori Barron | Ohio |
| Ken Allen | California | Teresa Green | Oklahoma |
| Michael Conway/Peg Brown | Colorado | Andrew R. Stolfi | Oregon |
| Andrew N. Mais | Connecticut | Shannen Logue/ Michael McKenney | Pennsylvania |
| Frank Pyle | Delaware | Michael Wise | South Carolina |
| Karima M. Woods | District of Columbia | Travis Jordan | South Dakota |
| Rebecca Smid | Florida | Carter Lawrence | Tennessee |
| Weston Trexler | Idaho | J'ne Byckovski/Rachel Cloyd | Texas |
| Judy Mottar | Illinois | Tanji J. Northrup/ Reed Stringham | Utah |
| Satish Akula | Kentucky | Scott A. White/Eric Lowe | Virginia |
| Tom Travis | Louisiana | Eric Slavich/John Haworth | Washington |
| Benjamin Yardley | Maine | Allan L. McVey | West Virginia |
| Kathleen A. Birrane/ Robert Baron/Ron Coleman | Maryland | Nathan Houdek | Wisconsin |
| Caleb Huntington | Massachusetts | | |
| Karen Dennis | Michigan | | |

Agenda Item #1

**Collaboration Forum on Algorithmic Bias Panel:
Discuss AI Risk Management, Governance and Bias Detection**

Perspectives on AI Risk Management and Governance
Scott M. Kosnoff (Faegre Drinker Biddle & Reath)

Bias Detection Methods and Tools
Eric Krafcheck (Milliman)

NAIC Big Data and AI Working Group



Some Perspectives on AI Risk Management and Governance

Presented by:

Scott Kosnoff

Partner
Insurance
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August 10, 2022

Insurers have good reasons to invest in AI and algorithmic decision-making

- These tools can facilitate better:
 - Marketing and customer engagement
 - Underwriting
 - Rating
 - Claims decisions
 - Utilization management
 - Fraud detection



As with all new technologies, there are potential hazards

- Some regulators, policymakers and consumer advocates have expressed concerns about:
 - Fairness
 - Unintended bias/discrimination against protected classes
 - Lack of transparency/explainability
 - Privacy
- We don't know whether insurance consumers actually have been harmed or to what extent
- Nevertheless, insurers that use AI are exposed to regulatory, litigation and reputation risk



Insurers can get the benefit of AI while managing their exposure

- Organizations that use artificial intelligence or algorithmic decision-making need to stay on top of the evolving regulatory standards and have a risk management framework in place that reflects those standards.



Risk Management Challenges

- The Colorado legislation and some insurance department bulletins prohibit organizations from unintentionally discriminating against protected classes, but fundamental questions remain from a risk management perspective
 - How should bias be identified and evaluated?
 - What level of correlation with a protected class is acceptable and under what circumstances?



The Goal: Have a Good Story to Tell

- Until regulators or standard setting bodies can provide more concrete guidance, organizations that use algorithmic models to make important decisions should strive to have a good story to tell
- The story should demonstrate that the organization...
 - Appreciates the concerns associated with algorithmic decision-making;
 - Takes those concerns seriously; and
 - Is taking reasonable steps to identify, manage and mitigate the risk of negative outcomes.



Basic Risk Management Framework

- The risk management framework should be an extension of the organization's ERM and compliance programs.
 - Written policies and procedures
 - Clear assignment of responsibility and accountability
 - Communication of policies/procedures to individuals who are expected to follow them
 - Training and supervision
 - Consistent use and application
 - Monitoring and corrective action
 - Documentation



Key Elements of Policies and Procedures

- Inventory the organization's algorithms
- Understand each algorithm's objective and how it will be used
- Identify potential risks for each algorithm
- For each identified risk, assess the seriousness of the potential harm and how likely it is to occur
- Identify and implement appropriate safeguards, including humans in the loop
- Consider testing for bias



People

- Multidisciplinary team that represents multiple departments of the organization
- Diversity is critical
- Clear assignment of roles, responsibility and accountability
- Board oversight



Some Things to Think About

- Questions about the data
 - Is it complete and representative of the affected population?
 - Is it accurate?
 - Is it up to date?
 - Is it free of embedded bias?
 - Are we entitled to use it?
- Questions about the algorithm
 - Is it reliably accurate?
 - Can the results be explained?
 - Does it rely on unlawful factors (i.e., race, gender, religion) or factors that could be seen as proxies?
 - Can it morph over time?



Closing Thoughts

- Risk management efforts should be proportional to the potential harm and its likelihood of occurring
- Framework should cover every stage of the AI life cycle
 - Pre-design: data collection, curation, or selection, problem formulation, and stakeholder discussions
 - Design and development: data analysis, data cleaning, model training, and requirement analysis
 - Test and Evaluation: technical validation and verification
 - Deployment: user feedback and override, post deployment monitoring, and decommissioning



Closing Thoughts, continued

- There's no one-size-fits-all risk management framework
- Need to reevaluate the framework periodically in light of regulatory developments and evolving best practices
- No compliance program is perfect
- Remember the goal: have a good story to tell that demonstrates an understanding of the risks and reasonable efforts to mitigate them



Scott M. Kosnoff

Partner | Insurance +1 317 237 1201 | scott.kosnoff@faegredrinker.com

Trusted by industry and regulators alike, Scott helps insurance clients capitalize on opportunities and address regulatory and legal issues related to artificial intelligence, big data and algorithms.

- Working with the firm's data consulting subsidiary, Scott uses his first-hand knowledge of evolving regulatory standards to help insurers assess their algorithms for unintended bias. It's important, cutting-edge work.
- Scott helps clients implement a risk management framework and minimize their risk of regulatory, litigation and reputational exposure. Effective risk management requires more than algorithmic testing; you need a holistic, multi-disciplinary approach throughout the AI life cycle.
- Scott also helps clients stay on top of the emerging standards and regulations that will govern AI. There's a lot going on.
- At the invitation of the NAIC's executive team, Scott briefed the nation's top insurance regulators on the benefits and risks of AI at a closed-door commissioners' roundtable. He presented to the NAIC's AI Working Group at the request of the chair, helped develop the Principles on Artificial Intelligence, helped the NAIC host a special screening of *Coded Bias* and has been invited to brief the insurance regulators again later this year.



**2022 Summer National
Meeting**
PORTLAND, OR
AUGUST 9-13

Bias Detection Methods and Tools

Eric Krafcheck, FCAS, CSPA, MAAA
Principal & Consulting Actuary

August 10, 2022

About Me



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Education and Qualifications

- Fellow, Casualty Actuarial Society
- Certified Specialist in Predictive Analytics, iCAS
- Member, American Academy of Actuaries
- BS, Actuarial Science & Applied Statistics, Purdue University



Relevant experience

- Over a decade of actuarial pricing and predictive modeling experience
- Deep line of business expertise in personal auto and homeowners
- Have assisted multiple companies with collecting protected class data & disparate impact analyses



Relevant skills

- Disparate impact analysis
- Pricing applications of predictive analytics (using GLMs)
- Ratemaking & class plan development
- Filing and implementation support
- Competitive analysis

Process for Evaluating Bias in Models

| | |
|----------|-------------------------------|
| 1 | Identify Scope of Analysis |
| 2 | Select Fairness Measure(s) |
| 3 | Collect Necessary Data |
| 4 | Conduct Tests to Detect Bias |
| 5 | Mitigate Bias (if Applicable) |

Bias Detection Complications for Insurance

- Insurance centers on the concept of fair discrimination
- While differences in risk characteristics can affect claim propensity, insurance claims ultimately have a component of randomness
 - Volatility and variability inherent in data

Selecting Methodologies: Considerations

- Tools for detecting bias in models may vary based on:
 - Type of model (e.g. GLM vs machine learning methodology)
 - Model use (e.g. facial recognition vs insurance pricing)
 - Output of interest (overall model prediction vs individual variable)
 - Volume of data available (credibility)
 - Granularity of protected class data available (e.g. individual vs zip-level data)

Questions to Answer:

1. Is the model/variable being used as a proxy for a protected class?
2. Is the predictive effect consistent across protected classes?
3. Does the model disproportionately impact risks that are the same in every other way except for their protected class and the evaluated variable?
4. Does the inclusion of the variable significantly improve the model's ability to predict across protected classes?

Is the model/variable a proxy?

e.g. Control Variable Test:

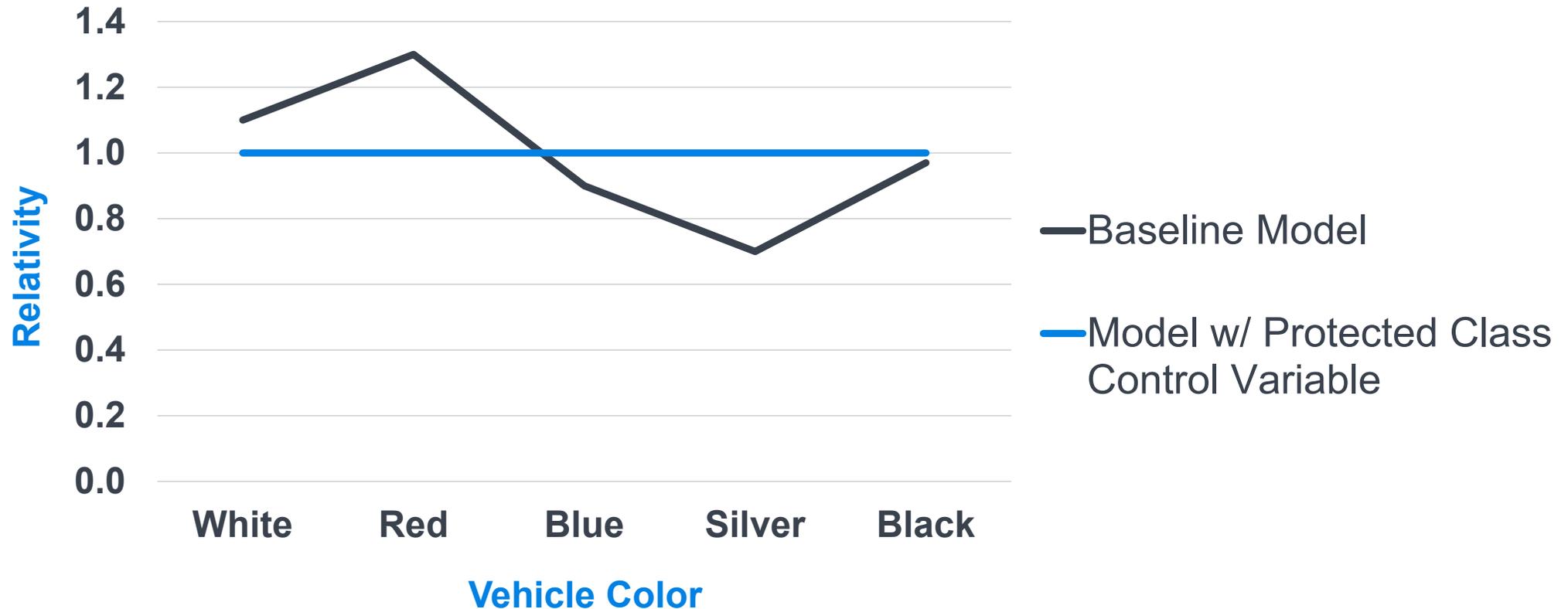
- 1) Add protected class variable as a predictor in model to account for predictive effect of the protected class.

(Goal: to the extent the protected class is correlated with other variables, let the model sort out these correlations accordingly)

- 2) Compare model parameter estimates and/or predictions before and after the protected class variable is included in the model.

Is the model/variable a proxy?

e.g. Control Variable Test:



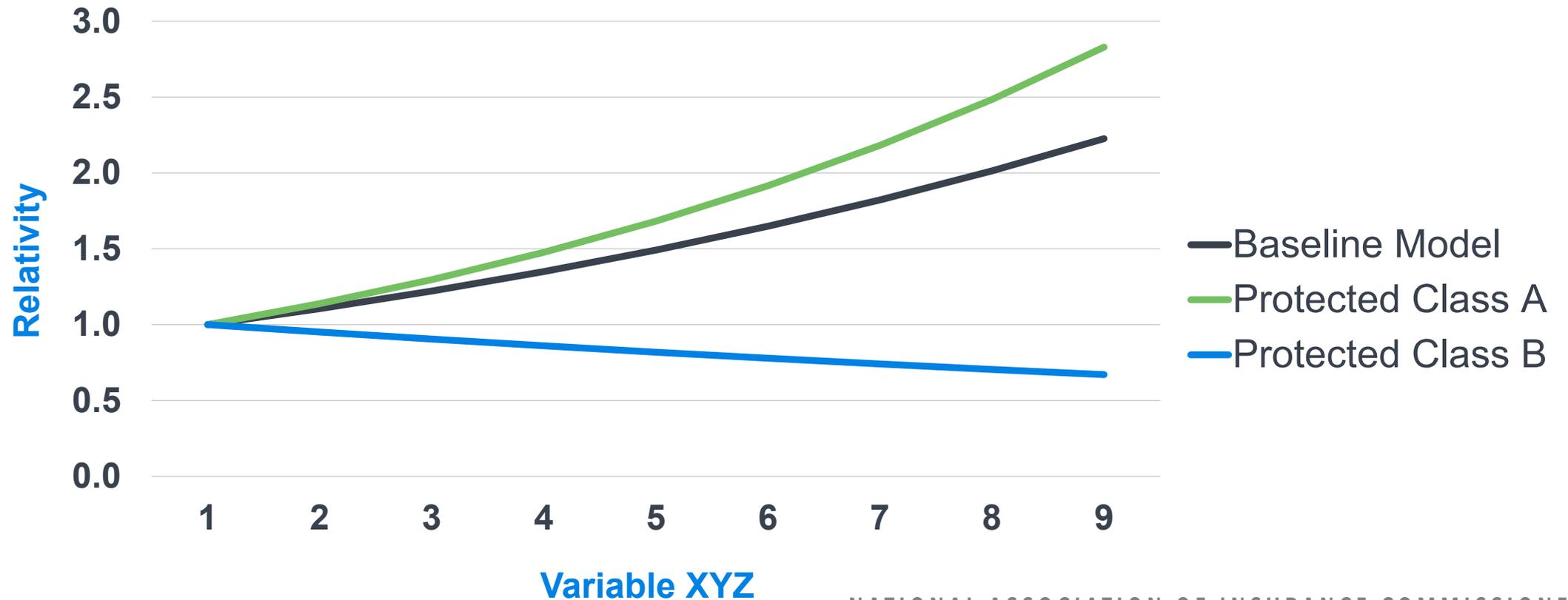
Is the predictive effect consistent across protected classes?

e.g. Interaction Test:

- 1) Add protected class variable into model as an interaction term to produce model indications for the evaluated variable for each protected class.
- 2) Compare consistency of model indications across protected classes.

Is the predictive effect consistent across protected classes?

e.g. Interaction Test:



Does the inclusion of variable disproportionately impact otherwise similar risks?

e.g. Nonparametric Matching (Matched Pairs) Test:

- 1) For every policyholder of a given protected class, match a policyholder not of the same protected class that has similar risk characteristics for all variables except for the evaluated variable.
- 2) For matched dataset from (1), compare average model predictions by protection class from model including evaluated variable and model excluding evaluated variable.

Does the inclusion of variable disproportionately impact otherwise similar risks?

e.g. Nonparametric Matching (Matched Pairs) Test:

| | Protected Class A* | Protected Class B* | Difference |
|--|--------------------|--------------------|-------------|
| Model Predicted Pure Premium <u>Including</u> Variable | \$140 | \$90 | \$50 |
| Model Predicted Pure Premium <u>Excluding</u> Variable | \$101 | \$100 | \$1 |
| Difference of Differences (\$) | | | \$49 |
| Actual Pure Premium | \$102 | \$99 | \$3 |

**Represents average predicted and actual pure premiums for matched dataset*

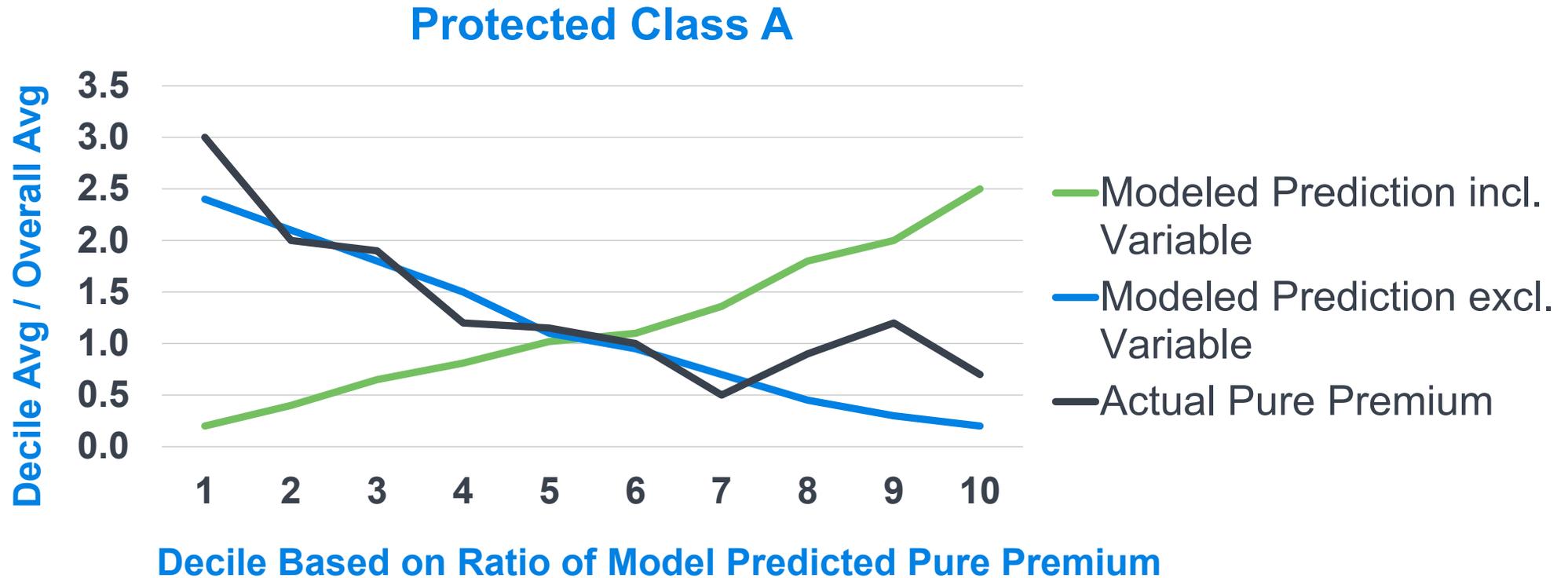
Does the variable improve predictions across protected classes?

e.g. Double Lift Chart:

For each protected class, compare model predictions when variable is included and excluded from model to assess which model better predicts the response variable.

Does the variable improve predictions across protected classes?

e.g. Double Lift Chart:



Evaluation of Results

- Evaluation of results must balance statistical and practical significance
 - Statistical Significance: Whether result of analysis occurred randomly
 - *Problem: Small differences (e.g. \$0.01) can be statistically significant with large sample sizes*
 - Practical Significance: Whether result of analysis has real-world relevance
 - *Problem: How to determine what is of value in a practical sense?*
 - *Example: Is a measured difference of \$1 material? \$10? \$100?*

Additional Considerations

- Multiple methods preferable to paint full picture
- Results of analyses may be limited by the data available
- May want to consider:
 - Intersectionality of protected classes
 - Evaluating the cumulative effect of a group of variables in addition to the evaluation of each variable individually
- Uncertainty / variability of results due to limited data

Questions?

Thank You!

Eric Krafcheck, FCAS, CSPA, MAAA
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Agenda Item #2

Consider Adoption of July 14 Minutes

Agenda Item #3

Receive Reports from Workstreams

- 1. Artificial Intelligence AI/ML Survey Work**
- 2. Third Party Data and Model Vendors**
 - 3. Available Tools and Resources**
- 4. Regulatory Framework/Governance**

Agenda Item #4

Discuss Any Other Matters

Agenda Item #5

Adjournment