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TO: District of Columbia Department of Insurance, Securities and Banking (DISB)
1050 First Street NE, Suite 801, Washington, DC 20002

FROM: Center for Critical Internet Inquiry, University of California.

SUBJECT: June 29, 2022 Hearing on gathering data related to unintentional bias in private passenger automobile insurance

SUBMISSION DATE: July 6, 2022

Thank you Commissioner Karima M. Woods of the District of Columbia Department of Insurance, Securities and Banking (DISB) for calling to order the June 29, 2022 hearing on gathering data related to unintentional bias in private passenger automobile insurance. We are honored to submit written testimony on behalf of this topic.

My name is Akina Younge and I am the Director of Policy at the Center for Critical Internet Inquiry (C2i2). C2i2 is a critical internet studies community committed to reimagining technology, championing racial justice, and strengthening civil rights in the digital age through research, culture, and public policy. Our community includes dozens of scholars, advocates, activists, thought-leaders, and more.

While our work hopes to be generative, imaginative, and future thinking, we know we cannot fully get to the work of thinking forward until we have addressed past and present harms. In our work, we have consistently seen how data is used in ways that reinforce systemic racism. We have seen how the default use of technology and data further erode our civil rights and deepen inequality along lines of race and class. The automobile insurance industry is one of the worst culprits in this system of encoding inequality.

In your hearing announcement, you state that the purpose of the hearing is to gather public input as DISB creates a process to collect data to "evaluate **whether** [*emphasis added*] there is any unintentional bias in private passenger automobile insurance rating or underwriting." Let us resolve this for you – unintentional bias in private passenger automobile insurance rating and underwriting is happening. It's not a question of whether it's happening, but understanding how bad the bias is, understanding who is harmed and how. The answers to these questions will inform what DISB can do next to redress and repair these harms and prevent them from happening in the future.

We know that this unintentional bias is happening in the automobile insurance marketplace because we know that data and algorithms are not neutral. The development, creation, and capture of data and subsequent decisions on how it is used and implemented in decision systems is value-laden (1, 2, 3, 4). People make decisions at every moment about what data should be collected, how information should be labeled and categorized. For example, in the automobile insurance marketplace, subjective decisions are made about what data defines a good driver or a risky driver. Data also reflects the history of policies and practices that have come before it. For example, in the automobile insurance marketplace, variables like zip code, credit scores, and even number of tickets and violations are embedded with the biases of our country's history of racist policing and ticketing practices, redlining, and systemic income inequality. It is no surprise then that study (5) after study (6), investigative report (7) after investigative report (8) have shown that bias exists in automobile insurance pricing against people of color and low-income people.

We know that this bias is real from the stories of people affected by the bias today. The bias is so deep, historical, and context specific that to give a technical solution like "de-biasing" the data or algorithm would only be a temporary, superficial solution (9, 10). Yes, we can make datasets that are aware of the historical racist policies that affect the underlying data (11). Yes, we can make algorithms that are intentionally race aware in order to yield equitable results (12, 13). These are improvements, but insufficient alone. The goal must be to design for social good, racial justice, and redress not only in the technical aspects, but in the surrounding policies that govern data and algorithms. We need wrap-around policies that put the data and algorithms into the context of how they impact everyday people and how they are part of a larger system.

Policies that put the algorithms and data into context and empower affected communities are essential for using data and algorithms in ways that promote racial justice and equity. We support policies that require algorithms to be transparent and explainable without oversimplifications and abstractions to the people they are affecting (14). If an algorithm is so complicated that it cannot be explained to the people whose lives are impacted by the algorithm without significant abstractions, then perhaps that algorithm should not be used. Even if that algorithm is more "accurate" based on the test data from its development, no predictive algorithm can be fully

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1 Noble, Safiya Umoja, "Algorithms of Oppression: How Search Engines Reinforce Racism," NYU Press (February 2018).
2 Benjamin, Ruha, "Race After Technology: Abolitionist Tools for the New Jim Code," Polity (2019).
3 Browne, Simone, "Dark Matters: On the Surveillance of Blackness," Duke University Press (October 2015).
4 Costanza-Chock, Sasha, "Design Justice: Community-Led Practices to Build the Worlds We Need," The MIT Press (March 2020).
5 Feltner, Tom Feltner and Douglas Heller, "High Price of Mandatory Auto Insurance in Predominantly African American Communities," Consumer Federation of America (November 2015).
6 Ong, Paul M. and Michael A. Stoll, "Redlining or risk? A spatial analysis of auto insurance rates in Los Angeles," Journal of Policy Analysis and Management (September 7, 2007)
7 Angwin, Julia, and Jeff Larson, Lauren Kirchner and Surya Mattu, "Minority Neighborhoods Pay Higher Car Insurance Premiums Than White Areas With the Same Risk," ProPublica (April 5, 2017).
8 "Effects of Varying Education Level and Job Status on Online Auto Insurance Price Quotes," Consumer Reports (January, 2021).
9 Julia Powles, "The Seductive Diversion of 'Solving' Bias in Artificial Intelligence." (December 7, 2018)
10 Hanna, Alex and Emily Denton, Razvan Amironesei, Andrew Smart, Hilary Nicole, "Lines of Sight," Logic (December 20, 2020).
11 For example, the work of the Data Nutrition Label project tries to evaluate data sets and give them a nutrition label that gives information about their context, use, and potential use. The nutrition labels for the datasets can also include alerts for potential harm when the dataset is used in certain contexts on certain communities.
12 Kim, Pauline, "Race-Aware Algorithms: Fairness, Nondiscrimination and Affirmative Action," SSRN; California Law Review, Forthcoming; Washington University in St. Louis Legal Studies Research Paper No. 22-01-02, (January 26, 2022)
13 Davis, Jenny L. and Apryl Williams, Michael W. Yang, "Algorithmic reparations." (October 4, 2021)
14 Ananny, Mike and Kate Crawford, "Seeing without knowing: Limitations of the transparency ideal and its application to algorithmic accountability." (2016)

accurate. The trade off of increasing tested accuracy while decreasing understandability of the algorithm to directly affected communities is not worth it. We are already psychologically predisposed to believe that an algorithm's prediction is correct (15). Having an algorithm that is so complex that its explanation is abstract leaves people impacted by the algorithm or people using the algorithm even more powerless to see potential problems and demand improvements.

We also support policies that require algorithms to show people the determination it made for the individual alongside community level determinations. Showing people their individual determinations is insufficient for algorithmic accountability. By showing people just their individual determinations, we isolate individuals, preventing our ability to see the impact data and algorithms are having across our communities. The individual determinations also can reinforce the logic of "deserving" and "undeserving." Because only seeing an individual determination means we do not see ourselves in context and because we often have trouble recognizing algorithmic errors to begin with, we assume the algorithms decision is correct and reflects on our individual worthiness. Providing only individual determinations makes it harder for people to come together to hold decision makers and algorithm designers accountable.

A final and essential policy for putting algorithms and data into context and empowering affected communities is to create reparation funds (16). Policies already exist to hold companies accountable if they are found to be discriminating against any protected classes. As governments begin to apply these policies to companies' use of algorithmic decision making systems, we recommend that monetary penalties be levied and put into a reparations fund. This fund can be used for direct payments to people who have been discriminated against and for projects that redistribute power and resources to communities that have historically been discriminated against. We also encourage local governments to consider putting money directly into these reparation funds from their own revenue bases. Governments have historically been a part of or complicit in policy making that has led to discrimination against protected classes, long before these more complex and ubiquitous algorithmic decision making systems existed.

These policies coupled with your work at DISB to uncover the depth of discrimination in automated automobile insurance pricing is what is needed. Our world is increasingly seeing the use of automated decision systems, algorithms, and data dependency. We must continually review and investigate these systems and put into place wrap-around policies that put these systems into a context of community accountability. In so doing, we can fight back against default designs that – intentionally or unintentionally – reinforce the systems of oppression and inequality that hold us back.

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15 Green, Ben and Yiling Chen. "The Principles and Limits of Algorithm-in-the-Loop Decision Making," Proceedings of the ACM on Human-Computer Interaction Volume. 3, CSCW, Article 50 (November 2019).
16 This idea builds on the idea of a media reparations fund by Media 2070.