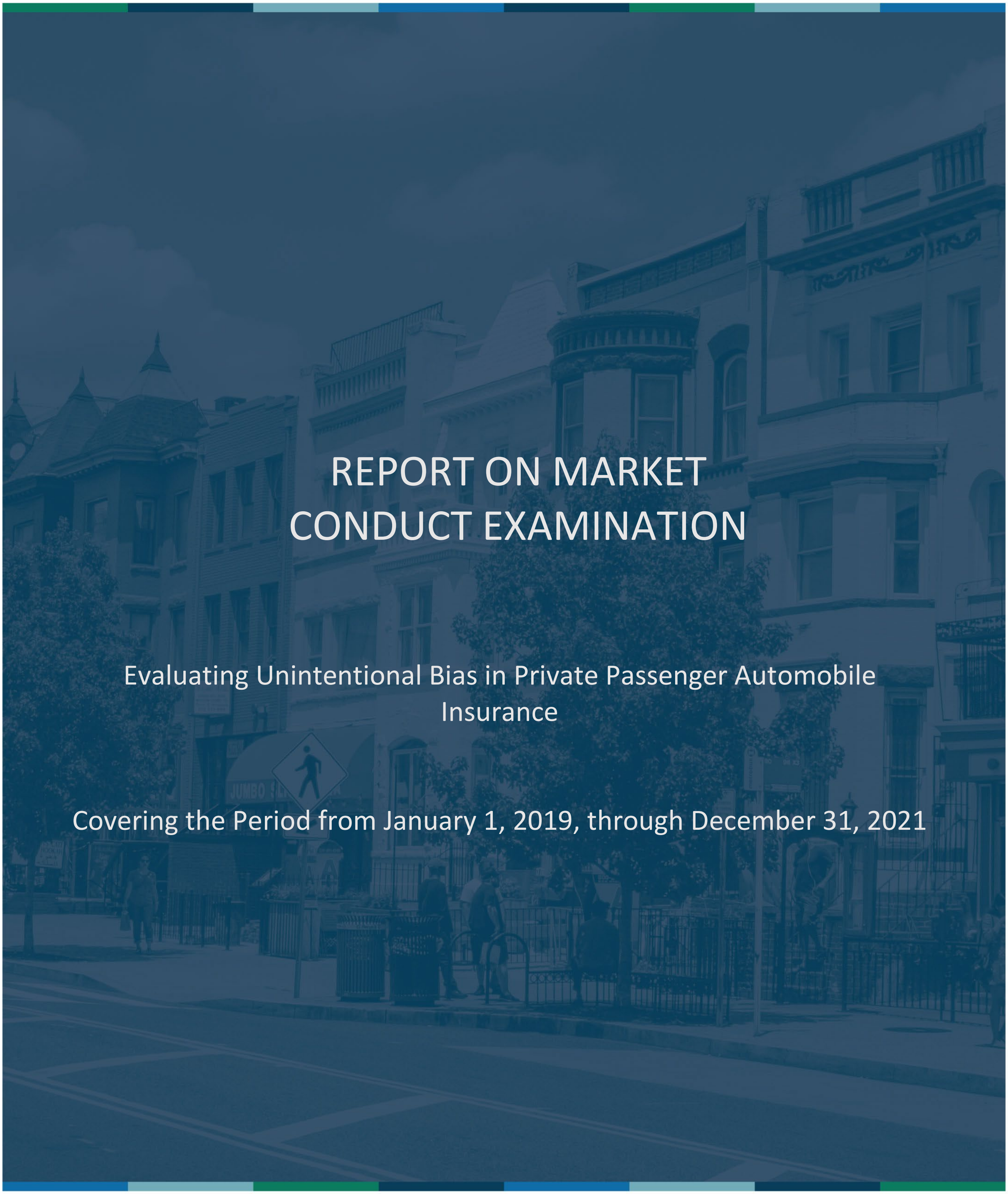
DC DEPARTMENT OF INSURANCE, SECURITIES AND BANKING



# REPORT ON MARKET CONDUCT EXAMINATION

## Evaluating Unintentional Bias in Private Passenger Automobile Insurance

Covering the Period from January 1, 2019, through December 31, 2021

DISB | WE ARE WASHINGTON DC GOVERNMENT OF THE DISTRICT OF COLUMBIA
MURIEL BOWSER, MAYOR

# Contents

## Background

In 2020, Commissioner Karima Woods, Commissioner for the District of Columbia Department of Insurance, Securities and Banking (DISB), directed the creation of DISB's first Diversity, Equity, and Inclusion Committee to engage in a wide-ranging review of financial equity and inclusion and to make recommendations to remove barriers to accessing financial services. DISB staff developed draft initiatives, including an initiative related to insurers' use of factors such as credit scores, education, occupation, home ownership and marital status in underwriting and ratemaking. Stakeholder feedback on this draft initiative resulted in DISB concluding that data was necessary to properly address this initiative. DISB staff conducted research and contacted subject matter experts before determining that relevant data was not generally available.

DISB undertook this project to collect the relevant data. DISB determined this initiative will be deliberative and transparent to ensure the resultant data would address the issue of unintentional bias. DISB also decided to initially focus on private passenger automobile insurance, as that line of insurance affects many District consumers, and DISB's staff have questioned insurers' use of non-driving factors in their rating and underwriting practices.

For this project looking at the potential for unintentional bias in auto insurance, DISB conducted a review of auto insurers' rating and underwriting methodologies. As a first step, DISB held a public hearing on Wednesday, June 29, 2022, to gather stakeholder input on the review plan. DISB engaged the services of O'Neil Risk Consulting and Algorithmic Auditing (ORCAA) to assist and provide subject matter expertise. Additionally, DISB held follow up meetings with industry and consumer representatives to address any items requiring additional information and provided exposures for public comment. Finally, DISB staff reached out to subject matter experts during the conduct of this examination to address specific issues. You can find all details of meetings, exposures and comments on our website — disb.dc.gov/page/evaluating-unintentional-bias-private-passenger-automobile-insurance.

### *Motivation*

DISB wanted to explore whether the use of certain information by auto insurers in the application and underwriting process may cause unintentional harm to those who are Black, indigenous, people of color, or belong to another protected class of Washington, DC consumers. Examples of such information that may be considered proxies for race include: credit scores, education, home ownership, occupation, and marital status.

This analysis builds off of earlier work undertaken by DISB. Previous work included a market conduct examination that looked at specific insurers' models used for auto insurance. From that examination, DISB concluded the models reviewed were working as intended and did not include any factors that would directly introduce bias into the rating process. However, the review could not determine if unintentional bias was present.

All private passenger automobile insurance rates are reviewed and approved by DISB actuaries to our statutory standard that the rates not be excessive, inadequate, or unfairly discriminatory. That includes the rates analyzed as part of this examination. This examination looked at those rates using methodologies that have been developed more recently to evaluate potential bias in the use of algorithms.

### *Approach*

DISB investigated these concerns by reviewing recent applications for auto insurance from consumers who reside in Washington, DC.

The review required all carriers writing private passenger auto policies in the District of Columbia to submit data from recent applications to DISB for testing through a data call. This report is based on a review of the data in aggregate. The elements of the data call were developed based on input at a public hearing and appropriate follow up.

The central purpose of these tests was to measure differences in underwriting decisions or pricing between applicants of different races or ethnicities. At this stage, DISB is not looking to determine which pricing or rating criteria might be introducing unintentional bias into the rates, but rather could the differences in premiums be explained by looking at factors that are not considered reflective of unintentional bias. The list of factors was developed by DISB based on input from our July 19, 2022 request for comments.

Since insurance carriers do not collect information about applicants' races or ethnicities, this information was inferred for the limited purpose of the testing in this review. ORCAA used the Bayesian-improved firstname surname geocoding (BIFSG) methodology to infer the race of policyholders, and applied it to call insurers in the same way. Appendix A of the report provides additional information about the BIFSG methodology.

### *Additional comments*

DISB did not require detailed information about carriers' underwriting or pricing models, such as a description of the models' structures, lists of variables used, and their weights. The focus was on the outcomes of these models.

The analysis relied on data provided by the examined insurers. Some data was excluded if elements necessary for the analysis were missing or corrupted. Neither DISB nor ORCAA audited the underlying data for accuracy or completeness.

DISB did not have sufficient information to evaluate one of the identified rating factors (vehicle make and model) and recognize that individual companies may have additional rating factors that are not reflective of unintentional bias and companies vary in the way factors are used in developing rates.

## Executive Summary

Through the data call, insurers provided data on car insurance premiums in the Washington, DC area for one-vehicle/one-driver policies, inferring race with the BIFSG methodology[1]. For reference, one-vehicle/one-driver policies represent 64% of all auto insurance policies in the District and 54% of aggregate premium.[2]

The examination found that inferred Black drivers pay 1.46 times as much as inferred white drivers, whereas inferred Hispanic drivers pay 1.20 times as much, and inferred Asian drivers pay 1.02 times as much. In dollar terms, that translates into the average annual premium of $705 for white drivers, $1,031 for Black drivers, $849 for Hispanic drivers, and $722 for Asian drivers. This will be referred to as a "Black/white premium gap" of $326.

The examination also looked into cumulative paid losses by race, and found that Black drivers, as a group, represented more claims on average than white, Hispanic, or Asian drivers. In fact, Black drivers' average losses were 2.38 times that of white drivers. From the actuarial perspective, this means Black drivers are less profitable as a group than the other groups, because although their premiums are high (relative to white drivers), their losses are even higher (relative to white drivers).

In undertaking this analysis, however, DISB did not to expect the exact same premiums for different race groups. Rather, DISB sought to identify causal factors that could legitimately explain the premium differences, and specifically the Black/white premium difference. For example, the agency looked at age, type of policy, driving record, claim history, gender, and many others factors to determine if and how those factors impact premiums. When accounting for all these factors, however, there was still an unexplained gap of $271 between Black and white drivers.

This study demonstrates that the aforementioned factors identified by DISB as having a causal relationship to losses do not fully explain the Black/white premium race gap. After including all the factors from the data call, there is still a significant difference in Black/white premiums. What, then, is the cause of the Black/white premium gap? Auto insurance companies are prohibited from using race or geographic data explicitly. Given there is nevertheless a demonstrable difference in premiums by race, there are legitimate concerns that insurers may be using other characteristics correlated with race and/or geography in determining premiums. For example, credit-based insurance scores, used by some auto insurance companies in the District, may be correlated with race.[3] Discounts, like home ownership discounts, can be correlated with both class and race.[4] Even so, the differences in premiums may not be

[1] See Appendix A for a discussion of this methodology.
[2] We did a preliminary review of premiums for multi-vehicle/multi-driver policies. Average premiums were about 50% higher overall than for one-vehicle/one-driver policies ($1,313 vs $884), which makes sense given that these policies have more exposures. Importantly, the distribution of average premium by race was similar to one-vehicle/one-driver policies.
[3] See Credit-Based Insurance Scores: Impacts on consumers of automobile insurance, FTC 2007, especially Figures 8 and 9
[4] E.g., "Homeownership is profoundly stratified by race and ethnicity, as is health. Approximately 74% of White households own their homes, compared to only 45% of Black and Latino households (U.S. Census Bureau 2013)." from Finnigan R. Racial and ethnic stratification in the relationship between homeownership and self-rated health. Soc Sci Med. 2014 Aug; 115:72-81. doi: 10.1016/j.socscimed.2014.06.019. Epub 2014 Jun 13. PMID: 24953499; PMCID: PMC4301401.

explainable by these additional causal factors. Unfortunately, because such data was not collected, this study could not analyze that information. Nevertheless, DISB concludes some of the factors that are correlated with losses but have no reasonable explanatory basis for losses may be introducing unintentional bias into the premium determination. The use of those additional factors should be subject to additional review to evaluate how they impact Black/white premium differentials.

On such opportunity for further analysis: at a recent Congressional hearing,[5] Mr. Robert Gordon, Senior Vice President, American Property and Casualty Insurance Association (APCIA) indicated the APCIA has studies showing a direct connection between credit scores and actual hard braking and hard acceleration driving behavior. Gordon also indicated they have studies showing credit scores are not discriminatory, but DISB believes the referenced study does not look at the racial impact of credit scores on insurance premiums. DISB believes that hard braking and hard acceleration are legitimate causal factors for insured losses and would not limit their use. However, when a proxy for hard braking and hard acceleration is used, the insurer should also be required to demonstrate how their proxy is applied in such a way it does not add to the Black/white premium gap.

## Background on This Study

DISB engaged ORCAA in connection with the work of its Diversity Equity and Inclusion Committee, as described above. ORCAA's dual mission is to help define accountability for algorithms, and to keep people safe from harmful consequences of AI and automated systems. Whether it's a hiring algorithm, healthcare AI, predictive scoring system, or generative AI platform, ORCAA thinks about how it could fail, for whom, and what can be done to monitor and mitigate these risks. Cathy O'Neil, CEO of ORCAA, has been an independent data science consultant since 2012 and has worked for clients including the Illinois Attorney General's Office and Consumer Reports. She wrote the book *Doing Data Science* in 2013 and *Weapons of Math Destruction: How Big Data Increases Inequality And Threatens Democracy*, released in September 2016. ORCAA's prior work in insurance includes assisting the Colorado Division of Insurance with implementation of SB21-169 — Protecting Consumers from Unfair Discrimination in Insurance Practices.

Following input submitted by stakeholders in writing and at a June 29, 2022, public hearing, DISB published a memo[6] further explaining its plans for this review and requesting comments. The memo includes a preliminary list of outcomes to be studied (Quoted prices; Underwriting decisions; Premiums; Loss ratio)[7] and a preliminary list of factors that DISB believes could legitimately explain differences across race groups in these outcomes.

Throughout the process, a wide range of stakeholders including insurers, regulators, consumer

[5] The Factors Influencing the High Cost of Insurance for Consumers, Thursday, November 2, 2023 2:00 PM, Subcommittee on Housing and Insurance at approximately 1:51 (available at: financialservices.house.gov/calendar/eventsingle.aspx?EventID=409012:).

[6] disb.dc.gov/sites/default/files/dc/sites/disb/page_content/attachments/request-comment-unintentional-bias-auto-insurance.pdf

[7] This report highlights the analysis of Premium, as price paid is a highly salient outcome for consumers, and the data provided on this outcome was relatively complete and commensurable across carriers. Data on Losses was also incorporated, as discussed in Sections 3 and 5. The data received on Quotes was noisier, but generally consistent with Premiums; it is discussed in Appendix B. While data on Underwriting decisions was collected in the data call, DISB determined the information was covered by the Quote and Premium analysis, in the sense that ratings and classifications are reflected in the prices consumers see and pay.

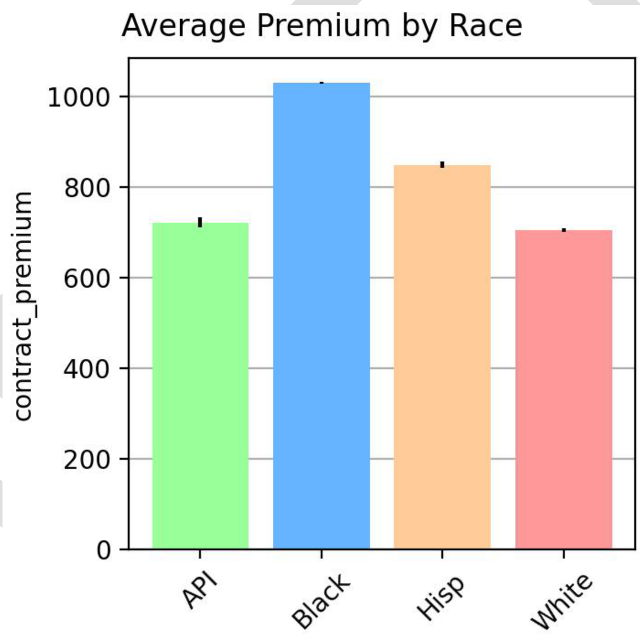
advocates, and professional organizations provided input and answered questions that strengthened this study. We acknowledge and appreciate their assistance.

The sections below describe the work performed by ORCAA to evaluate the data. DISB and ORCAA staff met weekly throughout the analysis and DISB staff provided input into the analysis process throughout the review.

## 1. Premium Gap by Race

After narrowing the dataset to one-vehicle/one-driver policies, and applying BIFSG to infer the "most likely race" of the insured, ORCAA studied average premiums by race and made the following graph:

**CHART 1**




The average annual premium is $705 for white drivers, $1,031 for Black drivers, $849 for Hispanic drivers, and $722 for Asian drivers. This shows a "Black/white premium gap" of $326.

## 2. Premium Compared to Losses, by Race[8]

ORCAA computed the overall losses by race and noted that on average, Black policyholders pay more in premium compared to white policyholders — a factor of 1.39 — but generate 2.4 times the losses, on average. That means Black drivers as a group have a higher loss ratio (note this loss calculation only includes pay-out to the insured and does not include operational costs for the insurers):

**TABLE 1**

[8] This analysis could only be conducted on a subset of the data because (1) some carriers submitted data to DISB in a format that did not permit linkage of claims data with premium amounts; and (2) policies written after 2020 were excluded from the analysis since their claims experience is relatively immature. The analysis in this section comprises 237,595 policies from 2019-2020 – a subset of the policies in the previous section's analysis of premiums.

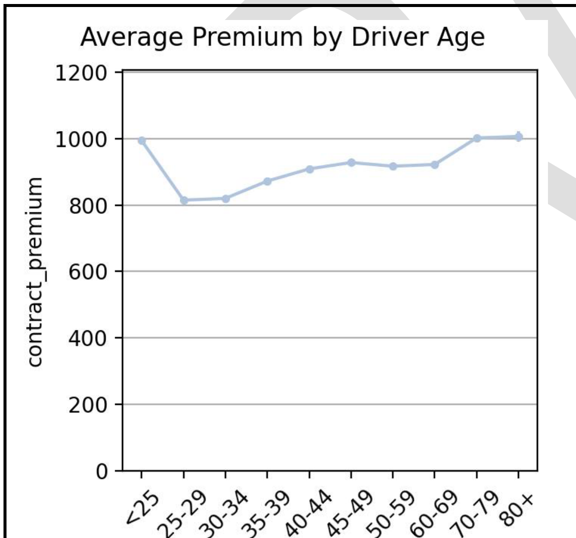
| inferred_race | Avg Premium ($) | Avg Loss ($) | Loss/Premium |
|---|---|---|---|
| API | 734.54 | 279.76 | 0.38 |
| Black | 1024.42 | 611.54 | 0.60 |
| Hisp | 858.82 | 370.32 | 0.43 |
| White | 709.96 | 256.49 | 0.36 |

## 3. Explanatory Factors

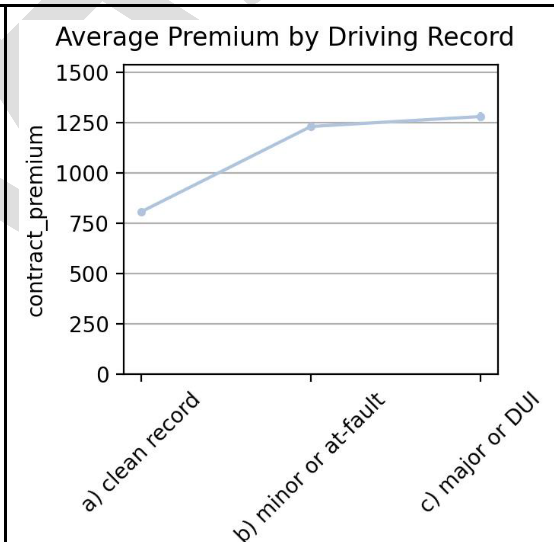
DISB and ORCAA looked for explanations for why premiums were higher for Black drivers. The method is shown here for four of the factors we investigated: age of policyholder, driving record of policy holder, gender, and age of vehicle. Appendix C includes a full list of factors we investigated.[9]

First, ORCAA takes a given factor and groups its values (into "bins") then looks at the average premium within each bin:

**CHARTS 2-5**

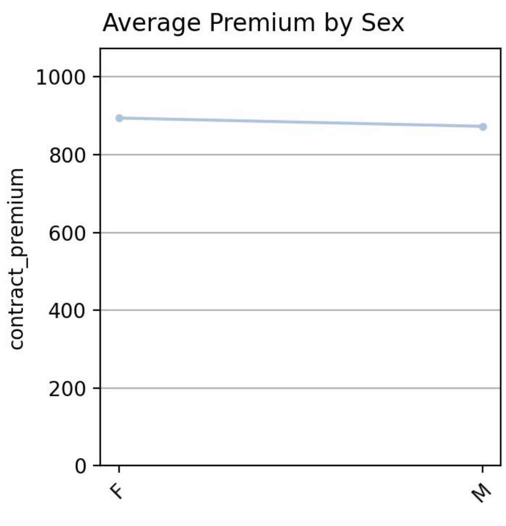



Except for the youngest drivers, younger drivers are less expensive

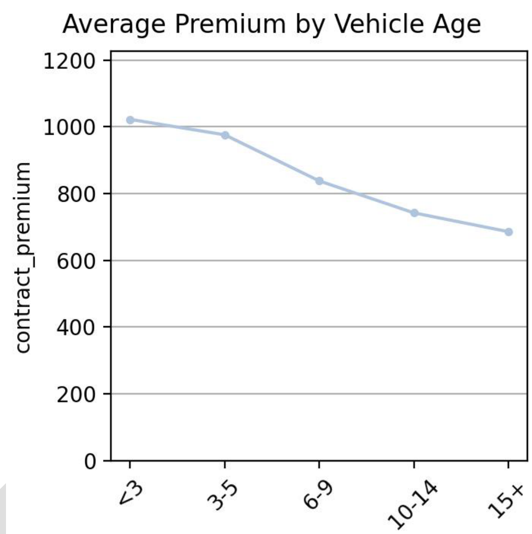



Prior incidents on driving records are associated with higher premiums, as expected

[9] DC does not allow territorial ratings; so, territory is not an explanatory factor in this analysis.



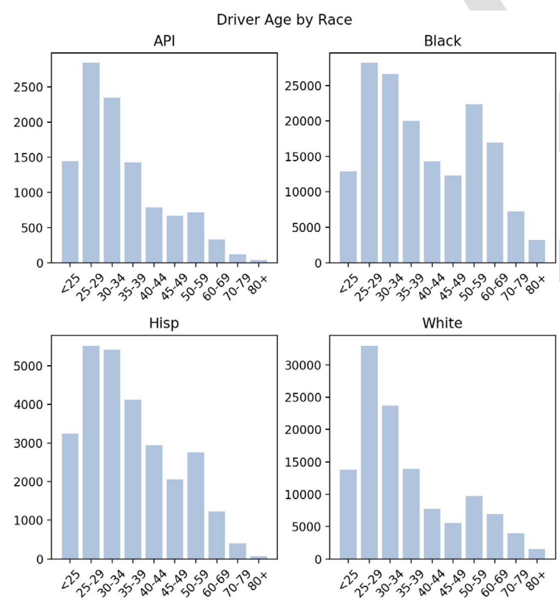

Premium does not vary much by sex.[10]



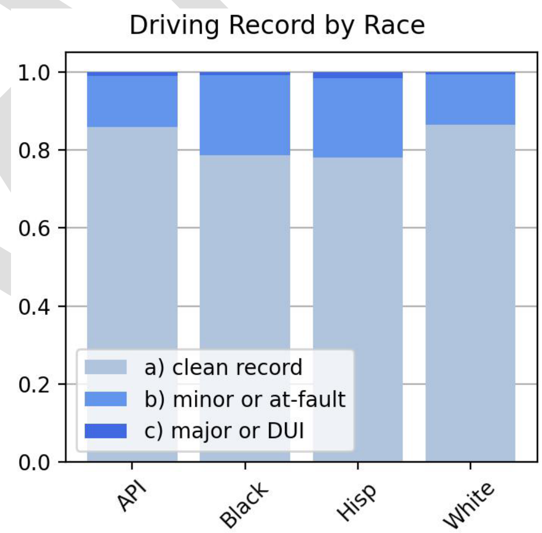

As expected, insurance costs are lower for older vehicles.

Next, ORCAA looked at the distribution of these factors by race:

**CHARTS 6-9**

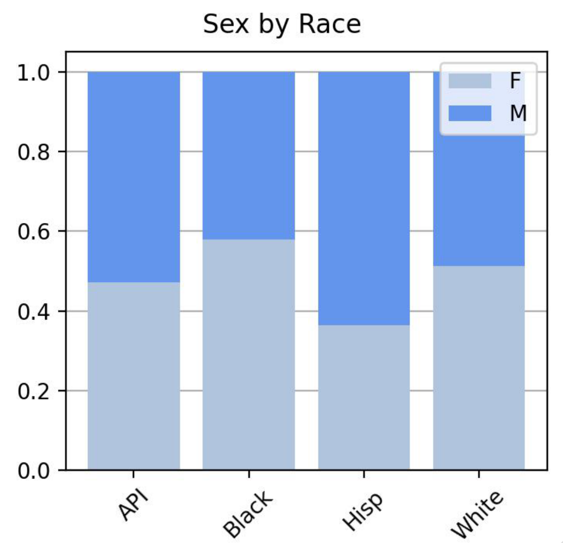



There are relatively more older Black drivers.

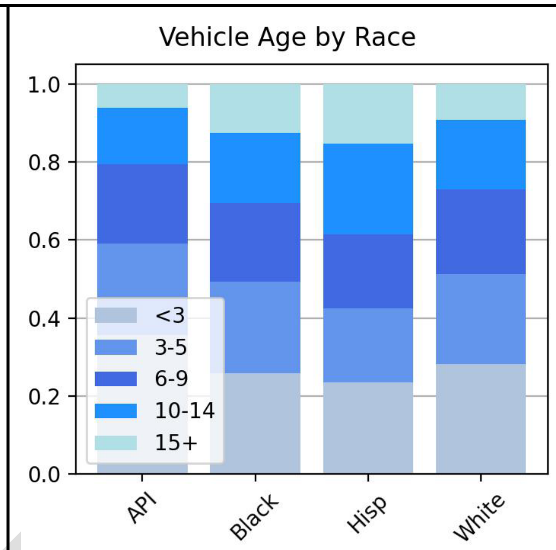



Black and Hispanic drivers have more minor or at-fault accidents.

[10] [10] F/M are the standard gender identity data points currently collected by insurers.



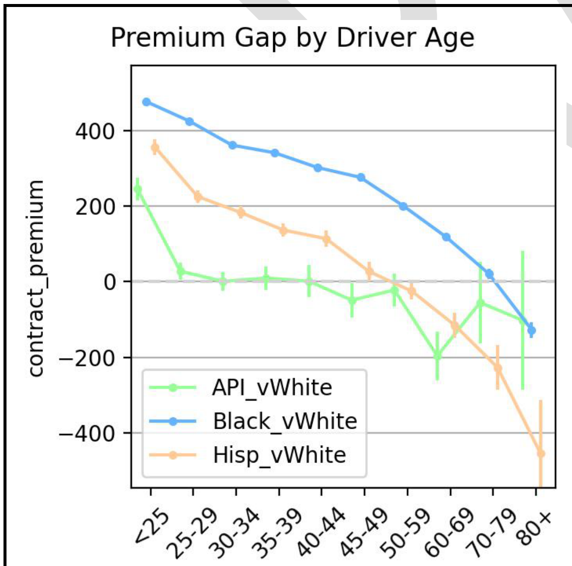

Black, white, and Asian and Pacific Islander (API) have similar M/F splits; Hispanic drivers are more male.



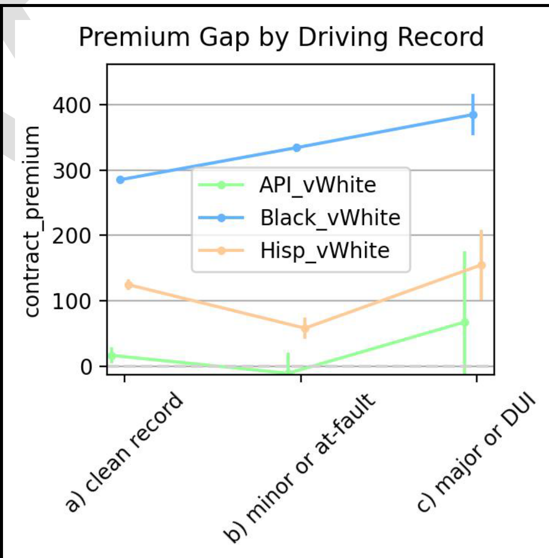

Vehicle ages are similar for Black and white, slightly older for Hispanic, and newer for API

Third, ORCAA looked at how rates vary by race across these factors individually, which is to say we see if the factors are "explaining" the race gap. Note that these are the premium gap relative to what white policyholders pay in the same bin, so we are seeing the amount non-white drivers pay *relative* to white drivers:

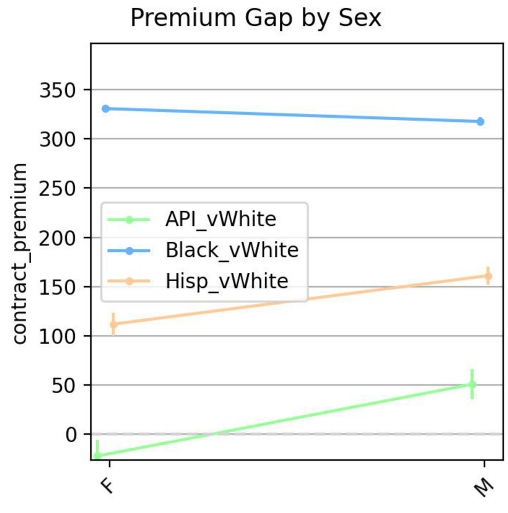
**CHARTS 10-13**



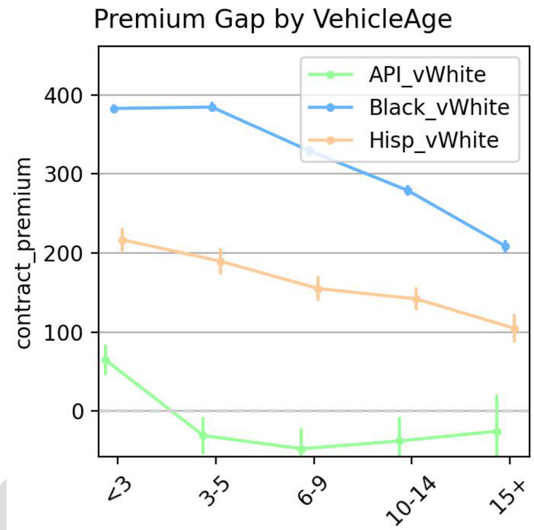

The gap disappears as people get older




The Black/white gap increases with severity of driving record



Black/white premium gap varies little across sex



The gap decreases with vehicle age

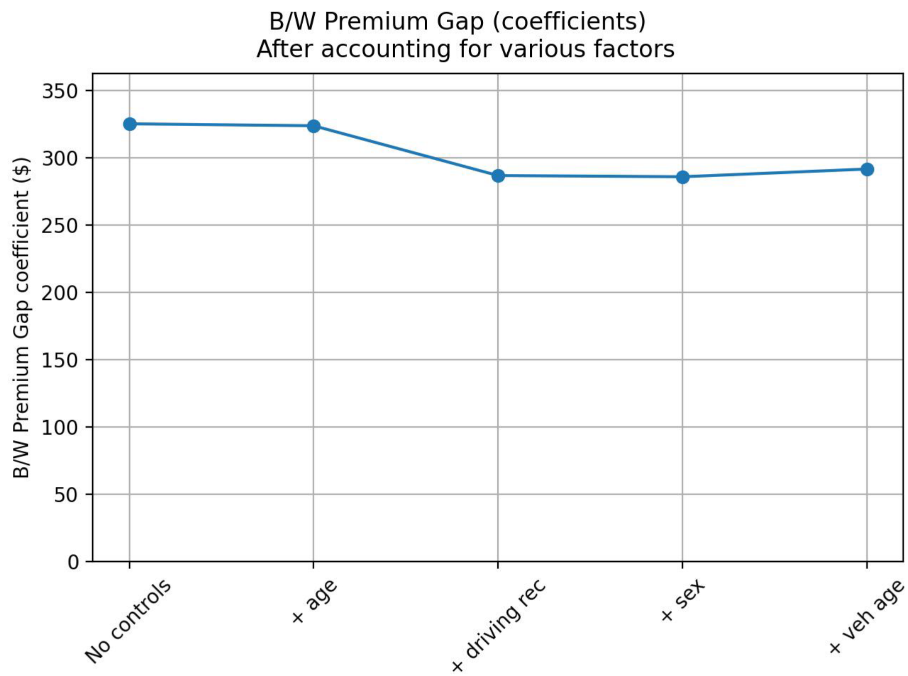
From the above examples, we can conclude that the driving record will "explain" some of the Black/white race gap in premiums, because we see more at-fault accidents for Black drivers *and* those policies tend to be more expensive. Indeed, we see that the gap is highest for policy holders that have a DUI in their record.

On the other hand, given the above picture we don't expect to see much "explanation" of the Black/white race gap in premiums due to the age of the driver or the age of the car.

The final step is to account for the above four factors and see how much the Black/white race gap in premiums is diminished.[11] Therefore, consider the following graph:

**CHART 14**

[11] See Appendix D for the methodology used here.




In other words, the Black/white gap in premiums has gone from $325 to $295 once we account for age of driver, driving record, payment type, and age of car.

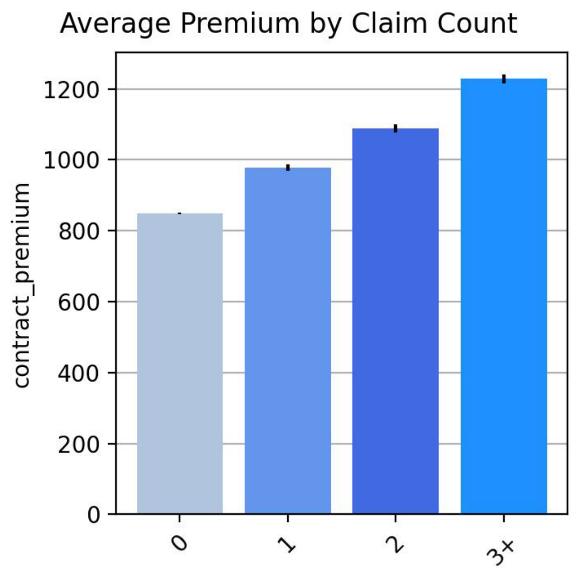
Appendix C includes a similar graph for the full set of explanatory factors we considered (adding marital status, coverage limits, policy year, new car, and prior lapse in coverage). Note: DISB did not collect data on the value of vehicles, so we could not take this into account. The Black/white gap in premiums after accounting for all these factors is $271.

## 4. Relationship of Premium to Claims and Losses

This report treats claims as an explanatory factor separately, for two reasons. First, while, ideally, DISB would have three prior years of a given driver's claims experience leading up to a given policy premium, but unfortunately only had claims data from the same three years that there was premium data (2019-2021). Also, DISB could not track a given driver across insurers, so if a driver's prior claims were with a different insurer, DISB could not see them. Claims data is statistically very different from the other kinds of factors considered here, in that it is both sparse (85% of drivers have no claims) and fat-tailed (the claims vary in size tremendously).

Even so, DISB learned some important things by looking at the claims data available. First, DISB looked at how premiums vary by the number of claims a policyholder has (note these claims occurred *during* the policy period, i.e., after the associated contract premium was set):

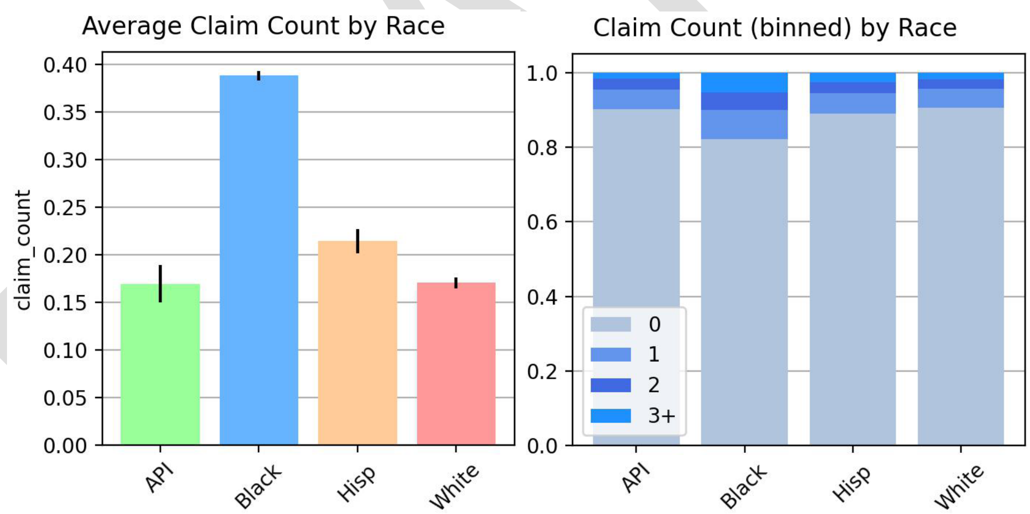
**CHART 15**




Customers who went on to file more claims were charged higher premiums.

Next, we look at the average number of claims by race:

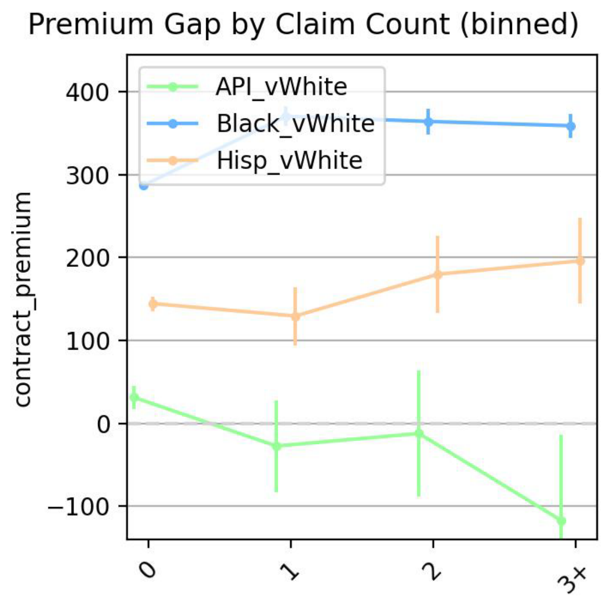
**CHARTS 16-17**




Black drivers have more than twice as many claims as white drivers on average (left), though most drivers of all races have no claims (right)

Third, we look at how the premium gaps vary with the number of claims:

**CHART 18**




The gap is bigger as soon as one claim arises.

As noted, DISB lacks sufficient information about "previous claims" for drivers, such that this report cannot conclude that claims do not explain the race gap. To make that conclusion would require a causal model, allowing DISB to predict the premium next period based on the premium this period and the count of claims this period. In fact, DISB did this with the (limited) data on hand, and found that the expected difference in next-period premium between policies that had claims this period and policies that had none is typically about $30 per claim.[12] Even though Black policyholders have over twice as many claims on average as white policyholders, the overall incidence of claims is low: in every race group, >80% of drivers have no claims. This $30-per-claim next-period premium difference, which applies to only a small fraction of policyholders, could not explain very much of the overall premium gap of $271.

## 5. What Does Explain the Premium Gap? Other Factors Not in Our Data

In the data call, DISB collected the kind of explanatory factors that it felt could legitimately and causally explain differences, if they existed, in premiums between people of different race categories. There are other factors that either were not collected or not analyzed as legitimate factors that are commonly used by insurers, and which are likely responsible for sizable differences in premium rates. They include credit-based insurance scores, discounts, and payment modes.

Based on comments from stakeholders familiar with insurance pricing, these factors are all important differentiators for the makeup of premiums. Moreover, they tend to be multiplicative factors, which is to say they pile up and amount to even more cumulatively.

However, they are arguably not causally related to auto insurance claims. Credit-based insurance scores may be strong proxies for wealth and race,[13] and although they've been established as correlated to

[12] See Appendix E for more on this.
[13] See Credit-Based Insurance Scores: Impacts on consumers of automobile insurance, FTC 2007

insurance risk, it is difficult to estimate the exact impact credit-based insurance scores have on premiums. Discounts likewise are often proxies for wealth — for example, there are discounts related to homeownership or education outcomes, and "multiline" discounts that reward customers who have more assets to insure — and therefore end up being proxies for race as well, again without a satisfying causal link. Finally, payment modes are once again a proxy of wealth because they are often based on the ability to pay in advance. With premium rates in mind, that translates to white drivers being asked to pay on average $705 in advance, whereas Black drivers are being asked to pay on average $1,031 in advance. This is indeed once again an extra charge against those who can least afford it.

## 6. Reflections and Next Steps

The analysis shows there is a race gap in premiums that is not explained by the explanatory factors DISB collected in this data call and analyzed here. The race gap is mirrored — in fact, magnified — in actual losses; so, while Black drivers pay higher premiums, they represent (even) higher costs to insurers. From an actuarial perspective, this could be the end of the analysis. But if we assume the factors analyzed here are "the obvious candidates that would explain different levels of auto risk and therefore different premiums," we are left with two open questions.

1. How are insurers finding and charging these higher-cost drivers, since the obvious rating factors investigated didn't seem to explain much?
2. Why are the race disparities in claims and losses so much larger than can be explained by the factors analyzed in this data call?

In terms of next steps, in addition to any regulatory steps DISB may take, additional analyses may be considered going forward. They are:

**TABLE 2**

| | **Area for potential future review** |
|---|---|
| Quotes: Our review showed that quote price gaps by race mirror actual premium gaps by race. From this we concluded that there was not likely quote bias introduced that would be separate from premium bias. The data shows that quotes given by agents were lower than quotes through other sales channels and Black consumers are less likely to get quotes through agents. | • Analysis to determine how the sales channel explains observed premium gaps by race. |
| Premiums: Our review showed that Black and to a lesser degree Hispanic drivers paid higher premiums than white and Asian & Pacific Islander drivers. However, our analysis of losses showed even larger differentials than premiums by race. From this we concluded that a difference in premiums by race is not sufficient to establish bias. | • Analysis of individual company premium race gaps.<br>• Detailed analysis of loss data to better understand the relationships between losses, premiums, race, and rating characteristics. |

| | |
|---|---|
| Loss ratio: As discussed above, reviewing premiums relative to insurance losses is important, but there should be a reasonable expectation that the factors used to develop premiums have a stronger relationship to losses than simply correlation or, if not, the factors do not materially impact the racial gap in premiums. Our review of premiums relative to losses first looked at whether "legitimate explanatory factors" could explain the differences in premiums by race. Legitimate explanatory factors are those that DISB believes are reasonably related to the risk of loss or provide reasonable risk mitigation incentives regardless of the relationship they have with the race of the insured. We acknowledge there may be additional legitimately explanatory factors that we did not capture, or we did not have sufficient information to evaluate the explanatory impact (e.g., make and model of vehicle) and therefore did not incorporate in the analysis. | • Analysis to determine if there are additional legitimate explanatory factors.<br>• Analysis of other underwriting factors to determine whether they materially impact the premium race gap either collectively or for individual insurers. |

# Appendices

## Appendix A: BIFSG methodology for race inference

**Background**

We used the Bayesian-improved first name surname geocoding (BIFSG) methodology to infer the race of policyholders.

A forerunner of this methodology, BISG, was developed by the RAND Corporation to "help U.S. organizations produce accurate, cost-effective estimates of racial and ethnic disparities within datasets—and illuminate areas for improvement."[14] At a high level, this approach leverages U.S. Census data to guess an individual's self-reported race/ethnicity based on their name and address. The Census publishes tables on the aggregate demographics of specific geographic areas (e.g., census blocks) and common surnames. For a given address (geocoded to a census block), we can make a guess of a person's race/ethnicity, and likewise for their surname. Then Bayes' theorem[15] is applied to combine the guesses.

We note this approach generates probabilistic guesses, but a given person's self-reported race/ethnicity is a definite label. BISG will not "guess right" for every individual; but still it can be "calibrated" in the sense that if you took many individuals with a 90% probability of being Hispanic (per BISG), 90% would indeed be self-reported Hispanic.

This methodology is used by regulatory agencies in fairness analyses. For example, the CFPB has written about its use of BISG in "conducting fair lending analysis of non-mortgage credit products in both supervisory and enforcement contexts."[16]

The BIFSG methodology we used incorporates another piece of information — the individual's first name (i.e., "F" in "BIFSG") – and another application of Bayes' theorem to further refine the race/ethnicity inference. This refinement of the methodology was proposed and validated by Ioan Voicu of the U.S. Department of the Treasury, Office of the Comptroller of the Currency (OCC).[17] We follow the implementation described in his paper.

**Details of our implementation**

In our implementation of BIFSG, for each individual we obtained a vector with seven entries. Each entry is a decimal value between 0 and 1 (inclusive) and indicates the probability that the individual belongs to a certain race/ethnicity category used in the 2010 U.S. Census: Hispanic, non-Hispanic Black, non-Hispanic white, non-Hispanic Asian or Pacific Islander ("API"), non-Hispanic American Indian or Alaska Native, Multiracial, Other. These categories are mutually exclusive and collectively exhaustive, so the seven probabilities sum to one.

We took the highest value among the seven and applied the corresponding race/ethnicity label to that individual. This report focuses on the largest categories (API, Black, Hispanic, and white); the graphs and charts omit the categories non-Hispanic American Indian or Alaska Native, Multiracial, and Other, which together represent less than 1% of all data.[18]

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[14] For background, see rand.org/health-care/tools-methods/bisg.html
[15] wikipedia.org/wiki/Bayes%27_theorem
[16] files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf
[17] Ioan Voicu (2018) Using First Name Information to Improve Race and Ethnicity Classification, Statistics and Public Policy, 5:1, 1-13, DOI: 10.1080/2330443X.2018.1427012
[18] In the policies data, these 3 race/ethnicity categories comprised 6,561 out of 1,607,113 records; in the quotes

We used the federal geocoding server[19] to find the associated Census block for each customer address provided by an insurer. Geocoding was successful — i.e., a Census block was found — for 303,260 of 322,329 addresses in the data insurers submitted.



data, they comprised 24,351 out of 2,607,088 records. Both are less than 1%.

[19] API documentation available at: geocoding.geo.census.gov/geocoder/Geocoding_Services_API.pdf

## Appendix B: Quotes analysis

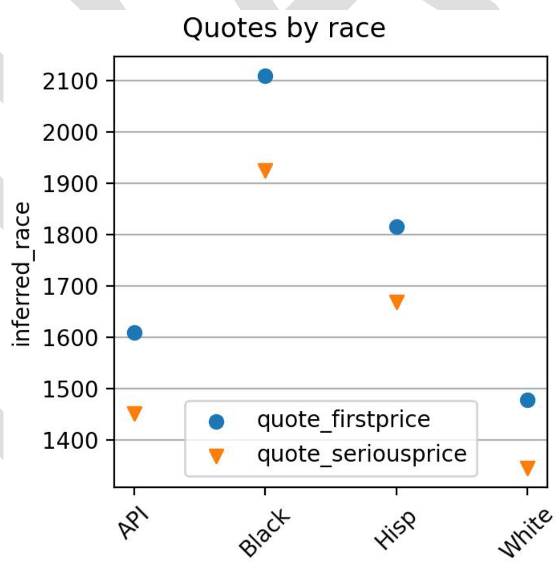
DISB's data call to carriers included a request for data on quotes for insurance coverage that were provided to consumers. Based on discussions with DISB and other stakeholders, we understand the quote process varies considerably across carriers. Different carriers may provide quotes at different junctures, through different channels, based on different information, and display the quotes in different ways.

DISB provided definitions in the data call[20] to collect comparable information from everybody. For instance, DISB defined a "serious quote" as one where the consumer's name and address were validated, a price was shown, some vendor data (e.g., motor vehicle records, credit based insurance scores (CBIS), comprehensive loss underwriting exchange (CLUE)) was pulled, and underwriting was called. Still, based on carriers' feedback we understand the data on quotes is somewhat noisy. Consequently, this analysis is preliminary.

Some key findings:

**<u>Quote prices by race mirror premium gaps</u>**
As with premiums, quotes are highest for Black consumers, lower for Hispanic consumers, and lowest for white and API consumers. For all race groups, the first price shown (quote_firstprice) is about 10% higher than the price shown when/if the quote becomes "serious" (quote_seriousprice).

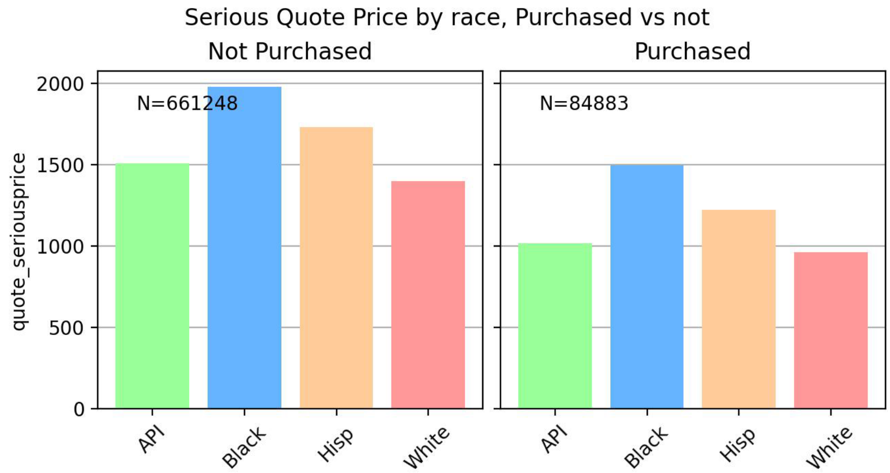
**CHART A1**




**<u>Consumers shop around</u>**
About 13% of serious quotes are purchased by consumers. Quotes that are purchased are lower on average, which is consistent with consumers shopping around for price. The pattern of race gaps is persistent across purchase.

[20] See data call tab "Quotes - Scope and definitions", rows 45 ("quote_firstprice"), 45 ("quote_serious"), and 52 ("quote_finalprice")

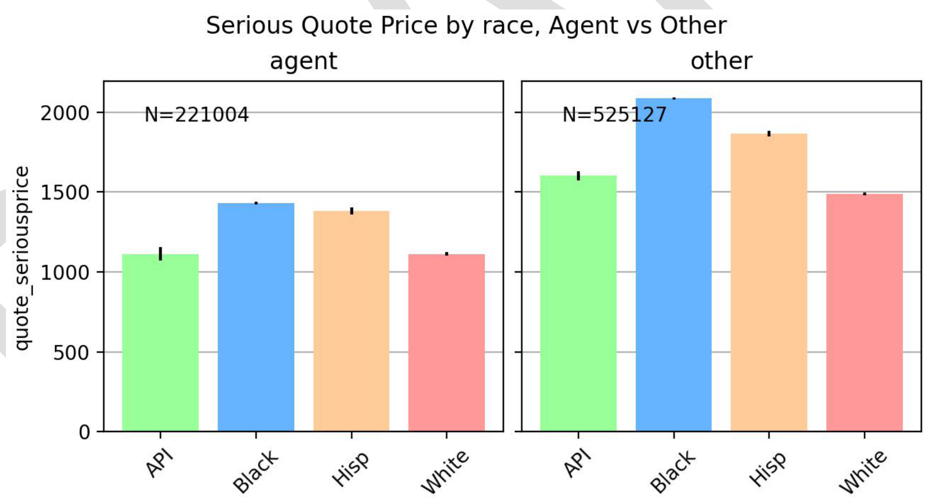
**CHARTS A2-A3**




**Quotes given by agents are lower than through other sales channels**

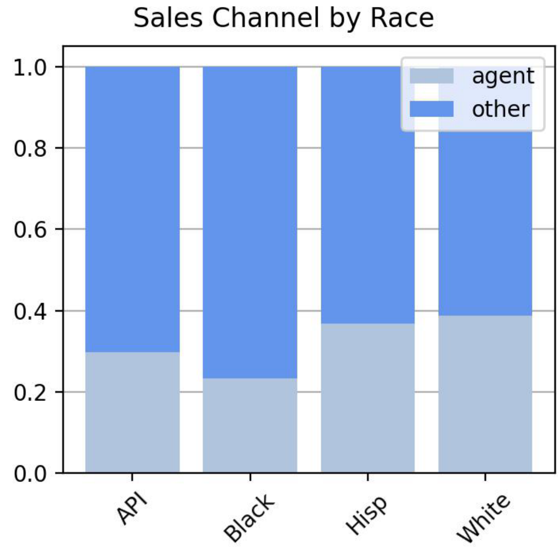
Quotes given by agents are lower on average than quotes given through other channels (e.g., online), and the race gap is smaller for quotes given by agents.

**CHARTS A4-A5**




However, Black consumers are less likely than others to get quotes through agents:

**CHART A6**




Anecdotally, some stakeholders suggested agents could be helping customers find discounts that lead to lower premiums. Future data calls by DISB could request more information about policy-level discounts to explore this issue.

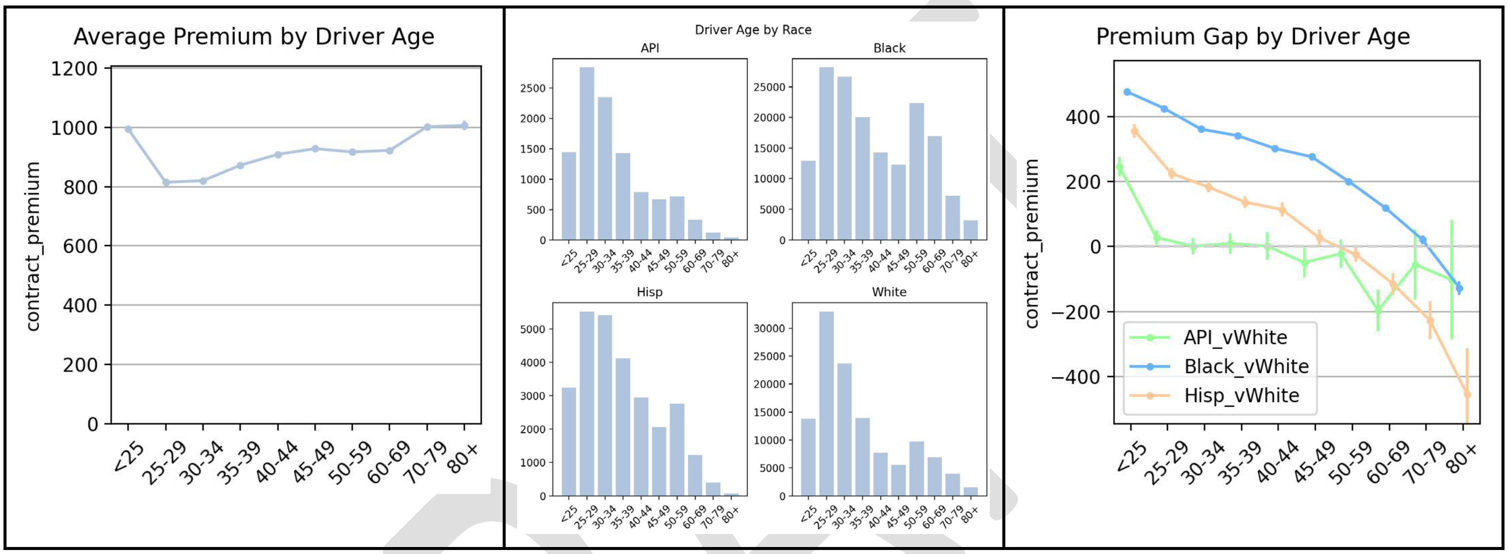
## Appendix C: Detail on explanatory factors we tried

Here is the full list of factors we analyzed as potential explainers of race differences in premium, using the analysis approach described in the "Explanatory Factors" section.

### *Driver age*

<u>Definition:</u> driver's age in years, as of the policy effective date
<u>Derivation from data call:</u> calculated as difference in years between "policy_effective_date" and "dob"

**CHARTS A7-A9**




### *Driving record*

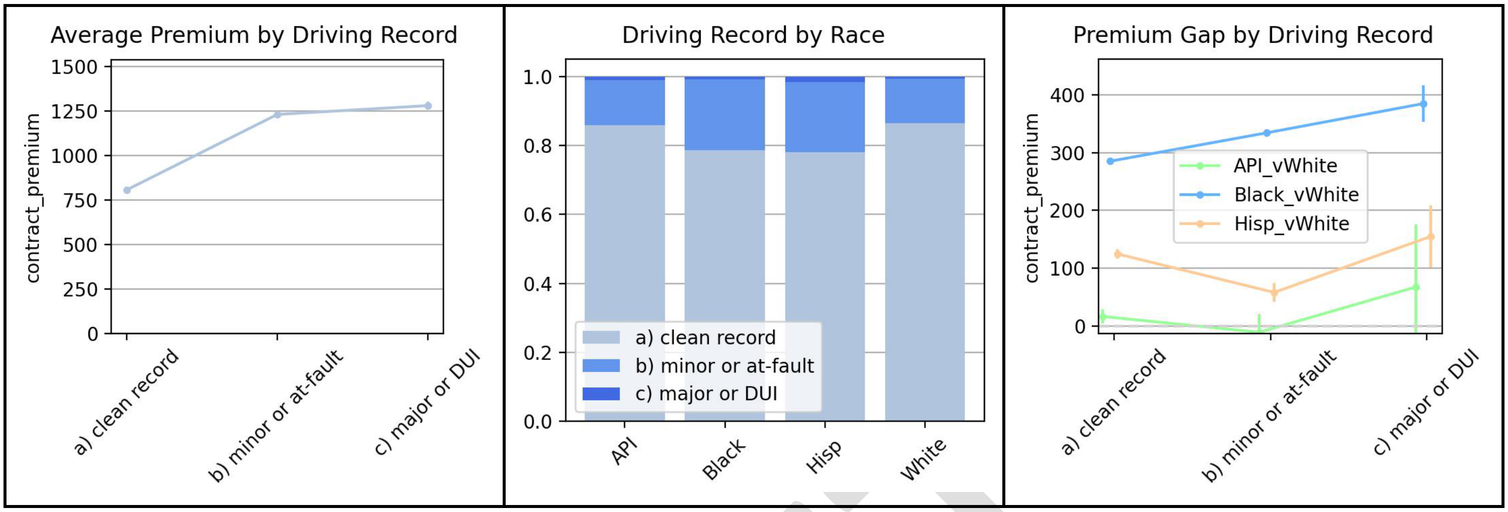
<u>Definition:</u> categorical variable

= "major or DUI" if driver has at least one major violation or DUI

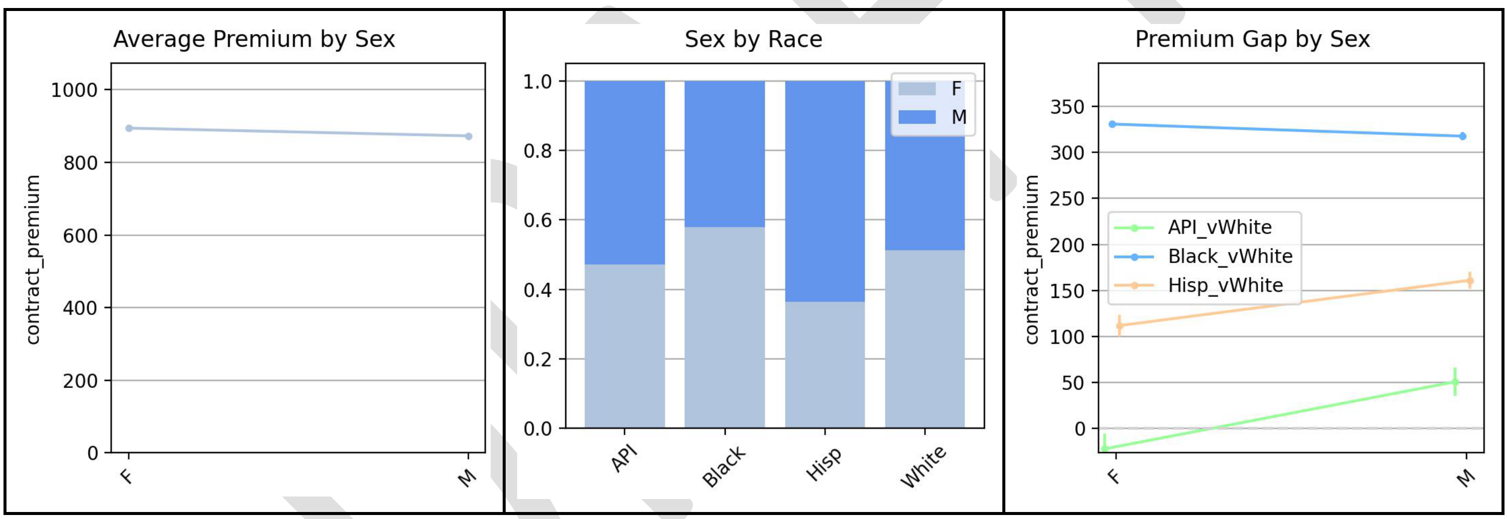
= "minor or at-fault" if driver has at least one minor violation or at-fault accident but no major violation or DUI

= "clean record" if driver has no major or minor violations or at-fault accidents or DUI

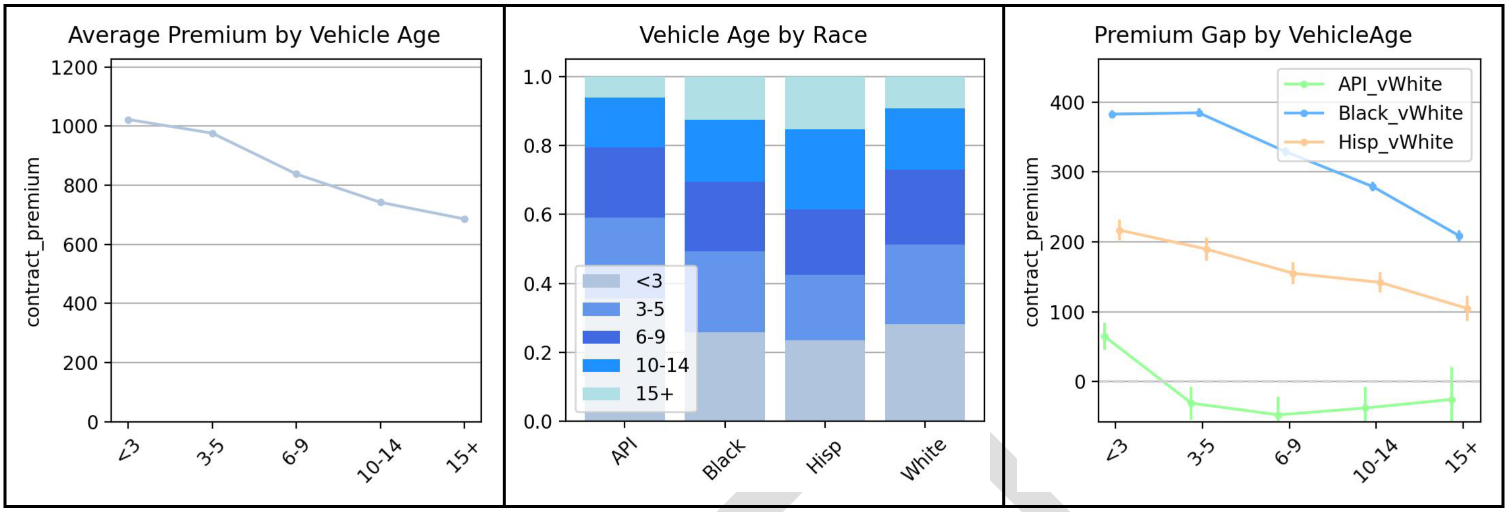
<u>Derivation from data call:</u> calculated based on "major_violations_count", "minor_violations_count", "dui_violations_count", "atfault_accident_count"




*Sex*
Definition: driver's sex
Derivation from data call: "sex"



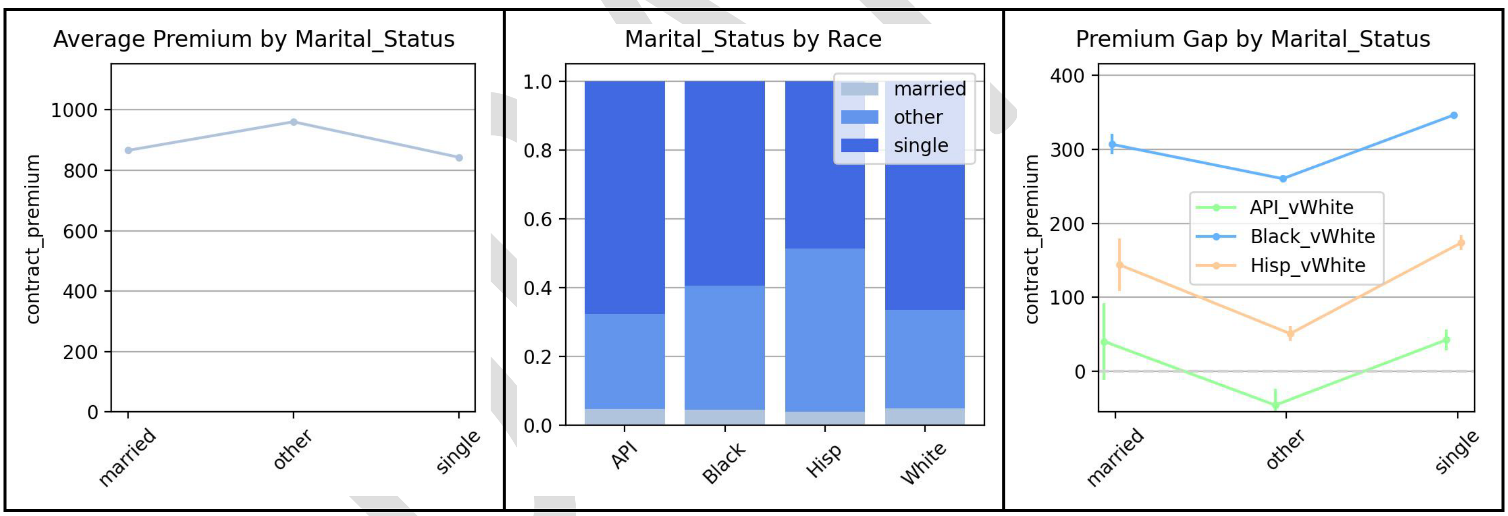

*Vehicle Age*
Definition: age of the insured vehicle in years, at the time of the policy effective date, then binned into <3, 3-5, 6-9, 10-14, 15+. Bins were chosen to divide the data relatively evenly.
Derivation from data call: calculated as the difference between the year in "policy_effective_date" and the "vehicle_year", then binned as above.




*Marital status*

Definition: driver's marital status, binned as "married", "single", or "other"

Derivation from data call: based on "marital_status"




*Coverage limits*[21]

Definition: categorical variable indicating common bundles of (bodily injury per-person, bodily injury per-incident, property damage per incident) liability coverage limits on the policy depicted

="minimums" if the limits are ($25k, $50k, $10k) [i.e., DC mandatory minimums]

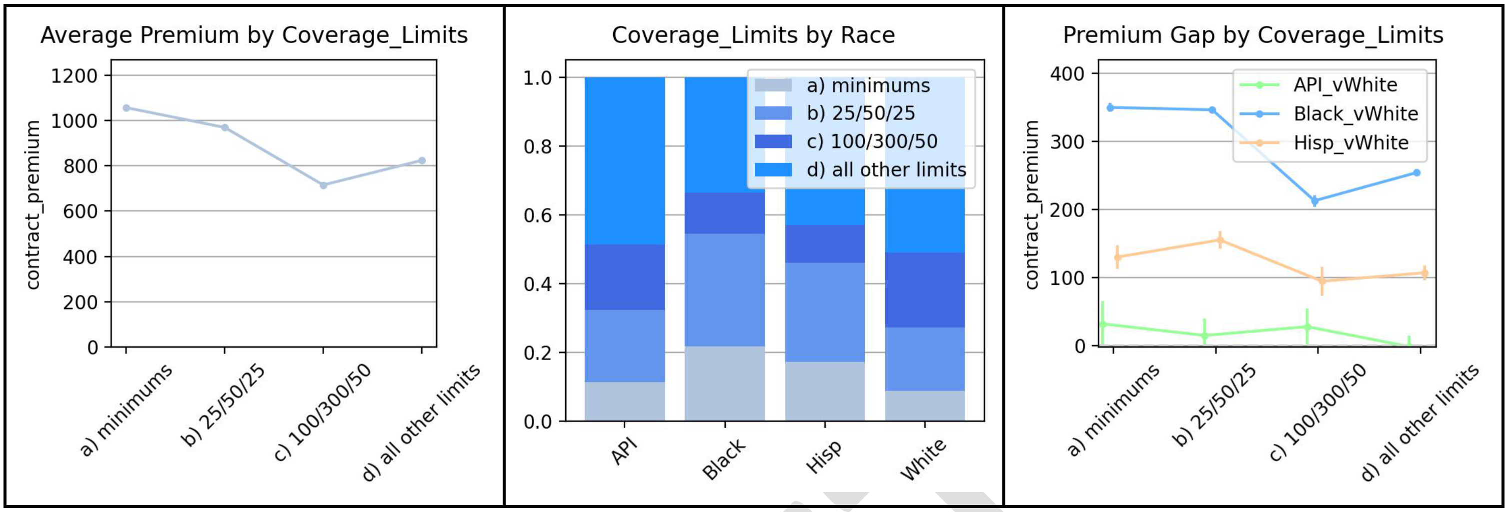
="25/50/25" if the limits are ($25k, $50k, $25k)

="100/300/50" if the limits are ($100k, $300k, $50k)

="all other limits" otherwise

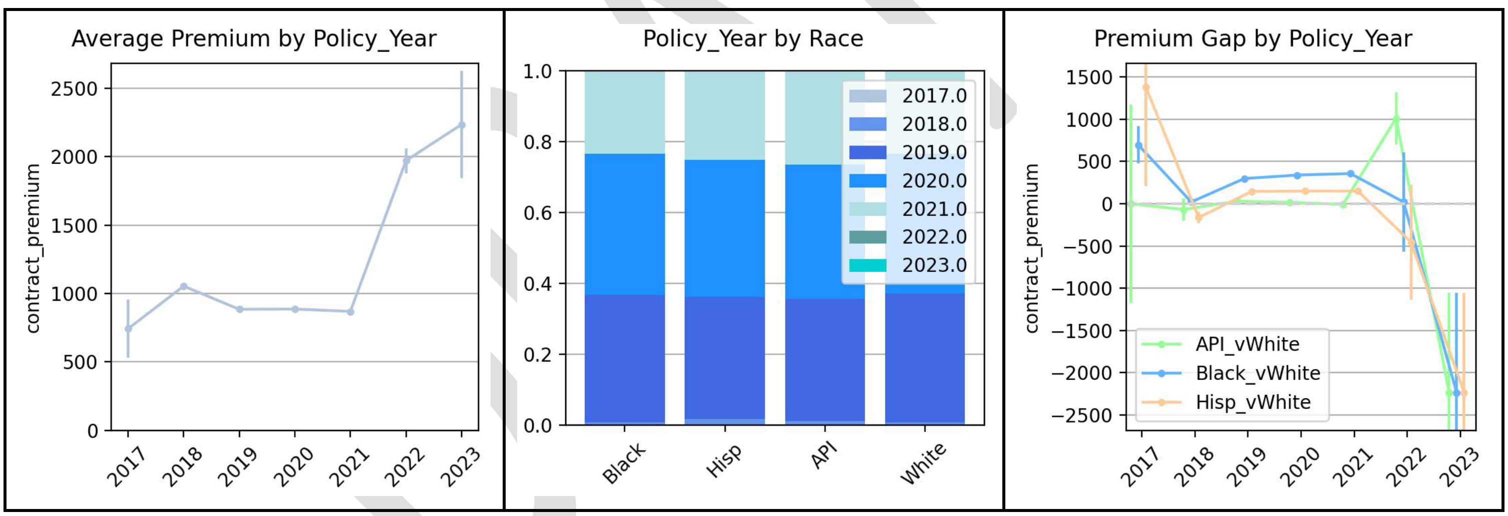
Derivation from data call: calculated from "BI_limit_perperson", "BI_limit_perincident", and "PD_limit"

[21] This explanatory factor is notably counterintuitive: minimum-limit policies cost more than higher limits. We suspect this is because the people who can only afford minimum limits are paying more for other reasons (e.g., their credit is worse, they don't own a home, they pay premium monthly rather than lump-sum).




*Policy year*

Definition: the calendar year of the effective date of the policy
Derivation from data call: calculated from “policy_effective_date”
Note: As the middle chart below shows, >95% of our data is from policy years 2019, 2020, and 2021. The extreme values of average premium and premium gap outside those years are a reflection of small data.




*New Car*

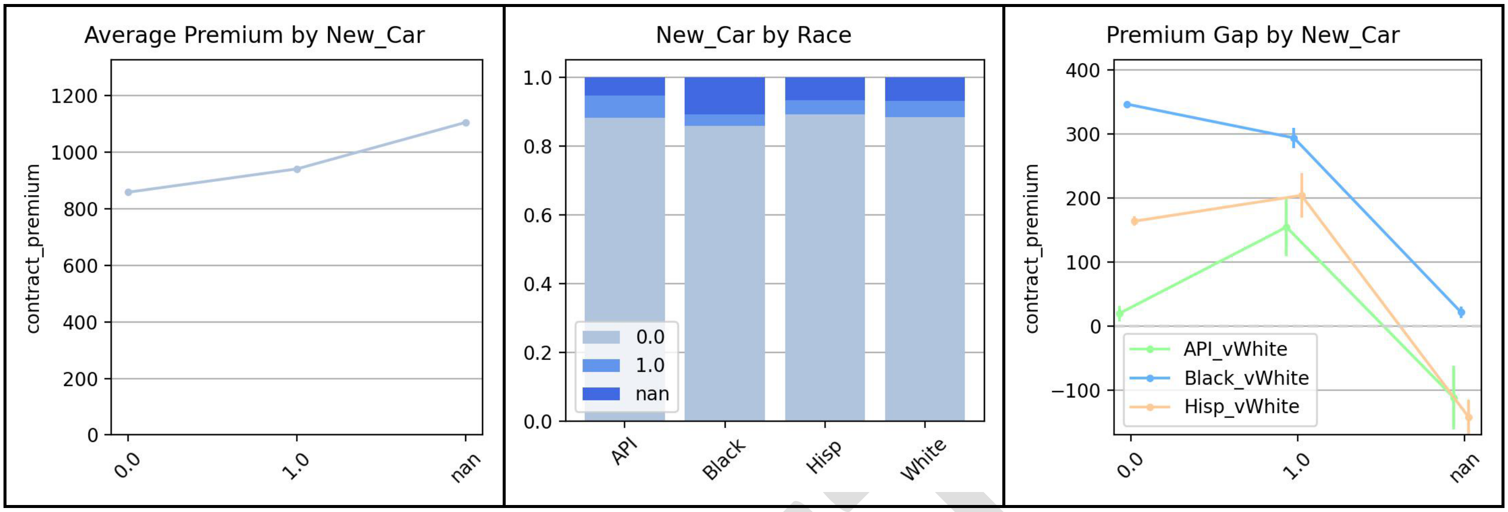
Definition: indicator variable for whether this is a new vehicle

=0.0 if the vehicleis not new

=1.0 if the vehicleis new

=nan if unknown

Derivation from data call: based on “vehicle_new”



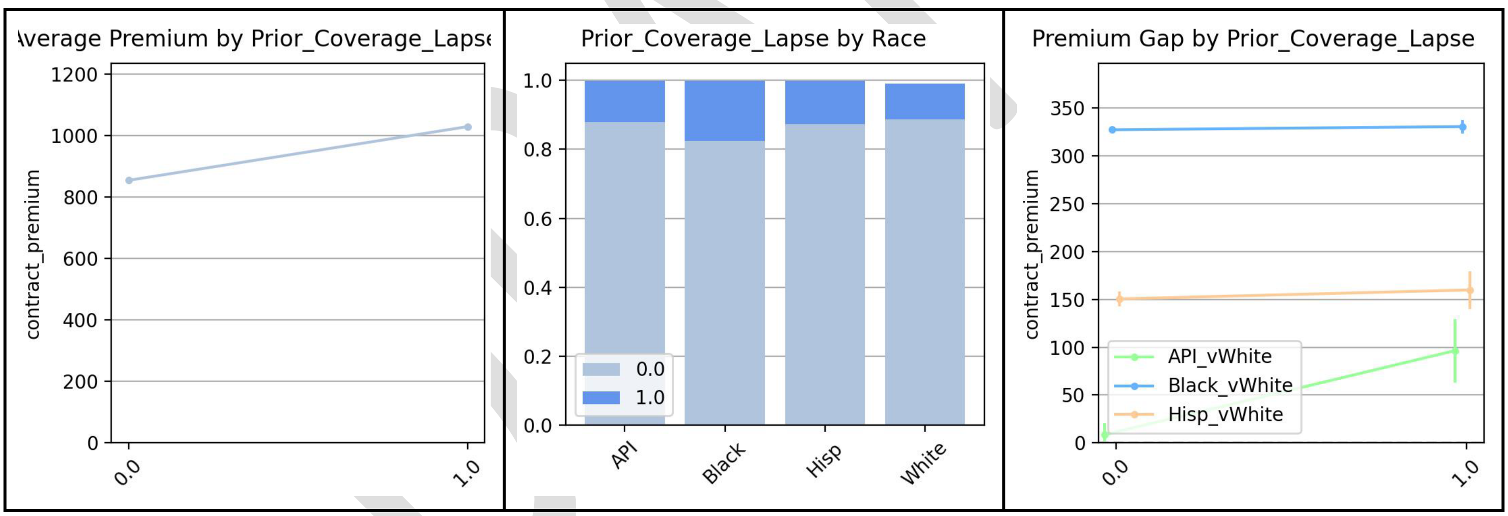

### *Prior Coverage Lapse*

Definition: indicator variable: did this driver have a prior lapse in auto coverage?

=0 if no prior lapse

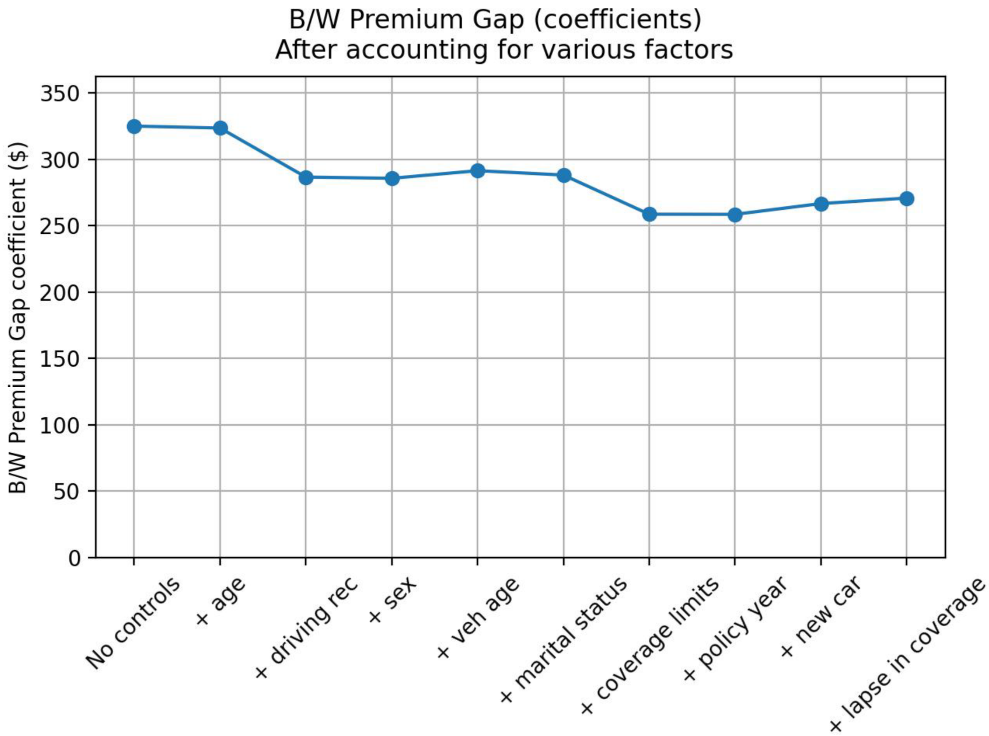
=1 if some prior lapse

Derivation from data call: based on "lapse_in_coverage"




### *Explaining the Black/white Premium Gap*

Taking all the above explanatory factors into account, the Black/white gap in premiums goes from $325 (at left) to $271 (at right). The regression methodology is explained in Appendix D.




*New vs renewal*[22]

<u>Definition:</u> categorical variable

="new" if this policy is new business

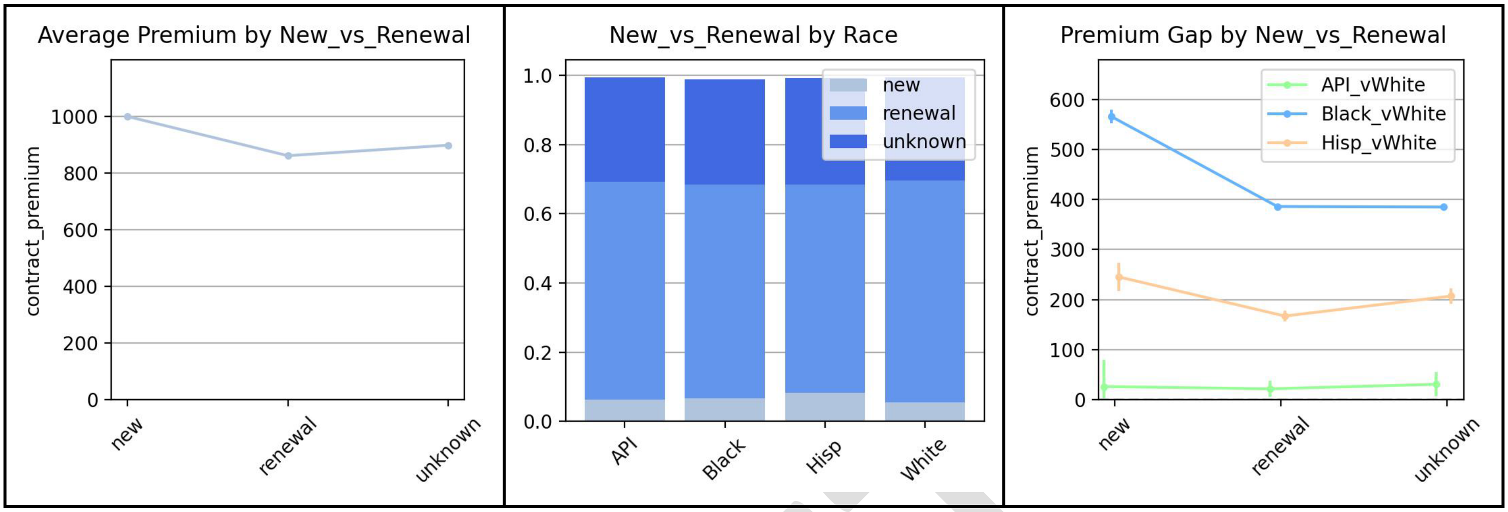
="renewal" if this policy is a renewal

="unknown" if we cannot tell from the data

<u>Derivation from data call:</u> this is derived based on matching "driverID" or "policyID" within a given insurer, across policy periods.

<u>Note:</u> only a subset of data submissions supported the matching of IDs across policy period based on the structure of the data, so this variable is available only for some insurers, representing about ⅔ of all policies.

[22] Note this is only borderline legitimate as explanatory factors go, and we were missing substantial coverage for this column in our data.


Average Premium by New_vs_Renewal
contract_premium
0
200
400
600
800
1000
new
renewal
unknown
New_vs_Renewal by Race
0.0
0.2
0.4
0.6
0.8
1.0
new
renewal
unknown
API
Black
Hisp
White
Premium Gap by New_vs_Renewal
contract_premium
0
100
200
300
400
500
600
API_vWhite
Black_vWhite
Hisp_vWhite
new
renewal
unknown

## Appendix D: Methodology detail: Measuring the Black/white premium gap while accounting for various factors

The basic structure of this analysis is a series of linear regressions that represent nested models predicting premium. Each successive model "accounts for" an additional explanatory factor by adding one or more control variables to the regression equation.

The first, and simplest, model predicts premium (P) based on race alone. Since race is a categorical variable with four possible values in our data (API, Black, Hispanic, white), this appears in regressions as three dummy variables.[23] We fix white as the reference category.

(1) $P = \alpha + \beta_1 * API + \beta_2 * Black + \beta_3 * Hispanic + \varepsilon$

The next model accounts for driver age as an explanatory factor for premium:

(2) $P = \alpha + \beta_1 * API + \beta_2 * Black + \beta_3 * Hispanic + \beta_4 * DriverAge + \varepsilon$

At each step, we add one or more variables to the right-hand side of the equation to account for another explanatory factor.

$\beta_2$ is the coefficient of interest throughout this analysis. Its interpretation is roughly "the expected difference (in dollars) between white and Black premiums, after accounting for the other explanatory factors in the equation." For equation (1), since there are no other included explanatory factors, $\beta_2$ is simply the difference in average premiums between white and Black.

**<u>Modeling premium vs log(premium) – robustness check</u>**

The regressions described in this appendix model premium, stated in dollars. As a robustness check we did the same analyses modeling log(premium) instead. This was motivated by two considerations:

1. We understand that in practice insurance premiums are often constructed by taking a base rate and *multiplying* relativity factors for a given applicant. Modeling log(premium) as a sum is equivalent to modeling premium as a product;[24] so this structure might better fit the data generation process.
2. Premium has a long tail (some premiums are very large). Taking the log of premium condenses the distribution and could reduce the impact of outliers on the estimated coefficients.

The results were substantially the same modeling log(premium) instead of premium.

[23] "Dummy variables" are binary variables that indicate when an observation belongs to a certain category. E.g., API=1 if this policyholder is Asian/Pacific Islander, and =0 otherwise.

[24] Since $\log(P) = \alpha + \beta \rightarrow P = e^{\alpha+\beta} = e^{\alpha} * e^{\beta}$

## Appendix E: Causal model of premium bump in response to claims

We merged policies and claims data then built a dataset of premium jumps as follows:

1. Group policies data by driverID
2. For driverIDs with N>1 rows of policies data (i.e. multiple policy periods of the same driverID), create N-1 "premium jump snapshots" showing premium in the previous policy period, claims in the previous policy period, and premium in this policy period
    - This approach excludes 101,456 policies that have just one row of data (i.e., we observe these driverIDs for only one policy period)
    - Overall, we get 84,565 "premium jump snapshots"

Then we do linear regressions to investigate the relationship between a given driver's premium in this policy period ($P_{now}$), their premium in the previous policy period ($P_{last}$), their claims activity in the previous policy period ($C_{last}$), and their race[25]:

1. $P_{now} = \alpha + \beta_1 * P_{last} + \varepsilon$
2. $P_{now} = \alpha + \beta_1 * P_{last} + \beta_2 * C_{last} + \varepsilon$

2B. $P_{now} = \alpha + \beta_1 * P_{last} + \beta_2 * C_{last} + \varepsilon$ [Black drivers only]
2W. $P_{now} = \alpha + \beta_1 * P_{last} + \beta_2 * C_{last} + \varepsilon$ [white drivers only]

3. $P_{now} = \alpha + \beta_1 * P_{last} + \beta_2 * C_{last} + \beta_3 * \text{Race} + \varepsilon$

The outputs of these regressions are below. We noted about these regressions:

- The coefficient on claim count ($\beta_2$) is positive and highly statistically significant. As expected, claims this policy period lead to higher premium next policy period. Specifically: for each claim this period, premium next policy period is about $30 higher on average.
- R-squared barely changes when adding claims to the regression (0.797 without [regression 1], vs 0.799 with claims [regression 2]). Given that claims do predict premium jumps, it is surprising that including claims information adds little explanatory power to the model. This may reflect the fact that claims are sparse.
- Running the regressions separately for Black and white drivers (regressions 2B and 2W), $\beta_2$ is positive and highly statistically significant in both cases, with similar values (28.83 in 2B and 27.52 in 2W). So, the bump in next period's premium based on a claim this period is roughly the same for both races.
- There is still a Black penalty: $35 hike after accounting for last period's premium and claims last period (regression 3)

[25] Race appears in regressions as 3 dummy variables, as described in Appendix D.

## Regression 1

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             prem_after   R-squared:                       0.797
Model:                            OLS   Adj. R-squared:                  0.797
Method:                 Least Squares   F-statistic:                 3.322e+05
Date:                Tue, 29 Aug 2023   Prob (F-statistic):               0.00
Time:                        13:43:31   Log-Likelihood:            -5.9084e+05
No. Observations:               84565   AIC:                         1.182e+06
Df Residuals:                   84563   BIC:                         1.182e+06
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      58.0150      1.643     35.301      0.000      54.794      61.236
prem_before     0.9217      0.002    576.359      0.000       0.919       0.925
==============================================================================
Omnibus:                    79070.621   Durbin-Watson:                   1.812
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         29940326.608
Skew:                           3.750   Prob(JB):                         0.00
Kurtosis:                      94.875   Cond. No.                     1.88e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.88e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

## Regression 2

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             prem_after   R-squared:                       0.799
Model:                            OLS   Adj. R-squared:                  0.799
Method:                 Least Squares   F-statistic:                 1.682e+05
Date:                Tue, 29 Aug 2023   Prob (F-statistic):               0.00
Time:                        13:43:31   Log-Likelihood:            -5.9042e+05
No. Observations:               84565   AIC:                         1.181e+06
Df Residuals:                   84562   BIC:                         1.181e+06
Df Model:                           2
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept            55.2416      1.638     33.724      0.000      52.031      58.452
prem_before           0.9147      0.002    568.405      0.000       0.912       0.918
claim_count_before   30.7377      1.055     29.138      0.000      28.670      32.805
==============================================================================
Omnibus:                    78301.647   Durbin-Watson:                   1.815
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         30162303.109
Skew:                           3.678   Prob(JB):                         0.00
Kurtosis:                      95.229   Cond. No.                     1.88e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.88e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

## Regression 2B

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             prem_after   R-squared:                       0.757
Model:                            OLS   Adj. R-squared:                  0.757
Method:                 Least Squares   F-statistic:                 6.503e+04
Date:                Thu, 21 Sep 2023   Prob (F-statistic):               0.00
Time:                        15:05:48   Log-Likelihood:            -2.9882e+05
No. Observations:               41726   AIC:                         5.976e+05
Df Residuals:                   41723   BIC:                         5.977e+05
Df Model:                           2
Covariance Type:            nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept             78.3996      3.013     26.023      0.000      72.495      84.305
prem_before            0.9088      0.003    354.032      0.000       0.904       0.914
claim_count_before    28.8300      1.499     19.229      0.000      25.891      31.769
==============================================================================
Omnibus:                    37840.124   Durbin-Watson:                   1.808
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          7252842.226
Skew:                           3.761   Prob(JB):                         0.00
Kurtosis:                      67.149   Cond. No.                     2.33e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.33e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

**Regression 2W**

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             prem_after   R-squared:                       0.839
Model:                            OLS   Adj. R-squared:                  0.839
Method:                 Least Squares   F-statistic:                 8.535e+04
Date:                Thu, 21 Sep 2023   Prob (F-statistic):               0.00
Time:                        15:05:48   Log-Likelihood:            -2.1681e+05
No. Observations:               32663   AIC:                         4.336e+05
Df Residuals:                   32660   BIC:                         4.337e+05
Df Model:                           2
Covariance Type:            nonrobust
======================================================================================
                         coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------
Intercept             41.2867      1.833     22.528      0.000      37.695      44.879
prem_before            0.9135      0.002    410.055      0.000       0.909       0.918
claim_count_before    27.5200      1.673     16.446      0.000      24.240      30.800
==============================================================================
Omnibus:                    23946.431   Durbin-Watson:                   1.819
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         51011362.708
Skew:                           1.998   Prob(JB):                         0.00
Kurtosis:                     196.561   Cond. No.                     1.50e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.5e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

**Regression 3**

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             prem_after   R-squared:                       0.800
Model:                            OLS   Adj. R-squared:                  0.800
Method:                 Least Squares   F-statistic:                 6.764e+04
Date:                Tue, 29 Aug 2023   Prob (F-statistic):               0.00
Time:                        13:43:31   Log-Likelihood:            -5.9023e+05
No. Observations:               84565   AIC:                         1.180e+06
Df Residuals:                   84559   BIC:                         1.181e+06
Df Model:                           5
Covariance Type:            nonrobust
=====================================================================================================================
                                                         coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------------------
Intercept                                             45.9190      1.829     25.107      0.000      42.334      49.504
C(inferred_race, Treatment(reference="White"))[T.API]   -13.8812      5.019     -2.766      0.006     -23.719      -4.044
C(inferred_race, Treatment(reference="White"))[T.Black]  34.9454      2.007     17.412      0.000      31.012      38.879
C(inferred_race, Treatment(reference="White"))[T.Hisp]    3.2631      3.383      0.965      0.335      -3.368       9.894
prem_before                                            0.9063      0.002    543.262      0.000       0.903       0.910
claim_count_before                                    29.0008      1.057     27.446      0.000      26.930      31.072
==============================================================================
Omnibus:                    78969.362   Durbin-Watson:                   1.814
Prob(Omnibus):                  0.000   Jarque-Bera (JB):         30559969.247
Skew:                           3.734   Prob(JB):                         0.00
Kurtosis:                      95.829   Cond. No.                     5.86e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.86e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```