Assessing the impact of age, race and sex on police vehicular stop outcomes in two New England states

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Abstract

We assess the impact of driver age, race and sex on police vehicular outcomes – warning, citation or arrest, and whether a search is conducted – in the U.S. states of Connecticut and Massachusetts for the period 2013-2015 from data of approximately 2.15 million stops. We ask the question, *How do driver age, race and sex impact the outcomes of police vehicular stops?*. To answer it, we use multinomial and binary logistic regression models to derive the odds of incidence for each outcome relative to the white/male reference group. We do so in order to provide insights into policing in the United States and to highlight possible areas of reform and advocacy. The findings suggest that age, race and gender do impact police vehicular stops differentially, with race having the greatest impact. Specifically we find that persons in the Black and Hispanic groups are much more likely to be issued citations or be arrested than the reference group, women are much more likely to receive a warning and avoid citation and arrest and age plays a less significant role relative to race and sex in vehicular stop outcomes. We also find that Blacks and Hispanics have higher odds of being the subject of a vehicular search but have lower odds of carrying contraband. The findings point to a continued need for vigilance, and reform and improvements in law enforcement.

Key words: police bias, vehicular stop outcomes, minority group policing, New England law enforcement, multinomial logistic regression

Introduction

Every day tens of thousands of vehicular traffic stops are made by law enforcement officials throughout the United States. Due to their transient nature and often isolated nature, these transactions have largely escaped public scrutiny and accountability. The absence of legal reporting requirements and a culture of obscurity together with large administrative backlogs conspire to shroud these every day interactions between citizens and law enforcement officials from the public eye.

Only recently in the last decade have police vehicular stops drawn attention in a systematic manner as an issue of urgent attention, catalyzed by increasing ubiquity of video recording, data availability and media coverage of events where these seemingly routine interactions often turn deadly. Legal reporting requirements remain spotty throughout the country due in part to the dispersed nature of law enforcement in the country. For example, the Massachusetts State Patrol maintains and reports relatively complete data, but data of similar scope is hard to come by for the state cities of Boston, Springfield, etc. In the jurisdictions where legal requirements do exist, the data is often incomplete or only captures a small subset of variables. However, a few states, most notably North Carolina, have enacted laws mandating the recording and reporting of these transactions.

The present study seeks to shed light on this relatively unexplored topic in law enforcement, capitalizing on the recent improvements in legal requirements and availability of data. The issue is germane to the on-going debate on the scope, funding and oversight of law enforcement and generally to the state of civil rights and the government accountability in the United States. We assess the impact of driver age, gender and race on the outcomes of police vehicular stops for the period 2013-2015 in the states of Connecticut and Massachusetts. Together, the two states account for more than two thirds of the population of the New England region. We ask the question, *Does driver age, race and sex factor in police vehicular stops? If so, how?* In the case of vehicular search, we ask the subsidiary question, *What is the relation between the rates of vehicular search and the rate of contraband found in the search?* To answer it, we use the data collected by the Stanford Open Policing Project drawn from the state-wide *State Patrol* data sets for the two states under study.

/ Literature review

The Stanford Open Policing Project, the source of the data used for this study, has conducted several studies looking at the issue of police bias in vehicular stops (Stanford Open Policing Project, 2022). It has found significant bias in police work, in particular bias against Hispanic and Black drivers. Similarly, professor Frank Baumgartner at the University of Carolina at Chapel Hill found significant outcome bias in his analysis of vehicular stop data for the state of North Carolina during the period 2002-2020 (Baumgartner, 2022). Using propensity scores rather than regression models, Ridgeway found significant bias in the behavior of police officers during traffic stops (Ridgeway, 2006).

/ Methodology

The data consists of 2,149,197 instances, 1,077,519 for Connecticut and 1,071,678 for Massachusetts, representing a police vehicular stop during 2013-2015. Data preparation consisted simply of variable selection and data type conversion, factor re-ordering and the elimination a relatively few missing values.

The outcomes of police vehicular stops – warning, citation, arrest – were modeled for each state with a multinomial logistic regression and three predictor variables: subject_age (numerical discrete), subject_race (categorical) and subject_sex (categorical). The probabilities for each outcome in each state were then plotted for subject_age and subject_race and for subject_age and subject age (Figures 1-4). The model exponentiated coefficients representing the odd-ratios/relative risks for each group are shown in the tables that follow the graphs.

We modeled whether a search was also conducted during the stop, True or False, with a binary logistic regression and the same three predictor variables: subject_age, subject_race, and subject_sex. Subsequently, in instances where a search was conducted we modeled the probability of finding contraband again with the same three predictor variables. The probabilities for both states and models, search conducted and contraband found, are plotted in Figures 5-8 and the odd-ratios/relative risks for both models in each state are displayed in tables following the graphs.

/ Experimentation and Results

All models were built to and achieved general significance at 95% confidence for all predictors, save for a couple of cases where predictor variable significance dropped to 90%. Variance inflation factors were very low in all cases.

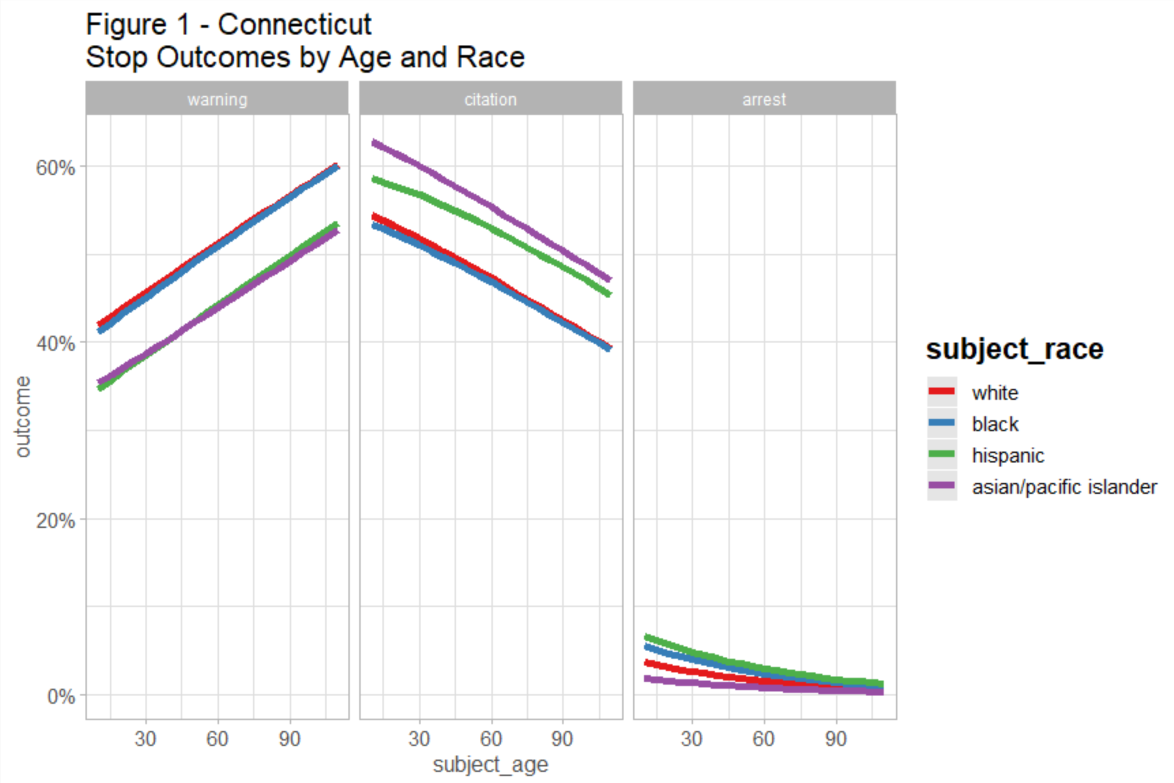
// Stop Outcomes

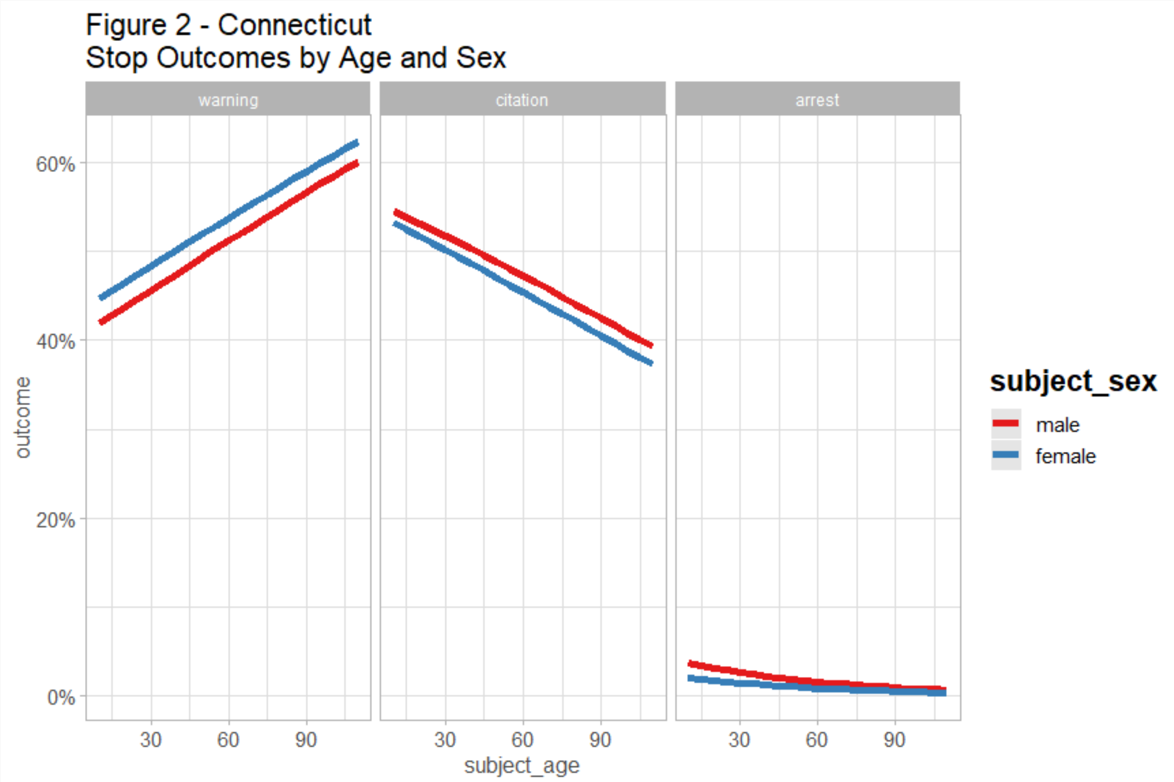
The results in both states show, unsurprisingly, that the probabilities for each stop outcome vary by age, race and sex. In both states, the probability of a warning increases with age, and the probability of both citation and arrest decreases with age.

On race, the data in both states shows that Whites and Blacks have higher probability of receiving a warning relative to Hispanics and Asians. In Connecticut, Asians and Hispanics are more likely to receive a citation than Whites and Blacks. In Massachusetts, Asians are more likely to receive a citation than all other groups. When it comes to arrest, the data in both states show that Blacks and Hispanics have a higher probability of being arrested.

Regarding sex, the data in both states shows that males have a significantly higher probability of warning, citation and arrest than females.

/// Connecticut





Multinomial Logistic Regression model: Connecticut			
Predictors	*Odds Ratios*	*p*	*Response*
(Intercept)	1.396	**0.0e+00**	citation
(Intercept)	0.108	**0.0e+00**	arrest
subject_age	0.993	**0.0e+00**	citation
subject_age	0.979	**0.0e+00**	arrest
subject_race: white	*Reference*		

subject_race: asian/pacific islander	0.599	**1.3e-12**	arrest
subject_race: black	1.533	**5.7e-128**	arrest
subject_race: black	0.996	5.4e-01	citation
subject_race: hispanic	2.191	**0.0e+00**	arrest
subject_race: hispanic	1.298	**0.0e+00**	citation
subject_race: asian/pacific islander	1.365	**2.2e-100**	citation
subject_sex: male	*Reference*		
subject_sex: female	0.511	**0.0e+00**	arrest
subject_sex: female	0.915	**5.7e-107**	citation
Observations	1077519		
R^2 / R^2 adjusted	0.007 / 0.007		

/// Massachusetts

Figure 3 - Massachusetts
Stop Outcomes by Age and Race

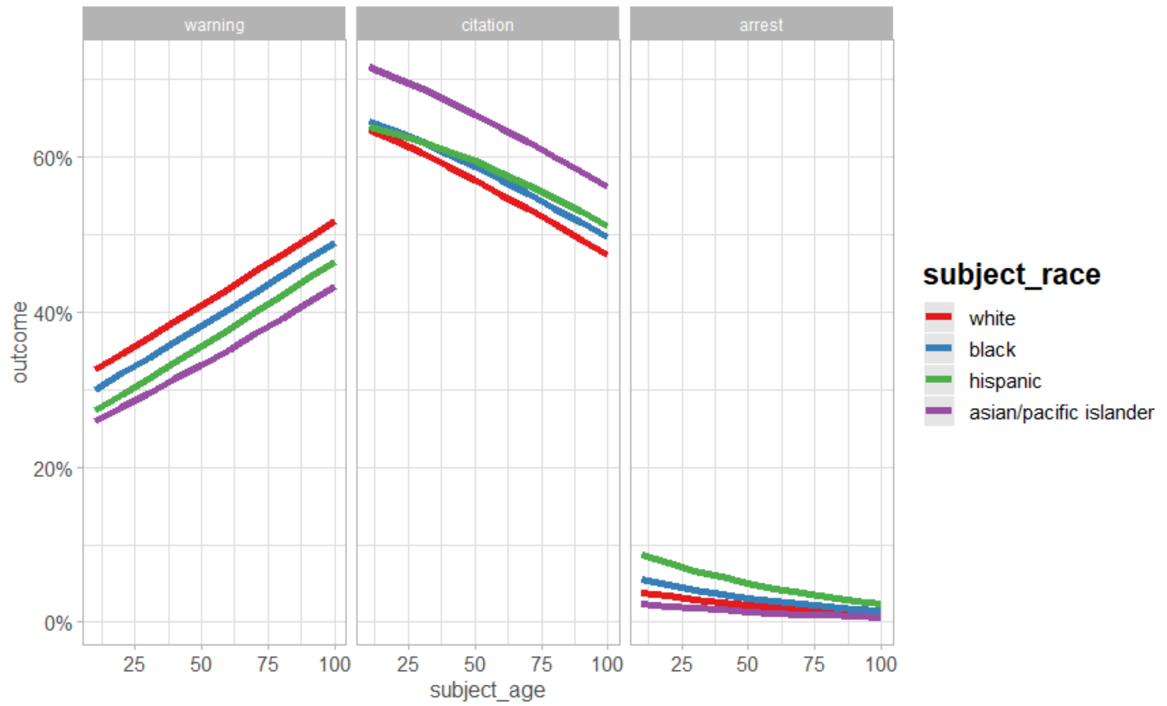
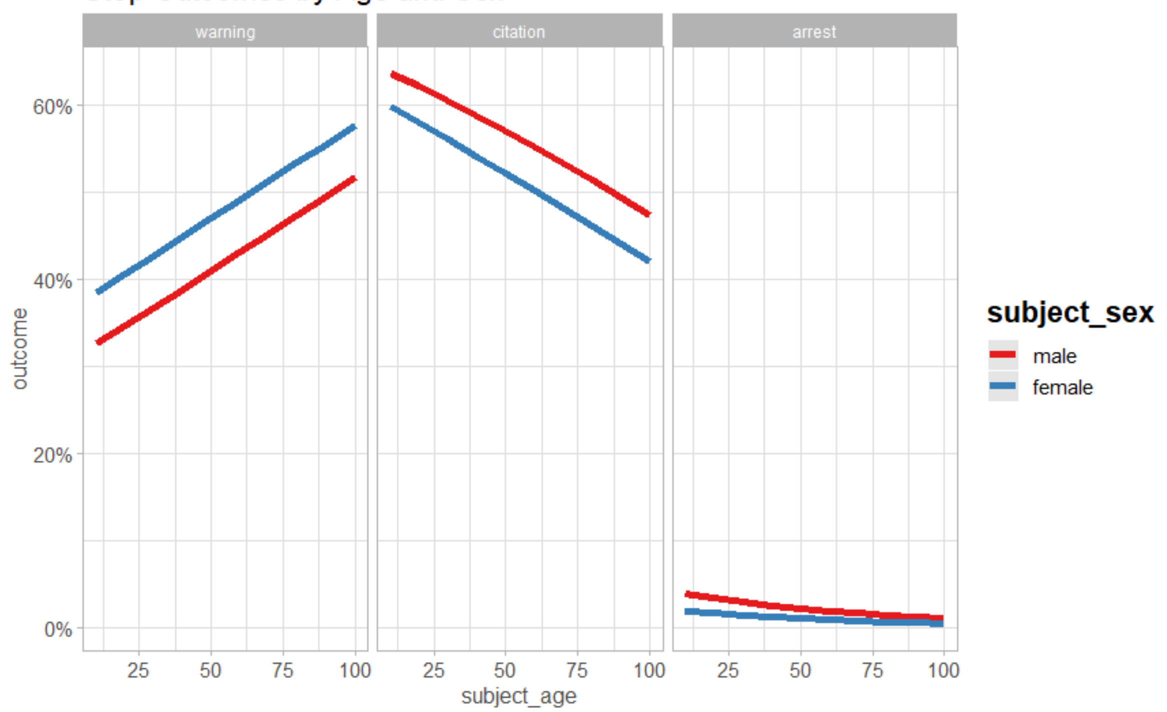


Figure 4 - Massachusetts
Stop Outcomes by Age and Sex



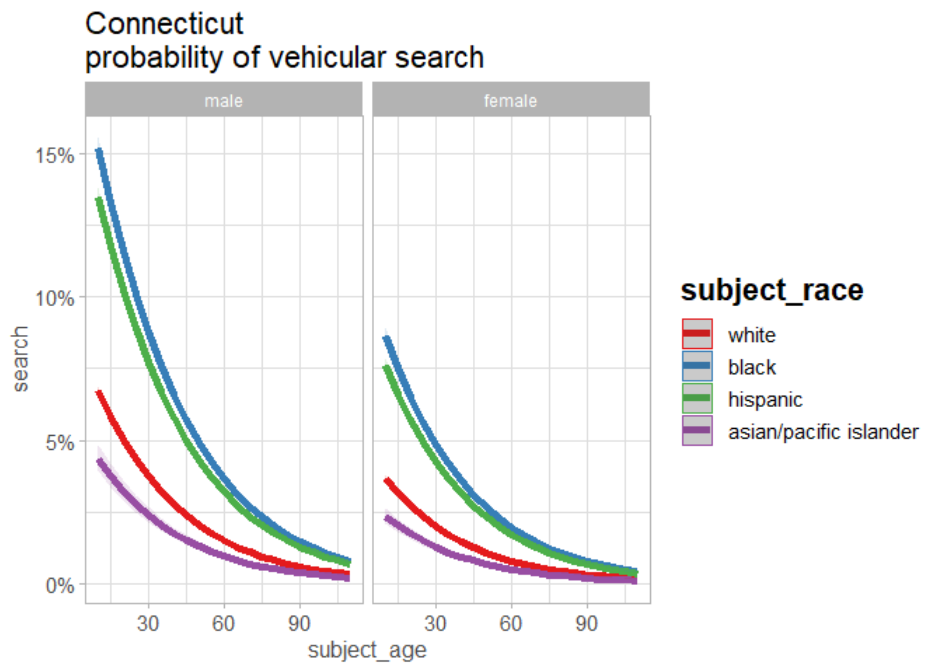
Multinomial Logistic Regression model: Massachusetts			
Predictors	*Odds Ratios*	*p*	*Response*
(Intercept)	2.121	**0.0e+00**	citation
(Intercept)	0.144	**0.0e+00**	arrest
subject_age	0.992	**0.0e+00**	citation
subject_age	0.980	**0.0e+00**	arrest
subject_race: white	*Reference*		
subject_race:	0.786	**2.8e-11**	arrest

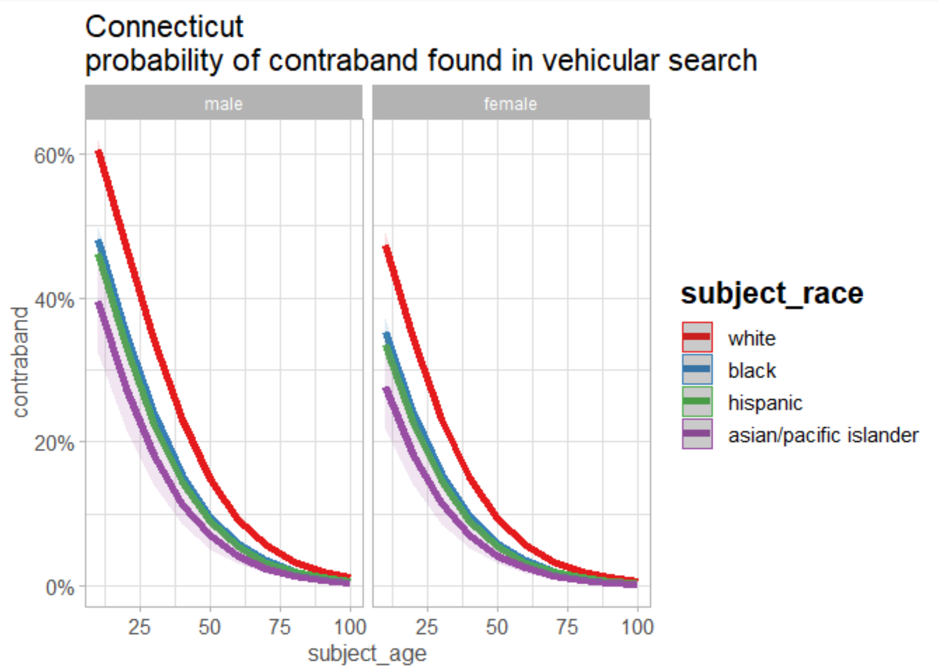
asian/pacific islander			
subject_race: black	1.539	**1.3e-118**	arrest
subject_race: black	1.103	**1.1e-50**	citation
subject_race: hispanic	2.701	**0.0e+00**	arrest
subject_race: hispanic	1.198	**2.2e-155**	citation
subject_race: asian/pacific islander	1.415	**1.5e-303**	citation
subject_sex: male	*Reference*		
subject_sex: female	0.405	**0.0e+00**	arrest
subject_sex: female	0.797	**0.0e+00**	citation
Observations	1071678		
R^2 / R^2 adjusted	0.010 / 0.010		

// Vehicular Search and Contraband

When Hispanics and Blacks are stopped on the road, the data in both states shows that they, males and females, have a significantly higher probability of undergoing a search relative to Whites or Asians. Nevertheless, when a search is conducted following a stop, there is a greater probability of finding contraband, not among Blacks and Hispanics, but rather among Whites.

/// Connecticut

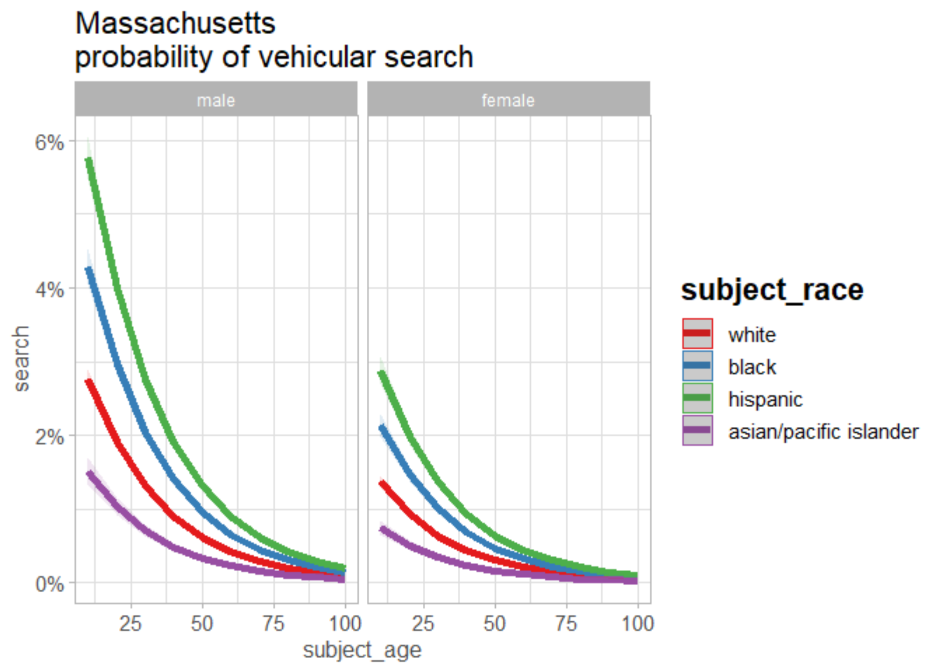


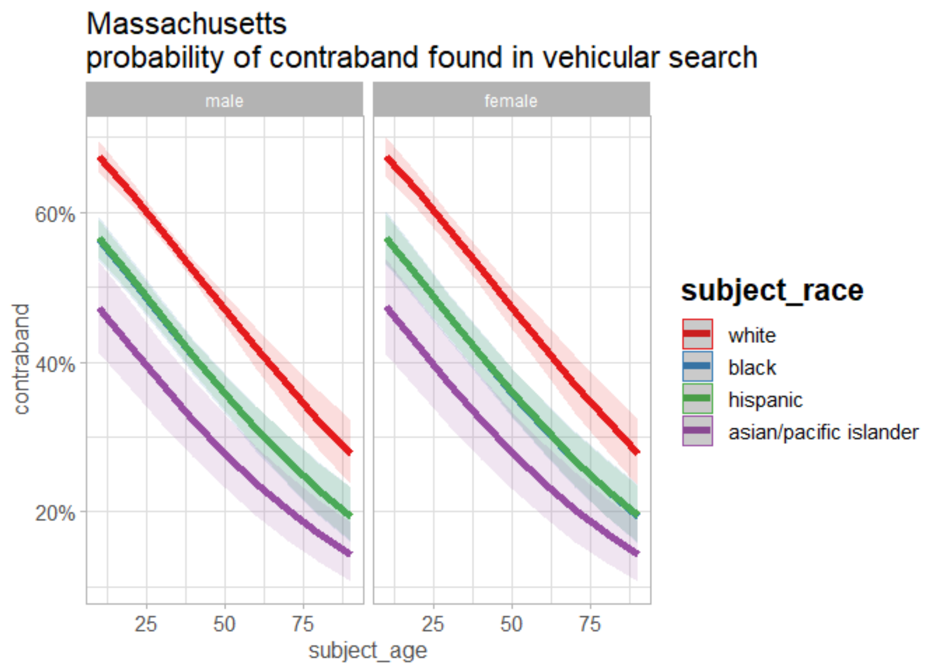


	Vehicular Search		Contraband Found	
Predictors	*Odds Ratios*	*p*	*Odds Ratios*	*p*
(Intercept)	0.098	**0.0e+00**	2.631	**6.9e-129**
subject_age	0.969	**0.0e+00**	0.947	**0.0e+00**
subject_race: white	*Reference*		*Reference*	
subject_race: black	2.478	**0.0e+00**	0.607	**3.2e-60**
subject_race: hispanic	2.158	**0.0e+00**	0.561	**1.4e-68**
subject_race: asian/pacific islander	0.633	**1.4e-16**	0.426	**6.7e-08**
subject_sex: male	*Reference*		*Reference*	
subject_sex: female	0.529	**0.0e+00**	0.586	**8.4e-64**
Observations	1077519		37275	

R^2 Tjur	0.017	0.081

/// Massachusetts





	Vehicular Search		Contraband Found	
Predictors	*Odds Ratios*	*p*	*Odds Ratios*	*p*
(Intercept)	0.042	**0.0e+00**	2.558	**4.2e-49**
subject_age	0.962	**0.0e+00**	0.979	**3.8e-31**
subject_race: white	*Reference*		*Reference*	
subject_race: black	1.573	**8.1e-66**	0.627	**1.6e-18**
subject_race: hispanic	2.146	**1.1e-237**	0.628	**1.3e-23**
subject_race: asian/pacific islander	0.536	**2.0e-26**	0.433	**6.6e-12**
subject_sex: male	*Reference*		*Reference*	

subject_sex: female	0.486	**3.6e-197**	1.003	9.6e-01
Observations	1071678		11832	
R^2 Tjur	0.005		0.025	

Discussion and Conclusions

The general findings suggesting that there is significant bias in vehicular policing is not surprising. In fact, it confirms what many suspect and many others have experienced in their interactions with law enforcement in the United States. Nevertheless, the detail of the findings are intriguing and offer a glimpse into hitherto undiscovered dynamics. For example, warnings are increasingly common with age, suggesting one of two things. One suggestion is that people become worse drivers with age and/or that there is age-ism in vehicular law enforcement. The other, more plausible suggestion is that warnings are more common with age because older folk are decreasingly considered for the more severe penalties of citation and arrest. This suggestion finds support in the fact that citation and arrest become less frequent with age. In any case, age alone with its odds-ratio ranging between 0.98-0.99 for the stop outcomes model and between 0.95-0.97 for the search and contraband models, that is, close to unity, is not a very impactful marginal predictor from age to age, but its cumulative effect across the range of ages is substantial.

The most impactful predictor and the widest differences among groups are found in the race predictor variable. Here we see odds-ratios consistently above unity for the Black and Hispanic groups, in some cases as high as 2.2 and 2.7 as in the case of arrest in Connecticut and Massachusetts, respectively. The odds-ratios also rise above two in the search conducted model for Hispanics in both states and for Blacks in Connecticut. Conversely, we see odd-ratios significantly below unity in the contraband found model for all non-reference groups. That is, the data suggests that contraband is most frequently found in Whites, but it is Blacks and Hispanics instead who are more often the subject of a vehicular search. The sex predictor is also impactful, showing large differences between males and females for all outcomes For example, the odds-ratio for female citation and arrest in Massachusetts is significantly lower than unity at 0.80 and 0.41, respectively. A similar, albeit less exaggerated trend is seen in Connecticut too.

In summary, age plays a minor incremental role in vehicular stop outcomes from age to age. Its impact is cumulative across the range of ages. Race is the most significant factor impacting stop outcomes, with Blacks and Hispanics seeing the largest increases in odd-ratios relative to the White/male reference group. The data suggests that *Driving while Black* and *Driving while Hispanic* may be quite real. The sex of the driver is also a significant predictor of stop outcomes, with women being less likely than men of all stop outcomes.

Limitations of the study and areas of future work
The diagnostics performed on the regression models used in the study do assure an acceptable level of statistical rigor of the results presented. Nevertheless, due to the size of the dataset and the computational power required in analyzing it, model diagnostics were not exhaustive in nature and could be expanded for even greater confidence in the results. Likewise, interaction terms among the predictor variables could be explored to improve model fit and explanatory power even further.

Another possible limitation of the study concerns data collection. The data is collected and reported by the same law enforcement officials performing the vehicular stop and search. It can be reasonably expected that they know that the data will be scrutinized by the public and hence, it can be likewise expected that the data is under-reported or mis-reported. An analysis of the data itself involving triangulation and cross-checks with other sources could be conducted to check this possibility.

There exist other factors that could well impact on who is the subject of a vehicular stop. The location of the stop and the time of the stop could play a significant role. If law enforcement conducts more stops where minority groups are more prevalent, it can only be expected that more minority group members will be stopped. Where law enforcement officials chose to conduct stops could be an important factor. Likewise, the time of the day and whether it's dark or light could have an effect on whether stops are made and who is stopped. We can imagine that under the cover of dark, there could be fewer stops due to the increased real or perceived danger of night-time work. On the other hand, in the cover of dark the age, race and sex of the drive is more difficult to determine from afar before a stop. All these factors are worth investigating to refine the results presented here.

/ References

Stanford Open Policing Project. (2022, May 19). The results of our nationwide analysis of traffic stops and searches. https://openpolicing.stanford.edu/findings/

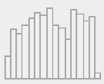
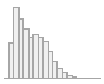
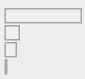
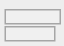
Baumgartner, F.R. (2022, February 1). Benchmarking Traffic Stop Data: Examining Patterns in North Carolina and the City of Raleigh. The University of Carolina at Chapel Hill. https://fbaum.unc.edu/TrafficStops/Baumgartner-benchmarking.pdf

Ridgeway, G. (2006, March 1). Assessing the Effect of Race Bias in Post-traffic Stop Outcomes Using Propensity Scores. Journal of Quantitative Criminology. https://www.jstor.org/stable/23367478

/ Appendices

// Appendix I: Supplemental figures

/// Data Summary: Connecticut

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	date [Date]	min : 2013-10-01 med : 2014-09-24 max : 2015-10-01 range : 2y 0m 0d	731 distinct values		1077519 (100.0%)	0 (0.0%)
2	subject_age [integer]	Mean (sd) : 38.7 (14.8) min ≤ med ≤ max: 10 ≤ 36 ≤ 109 IQR (CV) : 24 (0.4)	96 distinct values		1077519 (100.0%)	0 (0.0%)
3	subject_race [factor]	1. white 2. black 3. hispanic 4. asian/pacific islander	789403 (73.3%) 143355 (13.3%) 124736 (11.6%) 20025 (1.9%)		1077519 (100.0%)	0 (0.0%)
4	subject_sex [factor]	1. male 2. female	678123 (62.9%) 399396 (37.1%)		1077519 (100.0%)	0 (0.0%)
5	warning_issued [logical]	1. FALSE 2. TRUE	565730 (52.5%) 511789 (47.5%)		1077519 (100.0%)	0 (0.0%)
6	citation_issued [logical]	1. FALSE 2. TRUE	530308 (49.2%) 547211 (50.8%)		1077519 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
7	arrest_made [logical]	1. FALSE 2. TRUE	1053226 (97.7%) 24291 (2.3%)		1077517 (100.0%)	2 (0.0%)
8	outcome [factor]	1. warning 2. citation 3. arrest	508830 (47.2%) 544398 (50.5%) 24291 (2.3%)		1077519 (100.0%)	0 (0.0%)
9	search_conducted [logical]	1. FALSE 2. TRUE	1040244 (96.5%) 37275 (3.5%)		1077519 (100.0%)	0 (0.0%)
10	contraband_found [logical]	1. FALSE 2. TRUE	27561 (73.9%) 9714 (26.1%)		37275 (3.5%)	1040244 (96.5%)
11	search [integer]	Min : 0 Mean : 0 Max : 1	0 : 1040244 (96.5%) 1 : 37275 (3.5%)		1077519 (100.0%)	0 (0.0%)
12	contraband [integer]	Min : 0 Mean : 0.3 Max : 1	0 : 27561 (73.9%) 1 : 9714 (26.1%)		37275 (3.5%)	1040244 (96.5%)

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2022-05-19

/// Model diagnostics: Connecticut

|Multinomial model decomposed as three binary models

```
##
## Call:
## glm(formula = warning_issued ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = CT)
##
## Deviance Residuals:
##    Min       1Q  Median       3Q      Max
## -1.374  -1.137  -0.995   1.207   1.430
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -0.3840258  0.0059285  -64.78  < 2e-16 ***
## subject_age                     0.0073380  0.0001318   55.67  < 2e-16 ***
## subject_raceblack              -0.0188907  0.0057764   -3.27  0.00107 **
## subject_racehispanic           -0.2889859  0.0062382  -46.33  < 2e-16 ***
## subject_raceasian/pacific islander -0.2942101  0.0145606  -20.21  < 2e-16 ***
## subject_sexfemale               0.1096346  0.0040097   27.34  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1491057  on 1077518  degrees of freedom
## Residual deviance: 1483971  on 1077513  degrees of freedom
## AIC: 1483983
##
## Number of Fisher Scoring iterations: 4
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.014721  1        1.007334
## subject_race 1.017216  3        1.002849
## subject_sex  1.002660  1        1.001329
```

```
##                                 Model Fit Statistics
## ----------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -745528.539    Log-Lik Full Model:           -741985.253
## Deviance(1077513):          1483970.506    LR(5):                          7086.573
##                                            Prob > LR:                         0.000
## MCFadden's R2                     0.005    McFadden's Adj R2:                 0.005
## ML (Cox-Snell) R2:                0.007    Cragg-Uhler(Nagelkerke) R2:        0.009
## McKelvey & Zavoina's R2:          0.008    Efron's R2:                        0.007
## Count R2:                         0.540    Adj Count R2:                      0.032
## BIC:                        1484053.847    AIC:                         1483982.506
## ----------------------------------------------------------------------------------
```

```
##
## Call:
## glm(formula = citation_issued ~ subject_age + subject_race +
##     subject_sex, family = binomial(link = "logit"), data = CT)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -1.395  -1.185   1.029   1.164   1.355
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    0.2647008  0.0059123  44.771  < 2e-16 ***
## subject_age                   -0.0061510  0.0001316 -46.738  < 2e-16 ***
## subject_raceblack             -0.0206641  0.0057671  -3.583  0.00034 ***
## subject_racehispanic           0.2186403  0.0061800  35.379  < 2e-16 ***
## subject_raceasian/pacific islander  0.3259694  0.0145201  22.450  < 2e-16 ***
## subject_sexfemale             -0.0642423  0.0040032 -16.048  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1493493  on 1077518  degrees of freedom
## Residual deviance: 1488854  on 1077513  degrees of freedom
## AIC: 1488866
##
## Number of Fisher Scoring iterations: 3
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.015039  1        1.007491
## subject_race 1.017720  3        1.002932
## subject_sex  1.002787  1        1.001392
```

```
##                                 Model Fit Statistics
## ----------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -746746.673    Log-Lik Full Model:           -744427.134
## Deviance(1077513):          1488854.269    LR(5):                          4639.077
##                                            Prob > LR:                         0.000
## MCFadden's R2                     0.003    McFadden's Adj R2:                 0.003
```

```
## ML (Cox-Snell) R2:                0.004    Cragg-Uhler(Nagelkerke) R2:          0.006
## McKelvey & Zavoina's R2:           0.005    Efron's R2:                          0.004
## Count R2:                          0.526    Adj Count R2:                        0.036
## BIC:                         1488937.610    AIC:                           1488866.269
## ------------------------------------------------------------------------------------
```

```
##
## Call:
## glm(formula = arrest_made ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = CT)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.3644  -0.2403  -0.1983  -0.1689   3.3061
##
## Coefficients:
##                                       Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                         -3.0894999  0.0198671 -155.508   <2e-16 ***
## subject_age                         -0.0176444  0.0004891  -36.075   <2e-16 ***
## subject_raceblack                    0.4298140  0.0175015   24.559   <2e-16 ***
## subject_racehispanic                 0.6400317  0.0169287   37.807   <2e-16 ***
## subject_raceasian/pacific islander -0.6838730  0.0715946   -9.552   <2e-16 ***
## subject_sexfemale                   -0.6245351  0.0152572  -40.934   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 232268  on 1077516  degrees of freedom
## Residual deviance: 226699  on 1077511  degrees of freedom
##   (2 observations deleted due to missingness)
## AIC: 226711
##
## Number of Fisher Scoring iterations: 7
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.011052  1        1.005511
## subject_race 1.013753  3        1.002279
## subject_sex  1.002691  1        1.001345
```

```
##                                Model Fit Statistics
## ------------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -116134.087    Log-Lik Full Model:            -113349.409
## Deviance(1077511):           226698.818    LR(5):                            5569.357
##                                            Prob > LR:                           0.000
## MCFadden's R2                      0.024    McFadden's Adj R2:                  0.024
## ML (Cox-Snell) R2:                 0.005    Cragg-Uhler(Nagelkerke) R2:         0.027
## McKelvey & Zavoina's R2:           0.070    Efron's R2:                         0.006
## Count R2:                          0.977    Adj Count R2:                       0.000
## BIC:                          226782.159    AIC:                           226710.818
## ------------------------------------------------------------------------------------
```

|Search model

```
##
## Call:
## glm(formula = search ~ subject_age + subject_race + subject_sex,
```

```
##     family = binomial(link = "logit"), data = CT)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.5655  -0.3023  -0.2281  -0.1798   3.3722
##
## Coefficients:
##                                    Estimate Std. Error  z value Pr(>|z|)
## (Intercept)                      -2.3185748  0.0165625 -139.989   <2e-16 ***
## subject_age                      -0.0310007  0.0004333  -71.554   <2e-16 ***
## subject_raceblack                 0.9074929  0.0129397   70.132   <2e-16 ***
## subject_racehispanic              0.7692667  0.0139529   55.133   <2e-16 ***
## subject_raceasian/pacific islander -0.4573537  0.0553330   -8.265   <2e-16 ***
## subject_sexfemale                -0.6359038  0.0124584  -51.042   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 324039  on 1077518  degrees of freedom
## Residual deviance: 307576  on 1077513  degrees of freedom
## AIC: 307588
##
## Number of Fisher Scoring iterations: 6
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.005131  1        1.002562
## subject_race 1.007442  3        1.001237
## subject_sex  1.002319  1        1.001159
```

```
##                               Model Fit Statistics
## ----------------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -162019.289    Log-Lik Full Model:            -153787.944
## Deviance(1077513):           307575.889    LR(5):                          16462.690
##                                            Prob > LR:                          0.000
## MCFadden's R2                     0.051    McFadden's Adj R2:                  0.051
## ML (Cox-Snell) R2:                0.015    Cragg-Uhler(Nagelkerke) R2:         0.058
## McKelvey & Zavoina's R2:          0.131    Efron's R2:                         0.017
## Count R2:                         0.965    Adj Count R2:                       0.000
## BIC:                         307659.230    AIC:                           307587.889
## ----------------------------------------------------------------------------------------
```

Contraband model

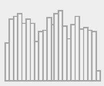
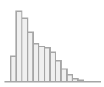
```
##
## Call:
## glm(formula = contraband ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = CT)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2437  -0.8349  -0.6022   1.1808   2.7815
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)                        0.967245   0.040046   24.15  < 2e-16 ***
## subject_age                       -0.054178   0.001251  -43.33  < 2e-16 ***
## subject_raceblack                 -0.498667   0.030464  -16.37  < 2e-16 ***
```

```
## subject_racehispanic              -0.578226   0.033038  -17.50  < 2e-16 ***
## subject_raceasian/pacific islander -0.852260   0.157827   -5.40 6.67e-08 ***
## subject_sexfemale                 -0.534289   0.031683  -16.86  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 42768  on 37274  degrees of freedom
## Residual deviance: 39584  on 37269  degrees of freedom
##   (1040244 observations deleted due to missingness)
## AIC: 39596
##
## Number of Fisher Scoring iterations: 4
```

```
##                 GVIF Df GVIF^(1/(2*Df))
## subject_age  1.001722  1        1.000861
## subject_race 1.005678  3        1.000944
## subject_sex  1.005978  1        1.002984
```

```
##                                  Model Fit Statistics
## ----------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -21384.196   Log-Lik Full Model:            -19792.105
## Deviance(37269):             39584.209   LR(5):                           3184.182
##                                          Prob > LR:                          0.000
## MCFadden's R2                    0.074   McFadden's Adj R2:                  0.074
## ML (Cox-Snell) R2:               0.003   Cragg-Uhler(Nagelkerke) R2:         0.076
## McKelvey & Zavoina's R2:         0.153   Efron's R2:                         0.081
## Count R2:                        0.738   Adj Count R2:                      -0.004
## BIC:                         39647.366   AIC:                            39596.209
## ----------------------------------------------------------------------------------
```

/// Data Summary: Massachusetts

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	date [Date]	min : 2013-01-02 med : 2014-06-20 max : 2015-12-31 range : 2y 11m 29d	1094 distinct values		1071678 (100.0%)	0 (0.0%)
2	subject_age [integer]	Mean (sd) : 37.3 (13.8) min ≤ med ≤ max: 10 ≤ 34 ≤ 94 IQR (CV) : 21 (0.4)	85 distinct values		1071678 (100.0%)	0 (0.0%)
3	subject_race [factor]	1. white 2. black 3. hispanic 4. asian/pacific islander	781296 (72.9%) 117881 (11.0%) 115140 (10.7%) 57361 (5.4%)		1071678 (100.0%)	0 (0.0%)

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
4	subject_sex [factor]	1. male 2. female	737610 (68.8%) 334068 (31.2%)		1071678 (100.0%)	0 (0.0%)
5	warning_issued [logical]	1. FALSE 2. TRUE	655685 (61.2%) 415993 (38.8%)		1071678 (100.0%)	0 (0.0%)
6	citation_issued [logical]	1. FALSE 2. TRUE	443949 (41.4%) 627729 (58.6%)		1071678 (100.0%)	0 (0.0%)
7	arrest_made [logical]	1. FALSE 2. TRUE	1043722 (97.4%) 27956 (2.6%)		1071678 (100.0%)	0 (0.0%)
8	outcome [factor]	1. warning 2. citation 3. arrest	415993 (38.8%) 627729 (58.6%) 27956 (2.6%)		1071678 (100.0%)	0 (0.0%)
9	search_conducted [logical]	1. FALSE 2. TRUE	1059846 (98.9%) 11832 (1.1%)		1071678 (100.0%)	0 (0.0%)
10	contraband_found [logical]	1. FALSE 2. TRUE	5675 (48.0%) 6157 (52.0%)		11832 (1.1%)	1059846 (98.9%)
11	search [integer]	Min : 0 Mean : 0 Max : 1	0 : 1059846 (98.9%) 1 : 11832 (1.1%)		1071678 (100.0%)	0 (0.0%)
12	contraband [integer]	Min : 0 Mean : 0.5 Max : 1	0 : 5675 (48.0%) 1 : 6157 (52.0%)		11832 (1.1%)	1059846 (98.9%)

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2022-05-19

/// Model diagnostics: Massachusetts

|Multinomial model decomposed as three binary models

```
##
## Call:
## glm(formula = warning_issued ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = MA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2898  -1.0069  -0.9192   1.3290   1.6292
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -0.8128978  0.0062694 -129.66   <2e-16 ***
## subject_age                     0.0088372  0.0001441   61.31   <2e-16 ***
## subject_raceblack              -0.1124833  0.0065007  -17.30   <2e-16 ***
## subject_racehispanic           -0.2278495  0.0067188  -33.91   <2e-16 ***
## subject_raceasian/pacific islander -0.3298456  0.0092804  -35.54   <2e-16 ***
## subject_sexfemale               0.2513575  0.0042782   58.75   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
```

```
##
##     Null deviance: 1431595  on 1071677  degrees of freedom
## Residual deviance: 1421227  on 1071672  degrees of freedom
## AIC: 1421239
##
## Number of Fisher Scoring iterations: 4
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.017238  1        1.008582
## subject_race 1.019630  3        1.003245
## subject_sex  1.008764  1        1.004373
```

```
##                               Model Fit Statistics
## ------------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -715797.696    Log-Lik Full Model:            -710613.722
## Deviance(1071672):          1421227.444    LR(5):                           10367.948
##                                            Prob > LR:                           0.000
## MCFadden's R2                     0.007    McFadden's Adj R2:                   0.007
## ML (Cox-Snell) R2:                0.010    Cragg-Uhler(Nagelkerke) R2:          0.013
## McKelvey & Zavoina's R2:          0.012    Efron's R2:                          0.010
## Count R2:                         0.614    Adj Count R2:                        0.005
## BIC:                        1421310.753    AIC:                           1421239.444
## ------------------------------------------------------------------------------------
```

```
##
## Call:
## glm(formula = citation_issued ~ subject_age + subject_race +
##     subject_sex, family = binomial(link = "logit"), data = MA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5743  -1.3025   0.9733   1.0450   1.2702
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     0.6389220  0.0061876  103.26   <2e-16 ***
## subject_age                    -0.0072530  0.0001428  -50.80   <2e-16 ***
## subject_raceblack               0.0695893  0.0063972   10.88   <2e-16 ***
## subject_racehispanic            0.0860305  0.0065169   13.20   <2e-16 ***
## subject_raceasian/pacific islander  0.3600027  0.0091667   39.27   <2e-16 ***
## subject_sexfemale              -0.1798503  0.0042427  -42.39   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1453989  on 1071677  degrees of freedom
## Residual deviance: 1447569  on 1071672  degrees of freedom
## AIC: 1447581
##
## Number of Fisher Scoring iterations: 4
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.017487  1        1.008705
## subject_race 1.020744  3        1.003428
## subject_sex  1.008852  1        1.004416
```

```
##                                 Model Fit Statistics
## ---------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -726994.386    Log-Lik Full Model:           -723784.300
## Deviance(1071672):          1447568.600    LR(5):                           6420.172
##                                            Prob > LR:                          0.000
## MCFadden's R2                     0.004    McFadden's Adj R2:                  0.004
## ML (Cox-Snell) R2:                0.006    Cragg-Uhler(Nagelkerke) R2:         0.008
## McKelvey & Zavoina's R2:          0.008    Efron's R2:                         0.006
## Count R2:                         0.588    Adj Count R2:                       0.005
## BIC:                        1447651.908    AIC:                          1447580.600
## ---------------------------------------------------------------------------------
```

```
##
## Call:
## glm(formula = arrest_made ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = MA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.4208  -0.2511  -0.2146  -0.1731   3.2184
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -3.0627483  0.0194312 -157.62   <2e-16 ***
## subject_age                    -0.0151499  0.0004879  -31.05   <2e-16 ***
## subject_raceblack               0.3707890  0.0181506   20.43   <2e-16 ***
## subject_racehispanic            0.8799681  0.0151558   58.06   <2e-16 ***
## subject_raceasian/pacific islander -0.4645469  0.0356149  -13.04   <2e-16 ***
## subject_sexfemale              -0.7672775  0.0160570  -47.78   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 259051  on 1071677  degrees of freedom
## Residual deviance: 251130  on 1071672  degrees of freedom
## AIC: 251142
##
## Number of Fisher Scoring iterations: 7
```

```
##                  GVIF Df GVIF^(1/(2*Df))
## subject_age  1.016646  1        1.008289
## subject_race 1.020839  3        1.003443
## subject_sex  1.006628  1        1.003309
```

```
##                                 Model Fit Statistics
## ---------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -129525.489    Log-Lik Full Model:           -125565.217
## Deviance(1071672):           251130.434    LR(5):                           7920.545
##                                            Prob > LR:                          0.000
## MCFadden's R2                     0.031    McFadden's Adj R2:                  0.031
## ML (Cox-Snell) R2:                0.007    Cragg-Uhler(Nagelkerke) R2:         0.034
## McKelvey & Zavoina's R2:          0.080    Efron's R2:                         0.009
## Count R2:                         0.974    Adj Count R2:                       0.000
## BIC:                         251213.742    AIC:                           251142.434
## ---------------------------------------------------------------------------------
```

| Search model

```
##
## Call:
## glm(formula = search ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = MA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.3258  -0.1751  -0.1320  -0.1030   3.6889
##
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -3.1762302  0.0302566 -104.98   <2e-16 ***
## subject_age                      -0.0382265  0.0008513  -44.90   <2e-16 ***
## subject_raceblack                 0.4529341  0.0264334   17.14   <2e-16 ***
## subject_racehispanic              0.7638249  0.0232015   32.92   <2e-16 ***
## subject_raceasian/pacific islander -0.6235863  0.0586189  -10.64   <2e-16 ***
## subject_sexfemale                -0.7215448  0.0240866  -29.96   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 130167  on 1071677  degrees of freedom
## Residual deviance: 125035  on 1071672  degrees of freedom
## AIC: 125047
##
## Number of Fisher Scoring iterations: 8
```

```
##                 GVIF Df GVIF^(1/(2*Df))
## subject_age  1.007135  1        1.003561
## subject_race 1.012630  3        1.002094
## subject_sex  1.007376  1        1.003681
```

```
##                              Model Fit Statistics
## ----------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -65083.483    Log-Lik Full Model:            -62517.385
## Deviance(1071672):          125034.771    LR(5):                           5132.196
##                                           Prob > LR:                          0.000
## MCFadden's R2                    0.039    McFadden's Adj R2:                  0.039
## ML (Cox-Snell) R2:               0.005    Cragg-Uhler(Nagelkerke) R2:         0.042
## McKelvey & Zavoina's R2:         0.134    Efron's R2:                         0.005
## Count R2:                        0.989    Adj Count R2:                       0.000
## BIC:                        125118.079    AIC:                           125046.771
## ----------------------------------------------------------------------------------
```

| Contraband model

```
##
## Call:
## glm(formula = contraband ~ subject_age + subject_race + subject_sex,
##     family = binomial(link = "logit"), data = MA)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4602  -1.1732   0.9588   1.1283   1.6752
##
```

```
## Coefficients:
##                                    Estimate Std. Error z value Pr(>|z|)    
## (Intercept)                        0.939345   0.063774  14.729  < 2e-16 ***
## subject_age                       -0.021093   0.001817 -11.606  < 2e-16 ***
## subject_raceblack                 -0.467386   0.053206  -8.785  < 2e-16 ***
## subject_racehispanic              -0.465312   0.046442 -10.019  < 2e-16 ***
## subject_raceasian/pacific islander -0.837067   0.121913  -6.866  6.6e-12 ***
## subject_sexfemale                  0.002737   0.048922   0.056    0.955    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 16383  on 11831  degrees of freedom
## Residual deviance: 16083  on 11826  degrees of freedom
##   (1059846 observations deleted due to missingness)
## AIC: 16095
##
## Number of Fisher Scoring iterations: 4
```

```
##                 GVIF Df GVIF^(1/(2*Df))
## subject_age  1.004701  1        1.002348
## subject_race 1.024759  3        1.004085
## subject_sex  1.020255  1        1.010077
```

```
##                              Model Fit Statistics
## ------------------------------------------------------------------------------
## Log-Lik Intercept Only:     -8191.497    Log-Lik Full Model:           -8041.398
## Deviance(11826):            16082.795    LR(5):                          300.199
##                                          Prob > LR:                        0.000
## MCFadden's R2                   0.018    McFadden's Adj R2:                0.018
## ML (Cox-Snell) R2:              0.000    Cragg-Uhler(Nagelkerke) R2:       0.018
## McKelvey & Zavoina's R2:        0.031    Efron's R2:                       0.025
## Count R2:                       0.562    Adj Count R2:                     0.087
## BIC:                        16139.067    AIC:                          16094.795
## ------------------------------------------------------------------------------
```

// Appendix II: R statistical programming code

This RMarkdown document and its R code are available for inspection and download here.