INVESTIGATING RACIAL BIAS IN MONTGOMERY COUNTY POLICING

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Abstract

This paper analyzes the outcomes of Montgomery County Police traffic stops from 2012-2018 and aims to understand whether the Montgomery County Police Department (MCPD) is racially biased in its enforcement of traffic laws. I utilize three methods of analysis: geographical, regression, and speeding. The geographical analysis splits Montgomery County into tens of thousands of squares and analyzes policing trends across these squares. The speeding analysis examines the different levels of preferential treatment that the MCPD has for different races. The regression analysis investigates the correlation between race and traffic stops after controlling for omitted variables, but I do not believe these omitted variables can be fully controlled for. Each method of analysis independently reaches the same conclusions – that the MCPD do not treat drivers of all races equally. I conclude that there is some evidence of racial bias in MCPD's policing.

Introduction

I am from Silver Spring, Maryland – a town within Montgomery County (MC), on the outskirts of Washington D.C. Recently, as policing across the United States has found itself under increasingly mainstream scrutiny, Montgomery County's police force has also been questioned. There have been calls from citizens to investigate and monitor police activity, but actions and reforms have been slow-moving. To my knowledge, there has not been an in-depth, publicly available analysis of the Montgomery County Police Department (MCPD) and their possible racial bias. This paper exists to perform said analysis.

My motivation is straightforward: if the MCPD applies laws unfairly, the constituents of MC deserve to know, and lawmakers *need* to know. As well as being unfair, systematic racial bias magnifies socioeconomic differences between races and/or demographic groups, leading to societies that are more stratified, with minority groups that are more incentivized to disrupt the status quo (e.g. the

Baltimore Riots of 2015). Everyone – from policy wonks to motorists – should feel incentivized to know the true effects of policing on such a large community.

The essential question I attempt to answer is, "Does the MCPD apply laws equally to all races?" To that end, I have chosen to analyze Montgomery County's public database of traffic violations. I believe that this is an appropriate choice since it is the most detailed database of MCPD actions (both in variables and observations), and because traffic stops are the most common form of police-civilian interaction in the United States (Davis, Langton, & Whyde, 2015).

As we will see in the Background section, some papers investigate police conduct at the individual officer's level – creating models to explain police incentives, decisions, and possible biases. This paper, however, does not seek to explain *why* MCPD officers are biased – its purpose is to clearly establish whether or not they are biased in the first place.

Before beginning to answer this question, I must explain the limitations of this research. Ridgeway (2009) faced the same restrictions, and summarized them by stating that any comprehensive analysis "must separate the [following] three factors when comparing the racial distribution of stops":

1. *Different rates of committing offences* – e.g. black drivers might be stopped more often because they are more likely to commit a traffic violation.
2. *Different rates of exposure* – e.g. there are more police officers in Hispanic neighborhoods, so Hispanic motorists are more likely to be stopped; or Asian citizens make up 20% of the population but 40% of motorists.
3. *Racial bias in policing*.

Given these three effects to separate, it follows that any effective analysis would have to do one or both of the following to be accurate:

1) Find a perspective of analysis that reveals *racial bias in policing* but is not affected by *different rates of committing offences* and/or *different rates of exposure.*
2) Accurately estimate *different rates of committing offences* and *different rates of exposure*, incorporate them into a model, and then separate their effects from those of *racial bias in policing*.

Unfortunately, as the following two paragraphs explain, it is not possible to do (2) – estimating *different rates of committing offences* and *different rates of exposure*.

> Any estimate of *different rates of committing offences* in MC would be tainted by any racial bias present in the dataset. For example, if black and Asian motorists have identical speed distributions but MCPD officers are more likely to pull over black motorists for speeding than Asian motorists, we would falsely believe that black motorists speed more than Asian motorists. Since we cannot reliably derive MC's *different rates of committing offences* from MC's data, one might think to look for this data elsewhere. However, we cannot use data describing other geographies because we cannot guarantee that it accurately describes MC's citizens.
>
> It is similarly impossible to derive *different rates of exposure* in MC, because we cannot separate the probability that an officer stops a driver of race *X* from the probability that they encounter said driver. Even if we knew how to overcome this issue, we do not have the data to do so – Montgomery County does not publish or disclose how many officers are assigned to any specific areas, nor does it disclose anything about the individual officer (e.g. years of experience, race, stop-history). Finally, since *different rates of exposure* affects *different rates of committing offences*' presence in the data, and vice-versa, an incorrect estimate of one of them will in turn bias the estimate of the other.

Since we cannot accurately estimate *different rates of committing offences* and *different rates of exposure*, it makes more sense to avoid or circumvent them than to incorporate them into a model. As a result, the speeding and geographical analyses – which circumvent – are assumed to be less biased than the regression analysis – which incorporates.

I believe that taking multiple routes of analysis is the best way to investigate racial bias in MC, given the nature of this dataset, because no single method can be unequivocally declared the "best". Each analysis that I conduct investigates a unique manifestation of racial bias, by examining (mostly) disjoint sets of variables. Crucially, this implies that each analysis is uniquely susceptible to omitted variable bias. That is relevant because if all three analyses produce corroboratory results, it is much more likely that they are accurate.

The speeding analysis follows the methodology of Goncalves and Mello (2017) (more in the Background section). It measures the varying levels of preferential treatment that police give to different racial groups by analyzing the speeds at which they are *reported* driving at (as opposed to the speeds they *actually* drive at). This analysis finds that the MCPD gives preferential treatment to racial groups in the following (descending) order: White, Asian, Other, Hispanic, Black, Native American. The geographical analysis divides MC into small squares (each is roughly 430 by 430 meters) and analyzes trends across these cells with the hypothesis that minorities are discriminated against when they drive through predominantly white neighborhoods. Results demonstrate a positive intracellular correlation between an area's proportion of white stops and the probability that a black or Hispanic motorist's stop ends in search, arrest, and/or other undesirable outcomes.

The regression analysis is two-pronged – one branch employs Probit regression to predict the probability that a driver receives a citation, is arrested, or is searched, by using their race as a predictive variable along with several control variables. The other branch – via Ordinary Least Squares and Zero-Truncated Poisson regressions – uses the same predictive and control variables, but estimates the number of citations a driver receives (a discrete variable).

Background

The most straightforward (and effective) type of paper that investigates racial bias in policing is one in which the authors have access to data at the level of individual officers. Ridgeway and MacDonald (2009) have one such paper, in which they concluded that 15 out of the 3,000 NYPD officers engaged in NYC's "stop and frisk" policy stopped a concerning, relatively high portion of black and Hispanic suspects.

The dataset I use does not identify the officer(s) who carry out traffic stops, so any conclusions I make will be generalizations of the MCPD as a whole. This anonymous-style data means that a police force with only a few extremely biased officers could produce the exact same patterns and results (with respect to my analyses) as a police force with a small department-wide bias. I will not attempt to distinguish between the two findings (or any combination of them), and I believe that MC needs to publish officer-level data before we can attempt to do so.

An example of a study conducted on a dataset akin to mine is Grogger and Ridgeway (2006), who found "little evidence of racial profiling in traffic stops" in Oakland, California. They compared stops of motorists during the day against those made at night (the assumption being that a racially biased police officer cannot see the race of a motorist at night, so their stops will be less biased at night). While their approach is ingenious, I am skeptical of its accuracy – in well-lit urban areas it is possible that police can see motorists at night, in which case the lack of differences that they found between day and night stops is to be expected. Additionally, while they try to control for temporal confounding variables, I believe that their analysis is still highly susceptible to them.

Goncalves and Mello's approach (2017) could also be applied to MC's data. They found that Florida police gave more preferential treatment to white motorists than to minorities. Their approach was simple:

> When a police officer pulls over a speeding motorist, it is common practice to report a lower speed than what the motorist was *actually* driving at, so as to reduce the fine that they have to pay (e.g. lowering 10 mph over the speed limit to 9 mph when there is a $150 difference between fines for speeding above and below 10 mph). If police officers are racially biased, there should be corresponding differences in leniency toward racial groups.

I prefer Goncalves and Mello's analysis because they focus on a narrow slice of data – motorists who have been pulled over speeding – whereas Grogger and Ridgeway analyze motorists of all kinds, given that they were pulled over at a certain time of day. The homogeneity of Goncalves and Mello's data – as well as its ordinal nature (30 mph over the speed limit is worse than 20 mph) – lead me to believe that it is less susceptible to omitted variables. For this reason, I recreate Goncalves and Mello's methodology, rather than Grogger and Ridgeway's

Data

The data I use are provided by Data Montgomery – an online collection of databases detailing information on Montgomery County. Their description of the dataset is:

> "This dataset contains traffic violation information from all electronic traffic violations issued in the County. Any information that can be used to uniquely identify the vehicle, the vehicle owner or the officer issuing the violation will not be published."

Each observation corresponds to a single electronic citation, warning, or repair order from an officer. Note that multiple citations, warnings, or repair orders can be issued in a single stop – and if a driver was pulled over and received an electronically recorded warning and citation, there will be one observation corresponding to the warning and one corresponding to the citation. The dataset has 44 variables[1] and over 1.5 million observations. Some key variables are a driver's *race* and *gender*, a (quasi) unique *Stop-ID*, a written *description* of the offence, the *latitude* and *longitude* of the stop, whether the write-up is due to an *accident*, *violation type* (e.g. citation, warning, repair order), and whether a driver was *searched* or *arrested*. The dataset covers all electronic traffic violations which have occurred since 2012 (updated daily), but I only use the years 2012-2018 for the sake of having balanced data.

Given my question, the most important variable in the dataset is *race*, which takes one of six values: "ASIAN", "BLACK", "HISPANIC", "NATIVE AMERICAN", "OTHER", "WHITE". Note that it is impossible to conduct a one-to-one mapping from these six racial categories to the eight categories that the official US census observes (at least one MCPD racial category would have to map to multiple Census racial categories, and there is no accurate way to do this). This makes it impossible to reliably compare MC's drivers to those in the rest of the United States.

It is also worth noting that Maryland driver's licences do not state the holder's racial background, so the *race* variable appears to be determined by the reporting officer. Fortunately, this way of collecting racial data does not pose a problem for finding officers' potential racial bias – in fact, an officer's *perception* of a driver's race is more useful information than the driver's actual race.

This dataset is relatively clean, so few changes were made solely for the sake of data-munging. Most of these changes were the removal of spurious outliers from variables like *latitude, longitude*, and *car age*. I added many variables to the dataset and ended up with 90 in total (although many are dummy variables).[2] The most important addition is a new, genuinely unique *Stop-ID* code. This is necessary because the original dataset contains entries that have the same (quasi) unique *Stop-ID* but take place at different locations with different cars and drivers. The new unique *Stop-ID* is created by concatenating the original *Stop-ID* with the date and time of the stop, thereby ensuring that the same *Stop-ID* cannot apply to multiple locations and times. Other important created variables are the *speed over posted limit* (in the case of speeding violations; in mph), *local racial demographics* of a stop, *car age*, *number of citations,* and *number of warnings*.

My process for creating *Speed over posted limit* and *local racial demographics* will be explained later, since they are part of my speeding and geographical analyses, respectively. *Car age* is created by

[1] See Appendix for a full list of variables
[2] The code for creating each variable can be found in the appendix.

subtracting *Year* (year the car was made) from the year the stop occurred. *Number of citations* and *number of warnings* are created by counting the number of citations and warnings, respectively, with the same Stop-ID (i.e. how many citations and warnings were given for this stop).

It is important to note that there are unclear definitions in the dataset. I reached out to Data Montgomery for clarification, but the manager of the dataset has been on paternity leave for the duration of my research. Some of my questions were briefly answered by Captain Thomas Didone – manager of MCPD's traffic division – but we still must proceed with some ambiguities.

The first such unclear definition is an "electronic traffic violation." According to Captain Didone,

> "Electronic traffic violations are when officers utilize the ETIX software to issue a warning citation a State Equipment Repair Order (SERO) or a traffic citations [sic]. If the officer is not certified to use the software or the equipment is not working, then paper versions of those documents are utilized. Those would not be electronic traffic violations…. not all stops are captured."

It is still unclear what makes an officer certified to use the software, but due to the large number of observations, it is clear that most MC traffic violations end up in this dataset. Provided that observations are randomly omitted (i.e. there is no relationship between an officer's performance or behaviour and their ability to enter stops into the database), the results of this project should still hold.

Summary Statistics

Percentage Distribution by Race of MC Traffic Variables

Race	MC Population	MC Accidents	Total in Dataset	Stops	Citations	Warnings	Searches	Arrests	Probable Cause	Nat. Fatalities per 100,000
ASIAN	16%	8%	6%	7%	5%	7%	3%	3%	2%	4
BLACK	20%	23%	32%	30%	33%	31%	40%	36%	54%	12.31
HISPANIC	20%	20%	21%	18%	25%	18%	28%	31%	19%	12.27
NATIVE AMERICAN	1%	0%	0%	0%	0%	0%	0%	0%	0%	31.17
OTHER	1%	6%	6%	6%	5%	6%	3%	3%	4%	-
WHITE	43%	43%	35%	39%	33%	38%	26%	27%	20%	12.5
Total	1,052,567	16,026	1,572,045	891,950	709,792	786,802	68,861	47,541	17,379	-

Table 1

While I stated earlier that I would not base any conclusions of racially biased policing on driver demographics (or estimates of them), the descriptive statistics of Table 1 still tell us a lot about MC and the MCPD.

Table 1 should be interpreted by comparing the differences in statistics within one race to differences in statistics within another. For example, depending on which benchmark you use (MC Population, MC Accidents, or Total in Dataset), black drivers make up between 20-32% of drivers, but 54% of searches conducted via probable cause.[3] Compare this to white drivers, who are between 35-43% of drivers but 20% of probable cause searches. Unless we are missing a massive omitted variable (which is possible), circumstantial evidence indicates that being black makes police officers more likely to believe that you have committed or will commit a crime and search you under the rationale of probable cause.

Model and Results

I use three models in my approach – speeding, geographical, and regression. I will begin by explaining the speeding model.[4]

Speeding Analysis

To briefly re-state the approach of the speeding model (following Goncalves and Mello (2006)):

> Police often reduce reported speeding offences to less serious speeds as a courtesy or favor to drivers. We would like to see if this preferential treatment is applied equally to all races in MC.

As mentioned in the Data section of this paper, each observation comes with a description. Each description is an extremely short – at most one line– description from the officer performing the stop. When an observation/citation is from a speeding offence (speeding offences always result in citations), it almost always comes with a description that describes that offence. Conveniently, these descriptions usually take the following form: “EXCEEDING MAXIMUM SPEED: *X* MPH IN A POSTED *Y* MPH ZONE”. I parsed each description– if it contained two numbers and the string “mph”, then

$$speed\ over\ posted\ limit = larger\ number - smaller\ number.$$

[3] In the United States, an officer can search you via Probable Cause if, based on the circumstances, they believe that you have committed or will commit a crime. Probable Cause has been recognized as “a major source of friction between the police and minority groups”, with minority groups claiming that it is sometimes used to conduct a baseless search. (Richardson, 2017)

[4] Python script is in the appendix

This gave me a raw count of citations at each speed over the posted limit, for reach race[5]. Since it makes more sense to compare proportionate distributions at each speed rather than raw counts, I next normalized the frequency of each speed over the limit, for each race. For example, there were 2,872 white drivers cited as going 15 mph over the speed limit, and after normalization we know that this represents 6.2% of white speeding citations. Now, races' distributions can be meaningfully compared to each-other:

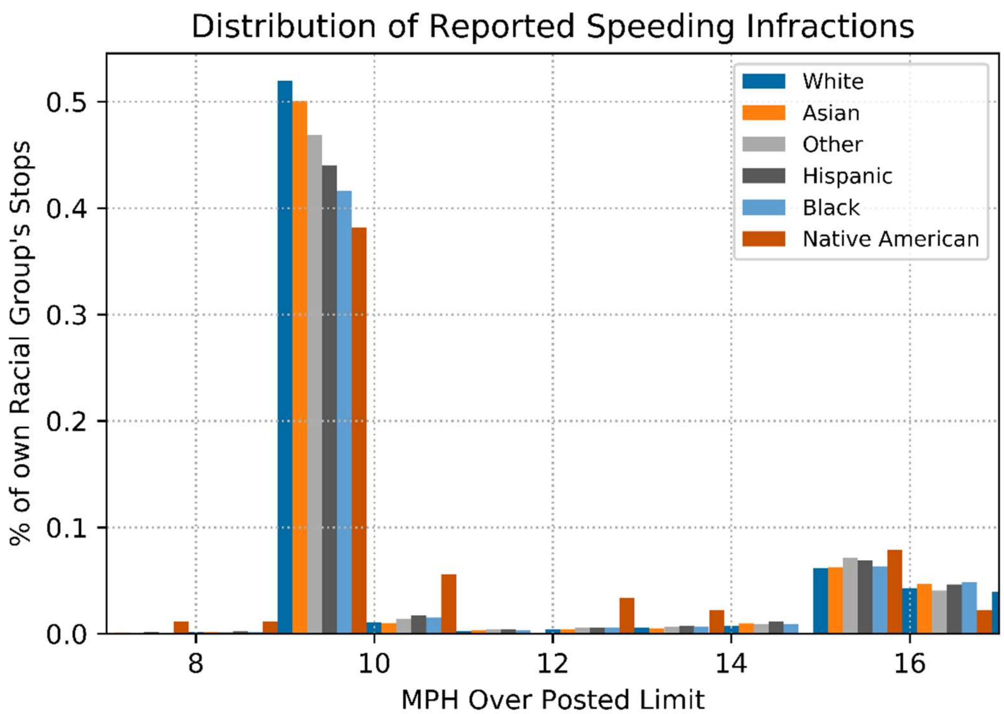


Figure 1

As you can see, Figure 1 features an unnaturally massive cluster of stops at 9 mph – this is because driver-punishment becomes much harsher at 10 mph over the speed limit. Equally evident to the naked eye is the difference between each race's proportion reported at 9 mph over the speed limit. As a robustness check, I calculated the z-static for differences between proportions – testing the two-sided null hypotheses (one at a time) that the proportion of each race cited at 9 mph is the same as the proportion of white drivers cited at 9 mph. That is, for each non-white race *i*, I calculated

[5] There were only 89 citations detailing Native American Speeding – a far lower sample size than the other racial categories

$$Z = \frac{(\hat{p}_{Race\ i} - \hat{p}_{White})}{\sqrt{\frac{\hat{p}_{Race\ i}(1 - \hat{p}_{Race\ i})}{n_{Race\ i}} + \frac{\hat{p}_{White}(1 - \hat{p}_{Whit\ })}{n_{White}}}}$$

where $\hat{p}_{Race\ i}$ = the proportion of non-white drivers (of race *i*) cited at 9 mph

and $\hat{p}_{White}$ = the proportion of white drivers cited at 9 mph

Here are the results of calculating this test statistic:

Race	**Z-statistic**	**P-Value**
Asian	-2.97	.003
Black	-26	<.00001
Hispanic	-16.98	<.00001
Native American	-2.67	.0076
Other	-7.59	<.00001

Every test was rejected at the 99% confidence level

It is still possible to play devil's advocate and claim that these differences are due to different driving habits, demographics, attitudes toward police, and cultures within races, rather than racial bias in policing. On the other hand, we saw (in summary statistics – Data section) that black, Hispanic, and white drivers have nearly identical fatality rates. Since speeding contributes to fatalities, and speeding and fatalities are both determined by driving culture and habits, it is likely that black, Hispanic, and white drivers have similar speeding rates. Nonetheless, this is not strong enough to overcome this devil's advocate's counterargument, so I slightly alter my analysis.

Re-examining Figure 1, we can see that reported speeds pick up frequency at 15 mph over the speed limit. In Figure 1.1 (the same data as Figure 1 – just zoomed out), we see that just as the frequencies at 9 mph look artificially *inflated*, the frequencies in the 10-14 mph range appear artificially *deflated*. Judging by the large portion of frequencies missing from 10-14 mph, it is likely (but not confirmed) that the MCPD will only adjust the reported speed for drivers caught speeding in the 10-14 mph range.[6] [7]

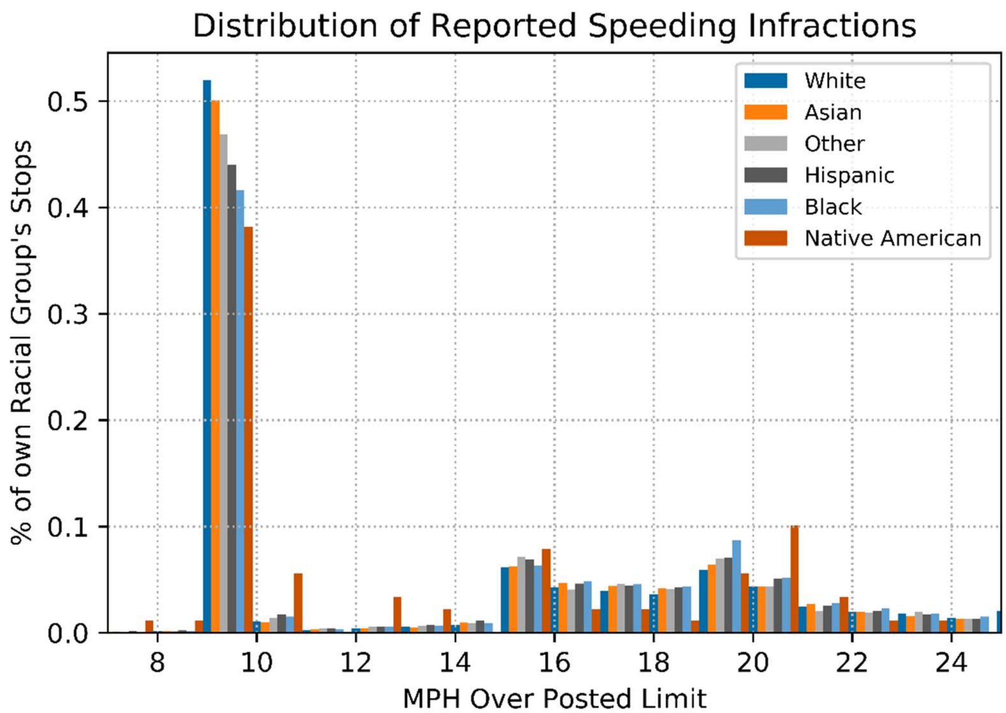


Figure 1.1

As a result, I compressed this data into a single statistic for each race – the proportion of stops of race *X* that *are* cited at 9 mph out of all stops that *could have been* cited at 9 mph (all stops between 9-14 mph). This new tweaked analysis may be less vulnerable[8] to omitted variable bias because we have isolated the portion of speeding frequency that corresponds to preferential treatment from police.

[6] We do not know if this is a top-down directive or something that officers do independently, but it does not make a difference for our analysis.

[7] Assuming that this is true allows the following analysis to be possible.

[8] One omitted variable that is not accounted for is the personal interaction between a driver and the police officer. There may be a positive correlation between a driver's friendliness and the probability that their fine is reduced, and different races may have different levels of friendliness toward police officers.

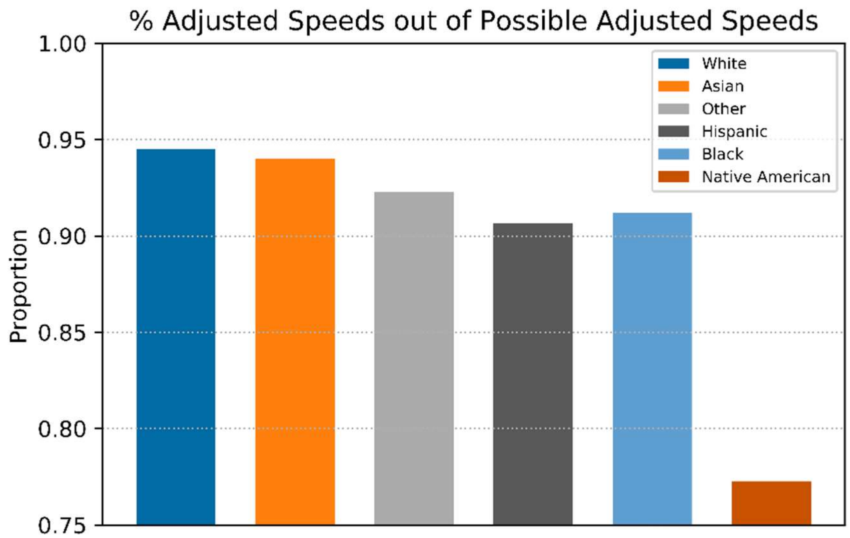


Figure 2

A difference in preferential treatment is still evident after the above correction for differences in speeding, and this is evidence of racial bias. Running the proportion z-test for the new proportions, we get the following statistics:

Race	**Z-statistic**	**P-Value**
Asian	-1.26	.21
Black	-10.96	<.00001
Hispanic	-10.5	<.00001
Native American	-2.73	.006
Other	-4.6	<.00001

This analysis indicates that the MCPD give statistically significantly *less* preferential treatment to black, Hispanic, Native American, and Other drivers than they do to white and Asian drivers. In addition, these results can be interpreted as an ordinal or quantitative "ranking" of how well the MCPD treats each racial group. Note that the rankings[9] are identical across both variants of the speeding analysis, with the exception of black and Hispanic drivers swapping 4th and 5th places.

[9] Original Speeding Analysis: 1) White 2) Asian 3) Other 4) Hispanic 5) Black 6) Native American
New Speeding Analysis: 1) White 2) Asian 3) Other 4) Black 5) Hispanic 6) Native American

Geographical Analysis

Unlike the speeding analysis, my geographical analysis does not have direct precedent in a peer-reviewed journal (that I am aware of). I began the geographical analysis with the hypothesis that if police are racially biased, then minorities might be more likely to be harassed (stopped, searched, searched with probable cause, arrested, etc.) when they drive through whiter neighborhoods. To this end, I decided to split up MC into many small "cells", aggregate all stops within each cell, and then analyze the trends between them.

To do so, I rounded the latitude and longitude of each observation in the dataset to the nearest .005[10] degrees. This means that each cell is a rectangle with side-length of .005 degrees – or roughly 430 meters. After aggregating stops by geolocation, I ended up with an entirely new dataset where each observation describes the police activity in a cell.

Each of these observations contains the following information specific to its cell (for all races):

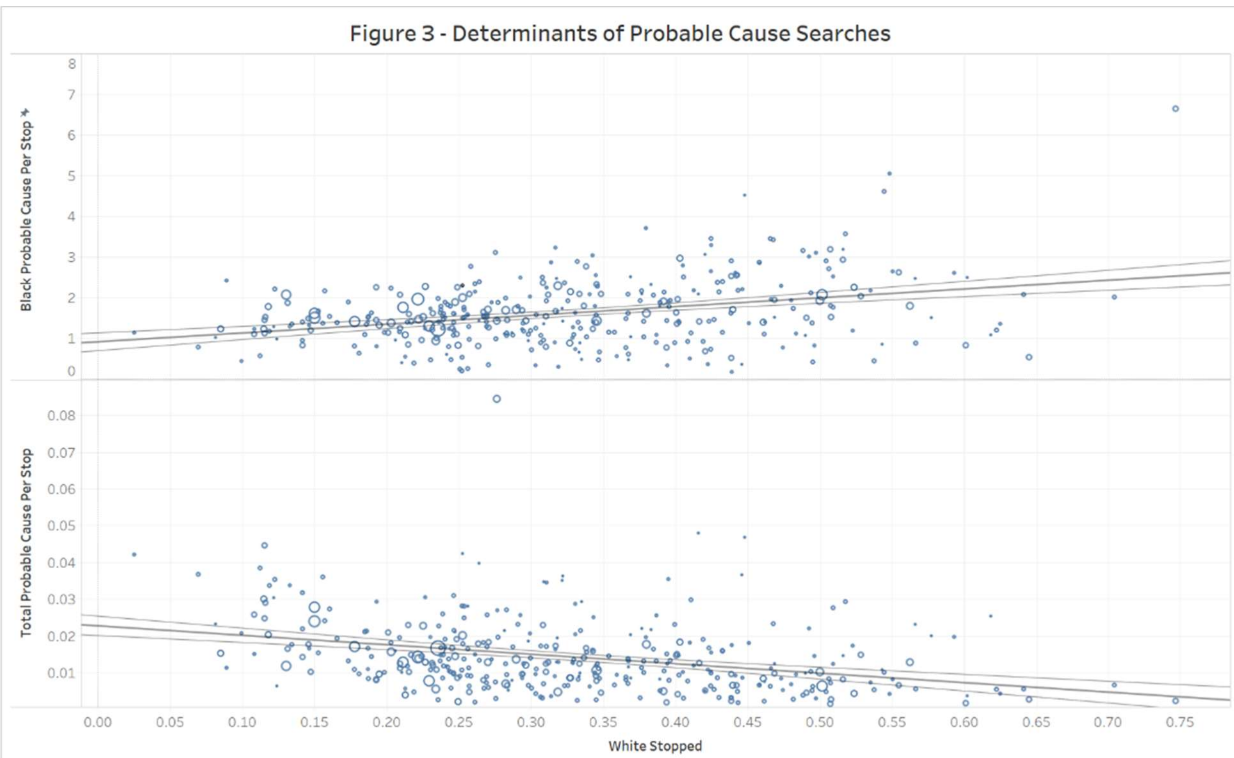
Race *i* Accidents as share of all races'
Race *i* Arrests as share of all races'
Race *i* Arrests per Race *i* Accident
Race *i* Arrests per Race *i* Stop
Race *i* Citations as share of all races'
Race *i* Citations per Race *i* Stop
Race *i* Probable Cause as share of all races'
Race *i* Probable Cause per Race *i* Stop
Race *i* Searches as share of all races'
Race *i* Searches per Race *i* Accident
Race *i* Searches per Race *i* Stop
Race *i* Stops as share of all races'

There are 87 variables in this new dataset, so there are too many relationships between variables to show them all. Nonetheless, I investigate some specific relationships in greater detail.

[10] .005 was arbitrarily chosen

Figure 3[11] has two scatterplots. In the both scatterplots, the farther right a dot is, the larger that cell's share of white drivers stopped (e.g. .75 means that 75% of drivers stopped in that cell are white). In the top scatterplot, the higher a dot is, the more likely it is that a black motorist will be searched with probable cause, given that they have been pulled over (e.g. 4 means that 4% of black drivers stopped in that cell are searched with probable cause). Finally, the larger a cell's dot is, the more stops occurred in the cell.

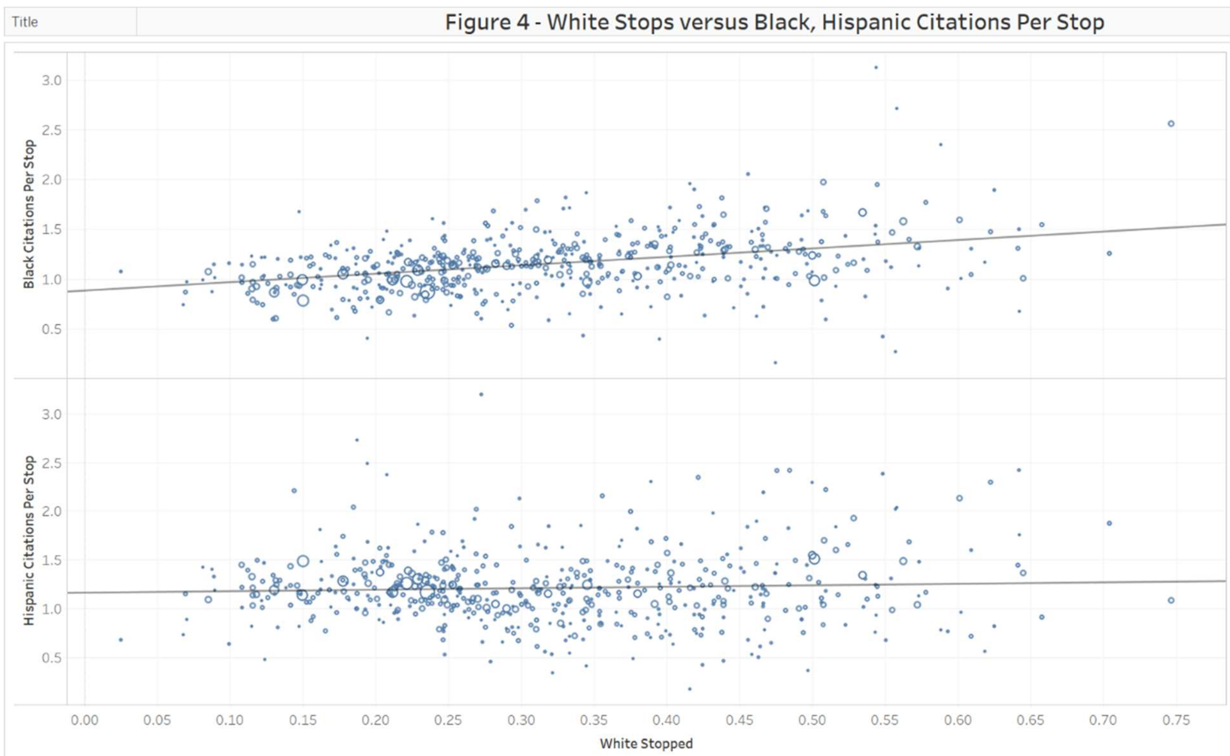
This tells us two important things: 1) the whiter the neighborhood, the more likely it is that a black driver will be searched with probable cause; and 2) the whiter the neighborhood, the less likely it is that *any* driver is searched with probable cause. Black drivers have by far the largest positive relationship between being in a white neighborhood and being searched with probable cause.



As a robustness check, I examined the relationship in Figure 3 across cells with varying numbers of stops (in case the analysis was skewed by small outliers – areas of MC which saw too few stops for the law of large numbers to apply). The relationship holds, whether we analyze the top-ten busiest cells, all of them, or any group in-between.

[11] These data were slightly filtered: restricted to cells with greater than 300 stops, greater than 0 black probable cause searches, greater than 0 white probable cause searches. The same relationships hold for any cell-size filter, this filter was only applied to make the visualization cleaner.

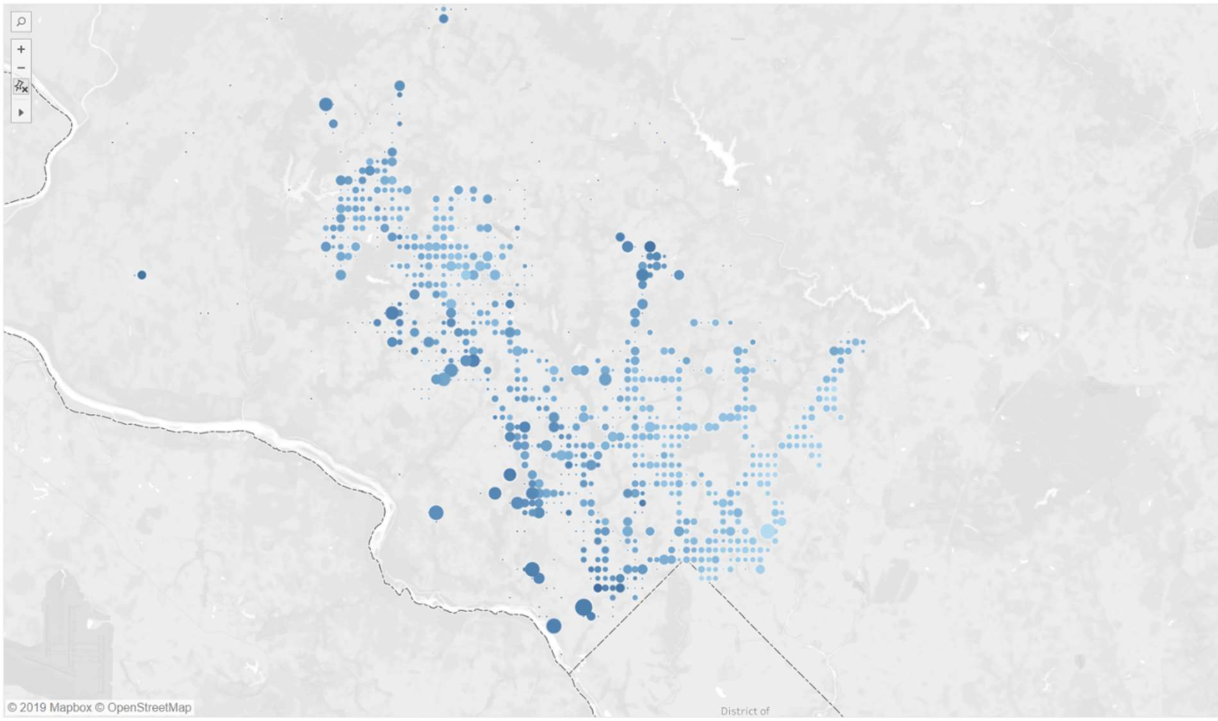
Unfortunately, Figure 3 is just one of many scatterplots that appears to display racial bias. Figure 4[12] (below) exhibits a positive relationship between white stops and the number of citations a black driver receives per stop, given that they have been stopped. Interestingly, Hispanic drivers receive (more or less) the same number of citations wherever they drive, as do the other racial groups. This is a curious result, since I have also found that Hispanic drivers are more likely to be arrested and/or searched with probable cause in whiter areas. It appears that black drivers are discriminated against more than other groups – the same trend that showed itself in the speeding analysis.



Finally, we examine a map of MC (Figure 5).

[12] Also filtered to cells with greater than 300 stops, greater than 0 black probable cause searches, and greater than 0 white probable cause searches.

Figure 5 - White Stop Percentage vs Black Arrests Per Stop



The darker the circle, the higher its cell's percentage of white stops. The larger the circle, the more likely a black driver is to be arrested in that cell, given that they have been stopped. We can clearly see that larger circles tend to be darker, especially in western cells. In other words, black drivers are arrested more frequently in cells that have more white stops.

Overall, this analysis strongly indicates that the MCPD discriminates against minorities – most notably black drivers – when they drive in areas with more white drivers (and therefore white people).

Regression Analysis

As stated earlier, I do not put much stock in the following regression analyses, since they are at the mercy of myriad omitted variables. Nonetheless, it is still a good idea to conduct regressions for the sake of better understanding the data and its trends. Table 2 contains various regressions which attempt to isolate the effect of a driver's race on the outcome of a traffic stop. Each race listed represents a dummy variable which equals 1 if the driver is of that race and equals 0 if not. To avoid multicollinearity, I dropped the *White* dummy variable from each regression. As a result, each coefficient is reported relative to the omitted *White* coefficient.

Each regression was conducted with control variables (not displayed in Table 2) accounting for the racial makeup of local stops, the police district that the stop occurred in, how much the driver was speeding (if they were speeding), and the car's age. Regressions are weighted by the number of entries in the dataset – i.e. rather than only considering a driver's characteristics for each *stop*, said driver's characteristics are weighted by the number of observations they correspond to (citations, warnings, and repair orders that they received).

Table 2

VARIABLES	(OLS) # Citations	(Trunc. Poisson) # Citations	(Probit) Search Conducted	(Probit) Arrested	(Probit) Probable Cause
Asian	-0.24***	-0.18***	-0.18***	-0.16***	-0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Black	0.43***	0.22***	0.16***	0.10***	0.33***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Hispanic	0.63***	0.19***	0.08***	0.12***	0.03***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Native American	0.17***	0.10***	-0.03	-0.01	-0.01
	(0.06)	(0.03)	(0.05)	(0.05)	(0.08)
Other	-0.17***	-0.10***	-0.15***	-0.17***	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Male	0.53***	0.22***	0.35***	0.30***	0.29***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Constant	0.80***	0.74***	-2.10***	-2.12***	-3.04***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
Observations	1,442,846	639,470	1,442,846	1,442,846	1,442,846
R-squared (Pseudo)	0.06	(.08)	(.06)	(0.07)	(0.05)

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

While I do not believe that these regression analyses can answer our question of racial bias in policing, it is worth noting that in most of these regressions, being a black or Hispanic driver makes you more likely to incur the negative outcome (dependent variable) than most other races. In fact, we can take this conclusion a step further and note that the "ranking" of these regression coefficients closely mirrors the "ranking" derived from the speeding analysis.

Discussion and Conclusion

In most of my findings, the devil's advocate cannot be refuted and we cannot conclusively declare that there is racial bias in the MCPD. This does not mean that there is no racial bias – on the contrary, the three analyses I have conducted all yield corroboratory evidence that there is racial bias. Specifically, they indicate that black and (less-so) Hispanic motorists are discriminated against by the MCPD, and that Asian and white motorists receive preferential treatment.

My speeding analysis ranked each race by how likely it is that a driver of that race will receive leniency from the MCPD – black and Hispanic motorists are firmly at the bottom of that ranking, while white and Asian motorists were just as firmly planted atop. My geographical analysis definitively concluded that minority drivers are more likely to be searched, arrested, and generally harassed by police when they drive in non-minority areas. Finally, my regression analysis – which could not be trusted on its own – corroborated the "ranking" findings of the speeding analysis.

Despite these strong results, the nature of this dataset always leaves room for questions. There is one data source that would instantly provide a cut-and-dry conclusion: speed-camera data. With speed-camera data, we could compare the objective rate at which cameras cite drivers of different races to the subjective rates at which officers decide to pull over and cite speeding motorists. Controlling for location, any difference between the two sets of citations would be the result of officers' biases.

In the future, I hope to expand my analysis and investigate causal links between negative stop outcomes for minorities and the following variables: whether it was raining, performance of the Washington Redskins and/or Baltimore Ravens football teams, whether a stop occurred during rush-hour, whether a stop occurred in darkness or daylight, and finally the wealth of a neighborhood – isolated from its demographics. Also, hopefully the dataset-manager is willing to answer some questions when he returns from paternity leave.

In my opinion, the next step forward in addressing these troubling statistics is getting more detailed data that describes the behavior of individual officers. As I said in the Background section, racial bias in a police force could be explained by a few bad officers or by widespread, systematic bias. We do not know what combination of these two institutional maladies is afflicting the MCPD, and our ignorance will persist until the MCPD provides officer-level data. Crucially, this ignorance makes it impossible to enact effective reform, except by blind luck.

Ultimately, this is the most comprehensive public analysis of the MCPD to date. While we can (and should) always conduct more robustness-checks and avoid hasty conclusions, I believe it would be inappropriate to deny or ignore these findings, given their consistency, strength, and importance.

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Appendix