The effect of air-pollution and Republican vote share on police performance and racial bias

Teona Ristova

Advisors: Talal Rahwan & Kinga Makovi

Abstract

Extensive research has been conducted on the topic of racial bias in policing, ranging from traditional surveys to large-scale data analysis. This existing research largely focuses on evaluating police behavior towards minority groups while controlling for socioeconomic factors such as neighborhood characteristics, vehicle type, poverty rate, and income level. Our research takes a less traditional approach in evaluating human behavior and racial bias by evaluating how police performance is affected by environmental factors such as air pollution and temperature. We show that higher temperatures and lower air quality are associated with higher efficiency rates among police officers. Our findings further suggest that these environmental conditions may also be associated with increased bias rates towards Blacks. We then explore the link between the proportion of votes for a Republican president against police performance and bias. We find that increased proportions of voters in support of a Republican candidate are associated with superior police performance. Nevertheless, we find no evidence suggesting that increased vote share in favor of a Republican president is associated with discriminatory behavior by the police.

1 Introduction, Specific Aims & Background

1.1 Air Pollution

In the United States despite the fact that equal opportunity laws have been in place, as well as racism is counter-normative, Blacks and other minorities experience discrimination and racism on a daily basis [1, 2]. Discrimination as a result of such bias has been prevalent in multiple fields such as health-care [3], the labor market [4, 5] as well as policing [6]. Police bias and misconduct have captivated the attention of lay audiences, inspired the Black Lives Matter movement, and led to substantial scientific inquiry. It has been found, for example, that Blacks are searched more often when compared to Whites at routine traffic stops. Moreover, when stopped by the police and searched, they were less likely to be found with contraband than otherwise comparable Whites [7]. Such findings have been confirmed not only on a national level, but also on a city level in New York and San Diego [7, 8]. In order to ensure that the observed bias is not caused by external factors, such as neighbourhood characteristics, economic factors, time of the day when stops take place, a number of papers have used big data lenses, and arrived at the same conclusion: racial bias against Blacks by the police in the US still persists [9, 10, 11].

In the pursuit of understanding how and why racial bias persists, in my capstone project I investigate how it may be affected by everyday external factors. This work falls in the same line of inquiry as the one by Obradovich and his colleagues, observing how weather conditions affect officials' behavior [12]. They find that extreme temperatures, such as heat waves, increase the possibility of health hazards while decreasing police officers' and safety inspectors' performance in times when it is needed the most. Inspired by this, I have taken a less traditional approach in observing biased behavior exhibited by police officers. While weather is just one of the factors to affect the populous, there are many more such as rent prices, gasoline prices, green space, and last but not least, pollution. I expect the presence of certain particles in air pollution to affect police officers' behavior in certain ways, similarly to how weather affects officials' behavior. After analyzing the disproportionate stops of Blacks by the police, my hypothesis is that different levels of air pollution would result in different stop outcomes. The assumption is that police officers' decisions are influenced by the levels of the pollutants present in a specific time and space.

Previous research has been conducted on how certain particles present in air pollution affect human behavior[13, 14, 15]. Lead has been found to lead to symptoms such as depression, anxiety, sleep disorders, difficulty concentrating, irritability, and fatigue. The intake of other heavy metals has also been associated with neurological distortions. Mercury, for instance, causes irritability, difficulty concentrating, and insomnia. This further leads to fatigue, shyness, embarrassment, discouragement, and apathy [16].

The relationship between human behavior, air pollution, and weather is one of great importance. Weather has been found to be a significant factor when evaluating air pollution and its corresponding effects on mental health and human behavior. Using archival data obtained from three sources, Rotton and Frey assess relations among ozone levels, nine measures of meteorological conditions, day of the week, holidays, seasonal trends, family disturbances, and assaults against persons [17]. They find that there is a relationship between ozone levels and aggression, as well as a relationship between weather conditions and levels of violence. In another study, Chen and his colleagues find that, in general, air pollution is higher during warmer periods in China [18]. This suggests that a relationship between weather and air pollution exists.

These observations raise the following question: Do contextual factors, such as extreme weather or pollution affect not only the overall effectiveness and activity of the police, but also how they deal with citizens of different ethnic backgrounds? In other words, is racial bias of the police affected by these commonly experienced factors?

Given the link suggested between air-pollution, weather and human behavior, my goal is to analyze how various particles, as well as weather condition,s affect police officers' behavior and their bias. More specifically, the main research questions of the paper are the following:

1. How does air pollution affect human behavior and police stops?
2. How does weather affect police bias?
3. How can we decouple the effect of weather from the effect of air pollution when studying their impact on police behavior?

Climate change and air pollution are closely linked. In particular, climate change is the result of increased emission of greenhouse gasses. Global warming, in turn, is associated with air pollution as it is responsible for the emission of hydrocarbon combustion products which when mixed with biological allergens form particulate matters (PM). Global warming is closely related to the emission of hydrocarbon particles since CO_2 and heat form the harmful particulate matter known as PM10. The formation of this matter is extremely harmful to human's health [19].

Urban cities suffer largely from the effects of air pollution and climate change. The high global temperature increases over the years have led to severe consequences such as floods, storms, droughts, the spread of diseases and more. Cities largely contribute to the emissions of greenhouse gasses [20]. As a result of the combined effect of climate change and air pollution, urban cities are victims of extreme environmental outcomes and health hazards. However, apart from these observable repercussions, the effect of human behavior is one that is less obvious and could easily be neglected. The worsening of the climate change and air pollution calls for immediate actions on all fronts. Cities address the alarming situation by developing renewable energy sources to slow down the emission of harmful gases [20]. As such, understanding the relationship between air pollution, climate change, and police performance can have important policy implications, especially for urban cities.

1.2 Presidential Elections

As a second part of my research I will be focusing on presidential elections. Literature has been concentrated towards the analysis of the link between the police and election votes. It has been found that Republicans tend to rate the honesty and ethical standards of police officers higher than Democrats do [21]. According to this research, Republicans hold higher regard for these people because they work in traditional institutions in American society and this supports their conservative ideology [21]. In fact, it has been found that among Republicans, only military members are regarded higher than the police, whereas among Democrats there are four groups rated significantly higher than the police [22]. Republicans have also been found to believe that people who assume roles as police officers tend to have "very dangerous jobs". 70 percent of Republican voters have expressed this belief compared to 65 percent of Democrats. Additionally, Republicans were found to hold a view that people show "too little respect" for the police. It was found that 77 percent of Republicans hold this view as opposed to 45 percent of Democrats [23]. We have decided to investigate the link between the police and the Republicans in this paper by using data on police stops and a dataset on presidential election votes between 2000 and 2016. We focus on investigating how police performance varies across counties depending on the share of votes towards a Republican candidate. We anticipate the analysis to reveal higher performance of the police in places where the majority of the county votes Republican. Our hypothesis is that if a certain county has a high number of Republican supporters then we could expect better performance on behalf of the police simply because they are trusted and supported more.

Another link we are exploring in this paper is how the racial bias changes based on the percentage of Republican votes within a county. The Republican party is known as a conservative party that tends to hold, primarily, the interests of the white population. Although in the past Republicans and Democrats shared a somewhat similar consideration of the interests of the Whites, each year the Republican Party seems to be increasingly protecting the views of the white, Christian, male and rural elements of the U.S. electorate, whereas the Democratic Party has moved towards protecting everything else [24]. For example, Democrats' support for the view that the "country needs to continue making changes to give blacks equal rights" has grown from 57 percent in 2014 to 80 percent in 2017 [25]. We analyze how racial bias as expressed by police officers varies within a county based on the percentage of Republican votes. Our hypothesis is that the police exhibit more discriminatory behavior towards Blacks in counties with a higher share of votes in support of Republicans.

2 Methodology

2.1 Results Obtained From The Replica Of The Stanford Open Policing Project

We confirmed the presence of racial bias on a nation-wide level by replicating the Stanford Open Policing project's racial bias analysis. This was done by aggregating the most up-to-date data on police stops in cities in each state where data is available and running the same disparity tests as the researchers. We downloaded the code as well as the files from the suggested Github account.

The programming language they used in their tutorial to perform the analysis is R, and as this is a replication of their findings we decided to stick with R. The replica helped in familiarizing myself with the Stanford open policing data and the statistical methods available for evaluating racial bias along with their strengths and shortcomings.

The tutorials and the shared code provided by the researchers were very helpful. Nevertheless, given the sheer size of the project, we still ran into multiple inconsistencies when performing the analysis. The column names as well as the value names were not cleaned by the researchers. For example, some of the names were capitalized, while others were lowercase. Significant effort went into making all variables and column names consistency across all the files and the code. Another issue we ran into was inconsistencies of the code with up to date R packages, which caused significant delays. The researchers have fortunately made the necessary updates recently and as such we were able to perform the analysis with the appropriate R packages. After cleaning the data we moved on to merging all the country level files into single files as each state had a file for each city and then within those city files we had missing values for counties. Where counties were missing we performed reverse geo-coding by using the given values for the latitude and longitude to determine the location.

As part of the replica, I performed the veil of darkness, the outcome, and the threshold test on Stanford's open policing dataset. The veil of darkness test, developed by Grogger and Ridgeway [26], compares how police stops on black drivers vary across different times of the day. The basic idea is that the darker it is, the less able the police officers are to identify the race of the driver. This means that as it gets darker, if police officers stop black drivers less just because they are unable to tell their race, then we can infer the presence of racial bias. The results of the veil of darkness test can be observed in Figure 1. The test was conducted on data available for the state of Texas and only includes data on black and white drivers. Three bins are created for three 15-minute windows (19:00 – 19:15, 19:15 – 19:30, 19:45) in order to account for the differences in time when it is considered to be dark throughout the year, especially since it gets dark earlier during winter. The time $t = 0$ represents dusk, after which we consider it to be dark. Figure 1 shows that as it gets darker the number of stops performed on black driver decreases. These results, thus, suggest the presence of racial bias.

The outcome test is another statistical approach in evaluating racial bias developed by Becker [27]. This test measures the proportion of searches that successfully turn up contraband, a proportion also known as the "hit rate". According to Becker's theory, if searches of minority drivers turn up contraband less often, then double standards are performed by the police officials, which implies the presence of bias. To perform this test, we aggregated the available data on a city level. The outcome analysis was performed on the state of Texas, North Carolina, South Carolina, Washington, Wisconsin and Connecticut. The results can be seen in Figure 2, where the hit rate of each minority group, i.e., Hispanic and Black, is plotted against the hit rate of Whites. As can be observed, searches for both minority groups, Hispanic and Black drivers, are less successful compared to those of Whites. The outcome test is, hence, indicative of racial bias. It should be noted that the results we obtained are slightly different from those obtained by Pierson and her colleagues. In their paper they find that while searches of Hispanic drivers are less successful, those of Blacks are comparable to those of Whites. This difference can be attributed to the use of different data. The dataset on Stanford's open policing website is updated regularly. As we used the most up to date version, differences in results could have arisen.

However, the outcome test suffers from the concept known as infra-marginality [28, 29], which reflects situations in which there are different distributions for a particular characteristic among two different groups. As an example of this shortcoming, let us assume that there are two easily distinguishable groups of white drivers: one group that has a 5% chance of carrying contraband,

and another that has a 75% chance of carrying contraband. Let us further assume that there are two types of Black drivers, one with a 5% chance of carrying contraband, and another with a 50% percent chance of carrying contraband. Now if the police decided to search only the drivers who have at least a 10% chance of carrying contraband, then the outcome test would suggest that searches for black drivers are successful less often, which would wrongly imply the presence of bias [6]. The threshold test accounts for this by estimating the threshold above which a certain race is searched by a police officer. When using the threshold test, we can observe in Figure 3 that the threshold for searching Blacks and Hispanic is lower than the threshold of Whites. This test more strongly confirms the presence of racial bias across locations for both of the minority groups.

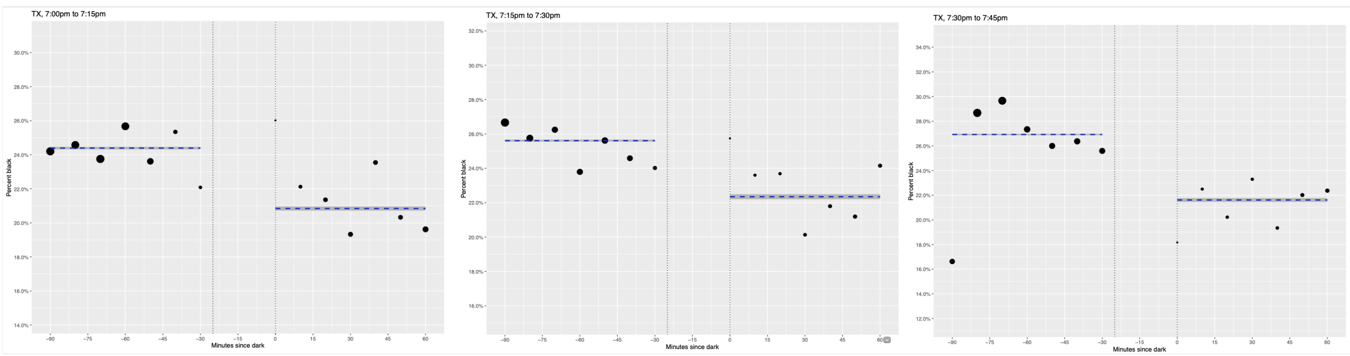

Figure 1: Veil of darkness plot for Texas.

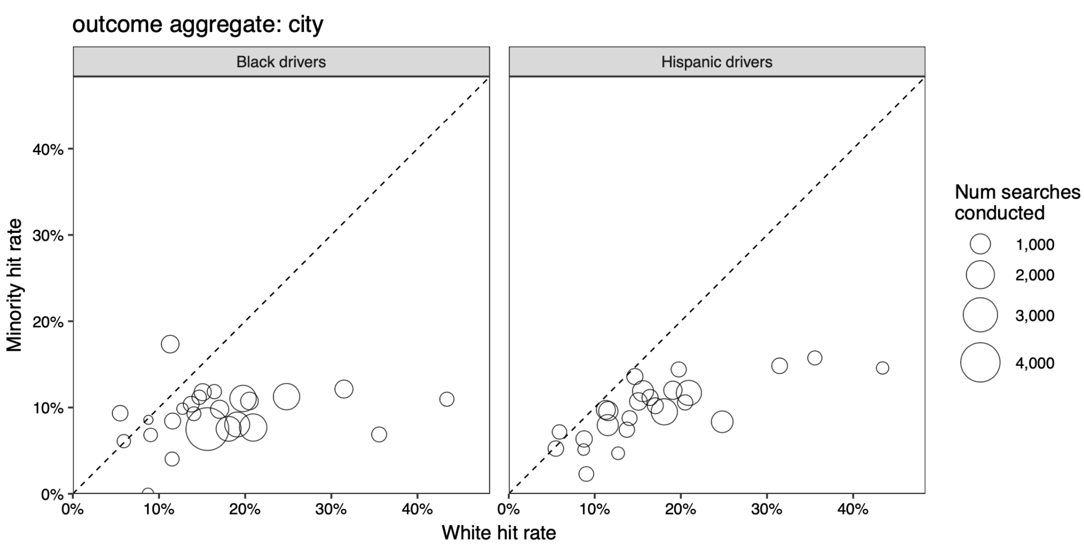

Figure 2: Outcome aggregation.

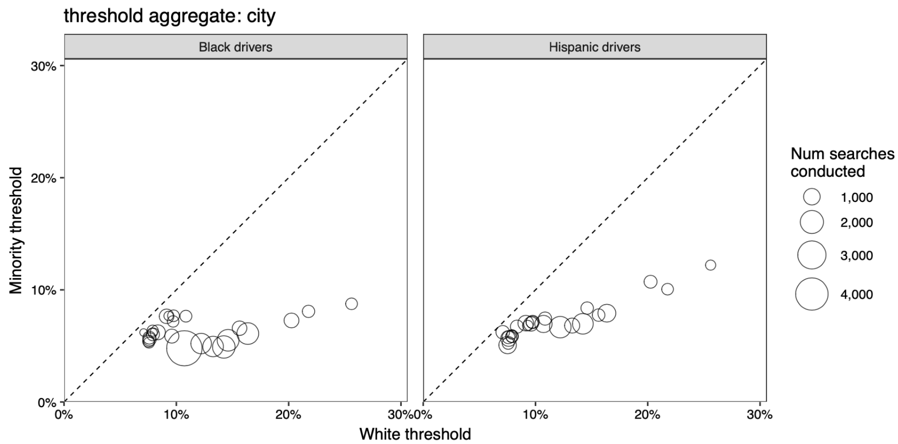

Figure 3: Threshold aggregation.

2.2 Results Obtained From The Replica Of The Paper Effects Of Environmental Stressors On Daily Governance

After confirming the presence of racial bias by obtaining similar results to those found by the Stanford research team, we decided to combine the Open Policing Project's dataset with another dataset on temperature. By merging these two datasets based on state, county name, and date we obtained a new dataset that contains information on police stops and on the weather conditions corresponding to the place and time of each such stop. This allowed us to perform similar analysis to the one conducted in the paper by Obradovich et al. [12]. The paper finds that as the temperature increases, the number of stops increases, up until a certain temperature threshold is reached. Once this threshold has been reached, which they found to be 29 degrees celsius, the police stops start decreasing. There has been previous research that finds a linear relationship between temperature and vehicular crashes [30, 31]. Given these results, the paper concludes that extreme weather affects police performance in time when it is needed the most.

Using the newly created dataset, we plotted a histogram to check if we would observe similar trends. Our results, which are presented in Figure 4, indeed exhibit comparable trends. As the temperature increases, the number of stops increases up until a temperature of around 87 Fahrenheit, or 30.5 degrees celsius, is reached. After this point the number of stops starts decreasing, indicating a decrease in police performance.

2.3 Datasets

To evaluate the possible links between air-pollution and human behavior as well as the link between presidential elections and racial bias, the following six main datasets were analyzed:

1. The Stanford Open policing dataset, which contains over 60 million state patrol stops in 20 US states between 2011 and 2017 [6].

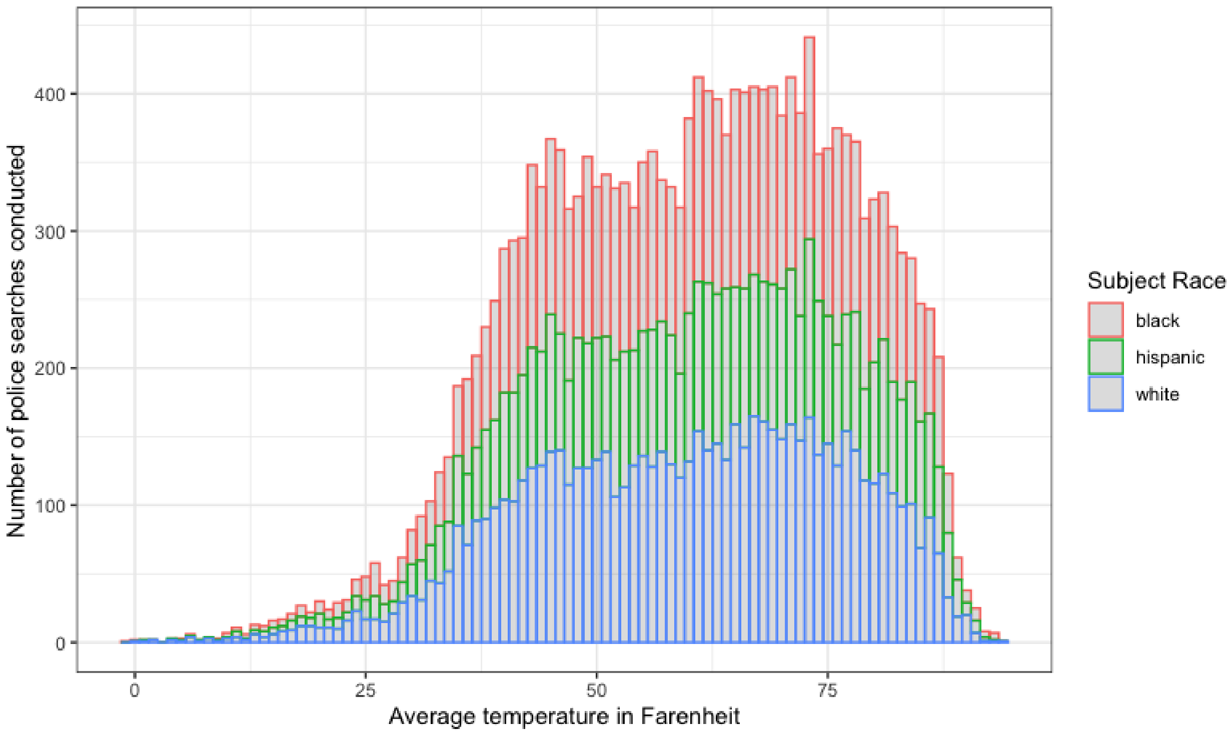

Figure 4: Histogram of the effect of temperature on the number of searches conducted.

2. An air-pollution dataset, which contains hourly data on the presence of various particles, such as ozone, lead and PM particles, as well as daily data on the air quality index (AQI) on a county level in the US [32].

3. A weather dataset, which contains hourly data on the temperature throughout the day, wind speed as well as humidity on a county level in the US [33].

4. Various controls at the county level come from the US census on the unemployment rate, poverty rate, household income, and occupation by industry, just to name a few [34].

5. Presidential election data published by MIT on a county level in the US for presidential elections between 2000 and 2016 [35].

6. Employment data provided by the Local Unemployment Statistics on a county level in the US annually [36].

2.4 Research Design

As part of the analysis a multivariate regression analysis was performed with the goal of determining the effect of air pollution on human behavior and racial bias as well as to explore the effect of the political party determination on human behavior and racial bias. The analysis was performed on a county level per year for the states of Texas, Washington, North Carolina, South Carolina, Wisconsin and Connecticut. These are the six states on which we had sufficient available data.

The main outcome variables are the number of searches conducted, the hit rate, and the ratio of the hit rate of Whites to that of Blacks. The hit rate was aggregated over all searches and was computed as the ratio of the number of stops where contraband was found over the number of searches conducted. The hit rate is used to measure the performance of the police officers; the higher the hit rate the greater the number of searches that turn up contraband, which in turns indicates superior performance. The ratio of hit rate of Whites to Blacks is used to measure racial bias; the higher the ratio the greater the hit rate of Whites compared to that of Blacks, which in turn suggests the presence of racial bias. The key independent variables are the air quality index (AQI) and the percent of population within a county that voted Republican for the presidential elections. The air quality index measure incorporates the worst/highest air quality index within a county when a stop was made.

The controls variables consist of the following: the year fixed effect, the population density, percent of population that belongs to the minority, the percent of population that is unemployed, the percent of population that is under 19 years old, and the percent of the population under the poverty line. Additional meteorological control variables are introduced when the key independent variable is the air quality index; those are: extreme temperature, wind speed, humidity and industrial occupation.

4 Results

The analysis consists of six multiple linear regression models. Three of the models explore the effect of air quality along with the controls as described in the previous section on three outcome variables, namely the number of searches conducted, the hit rate and the ratio of hit rate of Whites against the hit rate of Blacks. The other three models explore the link between percent of people who voted Republican along with the control variables against the same three outcome variables. The Appendix includes all the tables with the results obtained from running the regressions.

4.1 Air Quality Findings

The relationship between air quality and the number of searches conducted is depicted in Figure 5. As the air quality index increases, i.e., the air quality decreases, the number of stops increases. Similarly to the effect of climate change, after a certain threshold, the number of searches begins to decrease again. The multiple regression model carried out to investigate the relationship between AQI along with the control variables against the number of searches conducted demonstrate a significant relationship between the air quality index and number of searches conducted ($p = 0.03$), population density and number of searches conducted ($p = 0.00038$), wind speed and number of searches conducted ($p = 0.000460$), percentage of population working in the manufacturing sector and number of searches conducted ($p = 0.000339$), the temperature and number of searches conducted ($p = 0.000227$), unemployment rate and number of searches conducted ($p = 0.002870$), and percentage of population under 19 and number of searches ($p = 0.000227$). The relationship between the percentage of minority population within a county and number of searches conducted, and the relationship between the percentage of population below the poverty line and number of searches conducted are significant at 1 percent significance level. For each point increase in the air quality index, around 2 more searches are being conducted. For each increase in density per square mile of land area, the number of searches conducted decreases by 5. For each percent increase in the unemployment rate, the number of searches conducted decreases by 2. For each percent increase in the proportion of population under 19, the number of searches conducted decreases by 9. For each Fahrenheit increase in temperature, the number of stops decreases by 5. For each increase in wind speed per knot, the number of searches conducted decreases by 3. For each percent increase in the population whose occupation is manufacturing, the number of searches conducted increases by 7.

The adjusted R squared value is 0.4844 so around 48 percent of the variation in the number of searches conducted can be explained by our model. The model is robust to year fixed effects. These results are consistent with our expectations. The number of stops performed decreases in extreme temperatures and poor air quality conditions. This further supports the assumption that police officers' performance is affected due to the effect of environmental factors.

The relationship between air quality and the hit rate is depicted in Figure 6. As the air quality index (AQI) increases, i.e., the air quality decreases, the hit rate increases. This implies better efficiency of the searches carried out. The multiple regression model carried out to investigate the relationship between air quality alongside the control variables and the hit rate demonstrate a significant relationship between the air quality index and the hit rate ($p = 0.019363$), temperature when search was being conducted and the hit rate ($p = 0.0000456$), the percent of minority population and the hit rate ($p = 0.001226$) and the poverty rate and the hit rate ($p = 0.015896$). For each point increase in the air quality index, the hit rate increases by 0.05178 percent. For each Fahrenheit increase in temperature, the hit rate increases by 1.289 percent. For each percent increase in poverty rate, the hit rate decreases by 1.289 percent. For each percent increase in minority population, the hit rate decreases by 43 percent.

The adjusted R squared is 0.5245 which means that 52 percent of the variance in the hit rate can be explained by the model. The model is robust to year fixed effects. These results reveal some interesting findings. Even though high temperatures and low air quality lead to decreased number of searches, these same environmental conditions improve the efficiency of the police officers. Even though the number of searches conducted has decreased, this does not mean that the police officers efficacy decays. As the results reveal these environmental conditions seem to be motivating police officers to limit the searches to those that are necessary, thereby increasing their performance.

The relationship between air quality and the ratio of hit rate of Whites to hit rate of Blacks is depicted in Figure 7. It could be observed that as the air quality index increases, the ratio increases. This means that the hit rate of Whites is higher than the hit rate of Blacks, indicative of the presence of racial bias. The multiple regression model carried out to investigate the relationship between air quality alongside the control variables and the ratio of the hit rate of Whites to that of Blacks demonstrates a significant relationship between the air quality index and the white to black hit rate ratio ($p = 0.0301$), and percent days of the year when the temperature is above 87 Fahrenheit and the white to black hit rate ratio ($p = 0.0203$). It is important to note when running this multiple linear regression model, instead of the worst air quality index, the average quality index is taken. Moreover, instead of average temperature, the percentage of days when extreme temperature is experienced is taken as a control variable. These two changes result in a more significant model. The relationship between the Whites to Blacks hit rate ratio against population density, unemployment rate and the percentage of population in the manufacturing sector is significant at 1 percent significance level. For each point increase in the air quality index, the ratio increases by 6 percent. For each percent increase in number of days of the year when temperature is above 87 Fahrenheit the ratio increases by 19 percent.

The adjusted R squared value is 0.03064 which means that 3 percent of the variation in the ratio can be explained by the model. Given these findings the model does not seem to be significant. While we can observe increase in racial bias as the air quality gets worse, which is what we expected given the negative side effects of pollution, there is not enough evidence to support this relationship.

4.2 Presidential Elections Findings

The relationship between percent of the population that voted Republican and number of searches conducted is depicted in Figure 8. As the percent of the population who voted Republican increases the number of searches conducted decreases. The multiple regression model carried out to investigate the relationship between percent of population who voted Republican alongside the control variables and the number of searches conducted demonstrates a significant relationship between the percent who voted Republican and the number of searches (p = 0.00000382), the percent of the population under 19 and the number of searches (p = 0.012282), and the poverty rate and the number of searches (p = 0.000129). For each percent increase in population who voted Republican the number of searches decreases by 826. For each percent increase in the poverty rate, the number of searches decreases by 21. For each percent increase in population under 29, the number of searches increases by 1830. The adjusted R squared is 0.08335 so 8 percent of the variation of the number of searches can be explained by the model.

The relationship between percent of the population that voted Republican and the hit rate is depicted in Figure 9. As the percent of people who voted Republican increases the hit rate increases. The multiple regression model carried out to investigate the relationship between percent of population who voted Republican alongside the control variables and the hit rate demonstrates a significant relationship between the percent who voted Republican and the hit rate (p = 0.0000000323), population density and the hit rate (p = 0.017480), unemployment rate and the hit rate (p = 0.00000000016), and percent of population under 19 and the hit rate (p = 0.046568). For each percent increase in people who voted Republican the hit rate increases by 31 percent. For each increase in density per square mile the hit rate increases by 0.003781. For each percent increase in population under 19, the hit rate increases by 45 percent. For each percent increase in the unemployment rate the hit rate decreases by 3.5 percent. The adjusted R squared is 0.3024 so 30 percent of the variation in the hit rate can be explained by the model.

Based on the obtain results with respect to the number of searches conducted and the hit rate, it could be observed that there is some support in favor of the assumption we had at the very beginning. As the percentage of the votes in favor of Republicans increases, the police seem to be performing better as measured by the hit rate. We anticipated this result to take place as Republicans have been found to trust the police more compared to the Democrats.

The relationship between percent of the population that voted Republican and the ratio of Whites to Blacks hit rate is depicted in Figure 10. There does not seem to be any relationship. This is confirmed by the multiple regression model that explores the relationship between percent of population who voted Republican alongside the control variables and the hit rate ratio of Whites to Blacks. The overall p-value of the model is 0.02545 and the adjusted R squared is 0.02707 which means that 2 percent of the variance in the ratio can be explained by the model. Given the results, there does not seem to be any support of the hypothesis that the police exhibits racial bias when the percentage of votes for a Republican president increases.

5 Figures

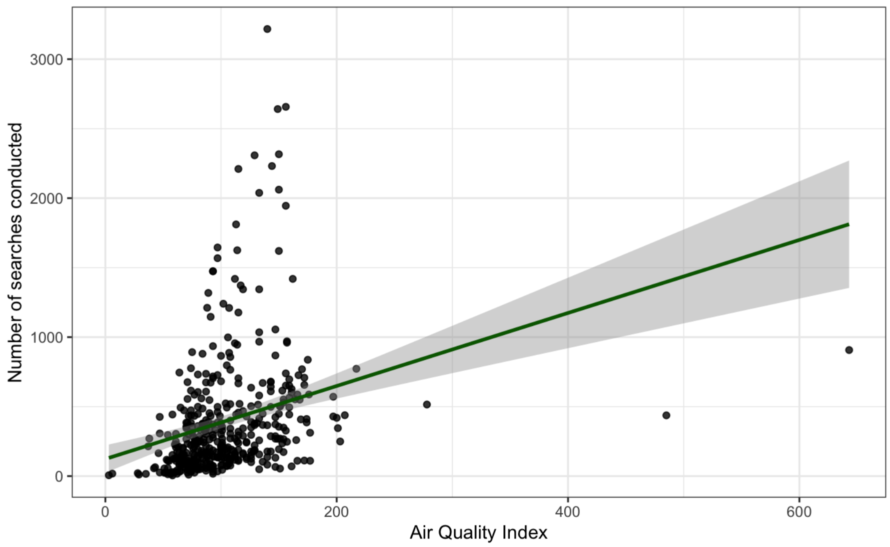

Figure 5: Relationship between the air quality index and number of searches conducted.

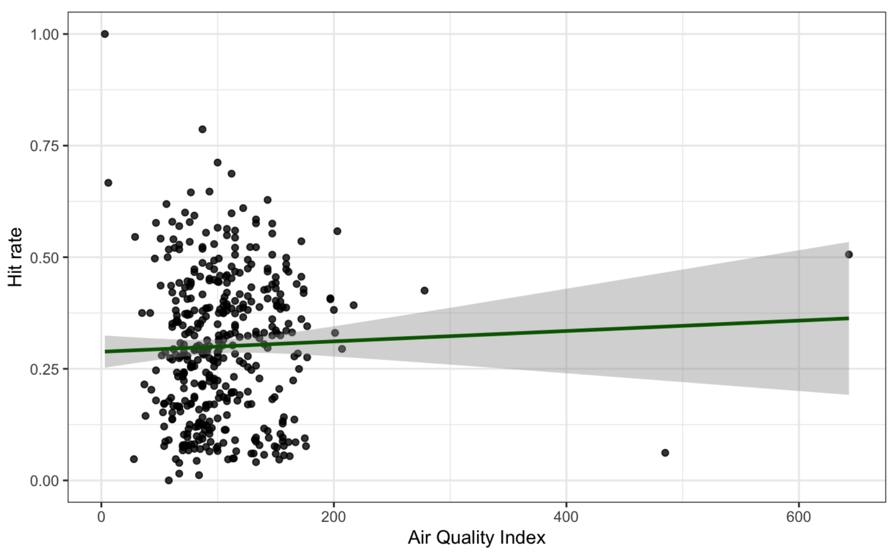

Figure 6: Relationship between the air quality index and hit rate.

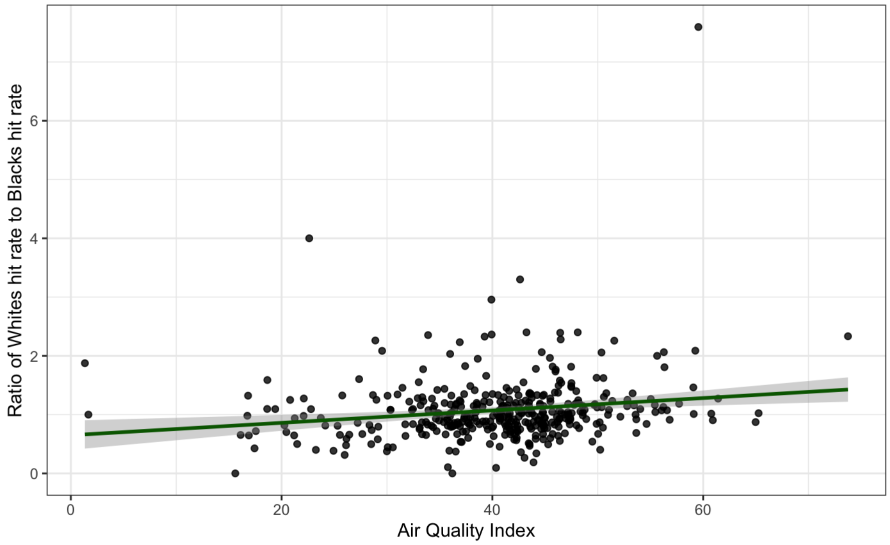

Figure 7: Relationship between the air quality index and the ratio of Whites hit rate to Blacks hit rate.

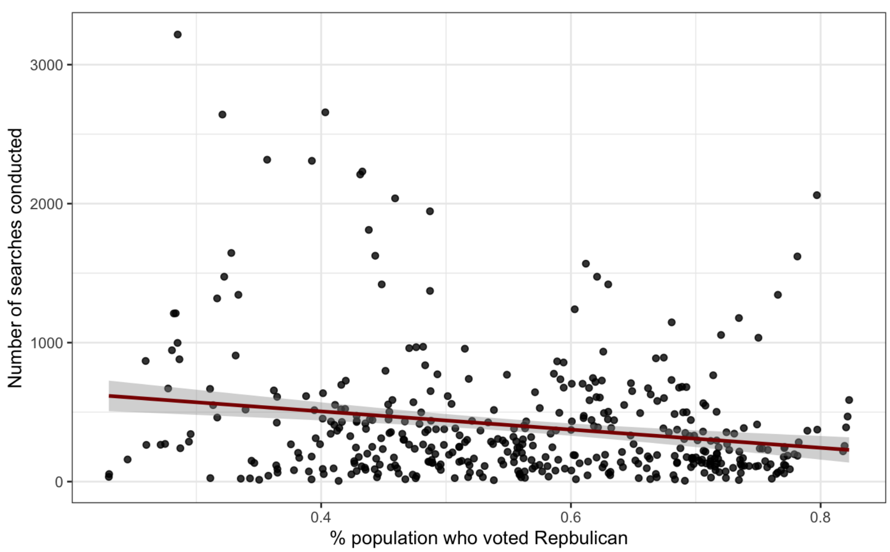

Figure 8: Relationship between percent Republican vote and number of searches conducted.

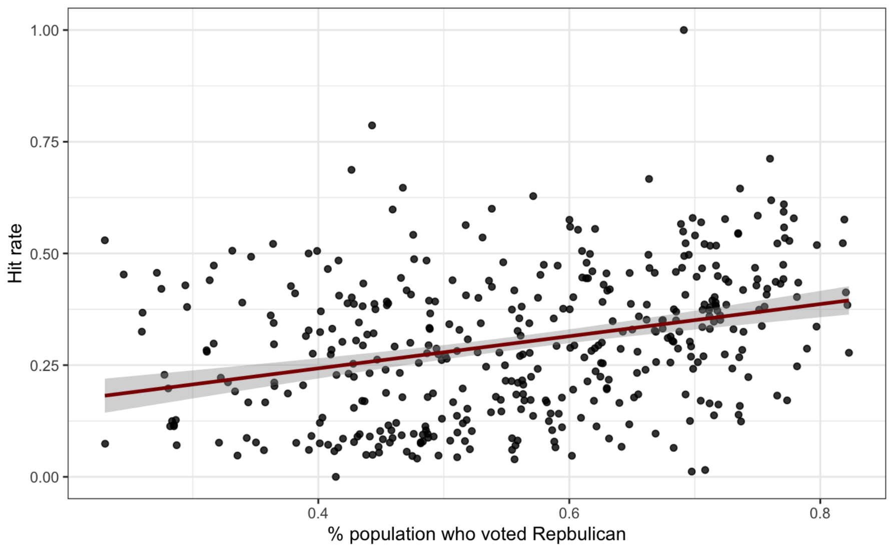

Figure 9: Relationship between percent Republican vote and hit rate.

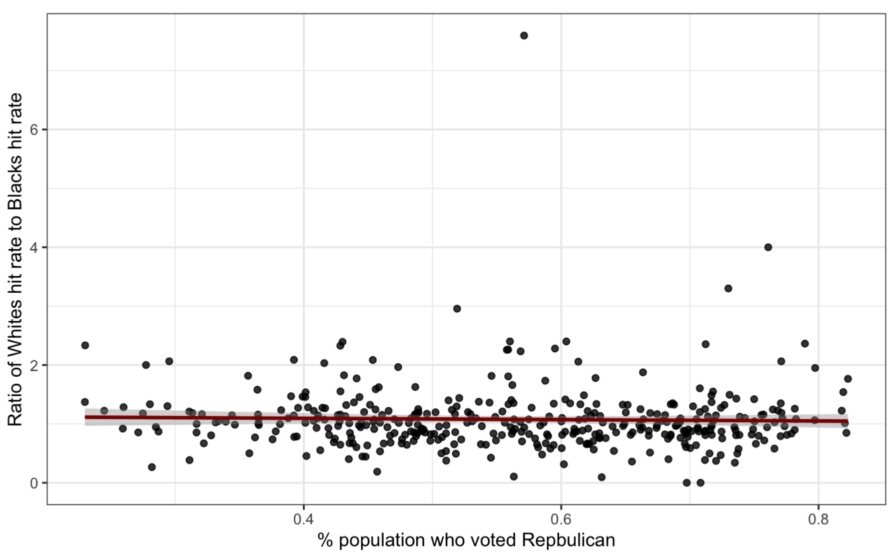

Figure 10: Relationship between percent Republican vote and ratio of hit rate Whites to hit rate Blacks.

6 Discussion

Our investigation of multiple datasets on police stops, environmental factors and socioeconomic factors reveals evidence of an effect of environmental factors on police performance. We have noticed that while the number of searches the police conducts significantly decreases due to extreme weather and pollution conditions, the efficiency of the police becomes greater under extreme weather; they become more alert and tend to stop and search vehicles that have higher likelihood of carrying contraband. Our findings also demonstrate an increase in racial bias towards Blacks in worsened conditions despite the overall increased hit rate efficiency. Further analysis could be done to understand these relationships better. A time series analysis on different time periods can be conducted to explore how the relationship varies across time. The Twitter API can be used in order to conduct a sentiment analysis and link it with our analysis on police bias. The Twitter API can be used with the data on implicit bias in order to evaluate racial bias. Another potential direction is to explore Machine Learning algorithms that could be trained to provide predictions of how the future development of climate change and air pollution would affect officers' behavior and racial bias, and examine whether such algorithms are biased.

The findings from this analysis have important policy implications, especially in times when global warming and air pollution continue to worsen. The two are not only environmental phenomena but are also important factors that negatively affect one's social and economic well being [37]. Most of the literature has focused on the effects of air pollution on health, while little attention has been given to the link between air pollution and other forms of human behavior. I believe that exploring this link yields a better understanding of the social consequences of air pollution and the relevant measures that need to be taken in response. It is important to realize and devise ways of preserving the efficiency of police officials while minimizing the high pollution rates and slowing down climate change.

Our analysis of the data on presidential elections and police stops shows some support of the link between police performance and votes for Republicans. We find that as the percentage of the votes for a Republican candidate increases, the police performance improves. This may be explained by Republicans holding higher regard and trust for the police. This would make police officers in these counties feel supported, which in turn leads to superior performance. No evidence of racial bias as manifested by the police was found based on the share of votes for a Republican president.

References Cited

[1] C. Giulietti, M. Tonin, and M. Vlassopoulos, "Racial discrimination in local public services: A field experiment in the united states," *Journal of the European Economic Association*, vol. 17, no. 1, pp. 165–204, 2019.

[2] D. S. Massey and G. Lundy, "Use of black english and racial discrimination in urban housing markets: New methods and findings," *Urban affairs review*, vol. 36, no. 4, pp. 452–469, 2001.

[3] C. V. Ziad Obermeyer, Brian Powers and S. Mullainathan, "Dissecting racial bias in an algorithm used to manage the health of populations," vol. 366,, no. 6464, 2019, pp. 447–453.

[4] J. Williams and V. Wilson, "Black workers endure persistent racial disparities in employment outcomes," 2019.

[5] A. Y. Agan and S. B. Starr, "Do employers ' neighborhoods predict racial discrimination ?" 2017.

[6] E. Pierson, C. Simoiu, J. Overgoor, S. Corbett-Vadies, V. Ramachandran, C. Phillips, and S. Goel, "A large-scale analysis of racial disparities in police stops across the united states." Stanford Computational Policy Lab, 2019, pp. 1–21.

[7] J. Chanin, M. Welsh, and D. Nurge, "Traffic enforcement through the lens of race: A sequential analysis of post-stop outcomes in san diego, california," *Criminal Justice Policy Review*, vol. 29, no. 6-7, pp. 561–583, 2018. [Online]. Available: https://doi.org/10.1177/0887403417740188

[8] K. D. Figures and J. Legewie, "Visualizing police exposure by race, gender, and age in new york city," *Socius*, vol. 5, p. 2378023119828913, 2019. [Online]. Available: https://doi.org/10.1177/2378023119828913

[9] J. West, "Racial bias in police investigations," 2016.

[10] F. R. Baumgartner, L. Christiani, D. A. Epp, K. Roach, and K. Shoub, "Race or place? the persistence of race effects in police behavior following traffic stops," 2018.

[11] S. Seguino, "A deeper dive into racial disparities in policing in vermont," 2018.

[12] N. Obradovich, D. Tingley, and I. Rahwan, "Effects of environmental stressors on daily governance," *Proceedings of the National Academy of Sciences*, vol. 115, no. 35, pp. 8710–8715, 2018. [Online]. Available: https://www.pnas.org/content/115/35/8710

[13] G. W. Evans, S. D. Colome, and D. F. Shearer, "Psychological reactions to air pollution," *Environmental Research*, vol. 45, no. 1, pp. 1 – 15, 1988. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0013935188800021

[14] X. Zhang, X. Zhang, and X. Chen, "Happiness in the Air: How Does a Dirty Sky Affect Mental Health and Subjective Well-being?" Global Labor Organization (GLO), GLO Discussion Paper Series 56, 2017. [Online]. Available: https://ideas.repec.org/p/zbw/glodps/56.html

[15] Y.-H. Lim, H. Kim, J. H. Kim, S. Bae, H. Y. Park, and Y.-C. Hong, "Air pollution and symptoms of depression in elderly adults," *Environmental health perspectives*, vol. 120, pp. 1023–8, 04 2012.

[16] A. LUNDBERG, “Psychiatric aspects of air pollution,” *Otolaryngology - Head and Neck Surgery*, vol. 114, no. 2, pp. 227 – 231, 1996. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0194599896701729

[17] J. Rotton and J. Frey, “Air pollution, weather, and violent crimes: concomitant time-series analysis of archival data.” *Journal of personality and social psychology*, vol. 49 5, pp. 1207–20, 1985.

[18] C. Chen, C. Liu, R. Chen, W. Wang, W. Li, H. Kan, and C. Fu, “Ambient air pollution and daily hospital admissions for mental disorders in shanghai, china,” *The Science of the total environment*, vol. 613-614, pp. 324–330, 09 2017.

[19] V. Patella, G. Florio, D. Magliacane, A. Giuliano, M. A. Crivellaro, D. Di Bartolomeo, A. Genovese, M. Palmieri, A. Postiglione, E. Ridolo *et al.*, “Urban air pollution and climate change: “the decalogue: Allergy safe tree” for allergic and respiratory diseases care,” *Clinical and Molecular Allergy*, vol. 16, no. 1, pp. 1–11, 2018.

[20] Cities and climate change. [Online]. Available: https://www.unenvironment.org/explore-topics/resource-efficiency/what-we-do/cities/cities-and-climate-change

[21] J. M. Jones. (2013) Honesty ratings of police, clergy differ most by party. [Online]. Available: https://news.gallup.com/poll/166487/honesty-ratings-police-clergy-differ-party.aspx

[22] P. R. Center, “Partisans differ widely in views of police officers, college professors,” *Pew Research Center*, 2017.

[23] E. Ekins, “Americans worry about police safety, but republicans most concerned about police being disrespected,” *Cato Institute*, 2016.

[24] R. K. Ghere, “Uncivil agreement: How politics became our identity,” *Public Integrity*, vol. 21, no. 2, pp. 214–219, 2019. [Online]. Available: https://doi.org/10.1080/10999922.2018.1511673

[25] P. R. Center, “The partisan divide on political values grows even wider,” *Pew Research Center*, 2017.

[26] J. Grogger and G. Ridgeway, “Testing for racial profiling in traffic stops from behind a veil of darkness,” *Journal of the American Statistical Association*, vol. 101, no. 475, pp. 878–887, 2006. [Online]. Available: https://doi.org/10.1198/016214506000000168

[27] G. S. Becker, “Nobel lecture: The economic way of looking at behavior,” *Journal of Political Economy*, vol. 101, no. 3, pp. 385–409, 1993. [Online]. Available: https://doi.org/10.1086/261880

[28] C. Simoiu, S. Corbett-Davies, and S. Goel, “The problem of infra-marginality in outcome tests for discrimination,” *Ann. Appl. Stat.*, vol. 11, no. 3, pp. 1193–1216, 09 2017. [Online]. Available: https://doi.org/10.1214/17-AOAS1058

[29] R. Neil and C. Winship, “Methodological challenges and opportunities in testing for racial discrimination in policing,” *Annual Review of Criminology*, vol. 2, no. 1, pp. 73–98, 2019. [Online]. Available: https://doi.org/10.1146/annurev-criminol-011518-024731

[30] S. M. Hsiang, M. Burke, and E. Miguel, “Quantifying the influence of climate on human conflict,” *Science*, vol. 341, no. 6151, 2013. [Online]. Available: https://science.sciencemag.org/content/341/6151/1235367

[31] M. Ranson, “Crime, weather, and climate change,” *Journal of Environmental Economics and Management*, vol. 67, no. 3, pp. 274 – 302, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0095069613001289

[32] U. S. E. P. Agency, “Daily aqi,” 2012-2017, data retrieved from: https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw.

[33] ——, “Meteorological,” 2012-2017, data retrieved from: https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw.

[34] U. S. C. Bureau, “United states census data,” 2012-2017, data retrieved from: https://www.census.gov/data.html.

[35] M. E. Data and S. Lab, “County Presidential Election Returns 2000-2016,” 2018. [Online]. Available: https://doi.org/10.7910/DVN/VOQCHQ

[36] U. B. of Labor Statistics, “Local area unemployment statistics (laus),” 2012-2017, data retrieved from: https://www.bls.gov/lau/.

[37] The link between climate change and air pollution. [Online]. Available: https://www.activesustainability.com/climate-change/link-between-climate-change-air-pollution/

Appendix

```
Call:
lm(formula = n_search_conducted ~ AQI_max + factor(year) + `Density per square mile o
f land area` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent +
    temp_average + humidity_average + wind_average + C24050_004,
    data = all_join)

Residuals:
   Min     1Q Median     3Q    Max
-865.4 -327.2  -43.4  195.5 1021.9

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                             1.070e+04  2.170e+03   4.930 5.32e-06 ***
AQI_max                                 2.151e+00  9.701e-01   2.217 0.029881 *
factor(year)2013                       -4.738e+02  1.744e+02  -2.717 0.008292 **
factor(year)2014                       -7.473e+02  2.167e+02  -3.449 0.000957 ***
factor(year)2015                       -8.436e+02  2.397e+02  -3.519 0.000766 ***
factor(year)2016                       -8.054e+02  2.680e+02  -3.006 0.003678 **
`Density per square mile of land area` -5.312e-01  1.208e-01  -4.399 3.81e-05 ***
minority_PER                            1.011e+03  5.787e+02   1.747 0.085028 .
Unemployment_rate                      -2.033e+02  6.581e+01  -3.090 0.002870 **
under_19_per                           -9.062e+03  4.263e+03  -2.126 0.037067 *
all_ages_poverty_percent                3.362e+01  1.840e+01   1.827 0.071960 .
temp_average                           -5.169e+01  1.329e+01  -3.888 0.000227 ***
humidity_average                       -1.054e+01  8.252e+00  -1.278 0.205570
wind_average                           -3.142e+01  8.545e+00  -3.676 0.000460 ***
C24050_004                              7.073e-03  1.877e-03   3.768 0.000339 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 449.7 on 70 degrees of freedom
  (331 observations deleted due to missingness)
Multiple R-squared:  0.5703,    Adjusted R-squared:  0.4844
F-statistic: 6.637 on 14 and 70 DF,  p-value: 2.545e-08
```

Figure 11: Dependent variable: Number of searches conducted.

```
Call:
lm(formula = hit_rate ~ AQI_max + factor(year) + `Density per square mile of land are
a` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent +
    temp_average + humidity_average + wind_average + C24050_004,
    data = all_join)

Residuals:
     Min       1Q   Median       3Q      Max
-0.22639 -0.05550  0.02026  0.06670  0.17505

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                           -6.757e-01  4.839e-01  -1.396 0.167069
AQI_max                                5.178e-04  2.163e-04   2.394 0.019363 *
factor(year)2013                       1.425e-01  3.889e-02   3.665 0.000477 ***
factor(year)2014                       1.549e-01  4.832e-02   3.206 0.002030 **
factor(year)2015                       1.432e-01  5.346e-02   2.679 0.009192 **
factor(year)2016                       2.166e-01  5.976e-02   3.624 0.000546 ***
`Density per square mile of land area`  4.380e-05  2.693e-05   1.626 0.108392
minority_PER                          -4.349e-01  1.290e-01  -3.370 0.001226 **
Unemployment_rate                      9.621e-03  1.467e-02   0.656 0.514215
under_19_per                          -6.136e-02  9.507e-01  -0.065 0.948724
all_ages_poverty_percent              -1.014e-02  4.103e-03  -2.471 0.015896 *
temp_average                           1.289e-02  2.964e-03   4.349 4.56e-05 ***
humidity_average                       4.267e-04  1.840e-03   0.232 0.817319
wind_average                           1.873e-03  1.906e-03   0.983 0.329065
C24050_004                            -5.277e-07  4.185e-07  -1.261 0.211537
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1003 on 70 degrees of freedom
  (331 observations deleted due to missingness)
Multiple R-squared:  0.6037,    Adjusted R-squared:  0.5245
F-statistic: 7.618 on 14 and 70 DF,  p-value: 2.074e-09
```

Figure 12: Dependent variable: Hit rate.

```
Call:
lm(formula = W_to_B_ratio ~ AQI_average + factor(year) + `Density per square mile of
land area` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent +
    percent_days + humidity_average + wind_average + C24050_004,
    data = all_join)

Residuals:
    Min      1Q  Median      3Q     Max
-1.4405 -0.3777 -0.0817  0.1968  5.2579

Coefficients:
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                            7.077e-01  3.930e+00   0.180   0.8576
AQI_average                            6.311e-02  2.851e-02   2.213   0.0301 *
factor(year)2013                      -5.208e-01  3.066e-01  -1.699   0.0938 .
factor(year)2014                      -9.630e-01  4.369e-01  -2.204   0.0308 *
factor(year)2015                      -1.169e+00  4.926e-01  -2.374   0.0204 *
factor(year)2016                      -8.140e-01  5.050e-01  -1.612   0.1115
`Density per square mile of land area`  3.771e-04  2.217e-04   1.701   0.0934 .
minority_PER                          -1.703e+00  1.046e+00  -1.628   0.1081
Unemployment_rate                     -2.393e-01  1.340e-01  -1.786   0.0784 .
under_19_per                          -1.158e+00  7.123e+00  -0.163   0.8713
all_ages_poverty_percent               2.100e-02  3.363e-02   0.624   0.5344
percent_days                          -1.897e-01  7.988e-02  -2.374   0.0203 *
humidity_average                      -3.812e-03  1.628e-02  -0.234   0.8155
wind_average                           6.154e-03  1.346e-02   0.457   0.6490
C24050_004                            -7.205e-06  3.742e-06  -1.926   0.0582 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8257 on 70 degrees of freedom
  (331 observations deleted due to missingness)
Multiple R-squared:  0.1922,    Adjusted R-squared:  0.03064
F-statistic:  1.19 on 14 and 70 DF,  p-value: 0.3027
```

Figure 13: Dependent variable: Ratio hit rate Whites to hit rate Blacks.

```
Call:
lm(formula = n_search_conducted ~ percent + factor(year) + `Density per square mile o
f land area` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent,
    data = all_join)

Residuals:
    Min      1Q  Median      3Q     Max
-697.47 -242.12  -85.14   98.94 2444.51

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                             860.39279  269.61739   3.191 0.001527 **
percent                                -826.11802  176.32137  -4.685 3.82e-06 ***
factor(year)2013                       -110.10670   66.45749  -1.657 0.098335 .
factor(year)2014                       -146.55011   74.12286  -1.977 0.048705 *
factor(year)2015                       -184.17470   79.38293  -2.320 0.020833 *
factor(year)2016                       -250.48454   91.78491  -2.729 0.006629 **
`Density per square mile of land area`   -0.06837    0.05069  -1.349 0.178122
minority_PER                            304.49895  206.04422   1.478 0.140230
Unemployment_rate                        -6.30917   17.20497  -0.367 0.714029
under_19_per                           1830.01510  727.57403   2.515 0.012282 *
all_ages_poverty_percent                -21.40029    5.53599  -3.866 0.000129 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 431.6 on 405 degrees of freedom
Multiple R-squared:  0.1054,    Adjusted R-squared:  0.08335
F-statistic: 4.773 on 10 and 405 DF,  p-value: 1.719e-06
```

Figure 14: Dependent variable: Number of searches.

```
Call:
lm(formula = hit_rate ~ percent + factor(year) + `Density per square mile of land are
a` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent,
    data = all_join)

Residuals:
     Min       1Q   Median       3Q      Max
-0.36610 -0.10093 -0.00381  0.09150  0.59651

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                             2.898e-01  8.429e-02   3.438 0.000647 ***
percent                                 3.105e-01  5.512e-02   5.633 3.32e-08 ***
factor(year)2013                       -3.008e-02  2.078e-02  -1.448 0.148463
factor(year)2014                       -5.946e-02  2.317e-02  -2.566 0.010644 *
factor(year)2015                       -7.651e-02  2.482e-02  -3.083 0.002189 **
factor(year)2016                        1.715e-03  2.869e-02   0.060 0.952358
`Density per square mile of land area`  3.781e-05  1.585e-05   2.386 0.017480 *
minority_PER                           -6.625e-02  6.441e-02  -1.029 0.304295
Unemployment_rate                      -3.531e-02  5.379e-03  -6.564 1.60e-10 ***
under_19_per                            4.541e-01  2.275e-01   1.996 0.046568 *
all_ages_poverty_percent               -1.615e-03  1.731e-03  -0.933 0.351187
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1349 on 405 degrees of freedom
Multiple R-squared:  0.3192,    Adjusted R-squared:  0.3024
F-statistic: 18.99 on 10 and 405 DF,  p-value: < 2.2e-16
```

Figure 15: Dependent variable: Hit rate.

```
Call:
lm(formula = W_to_B_ratio ~ percent + factor(year) + `Density per square mile of land
area` +
    minority_PER + Unemployment_rate + under_19_per + all_ages_poverty_percent,
    data = all_join)

Residuals:
    Min      1Q  Median      3Q     Max
-1.1891 -0.2821 -0.0949  0.1449  6.1601

Coefficients:
                                         Estimate Std. Error t value Pr(>|t|)
(Intercept)                             1.681e+00  3.879e-01   4.335 1.87e-05 ***
percent                                 1.151e-01  2.447e-01   0.470  0.63832
factor(year)2013                       -3.847e-02  8.896e-02  -0.432  0.66566
factor(year)2014                       -1.230e-01  1.028e-01  -1.197  0.23212
factor(year)2015                       -1.559e-01  1.087e-01  -1.434  0.15252
factor(year)2016                       -3.308e-02  1.247e-01  -0.265  0.79091
`Density per square mile of land area`  2.138e-04  6.763e-05   3.162  0.00169 **
minority_PER                           -3.890e-01  2.841e-01  -1.369  0.17169
Unemployment_rate                      -1.879e-02  2.376e-02  -0.791  0.42952
under_19_per                           -1.583e+00  1.083e+00  -1.462  0.14466
all_ages_poverty_percent               -4.817e-03  7.771e-03  -0.620  0.53568
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5621 on 377 degrees of freedom
  (28 observations deleted due to missingness)
Multiple R-squared:  0.05221,   Adjusted R-squared:  0.02707
F-statistic: 2.077 on 10 and 377 DF,  p-value: 0.02545
```

Figure 16: Dependent variable: Ratio hit rate Whites to hit rate Blacks.