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Analyzing Pretextual Traffic Stops and Racial Disparities in Policing

A Case Study of Berkeley and San Francisco RIPA Stops

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Introduction

Traffic stops are a routine occurrence in law enforcement, often seen as a tool for maintaining road safety. However, for many individuals from minority communities, particularly Black and Latino(a) populations, these stops can be fraught with inequity and the potential for harassment (Harris, 2020). Pretextual traffic stops, defined as stops conducted under the guise of a minor traffic violation to investigate unrelated criminal activity (Birzer & Birzer, 2006; San Francisco Police Commission, 2024), have come under increasing scrutiny for their disproportionate impact on minority communities (Lofstrom et al., 2022). This paper will explore if there are geographic trends in pretextual traffic stops, specifically focusing on how income levels and racial composition of neighborhoods. The geographic trends allow us further knowledge of how policing is practiced across neighborhoods and if there is evidence of racial discrimination. This analysis is also specifically useful as data from the Racial and Identity Profiling Act (RIPA) of 2015 does not include any income variables.

Problem Definition

Racial bias in policing, particularly in the context of pretextual traffic stops, presents a pervasive and complex challenge within law enforcement. Despite legal and policy efforts to address these issues, disparities persist, disproportionately affecting Black and Latino(a) communities (Open Justice, 2020; US Census Bureau, 2019). Assembly Bill 953, known as the Racial and Identity Profiling Act (RIPA) of 2015, was enacted in California to increase transparency and accountability in policing, particularly regarding racial profiling in traffic stops (Woods, 2023).

The issue of pretextual traffic stops extends beyond mere inconvenience; it raises fundamental questions about fairness, justice, and the integrity of law enforcement practices. These stops often result in searches, arrests, and fines that disproportionately burden Black and Latino(a) communities (Lofstrom et al., 2022), perpetuating cycles of poverty and mistrust in the justice system (Lee & Gibbs, 2015).

Furthermore, the financial implications of pretextual traffic stops can have long-lasting effects on individuals and communities (Friedman et al., 2022; Martin et al., 2018; Martin, 2018). The imposition of fines and fees, coupled with the threat of arrest for non-payment, contributes to a cycle of debt and legal entanglement that disproportionately affects economically disadvantaged individuals (Pettit & Gutierrez, 2018). For instance, in San Francisco, Black drivers account for 48.7% of traffic court warrants for 'failure to appear/pay' despite comprising only 5.8% of the total population, underscoring the disproportionate impact of traffic fines on Black communities.

The use of force during traffic stops further exacerbates these issues, with studies showing that Black and Latino(a) individuals are more likely to experience the use of force, including handcuffing and drawing of weapons, during traffic stops compared to white individuals (Kramar & Remster, 2018). This unequal treatment not only violates individuals' rights but also contributes to a broader pattern of systemic racism and injustice within law enforcement.

In light of these challenges, it is imperative to examine the root causes of racial disparities in pretextual traffic stops and explore effective strategies to address them. By analyzing RIPA data and conducting spatial analysis, some of the underlying factors contributing to these disparities can be identified. This allows for a better understanding of disparities in pretextual stops to propose evidence-based solutions to promote fair and equitable policing practices in California.

Data Sources

Since this analysis is focused on pretextual traffic stops, it draws its primary data from the Racial and Identity Profiling Act of 2015 (RIPA) for Berkeley and San Francisco. Access to this data was obtained through California Public Records Act (CPRA) requests and Open Data from the Berkeley Police Department and the San Francisco Police Department. The RIPA dataset provides detailed information on every law enforcement stop, including the race, gender, and age of individuals stopped, as well as the location and outcome of the stops.

I also utilized geographic shapefiles, created by ESRI, from ArcGIS Living Atlas for my analysis. The USA 2020 Census Race and Ethnicity Characteristics shapefile offers Census Block Group boundary information enriched with demographic data from the 2020 U.S. Census. The ACS Median Household Income shapefile offers Census Tract boundary information enriched with income data from the 2023 American Community Survey's (ACS) 5-Year Estimates. I chose to utilize these shapefiles because they are reliable sources of neighborhood characteristics and they have the smallest boundary units available for such data (e.g., Census Tract and Block Group).

Methodology

Before adding the data into ArcGIS, I cleaned the data extensively using Stata. For geographic analysis, I limited the sample to only include stops from January 2022 to September 2023, removed observations with unrealistic driver ages, such as 1 or 300 years old, and removed variables that I felt were not necessary. This prior data cleaning occurred because the RIPA data utilized was actually retrieved for a separate, comprehensive mixed-methods analysis project that included numerous California cities. Only Berkeley and San Francisco were used in this analysis as they were the only cities to include coordinate data for each traffic stop.

As for data processing for ArcGIS, I started off by mapping out where the pretextual traffic stops occurred in Berkeley and San Francisco. To do this, I added my RIPA datasets in an Excel format to a new map project as standalone tables. Then, I used the "Creates Points From Table" option to the "XY Table To Point" tool to select traffic stops in Berkeley and create a new layer, and I repeated this process for San Francisco.

After creating the stop points, I added the USA 2020 Census Race and Ethnicity Characteristics shapefile and the ACS Median Household Income shapefile. Using the USA 2020 Census Race and Ethnicity Characteristics layer, I created new layers of this shapefile for only Alameda and San Francisco County. To do this, I used the "Select By Attributes" tool for the USA 2020 Census Race and Ethnicity Characteristics layer to select by the county variable. While selecting only Alameda County, I used the “Export Features” tool for the USA 2020 Census Race and Ethnicity Characteristics layer to create an Alameda County Race and Ethnicity Characteristics layer. I repeated this process for San Francisco. Then, I joined the Alameda County Race and Ethnicity Characteristics layer with the ACS Median Household Income layer using the twelve-digit geographic identifier for each county. This creates a single layer with both racial and income information that is limited to only Alameda County. I then repeated this for San Francisco County.

After creating a single layer with racial and income information for both counties, I wanted to further restrict these to only include the parts of the county where stops were recorded. To do this, I used the “Select By Location” tool to select the Census Tracts and Block Groups that completely contain the traffic stop points. Then I exported these selected features to create separate layer containing race and income information for Berkeley. However, San Francisco County is San Francisco, the city, so a separate layer was not needed to be created.

Still, I planned on my analysis primarily being cluster analysis. I wanted to analyze clusters in stop points while uncovering which points were essentially noise. To do this, I used the “Density-based Clustering” tool. I used the stop points as my input to cluster on and used the “Self-adjusting (HDBSCAN)” clustering method with a minimum of 20 features per cluster.

Finally, I duplicated my map so that I could have five different maps for each city. For these five maps, I modified the symbology to map the following statistics: 1) the total number of residents, 2) the median income, 3) the percentage of residents who are Black or African American, 4) the percentage of residents who are Hispanic, and 5) the most predominant racial or ethnic group. All of these statistics came from the USA 2020 Census Race and Ethnicity Characteristics shapefile and the ACS Median Household Income shapefile. For maps of the total number of residents, the totals are mapped by color with darker blues representing the higher populated areas. For maps of the median income, the amounts are mapped by color with darker purples representing higher-income areas. For maps of the percentage of residents who are Black or African American, the percentages are mapped by color with darker blues representing areas with a high percentage of Black or African American residents. For maps of the percentage of residents who are Hispanic, the percentages are mapped by color with darker blues representing areas with a high percentage of Hispanic residents and lighter greens representing areas with a low percentage of Hispanic residents. For maps of the most predominant racial or ethnic group, groups are mapped by color with bright green, light green, grayish green, and bright blue representing areas that are predominantly Asian, Black or African American, Hispanic, and white, respectively.

Findings

Based on the analysis of pretextual traffic stop clusters in Berkeley and San Francisco, several potential patterns emerge.

First off, population density does not appear to consistently predict cluster locations. Clusters in Berkeley and San Francisco tend to be located in areas with varying population densities, as shown in *Figures 1* and *2*, respectively, with unclear patterns regarding population density. This variability is contrary to the expectation that pretextual traffic stop locations would be more prevalent in high-density areas.

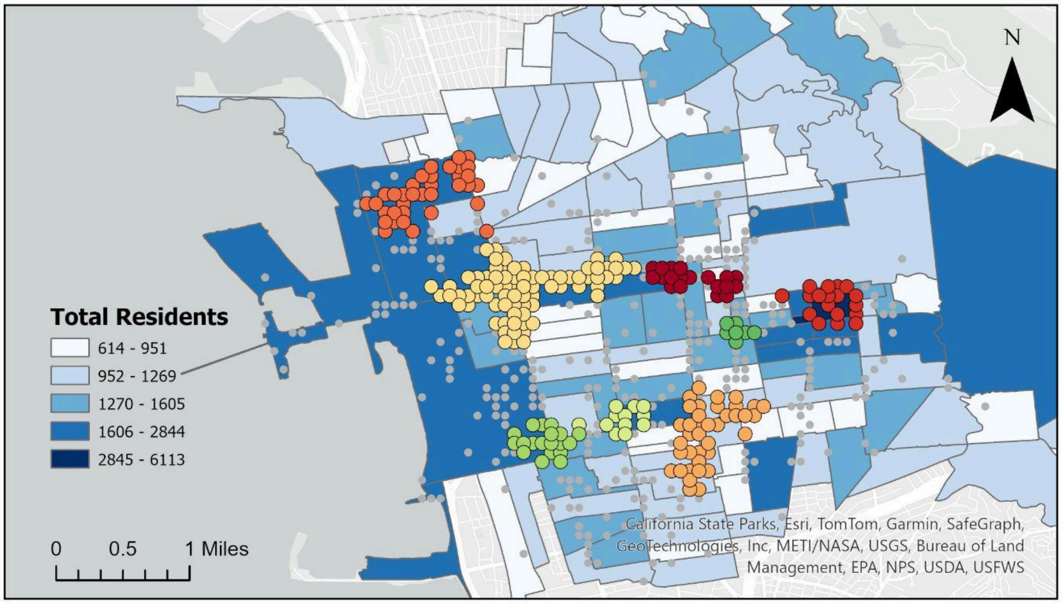

Figure 1: Population Size and Pretextual Traffic Stops in Berkeley

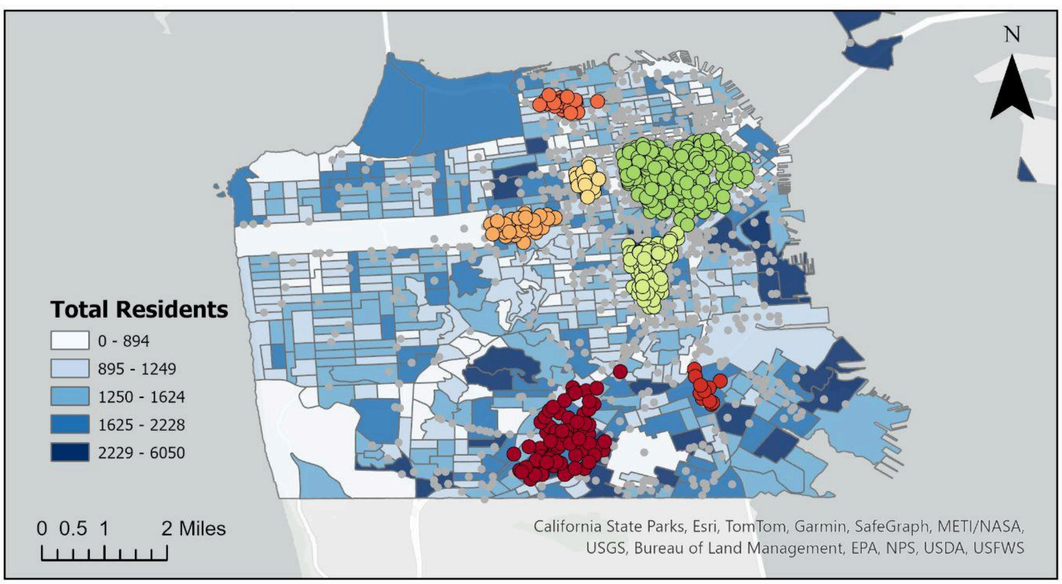

Figure 2: Population Size and Pretextual Traffic Stops in San Francisco

Income does appear to somewhat predict cluster locations. Lower and middle-income neighborhoods consistently host clusters, with few clusters in higher-income areas. In Berkeley, there were also no clusters found in the highest-income areas as shown in *Figure 3*. San

Francisco, however, had a few clusters in higher-income areas as shown in *Figure 4*. Overall, this indicates a link between income levels and pretextual traffic stop locations.

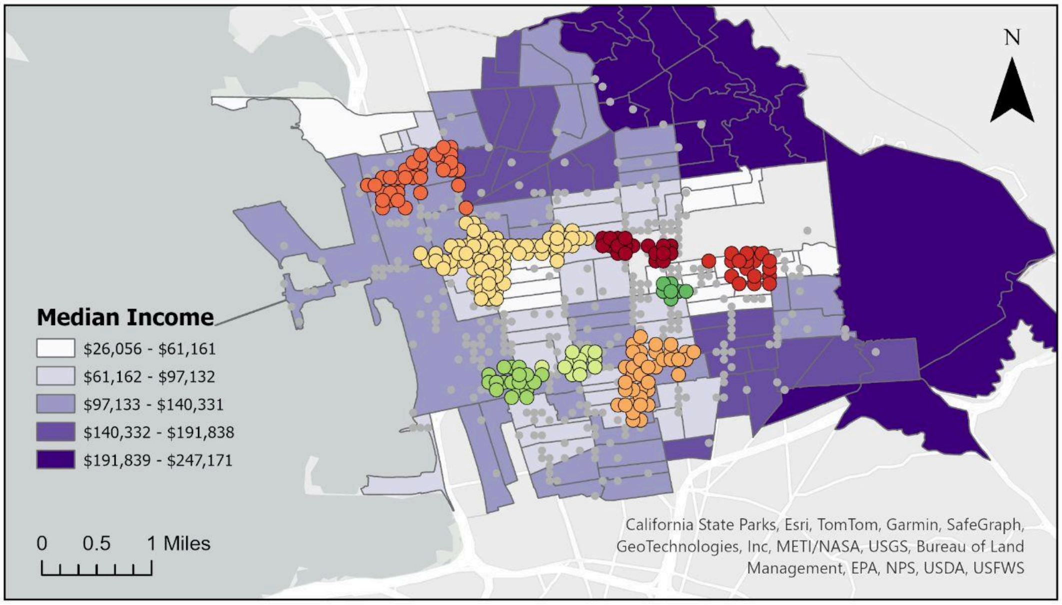

Figure 3: Median Income and Pretextual Traffic Stops in Berkeley

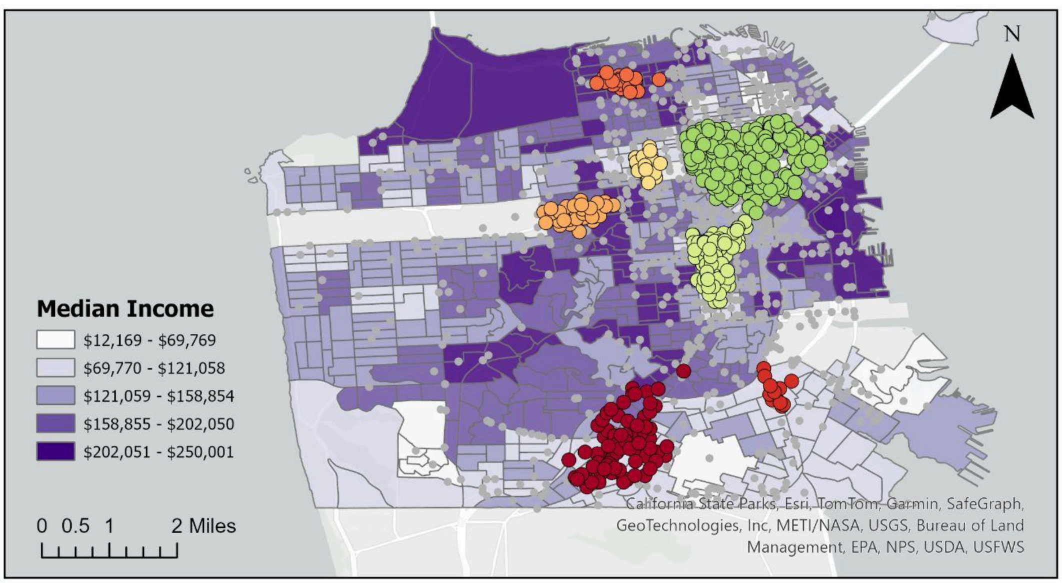

Figure 4: Median Income and Pretextual Traffic Stops in San Francisco

Racial composition appears to play a role in predicting cluster locations as clusters are consistently found in areas with higher percentages of Black and Hispanic residents. In Berkeley, clusters consistently occur in areas with higher percentages of Black residents (see *Figure 5*) and are always found in areas with higher percentages of Hispanic residents, with Hispanic areas consistently surrounded by clusters (see *Figure 7*). As for San Francisco. clusters are often in areas with a higher percentage of residents who are Black, although there is a predominantly Black area without any clusters in the southeast of the city (see *Figure 6*). Clusters in San Francisco also tend to surround areas with a higher percentage of residents who are Hispanic. These findings suggest a potential spatial relationship between the racial composition of neighborhoods and the occurrence of pretextual traffic stops.

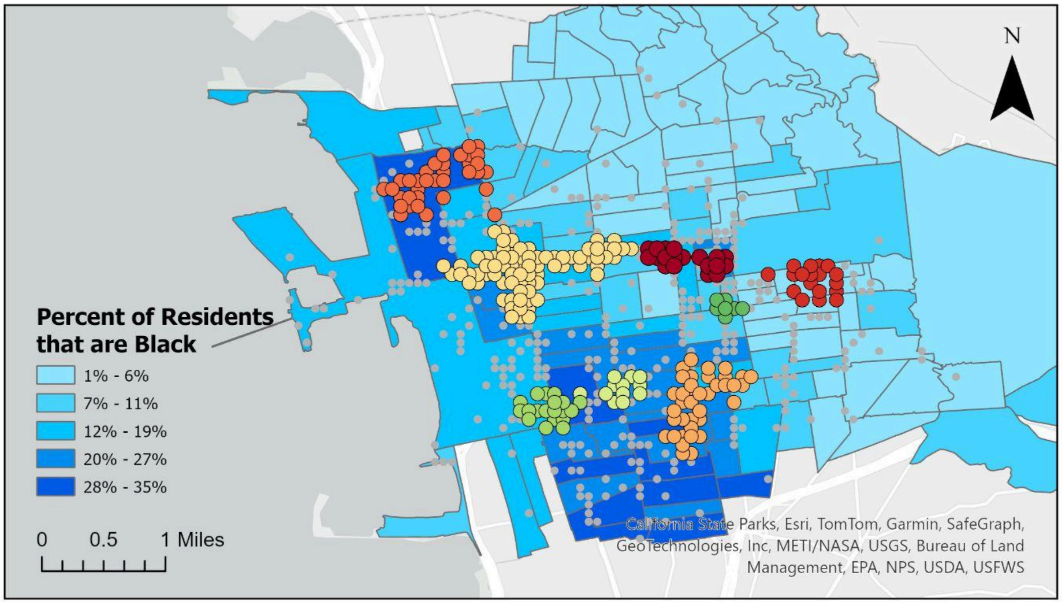

Figure 5: Black Residents and Pretextual Traffic Stops in Berkeley

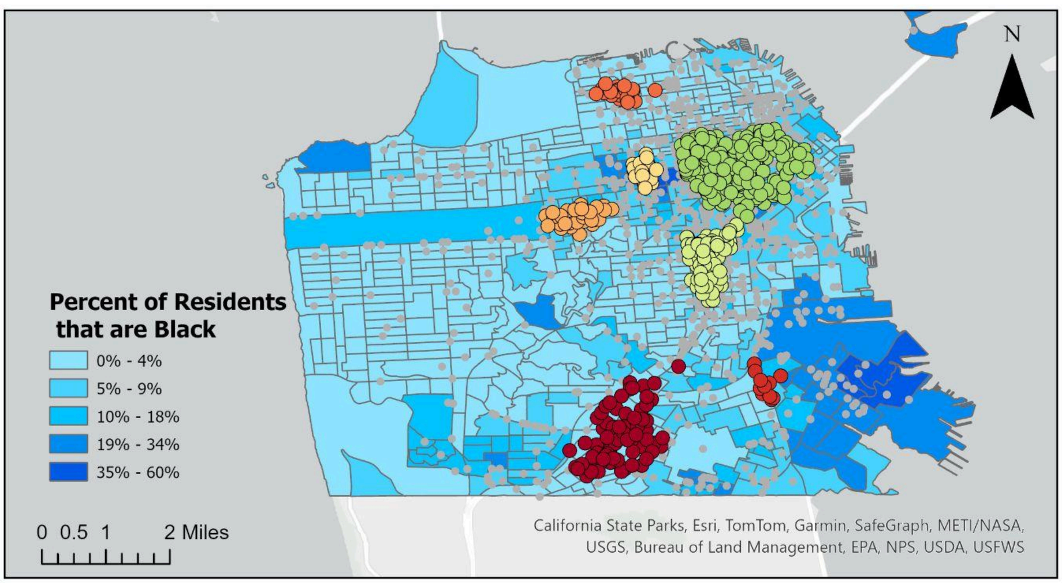

Figure 6: Black Residents and Pretextual Traffic Stops in San Francisco

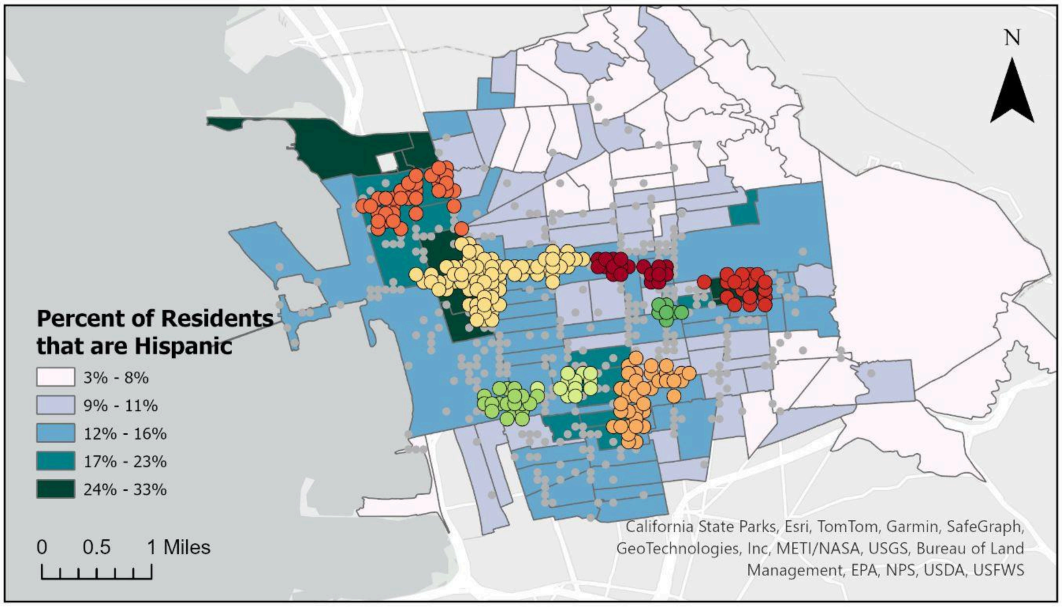

Figure 7: Hispanic Residents and Pretextual Traffic Stops in Berkeley

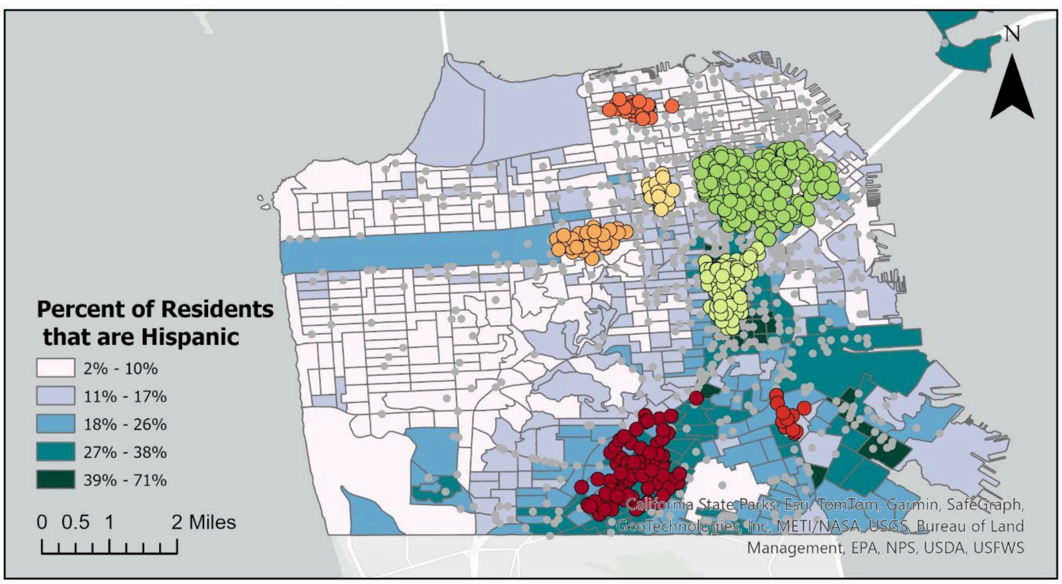

Figure 8: Hispanic Residents and Pretextual Traffic Stops in San Francisco

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Limitations

This analysis faces several limitations that could affect the accuracy and reliability of its findings. Inconsistencies in how data is reported, including differences in location data formats and conflicting information, pose challenges in standardizing and comparing data across different areas. These inconsistencies can arise from variations in reporting practices among police departments and officers, potentially leading to errors or discrepancies in the geographic representation of stop locations. Additionally, the lack of universal data availability across cities and time periods limits the ability to make comprehensive comparisons and draw generalizable conclusions about the geographic trends in stop locations. The reliance on data from Berkeley and San Francisco, which may not be representative of other cities, further restricts the generalizability of the findings.

Patrol concentration presents another limitation, as uneven patrol efforts across neighborhoods could influence stop rates, particularly in low-income areas. The use of residential data for demographics may also present limitations, as individuals stopped do not necessarily reside in the area where they were stopped. Therefore, the findings can only provide information about the neighborhoods where stops occur and cannot serve as a proxy for information on the individuals stopped. Moreover, one significant limitation of the GIS analysis stems from the inability to differentiate between pretextual and non-pretextual traffic stops. Since most datasets do not include a variable to indicate which stops were pretextual, the use of traffic violations as a proxy may have inadvertently excluded pretextual stops from the sample. This limitation could skew the analysis, as it may not accurately capture the full extent of police stops and their geographic distribution, potentially leading to biases in the findings.

If I could undertake this project without resource limitations, several key changes would enhance the study's quality and depth. Firstly, I would ensure that a third party records or verifies police data, ensuring its accuracy and reliability. This step would mitigate potential errors and discrepancies in the geographic representation of stop locations. Secondly, having coordinate data for all police departments in California would expand the scope of the analysis, enabling a more comprehensive comparison of geographic trends in stop locations across different areas. Additionally, implementing a method to distinguish pretextual stops would prevent the accidental exclusion of such stops from the analysis, thus reducing bias in the results. Moreover, I would invest time in learning more complicated clustering methods, such as multivariate clustering, which would allow for the identification of more nuanced and high-quality clusters. Also, using spatially joined data to conduct separate statistical analyses would enable the use of neighborhood data as proxy controls in outside multivariate statistical analyses for individual stops. Lastly, obtaining neighborhood demographic data on an even smaller scale would enhance the accuracy and variability of the demographics, leading to more reliable results.

Conclusions

This analysis sheds light on the geographic trends of pretextual traffic stops in Berkeley and San Francisco, providing insights into the factors influencing these patterns. Contrary to expectations, population density did not consistently predict cluster locations, indicating a more complex relationship between density and stop locations. Moreover, this suggests that the geographic trends of pretextual traffic stops cannot simply be explained away by population density and that some disparities likely occur. Income levels did show predictive power, with lower and middle-income neighborhoods more likely to host clusters. Racial composition emerged as a significant factor, with clusters consistently found in areas with higher percentages of Black and

Hispanic residents. These findings suggest that income and race play pivotal roles in the spatial distribution of pretextual traffic stops. The map visualizations reinforce these findings, highlighting areas where clusters are prevalent and indicating potential areas for policy interventions to address disparities in policing practices. The implications of these conclusions are far-reaching, underscoring the need for further research and targeted policy measures to promote fair and equitable policing practices across neighborhoods. Policymakers could use this information to develop more targeted strategies to address disparities in policing practices. Additionally, future research should explore the impact of other neighborhood characteristics or examine if clusters of pretextual traffic stops could be only a result of concentrated policing in these areas. Despite the limitations of this analysis, including data inconsistencies and limited availability, the findings offer insights into the complex interplay between neighborhood characteristics and pretextual traffic stops, challenging assumptions and supporting the call for nuanced approaches to address disparities in law enforcement.

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Appendix

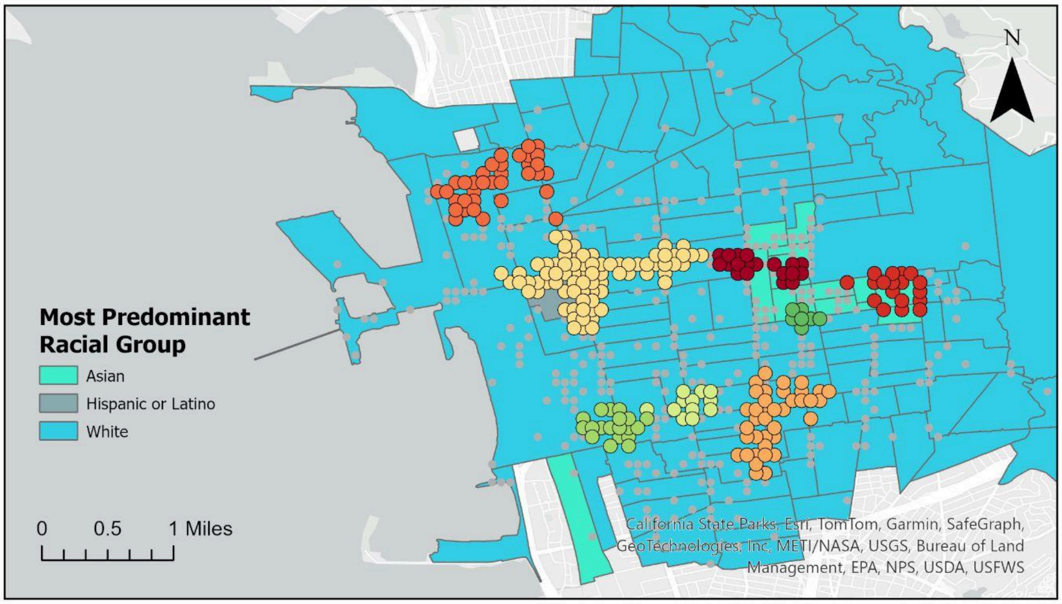

Figure 9: Predominant Racial Groups and Pretextual Traffic Stops in Berkeley

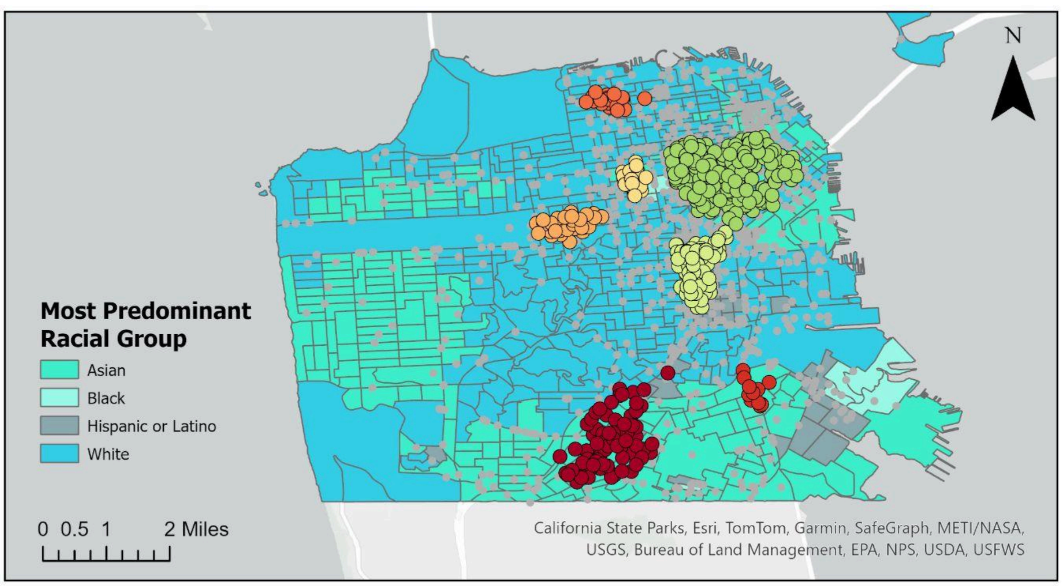

Figure 10: Predominant Racial Groups and Pretextual Traffic Stops in San Francisco