Methodology

Racial Bias in Policing: An In-depth Analysis of Stopping Practices by the San Diego Police Department

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To analyze racial bias in San Diego Police Department's (SDPD) patrol activities, we relied on data collected and reported by SDPD pursuant to the Racial and Identity Profiling Act (RIPA) of 2015. We combined this data with population data from the U.S. Census Bureau to identify racial disparities and inefficiencies in SDPD's patrol practices specifically related to gang profiling. We use information included in RIPA data to estimate the extent and harm done by SDPD's gang profiling activity. We focus on stops conducted in the year 2022—the most recent data available at the time of analysis—and the Southeast community.

As with all data, the findings seen in this analysis are dependent on the quality of the data collected. We strongly encourage readers to consider the limitations of RIPA data when interpreting findings. For instance, RIPA data are collected under state regulations for all law enforcement agencies, but this at times limits the applicability of data elements at the local level. For this project, this translated to officer assignment types collected under RIPA poorly correlating with SDPD units that conduct gang profiling. RIPA data are also based on officers' reports. The information attached to each stop is solely based on officer disclosure and perceptions. For example, officers report what they perceive as the race(s) of the people they stopped, rather than having the people they stopped self-report their race(s). Other reports suggest this leads to underreporting, misidentification, or even intentional obstruction of information by officers.[1] We encourage researchers using RIPA data to ground truth trends seen in the data with

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[1] Office of Inspector General, *The Sheriff's Department's Underreporting of Civilian Stop Data to the California Attorney General*, County of Los Angeles (June 10, 2022). Retrieved from https://assets-us-01.kc-usercontent.com/0234f496-d2b7-00b6-17a4-b43e949b70a2/ee467145-85c7-450c-

community to identify discrepancies between the data collected and everyday community experiences. This project was produced in partnership with Pillars of the Community –an organization that advocates and organizes for people harmed by the criminal legal system in Southeast San Diego.

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Data Sources

Police Stop Data

City of San Diego, San Diego Police Department, 2022, Police Stop Data (RIPA). Retrieved from https://data.sandiego.gov/datasets/police-ripa-stops/.

Population Estimates by Age and Race

U.S. Census Bureau, 2017-2021, American Community Survey, 5-Year Estimates. Tables DP05, B04006, B02018. Retrieved from https://data.census.gov/cedsci/.

U.S. Census Bureau, 2020 Decennial Census, Demographic and Housing Characteristics. Table P12. Retrieved from https://data.census.gov/cedsci/.

U.S. Census Bureau, 2021, TIGER/Line Shapefiles, Census Tracts. Retrieved from https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2021&layergroup=Census+Tracts.

Geographic Data

City of San Diego, 2023, San Diego Police Department Beats. Retrieved from https://data.sandiego.gov/datasets/police-beats/.

City of San Diego, 2023, San Diego Police Department and Divisions. Retrieved from https://data.sandiego.gov/datasets/pd-divisions/.

Data Limitations

Officer Reports of Race and Ethnicity

Race and identity fields included in RIPA data are imperfect and subject to officer bias. The race of people stopped in each incident is based on officer perceptions, rather than self-identification by the people involved. RIPA regulations require officers to report their perception of the race, gender, age, and other characteristics of the people they stop without input from the person involved.[2] Officers' perceptions are the proper lens to use for purposes of understanding racial profiling because this is the information the officer knew (or assumed) when they stopped the person. However, these perceptions

a73993e1f1d79f78/The%20Sheriff%E2%80%99s%20Department%E2%80%99s%20Underreporting%20of%20Civilian%20Stop%20Data%20 to%20the%20California%20Attorney%20General.pdf.
Barba, M., *Watchdogs want answers on how San Francisco cops misreported race data*, The San Francisco Standard (September 13, 2023). Retrieved from https://sfstandard.com/2023/09/13/san-francisco-cops-misreported-data-meant-to-curb-racial-profiling-now-watchdogs-want-answers/

[2] 11 Cal. Code. Regs. § 999.226. Available at https://oag.ca.gov/sites/all/files/agweb/pdfs/ripa/stop-data-reg-final-text-110717.pdf

are also subject to the officers' own bias or understanding of people's identities. Stop rates for certain groups may be over- or under-reported due to misidentification by officers. In other cases, officers may intentionally obscure the racial identity of the people they stopped.

Reports from other jurisdictions suggest officers log multiple races for individuals they stop or select the wrong race to mask their bias.[3] Other reports suggest that Latinx people are overrepresented in stops that are underreported by agencies. For example, an evaluation of stops made by the L.A. Sheriff's Department in 2019 found that the department underreported over 50,000 officer-initiated stops and Latinx people represented most of those stops.[4] In SDPD's 2022 data, we found that officers reported multiracial people as being six or more races one percent of the time. These numbers exceed the percentage of multiracial people in San Diego who are six or more races based on U.S. Census Bureau data.[5]

Additionally, RIPA data is limited in the number of racial categories included. For example, officers are provided a general racial category of Asian which can include individuals of East and Southeast Asian origin. The lack of granular data for Asian and other racial subgroups means that we are unable to analyze differences within these groups when it comes to experiences of racism and discrimination in policing. The Asian population in San Diego, like other places, is racially diverse. The largest Asian subgroups include Filipino, Chinese, and Vietnamese.[6] Each of these groups, and other Asian subgroups, may have different experiences with SDPD that is not captured in RIPA data.

The disparities we see in stop rates by race are only as good as the quality of the data reported. Community members and partners on the ground can help detect possible inaccuracies. We believe the racial disparities observed in this analysis demonstrate racial bias by SDPD officers. They may also undercount disparities for groups that are either underreported, misidentified, or intentionally withheld by officers.

Officer Assignments and Field Interview Cards

This project aimed to detail the extent of SDPD's gang profiling in Southeast San Diego, specifically the practices of SDPD's special units for gang profiling. However, RIPA data regulations do not require law enforcement agencies to report the unit of the officer who conducted the stop. They require the "type of assignment to which an officer is assigned at the time of the stop" be reported.[7] The regulations include 11 assignment types, including "gang enforcement." When we analyzed these assignment types, they showed an extreme undercount in the number of stops conducted by officers assigned to gang enforcement compared to Southeast community members daily experiences with officers. According to RIPA assignment fields, in 2022, 508 people were reportedly stopped by officers assigned to gang enforcement at the time of the stop.

[3] Barba, M., (September 13, 2023).
[4] Office of Inspector General, (June 10, 2022).
[5] Based on American Community Survey 5-year estimates from 2017-2021, less than 0.1% of people in San Diego who identified as multiracial, identified with six or more races. However, in SDPD's 2022 RIPA data, officers reported one percent of people they perceived as multiracial as six or more races.
[6] U.S. Census Bureau, 2017-2021, American Community Survey, 5-Year Estimates. Available at https://data.census.gov/table/ACSDT5Y2021.B02015?q=Asian%20&g=160XX00US0666000.
[7] 11 Cal. Code. Regs. § 999.226. Available at https://oag.ca.gov/sites/all/files/agweb/pdfs/ripa/stop-data-reg-final-text-110717.pdf

SDPD has approximately 39 departmental units to which officers are assigned, but RIPA only includes 11 assignment types. In sum, we attribute the undercount in gang enforcement stops to the lack of clarity and inconsistency between RIPA regulations and local police units. To account for this, we submitted a public records request to SDPD to determine whether there were additional stops related to gang enforcement that may not have been reported under RIPA's gang enforcement assignment. The request and an appeal were denied.

Because SDPD refused to provide data specific to its gang units, available data on stops that only resulted in a field interview card were analyzed as a proxy for identifying gang profiling activities. Officers use field interview cards as a method of interrogation to document personal information about community members and document them as a gang member or gang affiliated in California's CalGang database. We use this data, combined with limited data on the gang enforcement assignment and detailed stories from impacted community members, to reveal the extent of SDPD's harmful gang profiling.

Stop Duration Times

Officers are required to enter the approximate length of each stop in minutes. However, data input errors record some stops as being extremely long, over 24 hours, or extremely short, 1 minute. These most likely do not reflect the actual amount of time the stops took. To account for these extreme times, we identified certain stops as having outlier duration times and capped them to an upper or lower threshold value using a model of stop characteristics. About 5.7 percent of stops were identified as duration outliers and capped. This method is imperfect and does not calculate with complete accuracy the total stop duration time. We assume that our stop duration times are conservative estimates, and it is more likely officers spent more time on stops rather than less time on each stop dimension examined. Also, stop duration times logged by officers do not capture administrative or other department time spent due to officer patrol activities.

How We Use RIPA Race Categories

The race categories available to officers according to RIPA regulations are: Asian, Black/African American, Hispanic/Latine(x), Middle Eastern or South Asian, Native American, Pacific Islander, and White. We adjusted these categories and labels as needed to be more reflective and representative of each group based on our prior work and input from local partners. We also added a category for Multiracial to account for people officers perceived as being more than one race. We use the following categories in our analysis as compared to their original label in RIPA data. Not all categories are mutually exclusive.

- American Indian or Alaska Native (AIAN)=People perceived as Native American alone and non-Latinx.
- Asian=People perceived as Asian alone and non-Latinx.
- Black=People perceived as Black/African American alone and non-Latinx.
- Latinx=People perceived as Hispanic/Latine(x), whether alone or in combination with another race.
- Multiracial=People perceived as more than one race and non-Latinx.

- Native Hawaiian or Pacific Islander (NHPI)=People perceived as Pacific Islander alone and non-Latinx.
- Southwest Asian or North African, or South Asian (SWANA/SA): People perceived as Middle Eastern or South Asian, alone or in combination with another race or Latinx.
- White: People perceived as White alone and non-Latinx.

In a small percentage of cases (less than one percent) where officers reported people as being six or more races, we assume the officer made an error or intentionally obscured the race of the person they stopped. We do not include these cases in our analyses by race, but these stops are included in all other analyses.

How We Create Population Estimates by Race

We scale stop data to the City of San Diego's population to measure racial bias and disparities. We calculated population estimates for the city and each SDPD division using data from the U.S. Census Bureau's American Community Survey (ACS). Our population estimates by race correspond to RIPA's racial groups but are based on individuals' self-report. Other than Latinx and SWANA/SA, all groups are mutually exclusive, meaning they do not include Latinx or individuals identified as more than one race.

- American Indian or Alaska Native (AIAN)=AIAN alone, non-Latinx.
- Asian=Asian alone, non-Latinx.
- Black=Black or African American alone, non-Latinx.
- Latinx=Hispanic or Latino, alone or in combination with another race.
- Multiracial: People of two or more races, other than Latinx
- Native Hawaiian or Pacific Islander (NHPI)=NHPI alone, non-Latinx.
- Southwest Asian or North African, or South Asian (SWANA/SA)=Includes people who identified with Southwest Asian (Middle Eastern) or North African ancestry and/or as South Asian origin, alone or in combination with another race or Latinx.
- White=White alone, non-Latinx.

Calculating Proxy Estimates for SWANA/SA

RIPA data includes a category for Middle Eastern or South Asian, but this label is not commonly used in other datasets or by community members. We opt for the term "South Asian or North African, or South Asian" (SWANA/SA). This includes South Asian people and people of Southwest Asian or North African (SWANA) descent. Southwest Asian or North African is an alternative term to Middle Eastern or North African (MENA). SWANA people are often categorized as White in data collection, overlooking the experiences of this community as distinct from White people in the United States. In other data reporting, South Asians are typically grouped with the broad racial category Asian. However, when it comes to criminal justice and policing, many South Asians may be racialized by officers and others in ways like SWANA people. In other words, their experiences with being policed may be more like the SWANA community than other Asian communities, prompting the need for distinct data collection in criminal justice.

Census data have no equivalent category to help scale stop counts to population for the SWANA/SA communities. We have created our own proxy population estimates for these communities based on a combination of ancestry and race tables from the ACS. We estimate the number of people who identify as SWANA/SA by summing the number of people who reported any SWANA ancestry and/or South Asian racial origin. We define South Asian origin based on these categories: Asian Indian, Bangladeshi, Bhutanese, Maldivian, Nepalese, Pakistani, Sikh, Sindhi, and Sri Lankan. We define SWANA ancestry based on the following categories: Afghan, Algerian, Arab, Assyrian, Bahraini, Chaldean, Egyptian, Emirati, Iranian, Iraqi, Israeli, Jordanian, Kurdish, Kuwaiti, Lebanese, Libyan, Middle Eastern, Moroccan, North African, Omani, Palestinian, Qatari, Saudi, Sudanese, Syrian, Tunisian, Turkish, Yazidi, and Yemeni. Note that these are labels and terms used by the U.S. Census Bureau, which do not reflect more inclusive and preferred terms by these groups. This list is also not exhaustive and will continue to change. For instance, our estimates currently do not include people who identify as Armenian though this is a group that crosses national origins that are often included in SWANA. This list is also limited by census data collection. Some groups not included in the data are Amazigh, Copts, Druze, and Bedouin.

Consensus on the identity groups included in the terms SWANA or MENA is still being built. These groups encompass a diversity of origins and intersections between national, geopolitical, religious, and ethnic identities. For years, advocacy organizations representing these communities have advocated for the inclusion of a MENA category in the U.S Census to distinguish their experiences from the White experience.[8] While the U.S. Census Bureau still delays in including MENA in data collection, our proxy estimates are the best available to help bring to light the discrimination experienced by these communities when it comes to policing.

Calculating Population Estimates by San Diego Police Division

We used census tract-level data to calculate population estimates by race for each SDPD police division. Using a method called aerial apportionment, we matched census tracts to the divisions based on how much each census tract overlaps with each division. We intersected census tracts to divisions and calculated the percentage of each census tract area that overlapped with each division. We kept intersects, or census tract-SDPD division matches, where at least five percent of the census tract area overlapped with a division. We estimated the population of each division by multiplying the percentage overlap of each census tract by the census tract population for each race. We then summed these values by SDPD division. This produces an estimated count of each racial group in each division. This method assumes that populations are evenly distributed in a census tract, which may not always be true. However, this is a common method for extrapolating census tract population estimates to larger public jurisdictions.

How We Estimate Racial Bias and Inefficiencies

We estimate gang profiling stops through two methods—the officer assignment field and stop result field included in RIPA data. As described under limitations, while RIPA data includes a category for officers assigned to gang enforcement, the number of stops reported under this category far undercounts the experiences reported by community members. Because of this we used the stop result "field interview card completed" as a proxy for gang profiling stops. We include stops that only resulted

[8] The Leadership Conference on Civil and Human Rights, *Will you count? Middle Eastern and North African Americans (MENA) in the 2020 census,* (April 17, 2018). Retrieved from https://civilrights.org/resource/will-you-count-middle-eastern-and-north-african-americans-in-the-2020-census/

in a field interview card as opposed to stops that resulted in a field interview card and an infraction, arrest, or other result.

We demonstrate racial bias in gang profiling through two primary methods of assessing racial bias: benchmark and outcome tests. As a benchmark test, we compare stops by race to population by racial in the city and SDPD divisions. We compare differences in the distribution of the population by race to stops by race and analyze disparities in stop rates per 1,000 by race. For outcome tests, we look at the proportion of stops that result in no action, or a warning, an indicator of pretext. We also examine differences in hit rates, or the rate at 'successful' searches where officers find contraband. These methods are described in detail below.

Throughout our analysis, we focus on stops officers initiated themselves. We refer to these stops as "officer-initiated stops." Within the RIPA data, officers must report if they made a stop in response to a call for service (e.g., 911 call) or initiated a stop themselves, an officer-initiated stop. Officer-initiated stops help identify racial bias in the stops that officers specifically decide to conduct themselves versus in response to a community request. In 2022, SDPD officers stopped 88,099 people during officer-initiated stops compared to just 8,020 people during stops in response to calls for service.

Calculating Racial Bias in Stops

Calculating racial bias for SDPD overall

To analyze officer-initiated stop rates by race, we calculate the total number of officer-initiated stops conducted for each perceived racial group. It is important to note that observations may overlap depending on how the officer perceived a person's race. For example, a person can be perceived by officers as multiple races, like Latinx and SWANA/SA. In this case, they are counted twice in the analysis, once in each category. There were 17 people in the 2022 data who officers stopped and indicated as having 6 or more perceived races. We do not include these stops in analysis by race because of reports that officers may check all races to avoid reporting bias. After summarizing the total number of stops by perceived race, we then divided the total stops by each race's population count in San Diego and multiplied the result by 1,000 to get stop rates per 1,000 people of the same race.

We also analyzed racial bias in stops by focusing on stops that resulted in either a 'Warning' or 'No action.' To calculate this, we take the count of officer-initiated stops that resulted in 'Warning' or 'No Action' for each perceived racial group and divide it by the total officer-initiated stops for each group.

Calculating racial bias in gang profiling

To measure racial disparities in gang profiling, we focus on stops made by SDPD officers assigned to gang enforcement and stops that resulted in a field interview card.

To analyze racial disparities in stops made by SDPD officers assigned to gang enforcement, we filter for officer-initiated stops made by officers assigned to gang enforcement and then summarize the number of stops made for each perceived racial group. We divide this number by the total number of stops conducted under the gang enforcement assignment. We compare these proportions by race to the proportions of each racial group in San Diego's population.

Stops that resulted only in a field interview card are used as an additional proxy for understanding gang profiling activity. Officers not assigned to gang enforcement at the time of stop can still engage in gang profiling. To calculate racial disparities in stops resulting in a field interview card, we first summarize the number of officer-initiated stops resulting only in a field interview card for each perceived racial group. We divide this value by the total population of each racial group in San Diego to obtain the final rates per 1,000 of the same race.

We further demonstrate racial bias by examining the original reason for the stop and hit rates. We look at the original reason for stops that resulted in field interview cards to identify the use of pretextual stops. We first filter for the total number of people by race who only had field interview cards completed as a stop result. Out of these stops, we then calculate the number of people stopped for each stop reason by race, focusing on traffic violations. We divide the number of people stopped for each stop reason by the number of people with field interview cards completed by race. This analysis helps indicate racial bias in field interview cards given that while these stops were allegedly made in response to traffic safety risks, they concluded in results that indicate otherwise because field interview cards, rather than citations or arrests, were issued.

We then calculate hit rates and the rate of officers finding no contraband by race. We first filtered the data to include only officer-initiated stops that resulted in a field interview card completed. Then, we filtered the data to include stops where a person or their property was searched. We summarized whether contraband or evidence was found by race. The rate at which officers find contraband or evidence from searches is the 'hit rate', or the success rate of searches. Hit rates are used as an indicator for racial bias – the argument being if officers are not discriminating by race, then the hit rate should be similar across all races.[9] We calculated hit rates by dividing the number of people by race where a search was conducted and contraband was found, by the total number of people who were searched and had field interview cards completed. We also calculate and visualize the inverse hit rate to illustrate officers' ineffectiveness in determining when to stop and search individuals, considering the high rate of searches yielding no contraband across races.

Calculating Geographic Disparities in Stops Resulting in a Field Interview Card

In addition to testing racial bias in SDPD's activities, this project sought to identify geographic bias in SDPD's activities specifically for the Southeast community. The Southeast community is a primarily Black and brown community in San Diego that has been disproportionately impacted by SDPD's. Community stories collected by Pillars for this project highlighted the trauma and harm done by SDPD in Southeast San Diego. We analyzed RIPA data by SDPD division to test for additional evidence in racial profiling.

Matching stop data to SDPD divisions

SDPD stop data is matched to police divisions using a police beat to division crosswalk. A police beat is a small area of territory that a police officer patrols, while divisions are larger regions that encompass a group of police beats that are in the same geographic area. RIPA stop data for San Diego contains a field for the police beat where a stop took place. San Diego data's open data portal contains a separate data table that lists SDPD beats and which SDPD division each beat belongs to. Using this crosswalk, we assign police stops in RIPA data to SDPD divisions. Notably, the SDPD beats to division table did not assign the beat 'La Jolla Village 125' to a division, because this part of La Jolla is at the edge of the water. We mapped the police beats and manually assigned the beat 'La Jolla Village 125' to SDPD's Northern Division (Division 1) because it is right next to the beat 'La Jolla Village 124,' which is already assigned to Division 1.

[9] Open Policing, *Findings: The results of our nationwide analysis of traffic stops and searches,* Stanford University. Retrieved from https://openpolicing.stanford.edu/findings/.

Analyzing racial bias in gang profiling by SDPD division

We calculated officer-initiated stops that resulted in a field interview card completed by SDPD division. First, we summarized the total number of officer-initiated stops by race and police division that resulted in a field interview card completed. We then calculated the total number of officer-initiated stops by race and police division that resulted in a field interview card, divided by the total number of officer-initiated stops made for each racial group in each division, and multiplied the result by 100 to get a field interview card stop rate. This provided us with a comparison of how frequently each racial group is being stopped for field interview cards in each division. We compareD total numbers and rates to identify evidence of racially and geographically biased gang profiling in Southeast San Diego. To visualize the data, we used a point density tool available in the programming language, R. We mapped the distribution of field interview stops by race randomly across each police division with different colored points. Each point represents 5 people stopped, with the color representing one of eight racial groups. Because the points are randomly distributed throughout the respective police division, we use them to visualize the concentration of stops for people of different races in that division. We cannot use them to determine information about the specific locations (e.g., addresses, streets, blocks, etc.) of those stops.

To further test for bias, we calculate hit rates of searches done during field interview cards for each division. First, we filtered the data to include only officer-initiated stops that resulted in a field interview card completed. Then, we filtered the data to include stops where a person or their property was searched. Next, we summarized the total number of field interview card stops that resulted in a search across each police division by whether contraband was found or not. To calculate the no contraband rate by division (the inverse of the hit rate), we totaled the number of field interview card stops where a search occurred, and no contraband was found for each division. We then divided this total by the overall number of field interview card stops where a search took place and multiplied the result by 100 to express the rate as a percentage. We followed the same procedure, but specifically filtered for instances where contraband was found during the search to obtain a hit rate per 100 people. Finally, like the previous dot density map, we mapped the distribution of searches by whether contraband was found randomly across each police division with two colored points, with the color representing whether contraband was found. Because the points are randomly distributed throughout the respective police division, we visualize the concentration of searches by whether contraband was found in that division. The location of the stops does not determine the specific location of the search that took place.

Calculating How Officers Spend their Time

We conduct time spent analysis based on stop duration times clocked by officers to demonstrate inefficiencies in how officers spend their time. As described in limitations, this does not include the time officers spent patrolling between stops or administrative time that may be added across the department because of the stops conducted by officers. Whenever we calculate time spent on stops, we control for unique stop incidents to ensure we do not double-count the time officers spend on a stop. An officer can conduct a stop where more than one person is involved, e.g., if they stop two people on the street during a pedestrian encounter. For example, in the case of two people stopped, if the officer spent 15 minutes on the stop, the time would be counted as 15 minutes, rather than 30 minutes (e.g., 15 minutes per person). Officers report the total time they spent on the stop, rather than the time spent per person involved.

Identifying and capping outliers

There are some stops in the data that show up as having taken over 24 hours to complete or stops that took 1 minute. These outliers in stop duration times are likely due to data input errors, such as officers forgetting to clock the end of the stop until after the fact or forgetting to clock the stop at all. To ensure the outlier stop duration times do not impact any analyses, we created a regression model and conducted an outlier analysis to identify, and cap stops with extremely high or low stop times.

The first step in our outlier analysis was to create a robust model that accounts for the various factors that impact stop duration times. These factors, also known as independent variables, were used to create a regression model with stop duration time acting as the dependent variable (or the variable influenced by the independent variables).

Dependent Variable: Stop duration time

Independent Variables:

- Stop action
- Stop in response to call for service
- Age of person stopped
- Race of person stopped
- Stop reason
- Stop result
- Number of people stopped
- Person removed from vehicle
- Person detained
- Use of force
- Person handcuffed
- Search took place
- Property or Contraband seized
- Officer division

After the final model was determined, we used it to estimate the amount of time each stop should have taken given the combination of independent variables observed in each stop, along with a 95 percent confidence interval. This amount of time that a stop should have taken according to the model is called the predicted value. The 95 percent confidence interval tells us the lowest and highest amount of time a stop with those characteristics would have taken 95 percent of the time.

Using the confidence intervals of the predicted values, a stop was determined to be an outlier if the officer-reported duration time was either below or above the confidence interval. If a stop had a reported duration time within the confidence interval, then that duration time was not considered an outlier and remained unchanged. If the reported stop duration time was below the confidence interval, then it was replaced with the lower confidence interval value. Alternatively, if the reported stop duration time was above the confidence interval, then it was replaced with the upper confidence interval value. All subsequent stop duration analyses were done using a combination of original officer-reported and replaced ("capped") stop duration times. The replaced ("capped") stop duration times are applied only to outlier stops. About 5.7 percent of stops, or 4,942 out of 86,632 stops in 2022, were identified as outliers and capped.

Analyzing time spent on field interview cards and gang enforcement

Analysis was conducted to understand how much time SDPD spends on stops that result in a field interview card. Officer-initiated stops where a field interview card was the only result, not in combination with any other stop result, were used for this analysis. The percent of time officers spent on stops that resulted in a field interview card, or the stop duration rate, was calculated by taking the total amount of time officers spent on stops resulting in only a field interview card and dividing that value by the total amount of time officers spent on all officer-initiated stops. For these calculations, the adjusted stop duration time is used for stops where the stop duration was identified as an outlier.

Similarly, analysis was conducted to understand how much time SDPD officers assigned to gang enforcement spent on different stop results. This was calculated by first finding the total amount of time SDPD officers assigned to gang enforcement spent making officer-initiated stops. Then, we calculated the total amount of time officers assigned to gang enforcement spent on each category of stop results provided in RIPA data. We group stops that concluded in two or more results into a 'Two or More Results' category. All other categories indicate that the stop resulted in that stop result alone. We divided the time spent on each stop result by the total time officers assigned to gang enforcement spent on officer-initiated stops to obtain the rate of time officers assigned to gang enforcement spent on each result. For these calculations, the adjusted stop duration time is used for stops where the stop duration was identified as an outlier.

To further understand racial disparities in field interview stops, we analyzed the share of time officers spent in each SDPD division conducting field interview cards for people they perceived as Black and compared this to the Black population within each SDPD division. To conduct this analysis, we take the total amount of time SDPD spent on stops that resulted in a field interview card within each division, and we divide that by the total amount of time SDPD spent on stops resulting in a field interview card for people SDPD perceived as Black within each SDPD division. These rates are graphed alongside the proportion of Black people that reside in each SDPD division.

For more information about our methods, please visit our GitHub repository: https://github.com/catalystcalifornia/sdpillars/.