CAMPAIGN ZERO REPORT

Contact Cards in Cincinnati

A Review of Racial Bias in Police Stops, 2009–2025

CAMPAIGN ZERO RESEARCH & POLICY BRIEF

MAY 2026

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Executive Summary

April 2026 marks the 25th anniversary of the police killing of Timothy Thomas. Thomas, a 19-year-old young man, had become a father only 5 months before his death. The officer who shot and killed him, Stephen Roach, falsely claimed Thomas had a weapon. Roach kept his job on the police force after being acquitted by a Hamilton County judge before moving to the police force in nearby Evendale, OH, within the year.

Thomas was the 15th Black man killed by Cincinnati police officers from 1995–2001 and his death prompted hundreds of protesters to take to the streets and demand accountability for police officers' actions. Following community protests and sustained pressure on elected officials, the city entered into a Collaborative Agreement focused on revamping police training, department policies, and investigations of police use of force. One of the ongoing requirements of the Agreement is that Cincinnati police officers fill out a "contact card" each time they stop a member of the public. Each officer documents numerous data points for each stop, including the person's age, gender, race, and outcomes of the stop (whether or not the officer used force, whether an arrest was made, etc.).

Utilizing the data collected through Cincinnati's Collaborative Agreement, Campaign Zero has analyzed thousands of documented police-community interactions across Cincinnati. Spanning from 2009 to 2025, Cincinnati police stopped over 472,666 people – almost 1 in 10 residents per year, slightly above national average. The analysis shows that in 2025:

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- Cincinnati Police officers stopped Black people **3.4x** more often than White people.
- Black pedestrians were stopped **5.4x** more often than White pedestrians.
- Black people were stopped in vehicles **3.2x** more often than White people.

The Cincinnati Police Department's data shows that each step in the process – from where and when police stopped people, to who got stopped, searched, subjected to use of force, and arrested – was racially biased against Black people.

Cincinnati Police Department data from 2009–2025 shows:

- Once stopped by Cincinnati Police officers, Black people are:
  - → **2.1x** more likely to be searched than White people.
  - → **1.9x** more likely to have force used against them than White people.
  - → **1.8x** more likely to be arrested than White people.
- In majority White neighborhoods, Black pedestrians are stopped by Cincinnati Police **4.5x** more often than White people, and Black motorists experience discretionary traffic stops **5.5x** more often than White motorists.
- The more White the neighborhood, the more likely it is for a Black person to be stopped there. Crime rates do not explain this trend.

It is our hope that Cincinnati elected officials, police leadership, and community organizers will convene and use this research to develop policy changes to eliminate inequitable policing.

Table of Contents

About Campaign Zero

Campaign Zero is a research and data-driven organization working to end police violence and mass incarceration by shining a light on the impacts of harmful law enforcement policies and practices.

Learn more about our work: campaignzero.org

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Acknowledgments

We would like to express our deepest appreciation to the Hamilton County Public Defender Office. Their tireless oversight of law enforcement and commitment to justice for all people is inspiring and has a vital impact on ensuring all our freedom.

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Introduction

On April 7, 2001, Stephen Roach, a Cincinnati police officer, shot and killed Timothy Thomas — the 15th Black man killed by Cincinnati police in the previous 6 years.

Following widespread community protests and sustained pressure on elected officials, the city entered into a Collaborative Agreement[1] focused on revamping police training, department policies, and investigations of police use of force. A federal monitor, an independent overseer selected by all involved parties and the US Department of Justice, initially provided oversight to ensure compliance. After its expiration, the City of Cincinnati continued the terms of the agreement in an effort they refer to as the "Collaborative Agreement Refresh."

One of the ongoing requirements of the Collaborative Agreement is that every time a Cincinnati Police Department (CPD) officer stops a member of the public, the officer must fill out a "contact card" with details from the stop. These contact cards include personal information of the person stopped (name, race, gender, etc.), location information (coordinates of where the stop occurred), and case information (reason for stop, whether force was used, whether an arrest was made, etc.). From 2009 to 2025, over 446,262 contact cards have been completed across Cincinnati . Each card records a single police stop, which may involve one or more people. Across all cards in Cincinnati, at least 472,666 individual people were recorded – almost 1 in 10 residents each year, in line with the national average (Pierson et al 2020, Davis et al 2015) – though this does not represent unique individuals stopped.[2]

We examined CPD contact card data from 2009–2025[3] to better understand the distribution of these stops by race. The findings are consistent across every measure: ***On average, Cincinnati Police stop, search, use force against, and arrest Black people more often than their White neighbors.***

This report examines racial disparities in police stops and shows that although crime and criminality are not higher from one racial group to another, Cincinnati police officers disproportionately target Black people. The report also includes police stop levels by neighborhood and an officer-specific analysis that highlights the CPD officers with the greatest racial equity disparity in their stops. We hope these findings will be utilized by elected officials, police leadership, and community members to create a more equitable city.

An Examination of Cincinnati Police's Contact Cards

Data Sources & Methodology

DATA SOURCES

This report draws on the following data sources:

- **Cincinnati Police Department (CPD) Contact Card Data**
  The primary dataset was obtained through two separate public records requests submitted to the City of Cincinnati.
  - → **Record Management System (RMS) Data (2002–June 2024):** The first dataset was exported from CPD's Records Management System (RMS) and covers contact card stops from 2002 through June 2024. This dataset contains 104 variables in total.
  - → **Axon Data (June 2024–December 2025):** The second dataset was exported from the Axon platform and covers contact card stops from June 2024 through December 2025. This dataset contains 29 variables in total.
- **U.S. Census Bureau**
  - → **2020 Decennial Census:** The 2020 Census population figures for Cincinnati were used to calculate per-capita stop rates for all non-time-series charts and maps. The Decennial Census was chosen because it attempts a full population count rather than a sample estimate, making it the most precise source for racial population figures at the census

1 The original Collaborative Agreement was between the City of Cincinnati, the Fraternal Order of Police (FOP), the Cincinnati Black United Front, and the American Civil Liberties Union of Ohio.
2 The data does not include a unique person identifier. Date of birth was used as a proxy, but since individuals may be stopped multiple times or share the same date of birth, it is not possible to determine precisely how many distinct people were stopped.
3 Stops prior to 2009 were excluded due to the very small number of recorded stops in those years (fewer than 20), which is insufficient to support reliable or robust conclusions.

block level. Given that the study period spans 2009 to 2025, 2020 also serves as a reasonable midpoint.

Race totals were drawn from table P2, sex totals from table P12, and sex by race from tables PCT12A (White alone) and PCT12B (Black or African American alone).

- **2009–2024 American Community Survey (5-year estimates):** Annual population figures from this survey were used to calculate per-capita stop rates in time series charts. For each year from 2009 to 2024, the corresponding ACS 5-year estimate was used. For 2025, the 2024 ACS estimates were used as the 2025 data has not yet been released.

  Race totals were drawn from table B03002, median household income from table B19013.

- **TIGER/Line 2023 Primary Roads:** This dataset provided highway geometries used in the mile marker geocoding process.

- **TIGER/Line 2020 Shapefiles:** This dataset provided the geographic boundaries of Cincinnati city, tracts, and blocks.

- **Geocoding Services API:** Census-run geocoding service used to recover latitude and longitude coordinates for addresses provided in the contact card data.

- **Cincinnati Area Geographic Information System (CAGIS)**

  - **CAGIS Open Data Hub:** The CAGIS (Cincinnati Area Geographic Information System) Open Data Hub was used to obtain:

    - Cincinnati Statistical Neighborhood Approximations (SNA) 2010 shapefiles, used to define the city's geographic boundaries and filter stops to within Cincinnati's city limits.

    - Cincinnati Police District shapefiles, used to calculate officer-level stop rates at the district-level.

  - **Ohio Department of Transportation (ODOT)** County milepost data was retrieved from the ODOT ArcGIS REST API and used to anchor mile marker locations along Ohio interstate highways.

  - **Geocodio:** A commercial geocoding service used to recover latitude and longitude coordinates for records that could not be matched through the Census geocoder.

Open Data Cincinnati

Cincinnati's open data portal was used to download crime data from the following two sources:

- Police Data Initiative (PDI) RMS data (2010–6/2/2024)
- STARS Category Offenses (on or after 6/3/2024)

Records from both datasets were harmonized into the FBI's original 7 Unified Crime Reporting (UCR) Part I offenses: aggravated assault, burglary, homicide, larceny, motor vehicle theft, rape, and robbery. While arson was later added to UCR Part I offenses, it is not broken out in CPD data on the open data portal.

DATA CLEANING AND INTEGRATION

Given that the two main datasets were exported from different systems, significant cleaning was required before the datasets could be combined. This included identifying variables common to both datasets, standardizing variable names and category labels across systems, and appending the two datasets into a single unified file.

Each row in the data represents an individual person stopped, but a single stop event can involve multiple people (two people in a vehicle, etc.). To uniquely identify each person-stop, records were deduplicated using a combination of date of birth and interview number, which is the stop's unique identifier. A substantial number of duplicate records were removed through this process.

GEOGRAPHIC DATA AND COORDINATE COMPLETION

The dataset included several geographic variables: latitude, longitude, projected coordinates (xcoord,

4 This total includes stops recorded outside Cincinnati's city limits, such as those occurring elsewhere in Hamilton County and surrounding areas. The analytic sample is restricted to stops within Cincinnati's city boundaries (n=472,666).

ycoord), address, zip code, city, and state. Across both sources, there are 520,216[4] unique person-stop records. However, a significant portion of records were missing coordinate data. Because precise coordinates were necessary to map stops and filter to Cincinnati's city limits, a multi-step geocoding process was used to recover as many locations as possible.

1) Coordinate conversion: For records missing latitude and longitude but containing projected xcoord/ycoord values, coordinates were converted directly from the projected coordinate system to WGS84 (latitude/longitude).

2) Census Geocoder: For records still missing coordinates, available address components (street address, zip code, city, and state) were used to query the U.S. Census Bureau's geocoding API, which returned latitude and longitude where a match was found.

3) Geocodio: Records that could not be matched by the Census Geocoder were submitted in batch to Geocodio, a commercial geocoding service, to recover additional coordinates.

4) Mile marker interpolation: A subset of records contained only highway mile marker references (e.g. "I-75 MM 18.2") rather than street addresses, which standard geocoders cannot resolve. For these records, a custom interpolation method was developed using two data sources: U.S. Census TIGER/Line 2023 primary road geometries and Ohio Department of Transportation (ODOT) county milepost data retrieved via the ODOT ArcGIS REST API. Integer mileposts were projected onto continuous route geometries using geodesic distance calculations, and fractional mile markers were then interpolated between the two nearest ground-truth milepost anchors to produce precise latitude/longitude coordinates.

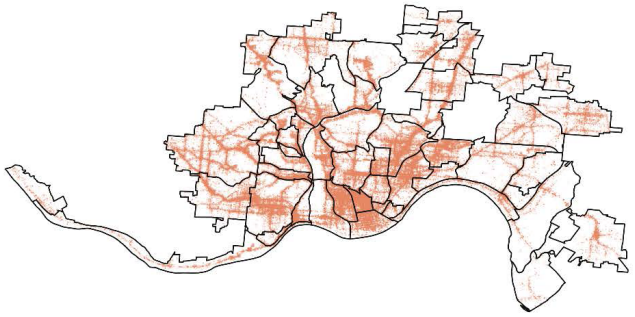
Records for which coordinates could not be recovered through any of these methods were excluded from the spatial analysis (n=15, <0.01%). The geocoded records were then spatially joined to Cincinnati's city boundary and filtered to stops occurring from 2009 onward, yielding a final analytic sample of 472,666 person-stop records.

GEOGRAPHIC FILTERING

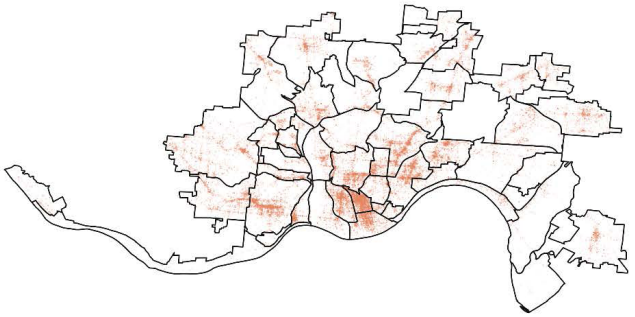
Our analysis begins with the cleaned, deduplicated dataset. Stops were then filtered to those occurring within Cincinnati's city limits using Cincinnati boundary shapefiles, resulting in a final dataset of 472,666 people stopped between 2009 and 2025. Stops prior to 2009 were excluded due to the very small number of recorded stops in those years, which is insufficient to support reliable or robust conclusions.

FIGURE 1 — **Contact Card Stop Locations, Motor Vehicle Stops vs. Pedestrian Stops (2009-2025)**

Motor vehicle stops (n= 403,037)



Pedestrian stops (n=56,176)



Each dot represents one person stopped by Cincinnati Police between 2009 and 2025. Dots are plotted at the recorded location of the stop. Lines denote neighborhood boundaries. Where dots overlap heavily, areas appear as solid color. White space indicates areas with few or no recorded stops. The two entirely blank areas in the middle and northeast portions of the map are the villages of St. Bernard and Elmwood Place and the city of Norwood, enclaves of Cincinnati with their own elected city governments.

POPULATION BENCHMARKS AND STOP RATES

Racial disparity calculations use 2020 U.S. Census population figures for Cincinnati as the benchmark. The unit of analysis is the individual person stopped rather than the stop event itself, which allows for demographic breakdowns by race across all outcomes.

Raw counts alone can be misleading when comparing groups of different sizes. A group with more residents will naturally produce more stops even in the absence of any disparity. To account for this, stop rates are expressed as average annual stops per 1,000 residents, per year, calculated as:

Stop Rate = ((Total Stops ÷ Population) × 1,000) ÷ Number of Years

This formula produces a rate that is comparable across racial groups regardless of their relative population size, and comparable across time periods regardless of how many years are included. Disparity ratios are then calculated by dividing the Black stop rate by the White stop rate, where a value of 1.0 indicates no disparity and a value of 2.0 indicates Black residents are stopped at twice the rate of White residents.

LIMITATIONS

This report draws on administrative data recorded by police officers. Outcome fields such as arrests and citations reflect documented actions, but fields such as stop reason and citizen attitude reflect officer perception and judgment and should be interpreted accordingly.

Data completeness varies considerably across fields (see Table 1). Fields like sex and race are nearly complete. However, several analytically important fields have substantial missing data like beat and district identifiers missing in 66% of records. Although officer-recorded citizen attitude **(otherexplainciti-zenattitude)** is available for only a subset of stops, an exploratory analysis illustrates its potential analytic value (see Appendix F).

For the legal basis for the search field **(legalbasisfor-searchid)**, only 19 records explicitly indicate that no search was conducted. Given this, we treat missing values in this field as indicating that no search occurred. Missing latitude and longitude data was completed with the method detailed above. For the remaining fields, records with missing data were excluded from the relevant analysis, resulting in varying sample sizes across sections.

TABLE 1 — **Missing Data for Sample Fields Used in the Analysis**

FIELD NAME	FILLED	MISSING	PERCENT MISSING
otherexplaincitizenattitude	2,426	470,240	99.5%
legalbasisforsearchcid	87,423	385,243	81.5%
beat	157,902	314,764	66.6%
district	158,935	313,731	66.4%
supervisorassignment	366,277	106,389	22.5%
supervisor	380,820	91,846	19.4%
stopreasoncid	426,388	46,278	9.8%
forceusedyesnocid	440,142	32,524	6.9%
reporting_officer_assignment	463,558	9,108	1.9%
contact_type	465,058	7,608	1.6%
person_dob	468,053	4,613	1.0%
person_age	468,177	4,489	0.9%

Figures reflect stops filtered from 2009 onwards within the geographic bounds of Cincinnati (N = 472,666). Missing values include blank and null values. Fields used in the analysis with fewer than 160 missing observations—rounding to 0.0% missing—as well as fully complete fields are omitted from Table 1 for clarity.

Additionally, some data entry errors were identified in a small number of records. For example, 80 records contain age values over 100 and were excluded from age-related analyses. Where such errors were identifiable, affected records were excluded; however, for fields such as geographic coordinates, erroneous values cannot always be detected and may remain in the data.

The source data does not include a unique identifier for people stopped. As a proxy, we use date of birth, but this has two limitations: the same person may have been stopped more than once throughout the study period, and different people may share the same date of birth. As a result, the total number of unique individuals stopped cannot be determined with certainty.

Use of force is self-reported by police officers in the contact cards and may not be complete. Search data is only available through 2023 because that variable was not included in CPD's response to the second FOIA records request covering June 2024–December 2025.

Racial Disparities in Overall Crime

This report documents racial disparities in how Cincinnati police stop, search, arrest, and use force against residents. A natural question is whether those disparities reflect underlying differences in how often people of different races exhibit reasonable articulable suspicion or probable cause, leading to the initial stop (and all ensuing actions). Where the two can be measured separately, the evidence says they do not.

For example, Black people and White people use illegal drugs at comparable rates, but Black people are far more likely to be arrested for drug-related offenses[5].

Additionally, when police patrol an area more heavily, they record more crime there, which is then used to justify even more policing. Researchers have found that Black and Latino pedestrians were stopped far more often than White pedestrians even in neighborhoods with the same crime rates (Gelman, Fagan & Kiss, 2007).

Higher crime rates also partly reflect decades of deliberate government policy such as redlining and intentional disinvestment that concentrated poverty in Black communities (Rothstein, 2017). It reflects where people live, not who they are.

Finally, by measuring crime not through police records but through federally-administered surveys that ask residents directly about what they experienced — a victimization rate, independent of whether police were called — researchers have shown that police are deployed in Black neighborhoods far beyond what residents report being victimized by (Simes, 2021). Additional research shows that aggressive policing makes residents less likely to report crimes to police, which ultimately makes communities less safe (Desmond, Papachristos & Kirk, 2016).

Racial Demographics of Cincinnati

Cincinnati, Ohio, is home to an estimated 315,000 people (US Census Bureau)[6]. Within the city limits, White people fall just short of an overall majority, comprising a plurality of 49% of the population. Black people are the second largest racial group at 36.5% followed by Hispanic or Latino (6.1%), Asian (2.7%), and Indigenous people (0.2%)[7].

While the contact card data includes stops across multiple racial groups, Hispanic, Asian American and Pacific Islander (AAPI), and other groups account for a very small share of stops. For this reason, this report, apart from Figures 1 and 2, focuses on Black and White residents. We have prioritized analysis where there is 1) enough data to make reliable comparisons and 2) where disparities are most pronounced.

The numbers of stops for other racial groups in Cincinnati's contact card data are too small to draw meaningful comparisons in many of the analyses presented in this report. This narrowed focus is not meant to diminish the experiences of these communities, who may also face significant policing disparities. As more data becomes available, future analyses should examine these groups more closely.

5 A 2015 study (Ojmarrh Mitchell & Michael S. Caudy, 2015) showed Black people are 53% more likely than White people to be arrested for a drug offense.
6 https://www.census.gov/quickfacts/cincinnaticityohio (2024 Population Estimates Program (PEP) estimates)
7 For a visual representation of where different racial groups live in Cincinnati, see Figure A.6 — Racial Majority by Census Block (2020 Census) in the appendix.

Racial Disparities in Police Stops Over Time

Aggregate Police Stops

Our review begins with the aggregate number of police stops in Cincinnati – how many total times CPD officers stopped a member of the public, including both traffic and pedestrian stops, broken down by race.

While the total number of police stops has fallen dramatically since 2009, Black people have consistently been the racial group stopped most each year, despite comprising a minority of the city's population (Figure 2).

Breaking these stops down by percentage, we see that Black residents have consistently accounted for 60–70% of all CPD stops over the past decade, nearly double their share of Cincinnati's overall population (See Appendix A.1).

Police Stops: Proportionality

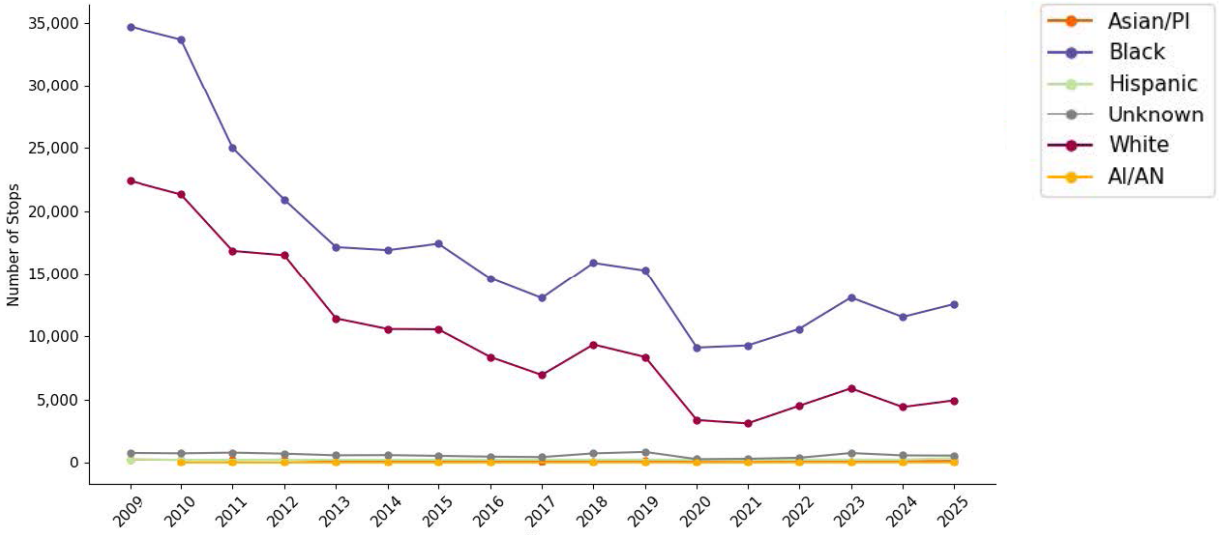
The data shows an undeniable, persistent, and worsening racial disparity in who Cincinnati police choose to stop. To properly assess disparities, we go beyond total stop counts and take population into account, looking at rates of police stops per 1,000 residents to account for differences in each racial group's total population. While the overall stop rate has fallen for both racial groups, Black people continue to be stopped at significantly higher rates per 1,000 residents[8] than White people (solid lines, Figure 3).

Turning this comparison into a disparity ratio, comparing stops by race in proportion to their populations, we see how much more likely Black people are to be stopped by police compared to White people for any given year (dashed line, Figure 3). While stop rates dropped sharply during the COVID-19 pandemic years (2020 and 2021), racial disparities in police stops rose.

One likely factor is that Black residents were disproportionately employed as essential workers during the pandemic, and therefore more likely to be commuting (Rogers et al., 2020). White residents disproportionately held white collar jobs that allowed them to work from home (Asfaw, 2022).

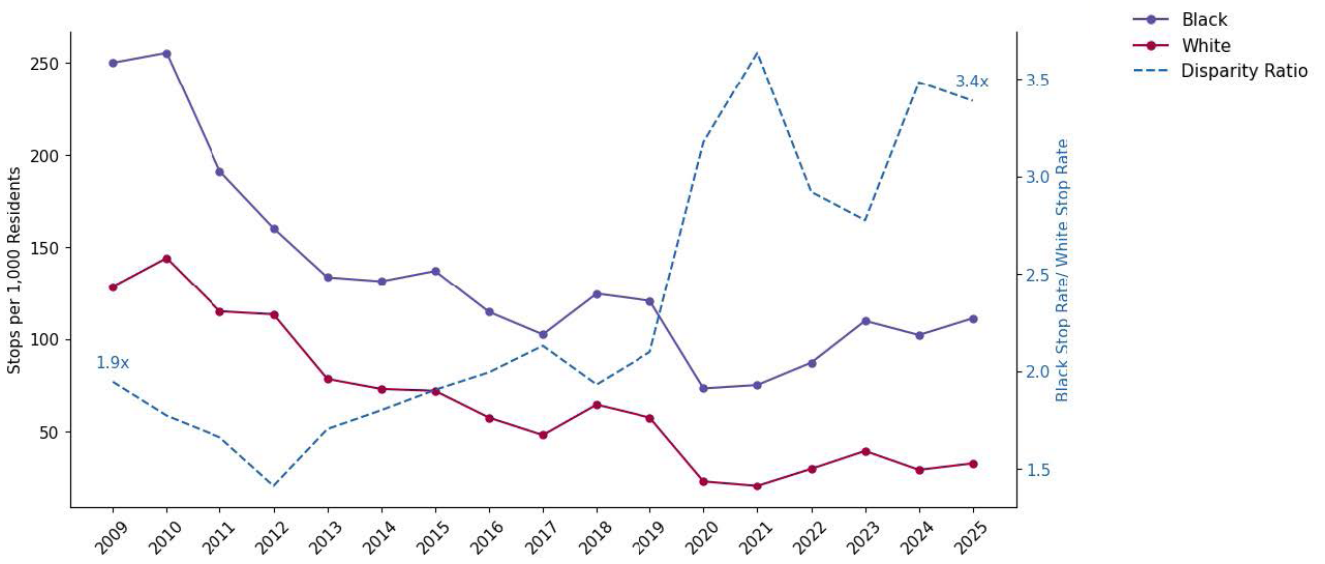
Even during a period of nationwide and local demands for equitable policing, CPD's stop patterns grew more racially disparate, not less.

FIGURE 2 — **Police Stops by Race (2009-2025)**



8 Stop rates are expressed per 1,000 residents to account for differences in population size across racial groups. Without this adjustment, a group with a larger population would naturally have more stops in raw numbers, even if individuals within that group were no more likely to be stopped than anyone else. The fi gure of 1,000 is a conventional scaling choice for city-level statistics, as stop rates per person are small fractions and multiplying by 1,000 produces more readable numbers (e.g. 12 stops per 1,000 residents instead of 0.012 stops per resident).

FIGURE 3 — **Police Stop Rate per 1,000 Residents and Racial Disparity (2009-2025)**



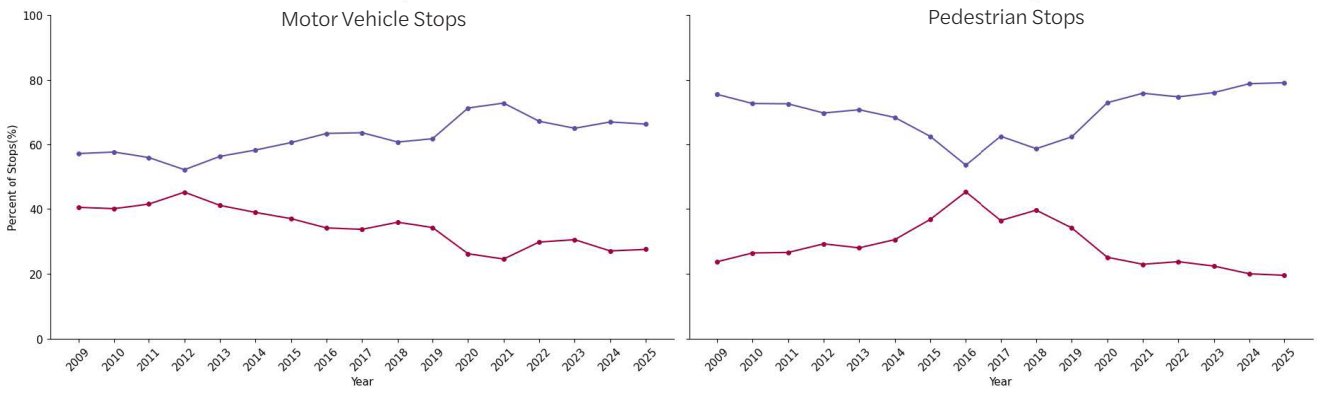
Stop rates are calculated as the number of police stops per 1,000 residents of each racial group. Disparity ratios are calculated as the Black stop rate divided by the White stop rate for each year. Population estimates are drawn from the U.S. Census Bureau American Community Survey (ACS) 5-year estimates for each year from 2009–2024. For 2025, 2024 ACS estimates were applied, as 2025 figures have not yet been published.

Pedestrian vs. Motor Vehicle Stops

Contact cards are filled out by police for both pedestrian stops and motor vehicle stops. The data shows that racial disparities in police stops are not uniform across all stop types — racial disparities are significantly worse in situations where officers have more discretion over who to stop.

Black residents accounted for approximately 66% of motor vehicle stops in Cincinnati in 2025, while White residents accounted for 27%, a gap of roughly 39 percentage points (Figure 4). That disparity has grown significantly over time. In 2009, Black residents accounted for 58% of stops and White residents for 41%, a gap of 17 points, meaning the racial divide has more than doubled in a span of 17 years.

FIGURE 4 — **Racial Demographics of Police Stops (2009-2025)**



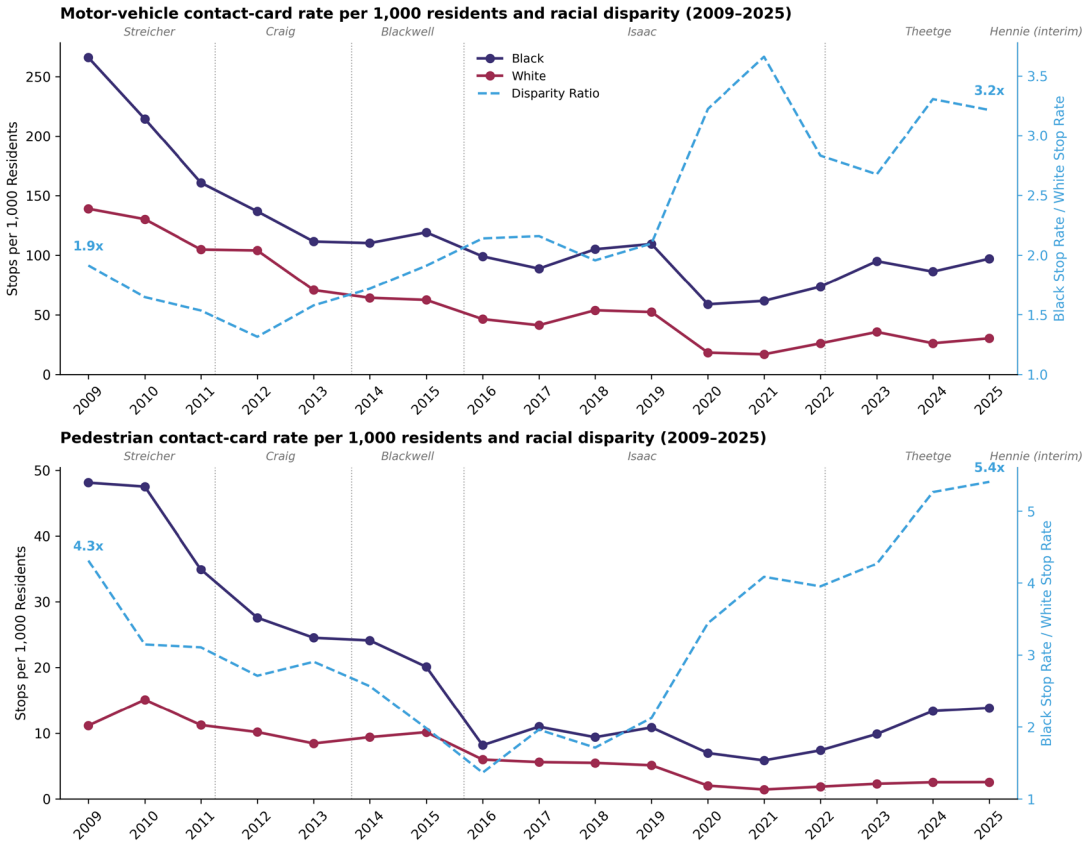
Pedestrian stop data shows deep racial disparities in 2009, shrinking towards the mid-2010's, and rapidly growing again to present day (Figure 4, right side). This racial gap has roughly doubled since 2015. Black people made up approximately 80% of all pedestrian stops in 2025, compared to just 19% for White people.

In 2009, the pedestrian stop disparity ratio stood at 4.0x (Figure 5) – Black pedestrians were stopped by CPD officers at four times the rate of White pedestrians. That gap plummeted in the mid-2010's but has since climbed steadily and, by 2025, it reached 5.4x. When Cincinnati police officers decide to stop someone on foot, they choose Black pedestrians at roughly five times the rate of White pedestrians.

Although racial disparities were nearly equal for pedestrian stops in 2016 and motor vehicle stops in 2012, there has been no year in the past decade where Black and White residents were stopped by CPD officers at equal rates**. These brief periods of near-parity demonstrate that more equitable policing outcomes are achievable in Cincinnati**. What policies, leadership, or practices enabled those improvements — and why they were not sustained — warrants serious investigation by CPD and city officials.

The accelerating pedestrian stop disparity, compared to relatively constant traffic stop disparities, suggests that racial bias is especially pronounced when officers exercise more subjective judgment. Even when a traffic violation provides a stated justification for a stop, officers retain significant discretion in choosing which violations — and which drivers — to enforce against (Epp, Maynard-Moody & Haider-Markel, 2014; Pierson et al., 2020). That discretion is even greater for pedestrian stops, which rely more heavily on officer discretion of what they might perceive as "suspicious" activity[9]. The data shows that when officers have more discretion to decide who to stop, Black residents bear the greatest burden.

FIGURE 5 — **Racial Disparity in Police Stops (2009–2025)**



Disparity ratios are calculated as the Black stop rate per 1,000 residents divided by the White stop rate per 1,000 residents. A ratio of 1.0 indicates no racial disparity; values above 1.0 indicate that Black residents are stopped at a higher rate than White residents. Stop rates are derived using the U.S. Census Bureau American Community Survey (ACS) 5-year population estimates for each year from 2009–2024. For 2025, 2024 ACS estimates were applied, as 2025 figures have not yet been published.

9 More detailed information regarding police suspicion is included in the "Initial Reason for Police Stops" section.

Geographic Analysis

Geographic Distribution of Police Stops

Police stops in Cincinnati are not evenly distributed across the city. A small number of neighborhoods account for a disproportionately large share of all recorded stops.

Avondale, Over-the-Rhine, West End, East Price Hill, and Downtown each recorded over 25,000 people stopped between 2009 and 2025 (see Appendix A.2). Notably, this concentration of stops is not simply a reflection of where most people live. Westwood is Cincinnati's most populous neighborhood, but it does not rank among the top five in total stops, while smaller neighborhoods like West End and Over-the-Rhine do (see Appendix A.3).

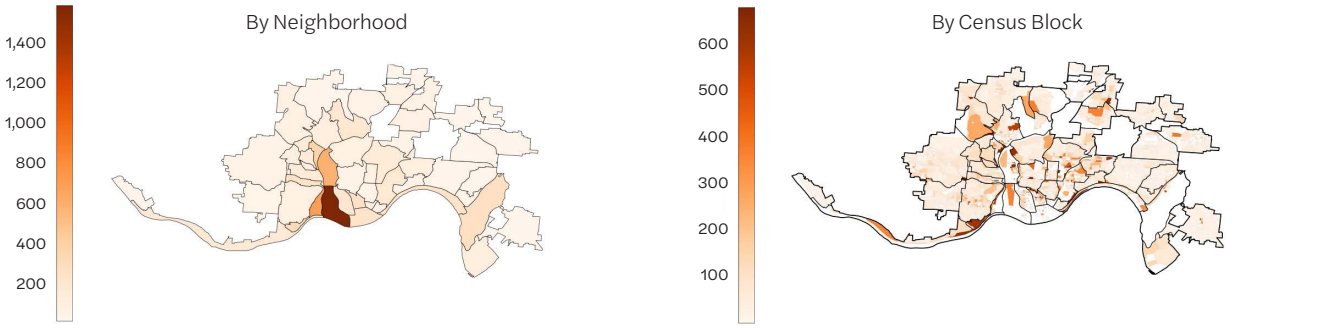
When population is taken into account, the picture shifts. The figures below (6 and 7) show the average number of people stopped, separated by traffic and pedestrian, per 1,000 residents each year at the neighborhood and census block levels. These rates reflect the average annual number of people stopped in each area relative to how many people live there.[10]

For motor vehicle stops—which account for the majority of all stops—Queensgate is the neighborhood with the highest stop rate at 2,689 people stopped per 1,000 residents per year (Figure 6, left). However, it is largely made up of industrial and commercial warehouses with very few residents, so its high rate is likely driven by the far greater number of people who pass through or work there during the day than actually live there. Similar dynamics may apply to a lesser degree in Downtown and Over-the-Rhine, which draw significant non-resident traffic, though both also have substantial residential populations.

Beyond Queensgate, the highest rates are in Lower Price Hill (759 per 1,000), meaning that on average, more than 3 out of 4 residents are stopped at least once every year. Next highest are Camp Washington (641 per 1,000), South Cumminsville (379 per 1,000), Sedamsville (328 per 1,000), and Over-the-Rhine (323 per 1,000).

Across the city, the burden of police contact falls heavily on a small number of mostly lower-income neighborhoods (see Appendix A.4) in the west side and urban core, where residents were stopped at rates far exceeding the rest of the city throughout this period.

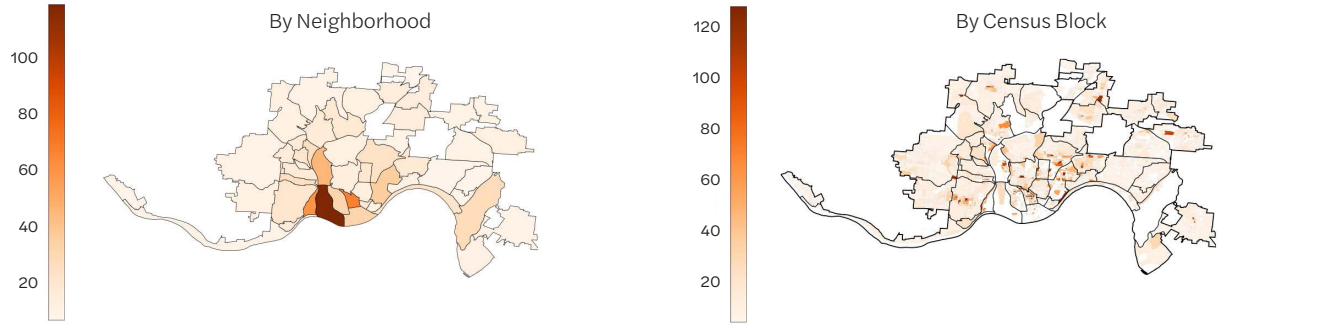
FIGURE 6 — **Motor Vehicle Stops: Annual Police Stop Rate per 1,000 Residents by Neighborhood and Census Block (2009–2025)**



Left: Average annual stops per 1,000 residents by neighborhood. Right: Average annual stops per 1,000 residents by census block. Each panel has its own color scale, capped at the 99th percentile, so that a small number of areas with unusually high stop rates do not compress variation elsewhere into a single pale color. Areas above the cap appear in the darkest color.

10 Not everyone stopped by police in a neighborhood actually lives there. For example, someone driving through or working in an area can be stopped and recorded even if they live somewhere else entirely, which may inflate the rate for that neighborhood. This effect is more likely to be present in motor vehicle stops, where drivers are passing through an area. In pedestrian stops, a person who is stopped is more likely to reside in that neighborhood. We present separate maps for both to account for these differences and the distinct nature of each type of police stop.

FIGURE 7 — **Pedestrian Stops: Annual Police Stop Rate per 1,000 Residents by Neighborhood and Census Block (2009–2025)**



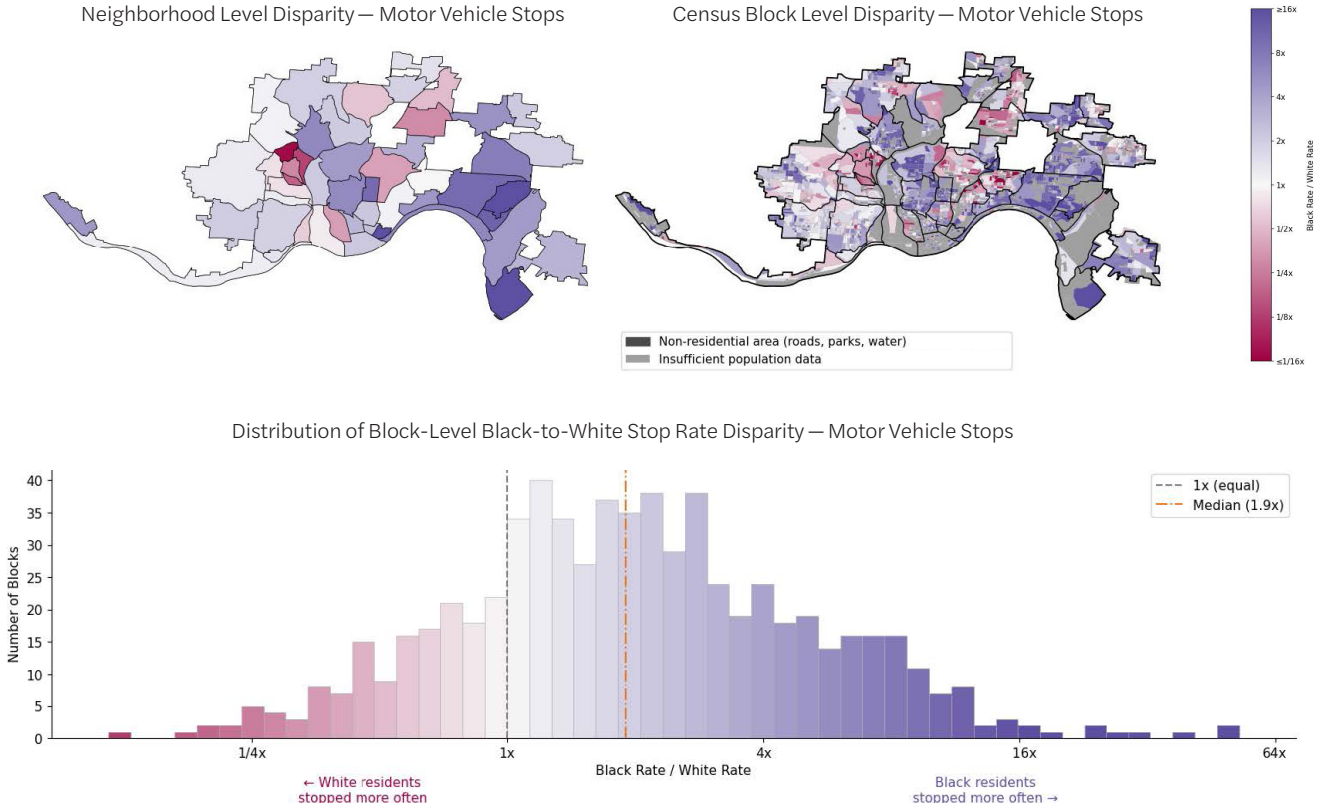
Left: Average annual stops per 1,000 residents by neighborhood. Right: Average annual stops per 1,000 residents by census block. Each panel has its own color scale, capped at the 99th percentile, so that a small number of areas with unusually high stop rates do not compress variation elsewhere into a single pale color. Areas above the cap appear in the darkest color.

As seen in Appendix A.5, Cincinnati's Black population is concentrated in the west and north-central parts of the city in neighborhoods like Avondale, West End, and Evanston. While much of the south and east has comparatively few Black residents, this pattern was not accidental — it was shaped by decades of redlining, urban renewal, and the mid-twentieth century displacement of Black communities from the West End (Rothstein, 2017)[11].

The geographic pattern for pedestrians is similar to motor vehicle stops but more spatially concentrated. High stop rates appear again in Queensgate, Lower Price Hill, and the urban core but with sharper clustering at the census block level (Figure 7). Clusters appear in Downtown (Central Business District), Over-the-Rhine, and nearby areas. This pattern is consistent with pedestrian enforcement being more localized, occurring in specific streets or areas, compared to motor vehicle stops, which are more spatially diffuse. The next section examines whether these geographic patterns reflect racial disparities in who is stopped, not just where stops occur.

11 Post-war highway construction and urban renewal projects in the West End forcefully displaced thousands of Black residents into surrounding neighborhoods including Avondale, Bond Hill, Mount Auburn, and Walnut Hills (Jackson, 2025).

FIGURE 8 — **Black-to-White Stop Rate Disparity by Neighborhood and Census Block, Motor Vehicle Stops (2009–2025)**



Left: Map shows Black-to-White stop rate disparity at the neighborhood level. Right: Map shows the same at the census block level. Bottom: Distribution of census block-level disparity ratios. Purple indicates areas where Black residents are stopped at higher rates than White residents; pink indicates the reverse; white indicates approximate parity. The color scale runs from 1/16x to 16x on a log axis; blocks where Black residents are stopped at more than 16x the White rate are shown at the maximum purple color so that variation across the majority of blocks remains visible. Dark gray areas are non-residential (roads, parks, water bodies). Medium gray areas indicate census blocks excluded from the analysis due to insufficient population data — blocks with fewer than 20 Black or 20 White residents (2020 Census) are omitted because stop rates become unreliable and highly sensitive to small changes in counts when populations are small.

Geographic Disparities by Race

MOTOR VEHICLE STOPS (ALL NEIGHBORHOODS AND BLOCKS)

Figure 8 examines racial disparity in motor vehicle stop rates: purple shading, indicating Black residents are stopped at higher rates than White residents, covers most of the city. This disparity is not limited to predominantly Black neighborhoods; it appears in predominantly White neighborhoods too.

The histogram (Figure 8 bottom) shows the median Black-to-White stop rate disparity for motor vehicle stops across all census blocks is 1.9x. This means that in a typical[12] block, Black residents are stopped nearly twice as often as White residents relative to their population.

The distribution is heavily skewed to the right: while some census blocks show higher stop rates for White residents (pink), the disparities against Black residents (purple) reach far greater extremes, with many census blocks showing Black residents stopped at 4x or 8x (or even more) the rate of White residents. While disparities are present throughout Cincinnati, they are not evenly distributed. The following section examines how motor vehicle stop disparities differ between majority Black and majority White areas.

12 "Typical" refers to the median value of the distribution, meaning half of census blocks have lower disparities and half have higher disparities than this value.

MOTOR VEHICLE STOPS (MAJORITY BLACK AND WHITE NEIGHBORHOODS ONLY)

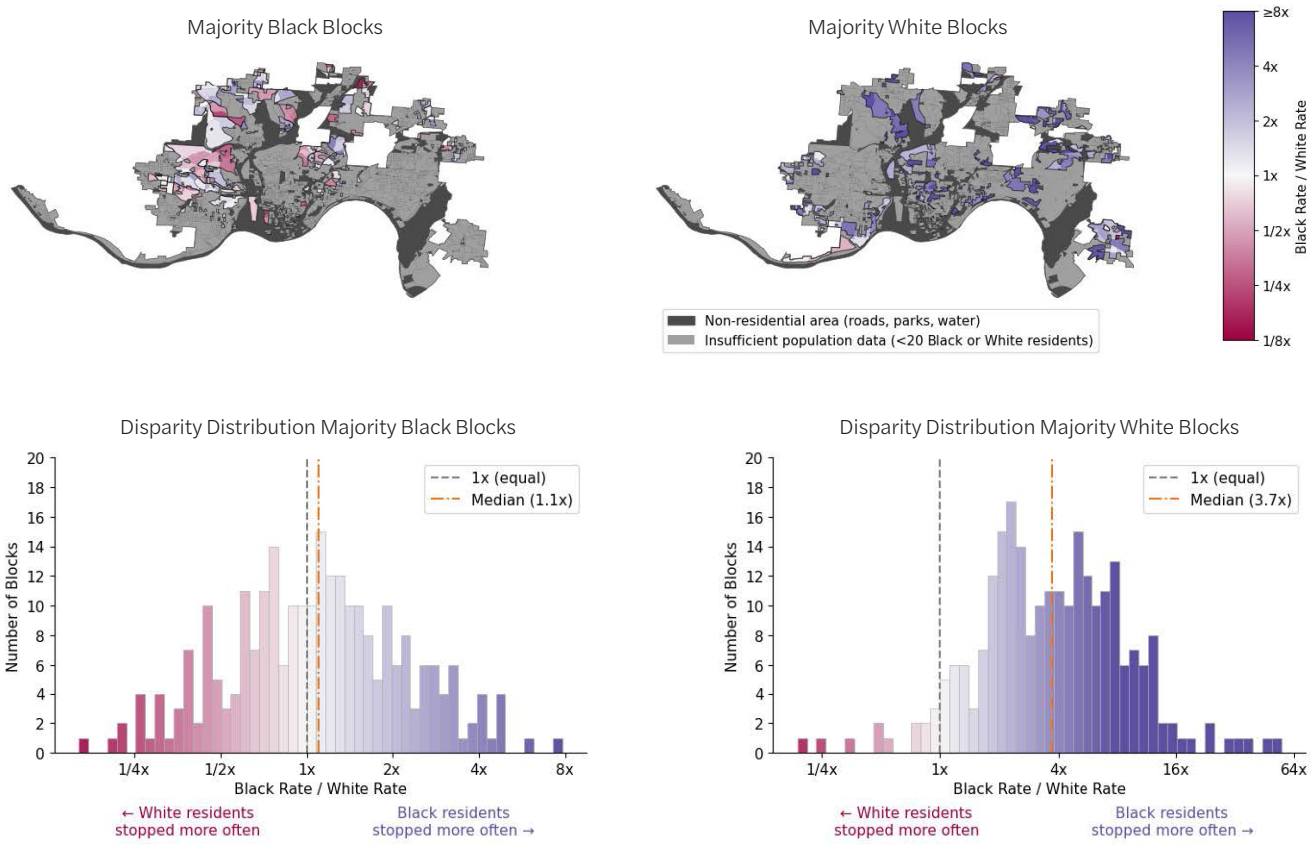
Disparities in motor vehicle stop rates vary sharply depending on the racial composition of an area. In majority Black census blocks, the median disparity is 1.1x, which is very close to equal stop rates for Black and White residents (Figure 9, bottom left). However, in majority White census blocks, the median disparity is significantly higher at 3.7x (Figure 9, bottom right).

The distributions make this contrast clearer. In majority Black census blocks (bottom left), the distribution of disparities is spread across both sides of the equal disparity line (1x). On the other hand, in majority White blocks (bottom right), the distribution is significantly skewed to the right, indicating that Black residents are stopped at dramatically higher rates in parts of the city where they are a minority.

PEDESTRIAN STOPS (ALL NEIGHBORHOODS AND BLOCKS)

In pedestrian stops, racial disparities are widespread across the city and more pronounced than in motor vehicle stops (Figure 10). Higher stop rates for Black residents (darker purple) appear in most areas, including predominantly White neighborhoods (see right figure on Appendix D.2).

FIGURE 9 — **Black-to-White Stop Rate Disparity by Block Racial Majority, Motor Vehicle Stops (2009–2025)**



Left: Map shows Black-to-White stop rate disparity at the neighborhood level. Right: Map shows the same at the census block level. Bottom: Distribution of census block-level disparity ratios. Purple indicates areas where Black residents are stopped at higher rates than White residents; pink indicates the reverse; white indicates approximate parity. The color scale runs from 1/16x to 16x on a log axis; blocks where Black residents are stopped at more than 16x the White rate are shown at the maximum purple color so that variation across the majority of blocks remains visible. Dark gray areas are non-residential (roads, parks, water bodies). Medium gray areas indicate census blocks excluded from the analysis due to insufficient population data — blocks with fewer than 20 Black or 20 White residents (2020 Census) are omitted because stop rates become unreliable and highly sensitive to small changes in counts when populations are small.

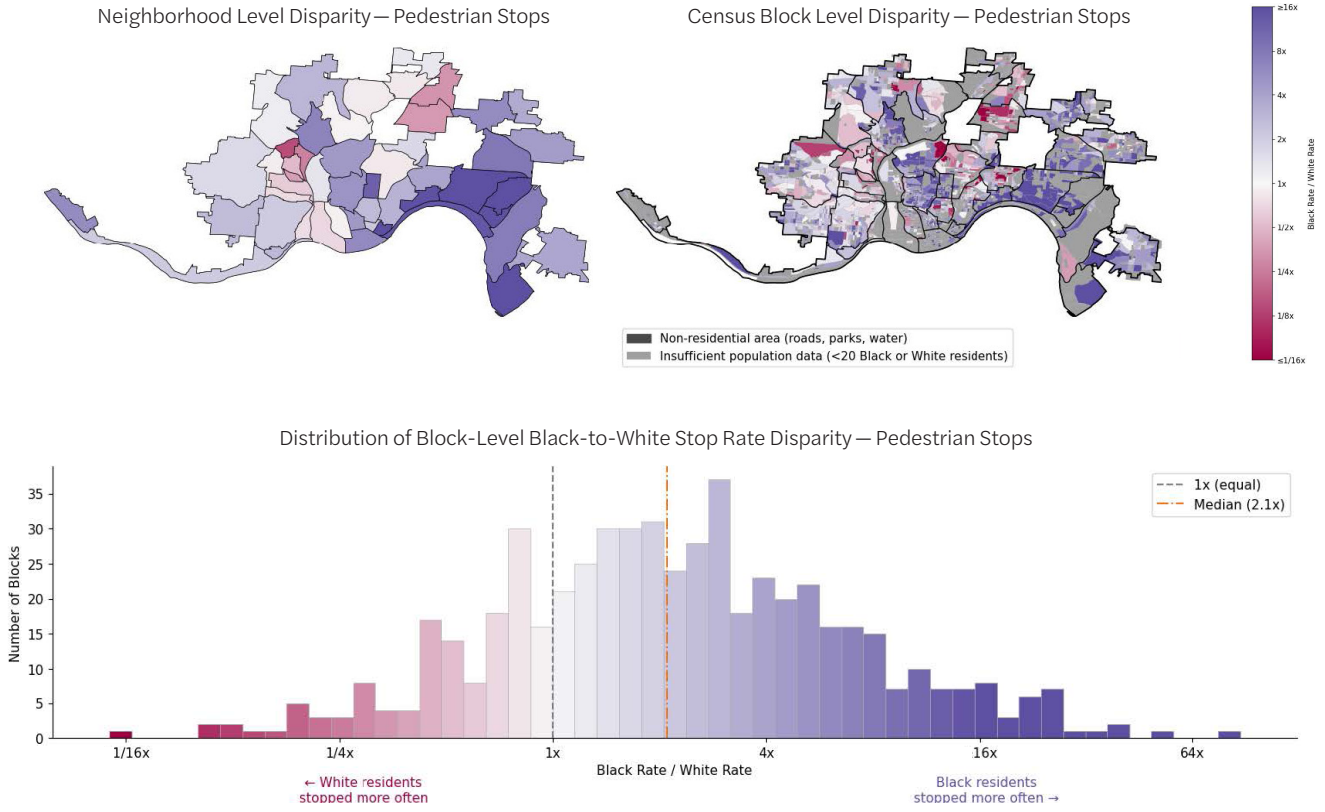
The median block-level disparity is higher (2.1x) and the distribution is even more skewed to the right (Black residents stopped more often) than in motor vehicle stops.

PEDESTRIAN STOPS (MAJORITY BLACK AND WHITE NEIGHBORHOODS ONLY)

By focusing the pedestrian stop analysis on majority Black and majority White blocks, we again see pronounced disparities (Figure 11). In majority Black census blocks, the median disparity is somewhat higher (1.3x) but still close to parity.

In census blocks that are majority White, the picture shifts dramatically. The distribution is almost entirely purple, with virtually no blocks where White residents are stopped at equal rates, let alone more often, than Black residents. **More striking still, the disparities stretch to substantially high levels — many majority White census blocks show Black pedestrians being stopped at 8x, 16x, even 32x the rate of White residents**. These are not outliers at the edges of the chart. They represent a sustained pattern of extreme disparity concentrated specifically in the parts of the city where Black residents are least likely to live.

FIGURE 10 — **Black-to-White Stop Rate Disparity by Neighborhood and Census Block, Pedestrian Stops (2009-2025)**

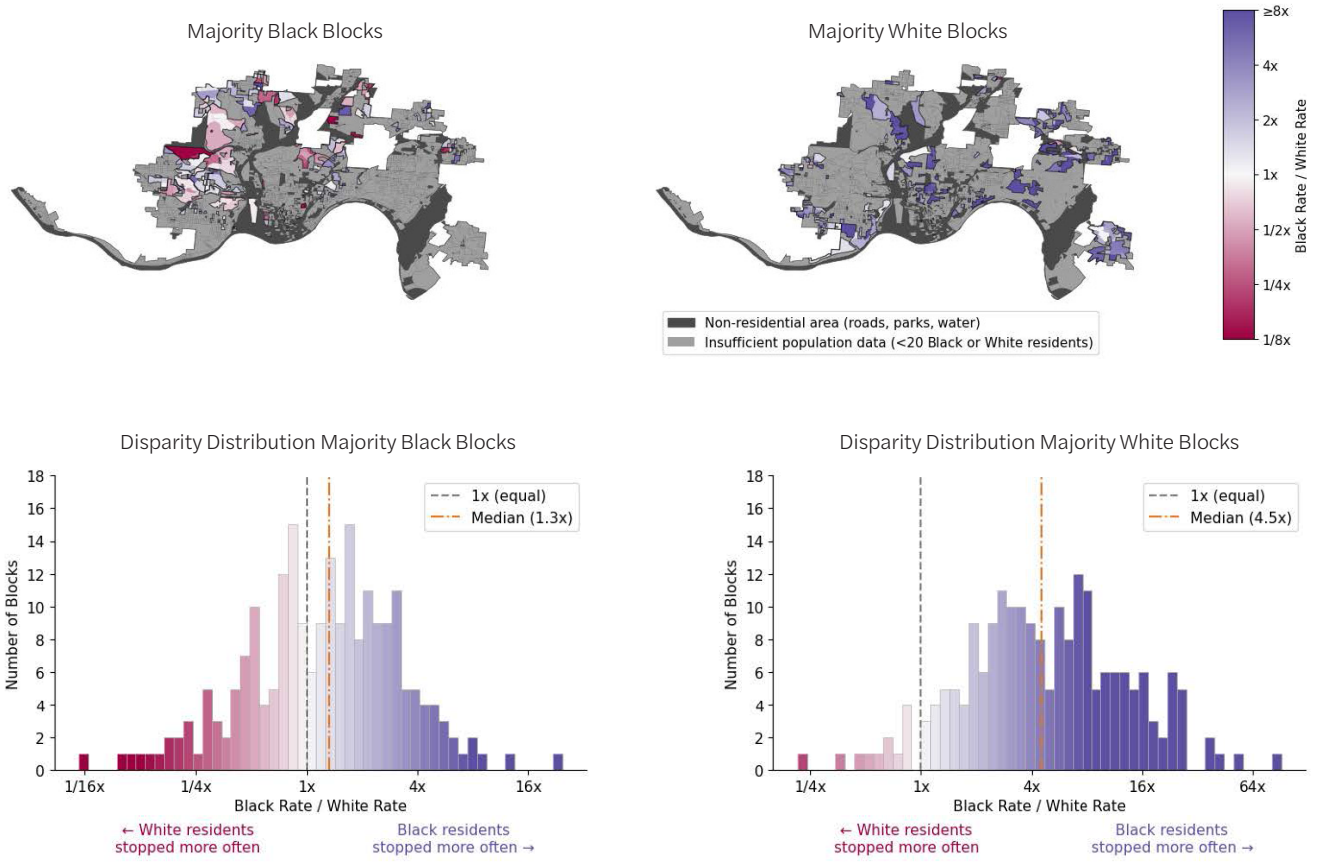


Left: Map shows Black-to-White stop rate disparity at the neighborhood level. Right: Map shows the same at the census block level. Bottom: Distribution of census block-level disparity ratios. Purple indicates areas where Black residents are stopped at higher rates than White residents; pink indicates the reverse; white indicates approximate parity. The color scale runs from 1/16x to 16x on a log axis; blocks where Black residents are stopped at more than 16x the White rate are shown at the maximum purple color so that variation across the majority of blocks remains visible. Dark gray areas are non-residential (roads, parks, water bodies). Medium gray areas indicate census blocks excluded from the analysis due to insufficient population data — blocks with fewer than 20 Black or 20 White residents (2020 Census) are omitted because stop rates become unreliable and highly sensitive to small changes in counts when populations are small.

In Cincinnati, racial disparities, both for motor vehicle and pedestrian stops, are most pronounced when Black residents are in predominantly White neighborhoods. This pattern is consistent with what scholars call "out-of-place" policing — the documented tendency for officers to subject people of color to greater scrutiny when they are in predominantly White spaces (Meehan & Ponder, 2002). It also aligns with racial threat theory (Blalock, 1967), which holds that the dominant group intensifies social controls when it perceives minority presence as a challenge to its existing economic and political position.

The data suggests that in Cincinnati, **a Black resident's likelihood of being stopped by police depends** not just on what they are doing, but **on where they are** — and specifically, on ***whether the people around them are White.***

FIGURE 11 — **Black-to-White Stop Rate Disparity by Block Racial Majority, Pedestrian Stops (2009–2025)**



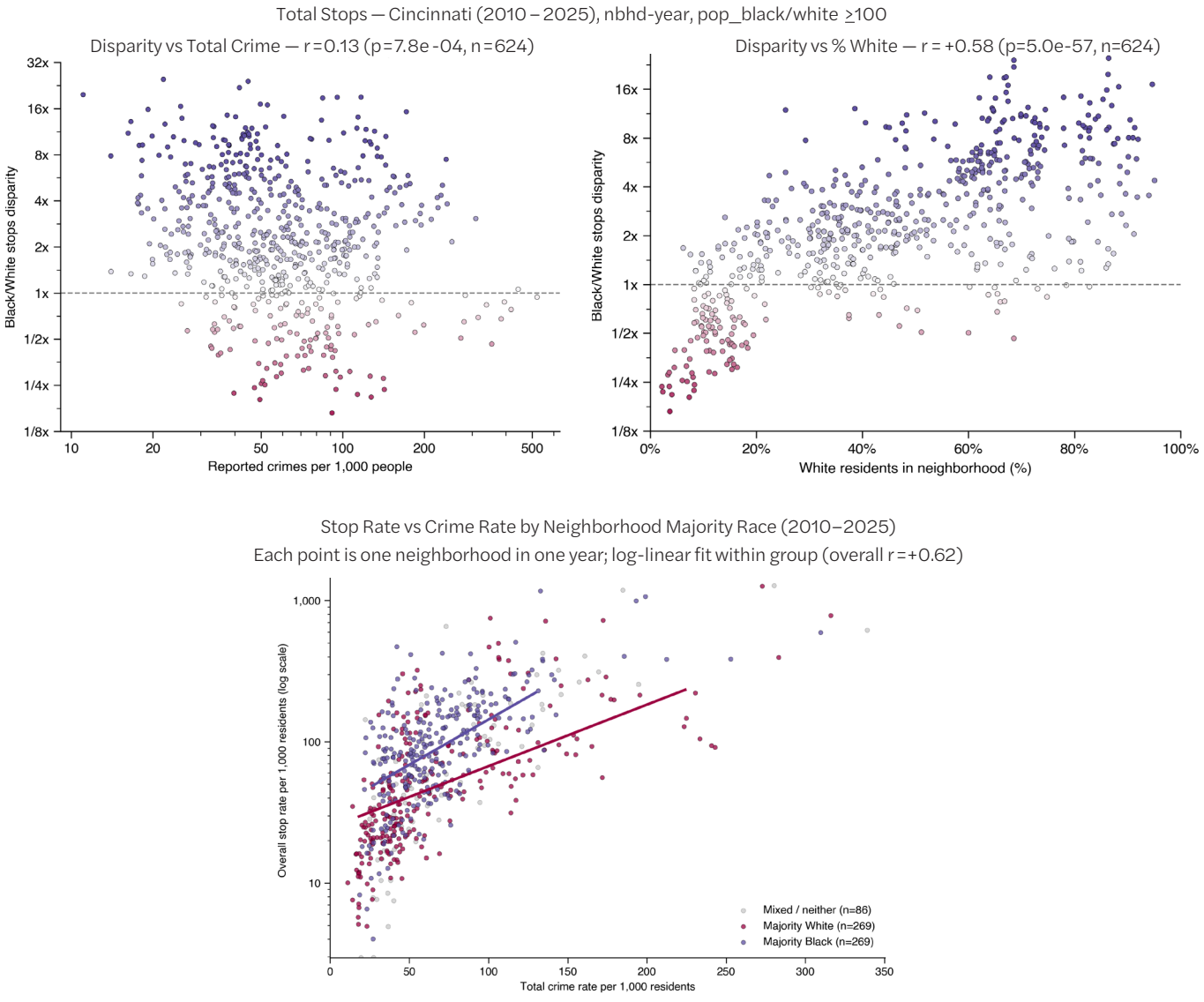
Top Maps show Black-to-White stop rate disparity for census blocks where Black residents exceed 50% of the population (left) and census blocks where White residents exceed 50% (right), based on the 2020 Decennial Census. Purple indicates census blocks where Black residents are stopped at higher rates than White residents; pink indicates the reverse. Dark gray areas within the city boundary are non-residential (roads, parks, water bodies) with no census population. Medium gray census blocks are excluded due to fewer than 20 Black or 20 White residents. The color scale runs from 1/8x to >= 8x on a log axis; blocks with disparities above 8x are shown at the maximum purple color so that variation across the majority of census blocks remains visible. Bottom Charts show the distribution of disparity ratios: the median is 1.1x in majority Black census blocks (near parity) and 4.1x in majority White census blocks.

Crime Rates and Police Stops

One argument for racially disparate stop outcomes is that officers stop more residents in areas with more crime and that areas with more crime have a higher proportion of Black residents. If this defense were true, we would expect lower (or no) racial disparities in police stop rates in White neighborhoods. We tested this directly using police-reported crime data from 2010 to 2025 across Cincinnati's 50 neighborhoods (mapped in Figure A.9).

The data does not support the "police go where crime is" explanation. Figure 9 shows two relationships

FIGURE 12 — **Black-to-White Stop Rate Disparity vs Total Crime and Neighborhood Percent White (2010–2025)**



Relationship between neighborhood stop disparity and two potential explanatory variables: total crime rate (left) and percentage of White residents (middle). Each point represents one neighborhood in one year (n = 624 neighborhood-years, 2010–2025). The y-axis shows the Black-to-White stop disparity ratio on a log scale, where 1x indicates equal stop rates. Crime rates show only a weak negative correlation with stop disparity (r = -0.13), while the share of White residents shows a strong positive correlation (r = +0.58). Neighborhood-years where either the Black or White population fell below 100 residents are excluded to prevent unstable ratios. Color gradient reflects the disparity ratio: purple indicates higher stop rates for Black residents, pink indicates higher stop rates for White residents.

side by side, three different ways. On the top left, neighborhood crime rates show only a weak negative correlation with stop disparity — the opposite of what the crime explanation would predict. On the top right, the share of White residents in a neighborhood shows a strong positive correlation with stop disparity.

On the bottom, the total crime rate and stop rates are plotted separately for majority White, majority Black, and all other neighborhoods. Best-fit lines through the data show that: (1) there is an overall trend where higher crime neighborhoods experience higher stop rates, and (2) for the same crime rates, stops in majority Black neighborhoods are always, on average, higher than in majority White neighborhoods.[13]

The contrast is stark: crime rates show only a weak correlation with police stop racial disparities. Meanwhile, the racial composition of a neighborhood is strongly and positively associated with stop disparity.

The **more White** the neighborhood, the **more likely it is for a Black person to be stopped there.**

Because whiter neighborhoods in Cincinnati also tend to have lower rates of reported crime, we needed to determine which factor is actually driving the disparity — race or crime. We ran a series of statistical tests designed to separate the two (see Appendix D for full methodology).

The results are clear:

- **Crime rates don't explain the racial disparities in police stops.** When crime rates and neighborhood racial composition are tested together, no crime measure — not total crime, not violent or property crime, and not any individual offense type like burglary or aggravated assault — predicts stop disparity once racial composition is accounted for. If anything, the direction runs the wrong way: once we hold racial composition fixed, higher-crime neighborhoods show slightly lower Black/White stop disparities, not higher.
- **The neighborhood racial composition pattern holds for both traffic stops and pedestrian stops.** Splitting the analysis by stop type strengthens the pattern further. We re-ran the tests separately for traffic stops and pedestrian stops. Racial composition is the dominant predictor in both, and it is in fact largest for pedestrian stops, where the effect reaches +0.85 standard deviations (Table 2).

We additionally applied two statistical models to the Cincinnati data from Chohlas-Wood et al., 2018, originally developed to assess stop disparities in Nashville. The first model asks whether stop rates are higher in areas with a higher proportion of Black residents. Unlike in Nashville where the test was inconclusive, in Cincinnati it conclusively said that traffic stops are 2.3x more frequent and pedestrian stops 1.8x more frequent in Black neighborhoods, after controlling for crime (see Appendix D for full methodology).

TABLE 2 — **Effect of Neighborhood Racial Composition On Stop Disparity, By Stop Type**

STOP TYPE	EFFECT	95% CONFIDENCE INTERVALS
All Stops	+0.79	[+0.64, +0.94]
Traffic Stops	+0.78	[+0.63, +0.94]
Pedestrian Stops	**+0.85**	[+0.69, +1.04]

The "effect" column reports the standardized association between a neighborhood's share of White residents and its Black/White stop disparity (log scale), holding total crime constant. Values are in standard-deviation units so they can be compared directly across rows. A higher value means racial composition is a stronger predictor of disparity; every estimate is statistically signifi cant at $p < 0.001$. The pedestrian row is the cleanest test of the "are we using the right comparison population?" concern, since pedestrians are overwhelmingly neighborhood residents. Racial composition is strongest there, not weakest.

13 This plot replicates the analysis done by Chohlas-Wood et al., 2018, on motor vehicle stops in Nashville.

The second model controls for location and asks whether stop rates are higher for Black individuals as opposed to White individuals. This model says that when controlling for location in Cincinnati, pedestrian stops are higher for Black individuals at 2.78x, and traffic stops higher at 1.73x[14].

Racial composition of neighborhoods is the strongest and most consistent predictor of stop disparity. The share of White residents in a neighborhood is associated with stop disparity in every test we ran, at every level of statistical stringency. Its effect is roughly 6x larger than the largest crime-rate effect and survives every robustness check we applied (Appendix D, Tables D.1 and D.2).

> The **strongest predictor** of whether **Black residents will be stopped at disproportionate rates is** not how much crime occurs in a neighborhood, but rather **how White is the neighborhood's population**.

Neighborhood racial composition in Cincinnati is not a neutral demographic fact. Decades of federal and municipal housing policy shaped which neighborhoods Black residents were permitted to live in and build wealth in (Rothstein, 2017), producing the racialized geography this analysis finds so tightly linked to stop disparity today.

Time of Day of Police Stops

Next we turn our attention to time of day — when are stops most racially disparate, and are there differences between vehicle and pedestrian stops based on the time of day?

The two top panels in Figure 13 reveal a relationship between when stops happen and how racially disparate they are. The average number of stops (top-left motor vehicle, top-right pedestrian) follows an inverted U-shape across the day, with the lowest number of stops in the early morning and the highest number of stops at night (9:00 p.m. to midnight for motor vehicle stops and around 4:00 p.m. for pedestrian stops).

Interestingly, for motor vehicle stops only, the racial disparity (bottom-left) follows the same early morning low point, when the Black-White ratio comes closest to parity. In the afternoon, when the second-highest peak of motor vehicle stops occur, racial disparity in police stops is moderate between 2x to 2.4x. Overnight, the racial disparity increases up to 3.3x on weekends despite the lower overall volume of stops.

Pedestrian stop disparities (bottom-right) follow a different pattern. They are persistently high throughout the day (almost always above 2x), with a peak around 8:00 p.m. near 4x.

The hours with the most police stops are not the hours with the most racial disparity. For both motor vehicle and pedestrian stops, disparity peaks roughly 4 hours after contact intensity peaks. This suggests that the type or context of enforcement at different hours may be what drives the racial gap.

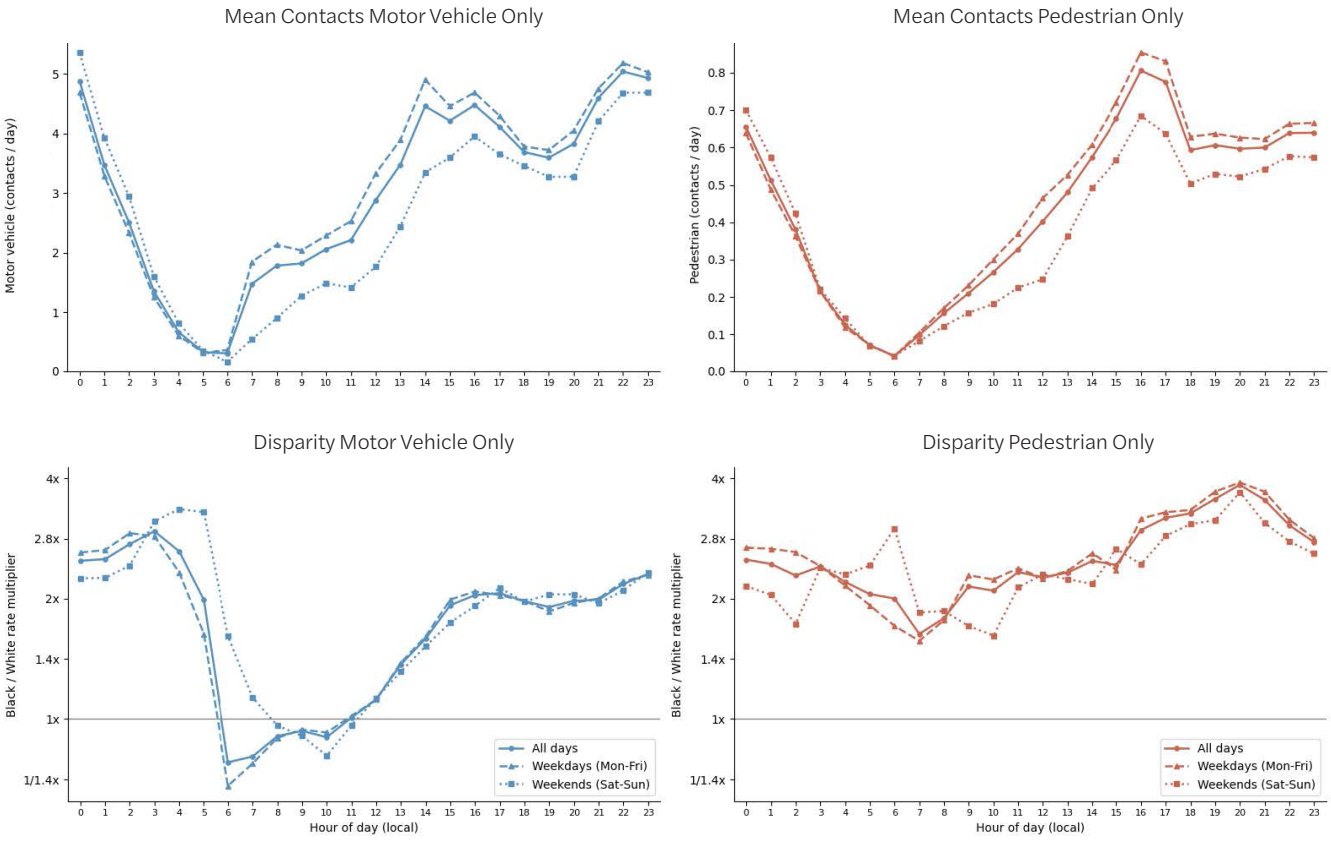
These patterns also complicate the "Veil of Darkness" (VOD) hypothesis commonly used in policing research, which predicts that racial disparities in vehicle stops should decrease after dark, when officers are less able to identify a driver's race before initiating a stop (Grogger & Ridgeway, 2006). A VOD analysis tests this theory by comparing stops at a fixed clock time that is daylight in the summer versus night time in the winter (e.g. 7:00 p.m.). People's schedules should be fairly consistent year round — returning home from work, etc. — allowing the seasonal shift in natural light to be the independent variable.

In Cincinnati, racial disparities for motor vehicle stops are highest overnight, not lowest[15] (Figure 13, bottom left). This hour-by-hour pattern is not itself a VOD test, since VOD is identified by seasonal light/dark variation at a fixed clock time rather than by hour-of-day

14 Chohlas-Wood et al., 2018 found traffic stops with non-moving violations (the subset of traffic stops to be more discretionary) in Nashville, under this model, to be 1.37x higher for Black individuals.

15 This finding is consistent with research from California, where a study analyzing 3.4 million traffic stops in 2019 found that racial disparities in traffic stops are larger at night, with Black drivers accounting for twice the share of White drivers stopped in the hours before and after midnight (29–34% vs. 15–17%), despite making up a far smaller share of the population (Lofstrom et al., 2022).

FIGURE 13 — **Racial Disparity and Mean Police Contacts by Time of Day and Stop Type (2009–2025)**



The top panels show stop volume normalized to a mean number of stops per calendar day at each hour, providing context for interpreting when disparities occur relative to overall police activity. Disparities in the bottom panels are calculated as the Black stop rate per 1,000 residents divided by the White stop rate per 1,000 residents using 2020 Decennial Census population figures. A value of 1x indicates no disparity. Hours reflect local Cincinnati time.

comparisons. A formal VOD analysis on Cincinnati contact cards (Appendix E) shows no detectable VOD effect for motor vehicle stops, consistent with the standing VOD literature. For pedestrian stops, however, the analysis points in the opposite direction: the Black share of evening pedestrian stops is higher in darkness than in daylight at the same clock time — opposite to what visibility-based profiling would predict, but consistent with the descriptive results shown in Figure 13.

The original design of VOD was based on the premise that if officers can see the individual's race they are about to stop and there is bias, that bias would lead to higher disparities during the day time. This premise ignores the impact of night time (lack of light) upon officers' fears and assumptions. While the original design of the VOD analysis would seem irrelevant to pedestrian stops because it is much easier for the officer to see the race of the individual, we believe the results we report here — the opposite effect that the VOD hypothesis would predict — provides evidence for an alternative hypothesis.

When routine, high-volume enforcement gives way to more discretionary policing — such as late at night — officers may be more likely to interpret ambiguous situations as warranting intervention. This pattern is consistent with scholarship describing how police decision-making is shaped by an organizational emphasis on anticipating and managing potential danger (Sierra-Arévalo, 2021).

Initial Reason for Police Stops

Police officers have vast discretionary authority when determining whether or not to stop a person any time they leave their home. Expansive criminal codes make it difficult for people to drive a car without making any infraction, no matter how minor (Epp et al., 2014).

The Supreme Court's decision in Whren v. United States (1996) reinforced this dynamic by holding that any observed traffic violation — no matter how minor — provides legal grounds for a stop, regardless of the officer's actual motivation. Police officers then decide whether or not the offense is worth stopping someone and potentially giving a citation or making an arrest. **Examining why stops occur in Cincinnati reveals a critical pattern: the more discretionary the stop reason, the worse the racial disparity**.

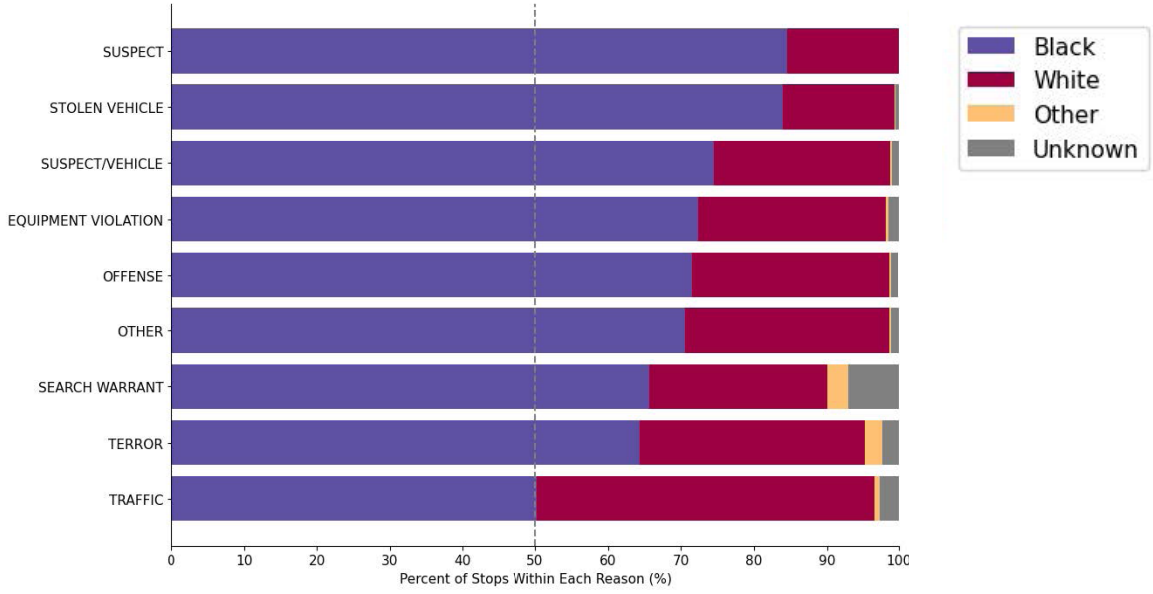
Black residents account for the largest share of stops in every category[16] (Figure 14). Even in traffic stops, where Black residents' share of stops is smallest, they still exceed White residents by four percentage points (a figure that is far from proportionality given that Black residents make up only 36% of Cincinnati's population). This pattern may reflect that traffic stops more often have a stated legal basis, though as discussed above, officers retain significant discretion in choosing which violations to act on.

In contrast, stops based on officer judgment, such as "suspect," show the greatest disparities. Overall, Black residents are stopped substantially more across every initial reason category.

When adjusting for population rates, these differences become even more pronounced (Figure 15). **Black residents are stopped at higher rates than White residents for every recorded reason for a stop**.

Traffic stops, the category with the smallest gap, are still racially disparate. Black residents are stopped 1.3x as often as White people for traffic violations. All other reasons for stops have much larger disparities, particularly equipment violations and suspect-related stops, with stop rates more than 3x higher for Black people compared to White people.

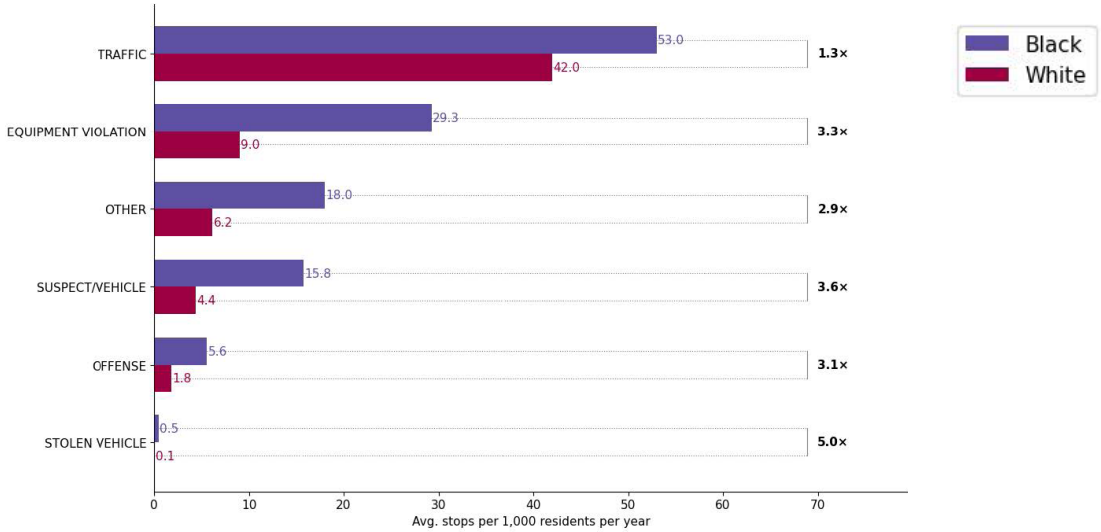
FIGURE 14 — **Initial Stop Reason By Race, Share Of Stops (2009–2025)**



Each bar shows the racial breakdown of stops within a given stop reason, summing to 100%. "Other" includes all races outside of Black and White (Hispanic, Asian/PI, AI/AN). The dashed line at 50% marks equal representation.

16 These categories reflect the initial reason for the stop as recorded by the officer in the contact card system. Traffic stops are included in multiple categories. For instance, "Traffic" refers to moving violations (e.g. speeding, failure to signal), while "Equipment Violation" refers to non-moving vehicle defects (e.g. tinted windows, broken tail lights).

FIGURE 15 — **Initial Stop Reason By Race, Average Annual Rate per 1,000 Residents (2009-2025)**



Initial stop reasons with fewer than 0.05 average annual stops per 1,000 residents for both Black and White residents are excluded (SEARCH WARRANT, SUSPECT, and TERROR). These categories have counts too small (as few as 6 total stops over 17 years) for disparity ratios to be stable. Rates are calculated using 2020 Decennial Census population and averaged across 2009–2025.

Non-Moving Violation Traffic Stops as Discretionary Stops

A discretionary stop is one where a driver is not a public safety threat, but the legal basis exists for a stop (e.g. a broken tail light, expired registration tag, tinted windows, or an air freshener hanging from the rearview mirror). The officer can ignore it, flash lights as a warning, or initiate a full stop.

Equipment violations — the category we track as "non-moving violations" here — are almost entirely discretionary. The infraction doesn't endanger other drivers; it functions as a lawful pretext to initiate contact, sometimes for reasons that have little to do with the equipment issue itself.

Using "Equipment Violation" stops, we re-ran the geographic analyses detailed in the "Geographic Disparities by Race" section above, but focusing only on these non-moving violation traffic stops, consistent with analyses done in Chohlas-Wood et al., 2018.

We find that for discretionary stops only, disparities are even higher:

Black people are 2.5x more likely to experience a discretionary traffic stop citywide
(as opposed to 1.9x for all traffic stops)

In majority Black neighborhoods, Black people are 1.4x more likely to experience a discretionary traffic stop
(as opposed to 1.1x for all traffic stops)

In majority White neighborhoods, Black people are 5.5x more likely to experience a discretionary traffic stop
(as opposed to 3.7x for all traffic stops)

See figures A.10 and A.11 in the appendix.

Police Stop Outcomes

To understand disparities in stop outcomes, this section compares what happens after a stop, focusing only on people who were stopped — not the broader population. For example: of all stops involving a Black resident, what share resulted in an arrest? What about for White residents? This analysis helps us determine whether differences in outcomes exist beyond differences in who gets stopped in the first place.

Arrests and Citations

Arrests and citations, respectively, are the most severe legal outcomes of a police stop. Figure 16 shows that once stopped, Black residents are 1.78 x (11.9% vs. 6.7%) more likely than White residents to be arrested.

This pattern reverses for citations: White residents are 1.20x more likely to receive a citation once stopped (52.1% vs. 43.5%).

Taken together, disparities suggest that, conditional on a stop occurring, Black residents are more likely to experience more punitive outcomes, while White residents are more likely to receive less severe ones.

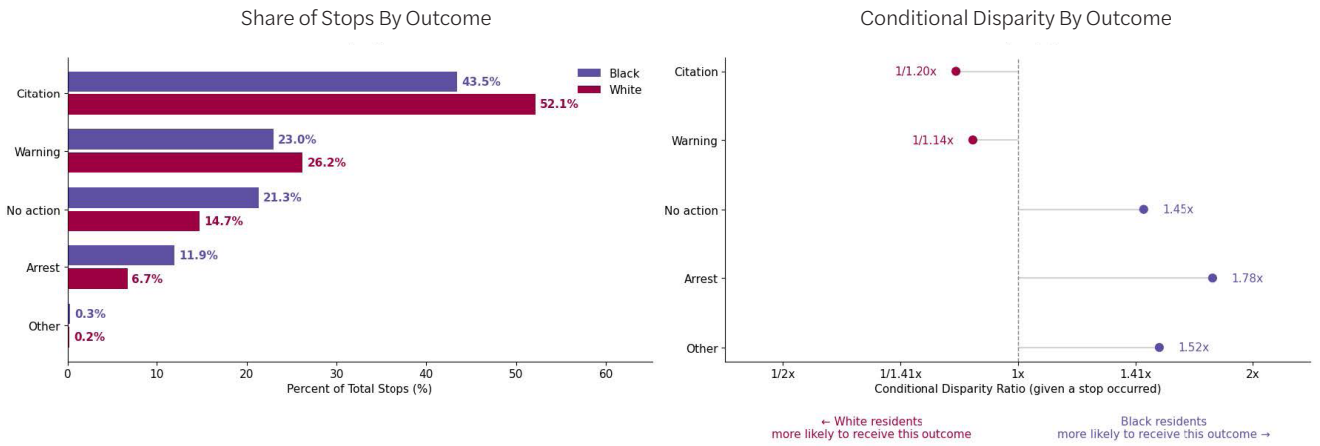
Once we disaggregate outcomes by type, these disparities persist across categories (see Figure 17). **After being stopped, Black residents are more likely than White residents to be arrested across all categories in the data: misdemeanors (1.84x), capias warrants[17] (1.65x), and felonies (2.05x).**

For citations, we find that disparities vary by enforcement context. White residents are 1.35x[18] more likely to receive traffic citations — the most common and generally less severe form of citation, often tied to observable violations (e.g. speeding) and involving less officer discretion. On the other hand, Black residents are more likely to receive citations for misdemeanors (2.24x) and capias warrants (1.87x).

Warning

Warnings represent the lowest level of enforcement actions — an officer acknowledges a potential violation but either doesn't find something to act on or chooses not to impose a penalty. Once stopped, White residents are 1.14x more likely than Black residents to receive a warning (Figure 16).

FIGURE 16 — **Stop Outcomes By Race, Conditional on Being Stopped (2009–2025)**



Left: Share of each race's stops by outcome — of all stops involving a Black (or White) resident, what percentage ended in each outcome? Bars for each race sum to 100%. Right: Conditional disparity ratio for each outcome, calculated as the Black share divided by the White share. A value of 1x indicates no disparity; values above 1x (purple) mean Black residents were more likely to receive that outcome once stopped, values below 1x (pink) mean White residents were more likely.

17 A capias warrant is a court-issued arrest order, often related to failure to appear in court or noncompliance with a court case.
18 The 0.74 ratio in the chart reflects the likelihood of Black residents relative to White residents. To express the disparity from the perspective of White residents, the ratio is inverted (1 ÷ 0.74 ≈ 1.35).

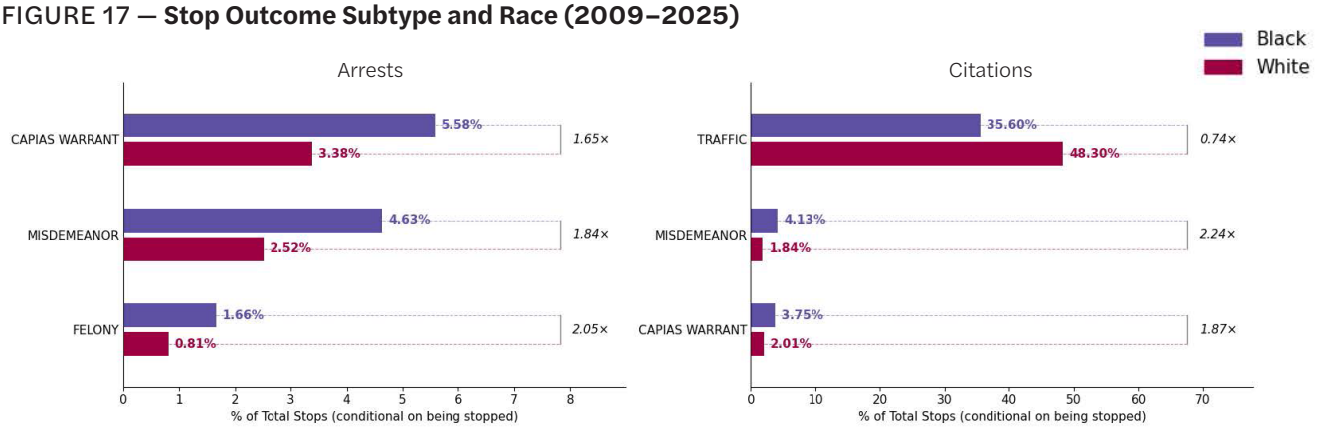
While the disparity is smaller than for arrests and citations, it follows the same pattern: White residents are more likely to receive less punitive outcomes.

No Action

A police stop that ends in no action — produces no arrest, citation, warning, or any other recorded outcome — raises questions about whether there was sufficient cause for the stop in the first place. When a stop ends with no enforcement action, it suggests the encounter may not have been necessary. In Cincinnati, Black residents are not only stopped more often, those stops are also more likely to end without any action taken.

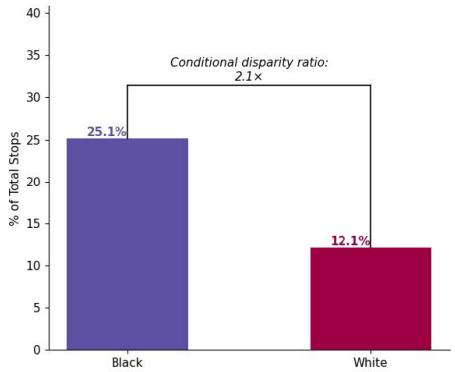
In Cincinnati, nearly 1 in 5 police stops of Black residents results in no action at all, compared to 14.7% of White stops (Figure 16). In other words, once stopped, Black residents are about 1.45 times more likely to experience a stop that results in no action.

FIGURE 17 — **Stop Outcome Subtype and Race (2009–2025)**



Conditional stop rates by outcome subtype, calculated as the number of stops resulting in each outcome divided by the total number of stops for each racial group (Black: 290,707 total stops; White: 168,792 total stops). The disparity ratio shown to the right of each pair of bars is the Black rate divided by the White rate. A value of 1x indicates no disparity; values above 1x mean Black residents were more likely to receive that outcome once stopped, values below 1x mean White residents were more likely.

FIGURE 18 — **Search by Race, Conditional on Being Stopped (2009–2023)**



The percentage of stops resulting in a search is calculated separately for each racial group. The conditional disparity ratio is the Black percentage divided by the White percentage. Search data is only available through 2023, as the variable was not included in CPD's response to the second FOIA request.

Searches During a Police Stop

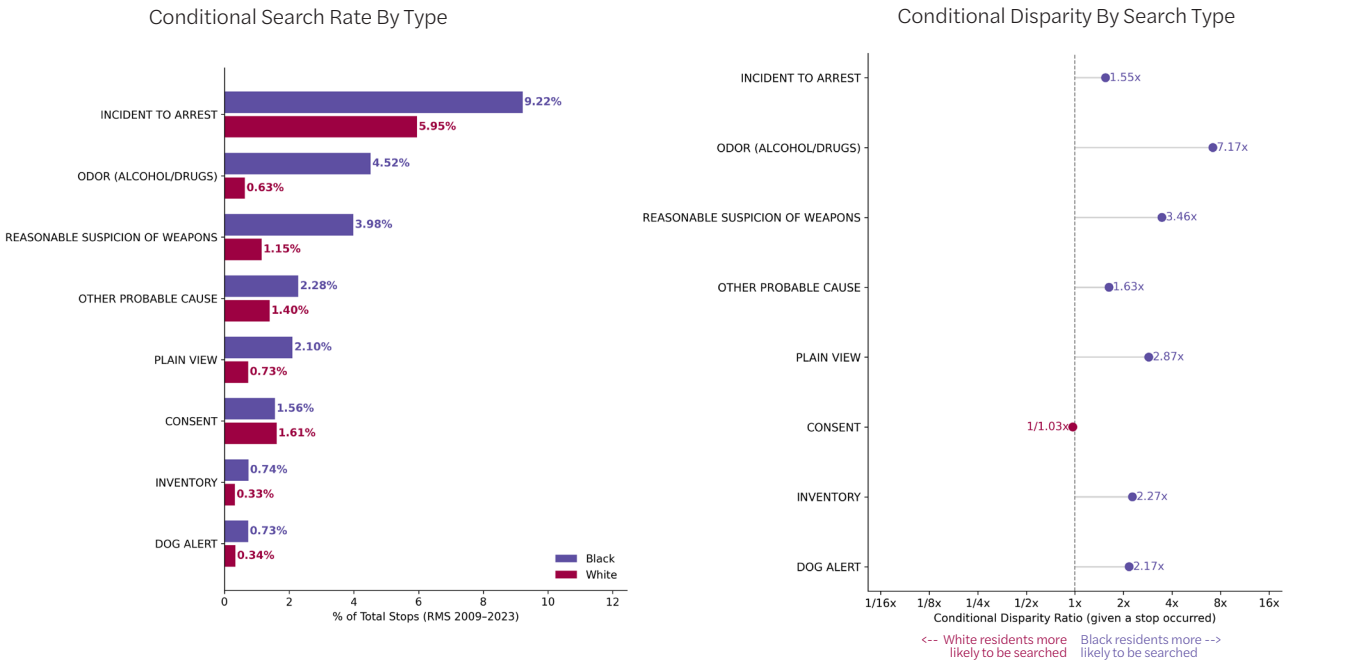
Another variable provided in the contact card database is whether or not police searched a person during a stop.[19] The trend continues: once stopped, Black residents are more likely than White residents to be searched. One in four stops (25.1%) of Black residents results in a search, compared to one in eight stops (12.1%) of White residents. **This means that even after adjusting for the disparities observed in the likelihood of being stopped, Black residents are still 2.1x more likely to be searched than White residents (Figure 18)**.

Disparities in searches differ by legal basis (Figure 19). The largest disparities appear in categories based on more subjective recorded justifications.

For example, once stopped, Black residents are 7x more likely than White residents to be searched based on a claimed odor of alcohol or drugs, despite White people being more likely to drink alcohol than Black people and both groups using drugs at comparable rates.[20] Black residents are also 3.46x more likely to be searched based on reasonable suspicion of a weapon.

In contrast, the smallest disparity is for searches conducted incident to arrest[21] — Black people experience these searches 1.55x more often than White people. In these cases, the search is tied to the arrest itself and is typically conducted as part of the standard procedure, making it less dependent on a separate judgement call at the moment of the stop. Consent searches, which occur when an individual agrees to be searched, show little to no disparity.

FIGURE 19 — **Search by Legal Basis and Race, Conditional on Being Stopped (2009–2023)**



Left: Share of each race's stops that involved each legal basis for search — of all stops of Black (or White) residents, what percentage included a search of that type? Right: Conditional disparity ratio for each legal basis, calculated as the Black rate divided by the White rate. A value of 1x indicates no disparity; values above 1x (purple) mean Black residents were more likely to be searched on that basis once stopped, values below 1x (pink) mean White residents were more likely. "Unknown (Axon)" reflects stops where no legal basis for the search was recorded in the department's data system. Search data is only available through 2023, as the variable was not included in CPD's response to the second FOIA request.

19 Both the Fourth Amendment of the United States Constitution and Article I, Section 14 of the Ohio Constitution protect all people from unreasonable searches.

20 According to the 2023 National Survey on Drug Use and Health, 52.3% of White people aged 12 or older drank alcohol in the past month compared with 42.5% of Black people. White people were also more likely to be heavy alcohol users (6.7% vs. 4.7%). For illicit drug use, both groups reported similar use rates (27.7% vs. 26.1%) in the past year (SAMHSA, 2024).

21 Searches incident to arrest are searches made after a person has been arrested, rather than prior to an arrest.

A caveat to this analysis is that the data records a single legal basis for each search. In practice, multiple justifications may apply during a stop. For example, an officer may first frisk someone based on suspicion, find a weapon, make an arrest, and then conduct a search incident to the arrest. In such cases, the data does not allow us to distinguish between discretionary and less discretionary reasons for the search, since both may occur in the same encounter.

Use of Force During Police Stops

When force is used during a stop, it too falls disproportionately on Black residents.[22] Between 2009 and 2025, officers reported using force in 749 stops involving Black residents, compared to 239 stops involving White residents. **Not only are Black residents stopped far more often, but once they are stopped, Black residents are nearly twice as likely (1.9x) as White residents to experience force (Figure 20)**.

Age of People Stopped by Police

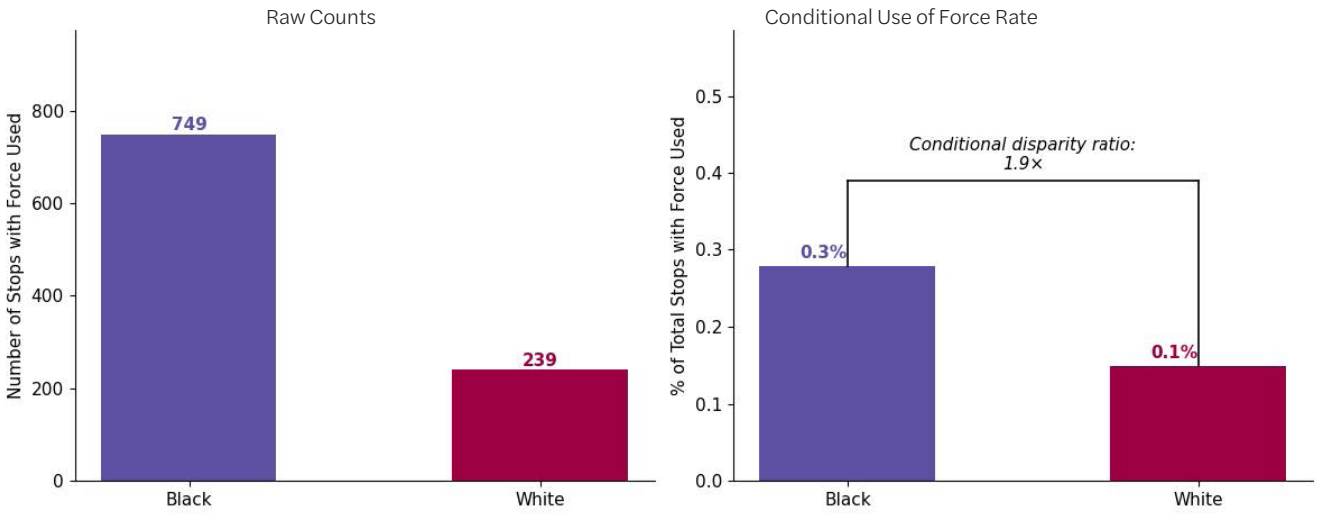
It is well established that arrests nationally are concentrated among young adults (Snyder, 2012). But in Cincinnati, this age concentration is far sharper for Black residents than for White residents.

Black residents in Cincinnati are stopped at younger ages than White residents (Figure 21). The median age of a Black person stopped by CPD is 29 years old, compared to 33 years old for White residents.

This four-year difference across race reflects a broader pattern visible in the age distribution. Police stops of White people are spread more evenly across age groups, with a notably larger share of people in their 40s, 50s, and 60s, whereas police stops of Black people are heavily concentrated among teenagers and young adults.

For pedestrian stops specifically, this effect is more pronounced (Figure 22). When Cincinnati police stop a Black person on foot, they are overwhelmingly stopping teenagers and young adults.

FIGURE 20 — **Use of Force By Race (2009–2025)**



Left: Raw count of stops where force was used, by race. Right: The percentage of each race's stops that resulted in use of force — that is, of all stops involving a Black (or White) resident, how many included use of force. The conditional disparity ratio is the Black percentage divided by the White percentage.

22 Use of force is self-reported by officers and may be underreported. The figures presented here represent only incidents documented in the contact card data.

FIGURE 21 — **Age Distribution of Motor Vehicle Stops by Race (2009–2025)**

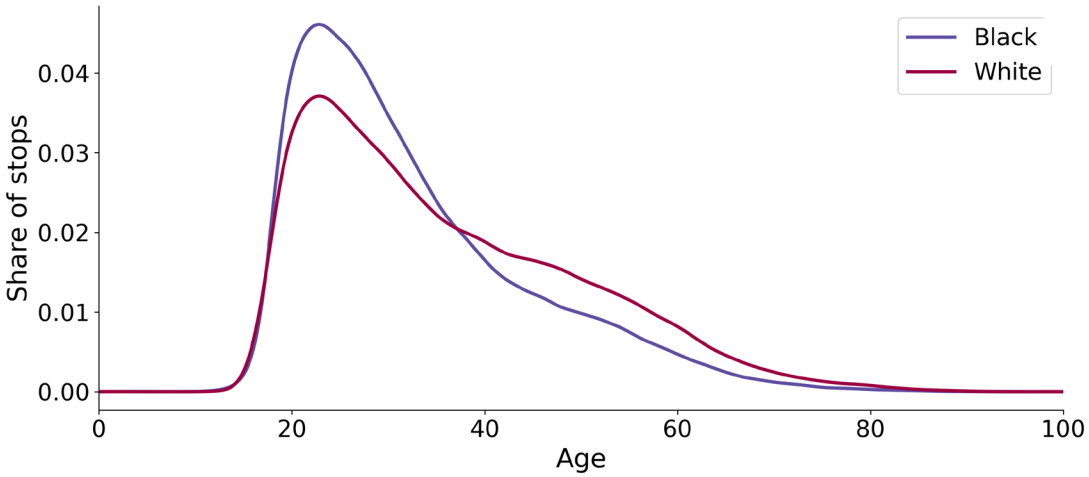
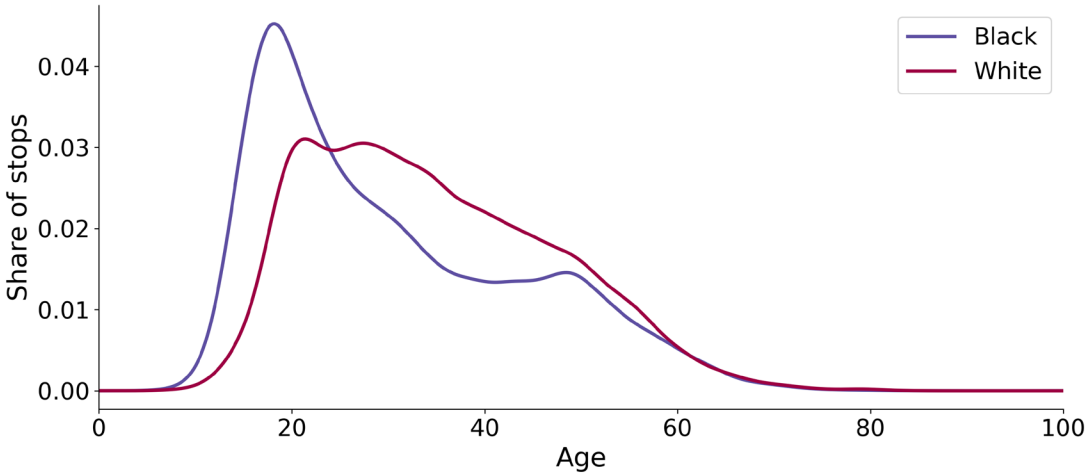


FIGURE 22 — **Age Distribution of Pedestrian Stops by Race (2009–2025)**



The age distribution for Black pedestrian stops peaks sharply in the late teens and early 20s, while this pattern is largely absent for White pedestrian stops, which are more evenly distributed across age groups.

This concentration of police contact on young Black residents carries serious consequences beyond the immediate stop. Research has shown that Black boys are routinely perceived as older, less innocent, and more threatening than their White peers, a bias documented among both the general public and police officers (Goff et al., 2014). National data confirms that Black boys experience more frequent and more aggressive police contact than White peers, even after accounting for differences in behavior (Geller, 2021). Police encounters during adolescence and early adulthood can disrupt education and employment, create records that follow people through their lives, and erode trust between communities and law enforcement at formative ages (Rios, 2011).

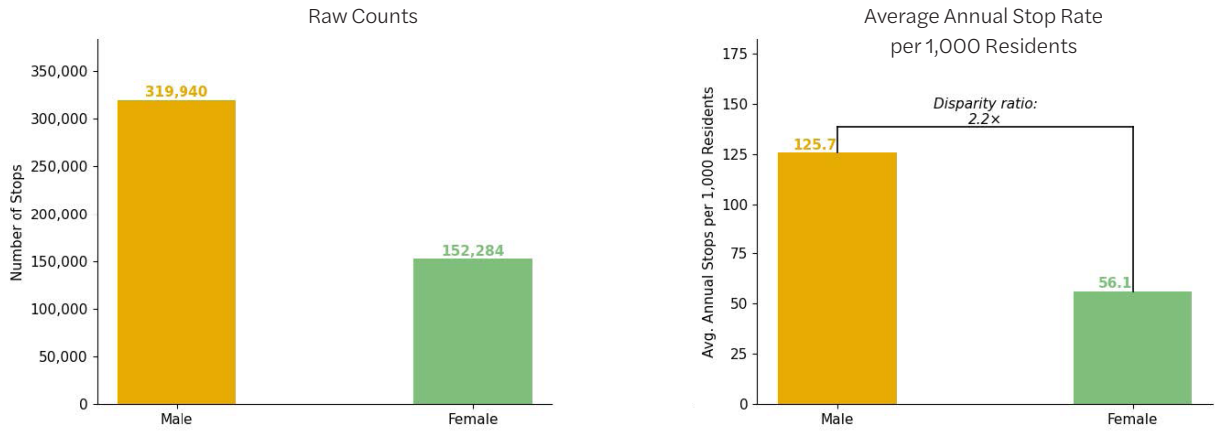
Gender of People Stopped by Police

Examining police stops by gender reveals how race and gender intersect to shape who CPD officers stop.

Police stops in Cincinnati are heavily skewed toward men: 319,940 male stops versus 152,284 female stops across the study period (Figure 23). On a population-adjusted basis, men are stopped at an average annual rate of 125.7 per 1,000 residents, compared to 56.1 per 1,000 for women. Men in Cincinnati are 2.2x more likely to be stopped than women.

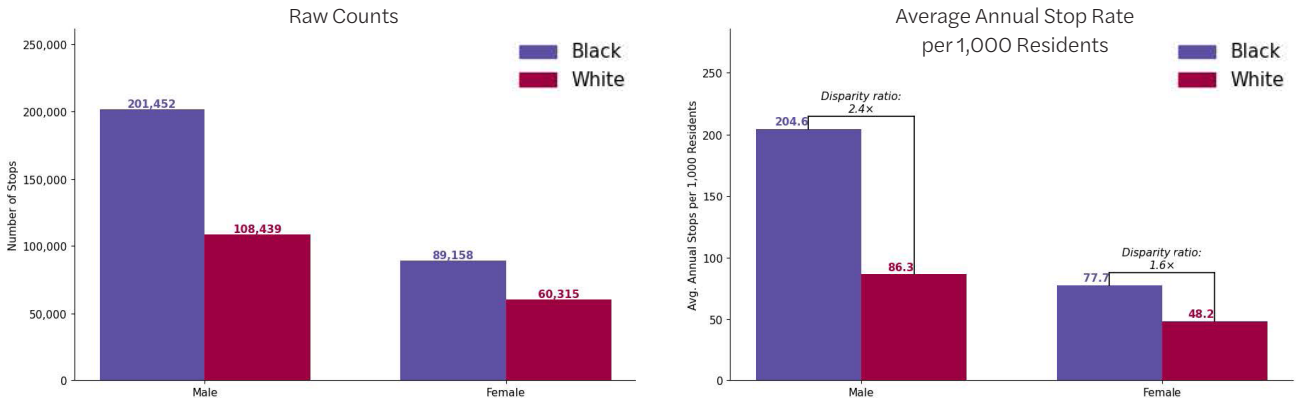
When you compare race and gender together, Black women are stopped much more often than White women (77.7 vs. 48.2) and only somewhat less often than White men (77.7 vs. 86.3). This means the racial gap among women is larger than the gender gap between Black women and White men (Figure 24). Black men are stopped at the highest rate of any group at 204.8 per 1,000 residents.

FIGURE 23 — **Police Stops By Gender (2009–2025)**



Rates are calculated using 2020 Decennial Census P12 table with a 48.4% male and 51.6% female split. Stops where gender was not recorded are excluded.

FIGURE 24 — **Police Stops By Race and Gender (2009–2025)**



Population figures are drawn from the 2020 Decennial Census: male and female counts for Black residents from table PCT12B and for White residents from table PCT12A. Stops where gender was not recorded are excluded.

Individual Analysis – Officers and Supervisors

The racial disparities documented in this report are not only systemic — systems are made up of individuals. The following tables identify the officers and supervisors whose stop patterns show the most pronounced racial disparities since 2020.

Due to data limitations at the beat level and because district assignments are not reliably recorded in the contact card data[23], we divide each officer's stops by the population of their primary CPD district (the one where they made the majority of their stops) rather than by citywide population (See Appendix B.1 for total police stops by district) . This partially controls for deployment — an officer assigned to a majority-Black district would show a high Black stop rate even absent individual bias — but does not eliminate it. **However, no CPD district has a Black-to-White residential ratio above 1.6x[24], so any officer disparity substantially above that ceiling cannot be explained by deployment alone; it requires disproportionate enforcement within the district itself**.

The remaining ambiguity cuts in a particular direction: if an officer's high disparity ratio persists even after accounting for the demographics of their patrol district, that is a strong signal of disproportionate enforcement at the individual level. If it is still partly a product of deployment, that raises an equally serious question: ***Why is CPD concentrating its officers so heavily in Black neighborhoods?*** As this report has documented,[25] the deployment pattern is itself a central driver of racial inequality in Cincinnati policing. Whether the disparity originates with the individual officer or the department that assigned them, it demands scrutiny and accountability.

What these tables can do is identify officers and supervisors whose stop patterns warrant closer examination by CPD leadership. Officers with high disparity ratios should prompt the department to ask: is this ratio a product of geography, individual decision-making, or both?

That question can only be answered with internal data the department holds—including beat assignments, shift schedules, and the demographic composition of each officer's patrol area. We call on CPD to conduct that analysis.

For this analysis, we've focused on data from 2020 onwards. These officers and supervisors are more likely to still be on the police force and in their same positions than those from the early 2000's.

Each table contains the following variables:

- **Officer:** the police officer's name
- **Personnel ID:** the officer's unique personnel identifier within the Cincinnati Police Department
- **Years:** the years for which the officer has recorded stops from 2020-2025
- **Total Stops:** the total number of stops the officer has made
  - → *Use in a sentence: "[Officer name] stopped x Cincinnati residents."*
- **Black Stops:** the total number of Black people the officer has stopped
  - → *Use in a sentence: "[Officer name] stopped x Black residents in Cincinnati."*
- **White Stops:** the total number of White people the officer has stopped
  - → *Use in a sentence: "[Officer name] stopped x White residents in Cincinnati."*
- **% Black**: the percentage of people stopped by the officer who are Black
  - → *Formula: (Black Stops) / (Total Stops)*
  - → *Use in a sentence: "x% of [Officer name]'s stops were Black people."*

23 Beat-level analysis is not feasible due to missing data in roughly 66% of stops and because the shapefile from the Cincinnati Open Data Portal maps beats to the same boundaries as districts, providing no additional geographic detail. District fields are also blank on roughly 66% of stops, and where recorded, disagree with the stop's geographic district in 35.8% of cases. This may be partially driven by the fact that CPD previously included an additional district (District 5) until 2023. It is also possible that officers are reassigned across districts over time. To work around this, we imputed each stop's district from its latitude/longitude and took the district where each officer made the majority of their stops as their primary assignment.

24 Computed from 2024 Census American Communities Survey (ACS) tract-level populations aggregated to CPD district boundaries.

25 See the "Crime Rates and Police Stops" section above.

- **Black Rate / 1k:** the total number of Black residents stopped by the officer per 1,000 Black residents in the officer's primary CPD district, per year.
  - → *Formula: ((Black Stops / Black Population of the officer's primary CPD district) × 1,000) / number of years in data*
  - → *Use in a sentence: "For every one thousand Black people in [Officer name]'s primary CPD district, they stopped x Black residents."*
- **White Rate / 1k:** the total number of White residents stopped by the officer per 1,000 White residents in the officer's primary CPD district, per year.
  - → *Formula: ((White Stops / White Population in the officer's primary CPD district) × 1,000) / number of years in data*
  - → *Use in a sentence: "For every one thousand White people in [Officer name]'s primary CPD district, they stopped x White residents."*
- **Disparity Ratio:** takes Black and White population levels in the officer's primary CPD district into account to compare their stop rates.
  - → *Formula: ("Black rate / 1k" / "White Rate / 1k")*
  - → *Use in a sentence: "[Officer name] stopped Black residents at x times the rate of White residents."*

Police Officer Analysis

Table 3 below shows the top 10 officers ranked by disparity ratio between Black and White stop rates. These 10 CPD officers made the most racially disparate stop decisions of any officers on the police force. **One CPD officer stops Black people 29x more often than White people while seven officers stop Black people over 20x more often than White people**.

There is not a neighborhood in Cincinnati where Black people are over 10x, let alone 20x, the population of White people.

TABLE 3 — **Top 10 Officers By Disparity Ratio (2020–2025)**

OFFICER	PERSONNEL ID	YEARS	TOTAL STOPS	BLACK STOPS	WHITE STOPS	% BLACK	BLACK RATE/1K	WHITE RATE/1K	DISPARITY RATIO
KEMME, JOSEPH D	35796	2020–2025	300	282	14	94.000	3.490	0.119	29.330
FOLLROD, BRIAN	31200	2020–2025	181	160	18	88.400	1.248	0.051	24.470
FLIEHMAN, RYAN S.	38808	2024–2025	110	96	11	87.270	2.246	0.093	24.150
KNAPP, CHARLES F. III	22694	2020–2022	209	202	7	96.650	1.216	0.053	22.940
KRESS, ZACHARY A.	34090	2020–2025	361	340	12	94.180	1.023	0.045	22.730
CRONIN, SARAH M.	35783	2020–2025	216	197	13	91.200	2.438	0.111	21.960
CORTEZ, CARLOS X.	37254	2022–2025	142	126	16	88.730	1.474	0.068	21.680
MAURIC, MATTHEW A.	32269	2020–2025	501	459	36	91.620	5.680	0.307	18.500
WALLACE, JASON A.	31177	2020–2025	266	254	12	95.490	0.764	0.045	16.980
CORNACCHIONE, WILLIAM S.	34075	2020–2025	100	97	3	97.000	0.484	0.029	16.690

How to read the chart: **Officer Kemme stopped Black residents at 29x the rate of White residents.**

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each officer made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only officers with at least 100 total stops between 2020–2025 are included.

Police Supervisor Analysis

Table 4 below shows the top 10 supervisors ranked by the disparity ratio between Black and White stop rates per year by the officers under their command. These 10 CPD supervisors oversaw the most racially disparate stop decisions by the officers under their command.

One CPD supervisor oversaw officers who stopped Black people over 13x more often than White people, while four additional supervisors oversaw officers who stopped Black people over 8x more often than White people.

TABLE 4 — **Top 10 Supervisors By Disparity Ratio (2020–2025)**

SUPERVISOR	PERSONAL ID	YEARS	TOTAL STOPS	BLACK STOPS	WHITE STOPS	% BLACK	BLACK RATE/1K	WHITE RATE/1K	DISPARITY RATIO
DAVIS, JAMES	13156	2020–2024	976	909	55	93.140	3.282	0.249	13.181
SULTON, CHRISTOPHER	13237	2021–2024	122	112	8	91.800	0.506	0.045	11.244
PUTNICK, LUKE M.	18768	2020–2023	162	137	21	84.570	2.543	0.268	9.489
LANTER, TIMOTHY	24423	2020–2024	146	131	13	89.730	0,473	0.059	8.017
ZUCKER, JEFFREY	10477	2021–2023	106	89	13	83.960	0.536	0.098	5.469
DOWNING, DANIEL	20986	2020–2023	175	135	38	77.140	0.609	0.215	2.833
KINNEY, WILLIAM	22442	2020–2023	119	89	27	74.790	0.402	0.153	2.627
NORRIS, BRIAN	13571	2020–2021	273	122	131	44.690	2.854	1.108	2.576
HUDEPOHL, MICHAEL	13187	2020–2020	143	98	36	68.530	1.769	0.815	2.171
HEINE, SHANNON	13175	2020–2021	116	80	32	68.970	0.722	0.362	1.994

How to read the chart: Officers under the command of James Davis stopped Black residents at 13x the rate of White residents.

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each officer made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only supervisors with officers under their command who made at least 100 total stops between 2020–2025 are included.

Conclusion

Seventeen years of contact card data has provided us with a way to examine whether or not racially disparate policing still exists in the city of Cincinnati. In 2025, the Cincinnati Police Department stopped Black people 3.4x more often than White people. Black people are stopped in vehicles 3.2x more often than White people and Black pedestrians are stopped 5.4x more often than White pedestrians.

Overall, Cincinnati Police Department data from 2009–2025 shows:

- Once stopped by Cincinnati Police officers, **Black people are:**
  - → **2.1 x more likely to be searched than White people.**
  - → **1.9 x more likely to have force used against them than White people.**
  - → **1.8 x more likely to be arrested than White people.**
- In majority White neighborhoods, **Black pedestrians are stopped by Cincinnati Police 4.5x more often** than White people.
- The **more White** the neighborhood, **the more likely it is for a Black person to be stopped there.** Crime rates do not explain this trend.

Black people stopped by police are younger, more likely to be stopped based on subjective reasons like "suspicion," and subject to disproportionate police contact regardless of their recorded demeanor.

Some individual officers show disparity ratios exceeding 10x — ratios that cannot be fully explained by patrol assignment alone, and that CPD has not investigated or addressed.[26]

While the racial disparities are clear and consistent in the data, it is also true that numerical data on its own will never tell the entire story about how and why these disparities persist. This analysis is dependent on Cincinnati's elected officials, police leadership, and community members to further contextualize these data findings in order to implement structural policy improvements.

26 No neighborhood demographics can account for an officer stopping Black people at 10x or 20x the rate of White people. Millvale is the neighborhood with the highest concentration of Black residents in Cincinnati (86.2%, 6.2x the non-Black population).

Some unanswered research questions include:

1. How do we account for police officer deployment and department policy when analyzing neighborhood stop disparity?
2. Force is recorded as a binary (yes, force was used /no, force was not used). Is the 4x use of force disparity concentrated in minor uses of force, serious uses, or both? What is the type and severity of the force used for each race and was there resistance?
3. Do any department or city policies, changes in leadership, or other factors account for the large changes in disparities year-to-year in the dataset?
4. What policies, leadership, or practices produced the near-parity observed in 2012 (motor vehicle stops) and 2016 (pedestrian stops), and what shifts followed that led to disparities increasing again?
5. How much of the disparity in stops is driven by departmental deployment and officer-initiated activity versus calls for service from the community? Distinguishing between the two is essential for identifying where policy change can most effectively reduce disparities.
6. Is there a relationship between fluctuating police staffing levels and changes in racial disparity rates?

We hope this report will be a helpful contribution to the long-running conversation around race and policing in Cincinnati. With courage and commitment, real change is possible in Cincinnati. **Together we can live in a world with *zero* racial bias in policing.**

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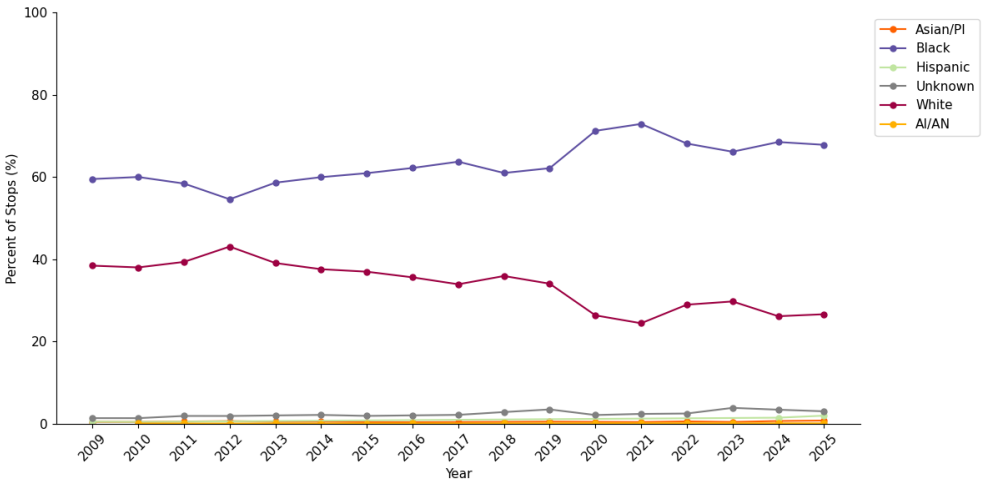
Appendix

Appendix A. Supplemetary Figures and Tables — City Data

Figure A.1 — Percentage Of Police Stops By Race (2009–2025)



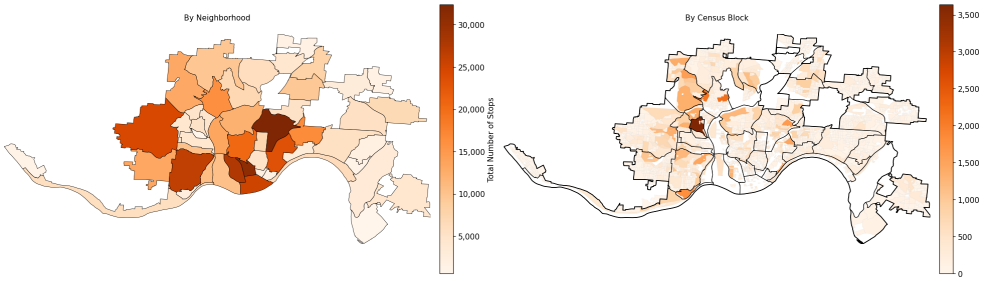
Each line shows the share of all police contact card stops recorded for a given racial group in that year. Each data point represents one calendar year.

Table A.1 — Racial Disparity In Police Stops By Year (2009–2025)

Year	Black Stops	White Stops	Black %	White %	Black Rate/1k	White Rate/1k	Disparity Ratio
2009	34,693	22,397	59.5%	38.4%	250.1	128.6	1.9x
2010	33,656	21,312	60.0%	38.0%	255.6	144.2	1.8x
2011	25,004	16,838	58.4%	39.3%	191.1	115.0	1.7x
2012	20,903	16,492	54.5%	43.0%	160.3	113.4	1.4x
2013	17,143	11,421	58.6%	39.0%	133.7	78.4	1.7x
2014	16,899	10,585	59.9%	37.5%	131.5	73.0	1.8x
2015	17,409	10,557	60.9%	36.9%	137.1	72.0	1.9x
2016	14,640	8,373	62.2%	35.5%	114.7	57.5	2.0x
2017	13,049	6,939	63.7%	33.9%	102.5	48.1	2.1x
2018	15,883	9,352	60.9%	35.9%	124.6	64.5	1.9x
2019	15,271	8,362	62.1%	34.0%	120.7	57.6	2.1x
2020	9,109	3,366	71.2%	26.3%	73.3	23.1	3.2x
2021	9,275	3,104	72.9%	24.4%	75.1	20.7	3.6x
2022	10,592	4,496	68.1%	28.9%	87.2	29.9	2.9x
2023	13,084	5,876	66.1%	29.7%	109.8	39.6	2.8x
2024	11,535	4,397	68.5%	26.1%	102.1	29.3	3.5x
2025	12,562	4,925	67.8%	26.6%	111.2	32.8	3.4x

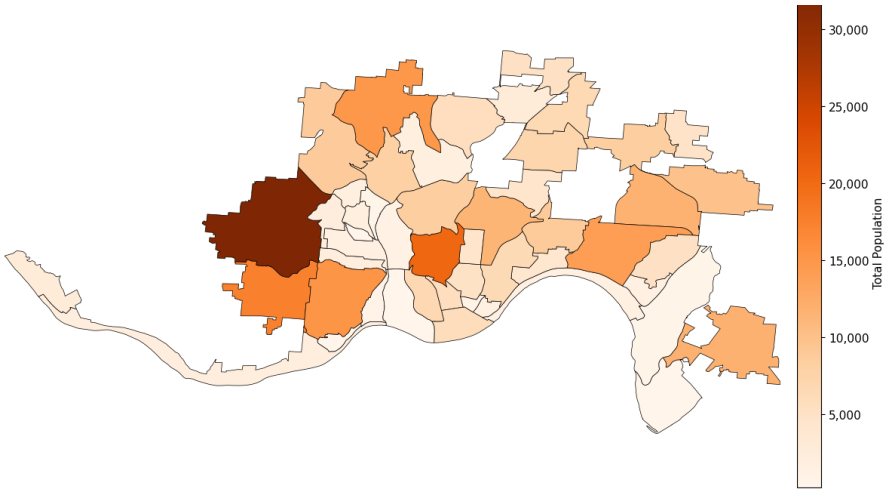
How to read the chart: *Cincinnati police officers stopped Black residents at 3.4x the rate of white residents in 2025.*

Figure A.2 — Total Number Of Police Stops By Neighborhood And Census Block (2009–2025)



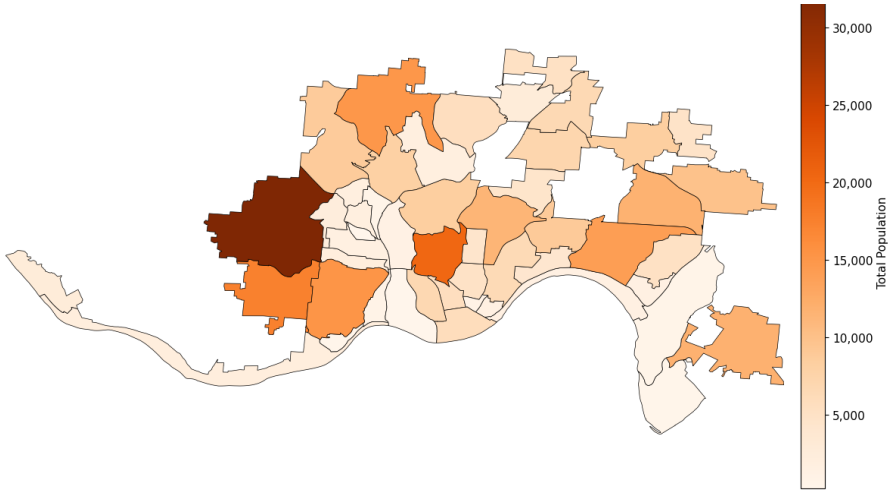
Total number of people (of any race) recorded on contact cards between 2009 and 2025, shown at the neighborhood level (left) and census block level (right). Each panel uses its own color scale. Neighborhood boundaries are shown in both panels.

Figure A.3 — Population Per Neighborhood (2020 Census)



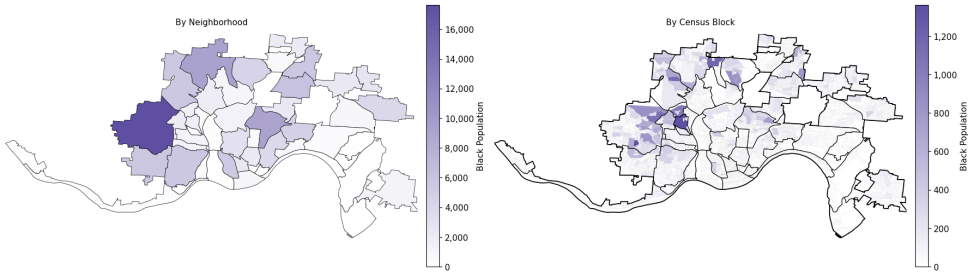
Total residential population by neighborhood, estimated from 2020 Decennial Census block-level counts and allocated to neighborhoods based on the share of each block falling within neighborhood boundaries.

Figure A.4 — Median Household Income By Neighborhood (2024 ACS)



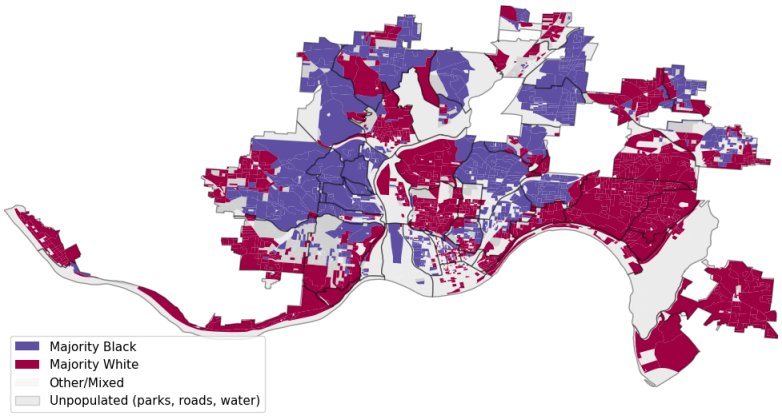
Median household income by neighborhood, estimated from 2024 ACS 5-year data at the census block group level. Since ACS does not publish income data below the block group, neighborhood estimates are derived by population-weighting the median household income of each block group by the number of residents allocated to that neighborhood. Results should be interpreted as approximate. Gray indicates neighborhoods where no income estimate was available.

Figure A.5 — Black Population By Neighborhood And Census Block (2020)



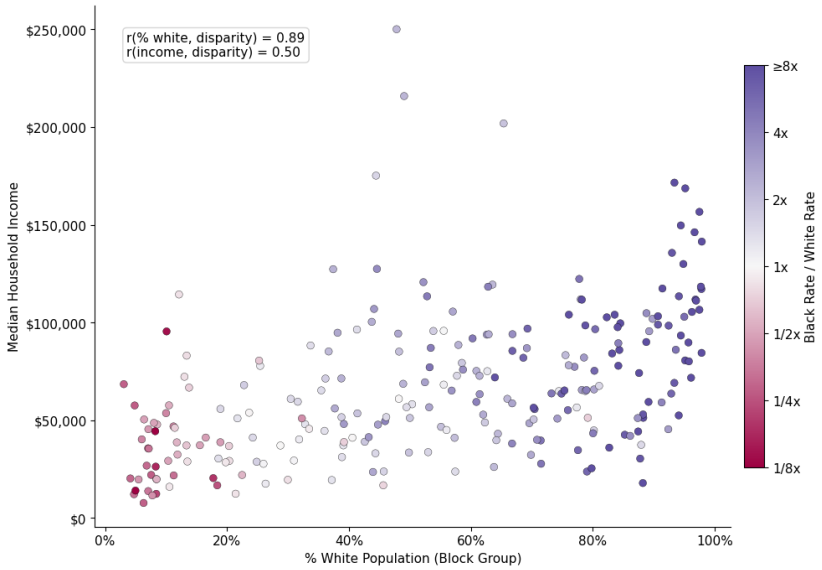
Black population by neighborhood (left) and census block (right), based on 2020 Decennial Census data. Neighborhood totals are aggregated from census block counts. Neighborhood boundaries shown in both panels.

Figure A.6 — Racial Majority By Census Block (2020 Census)



Gray blocks are unpopulated census areas (parks, industrial land, and similar) with no residential population recorded in the 2020 Census. A block was classified as Majority Black if Black residents made up more than 50% of its total population, and Majority White if White residents made up more than 50% of its total population, both based on the 2020 Decennial Census P2 table. Blocks where neither group exceeded 50% are shown in grey.

Figure A.7 — Black-To-White Stop Rate Disparity By Census Block Group Vs. Percent White Population And Median Household Income



Each point is a census block group with at least 20 Black and 20 White residents, ensuring both stop rates are based on sufficient population. Color indicates the Black-to-White stop rate disparity: purple means Black residents are stopped at higher rates, pink means white residents are stopped more. Stop rates are aggregated from census block to block group level by summing stops and population before computing rates. Median household income is from ACS 2024 5-year estimates at the block group level. Correlation coefficients are shown in the upper left.

Figure A.8 — Initial Stop Reason By Race, Total Number Of Stops (2009–2025)

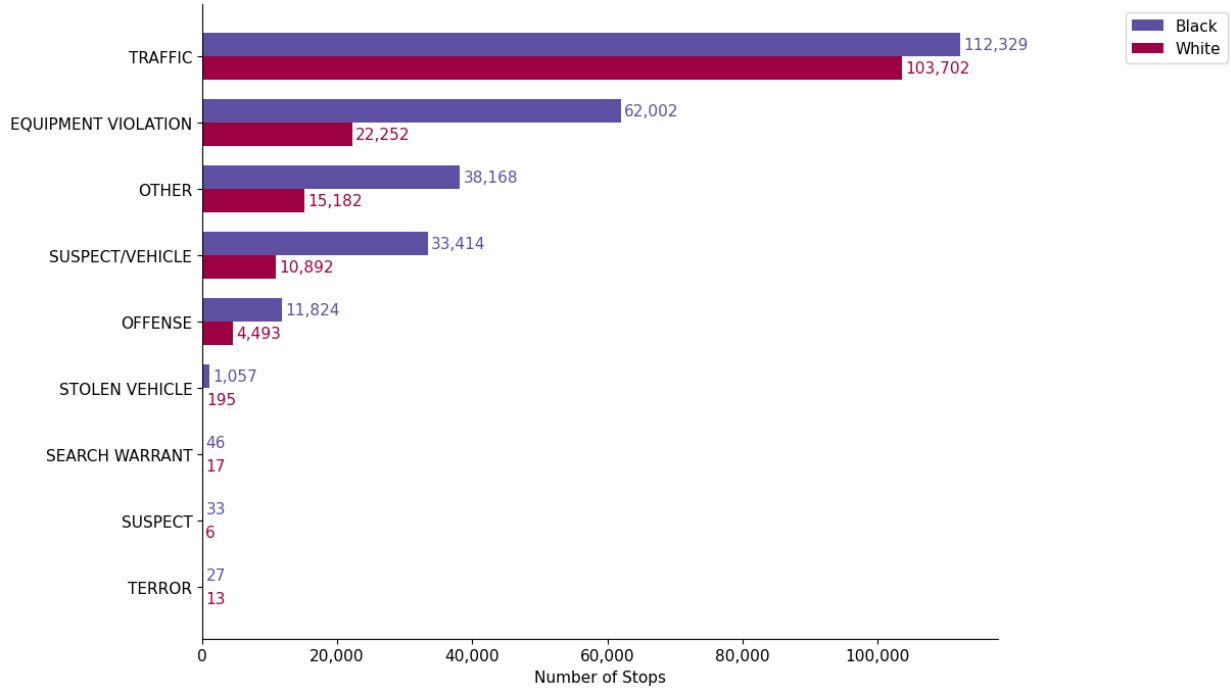
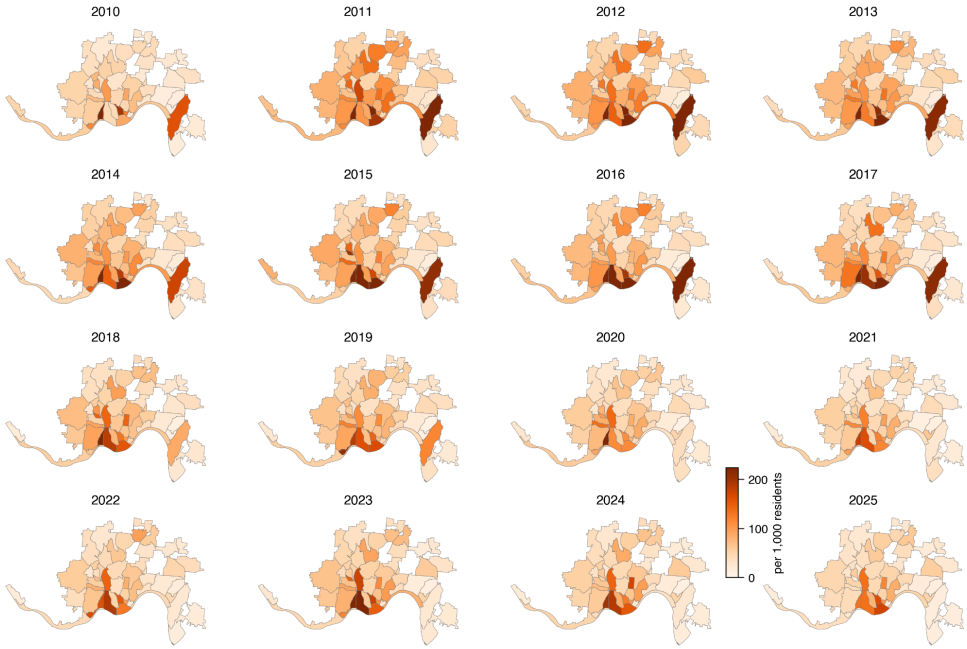
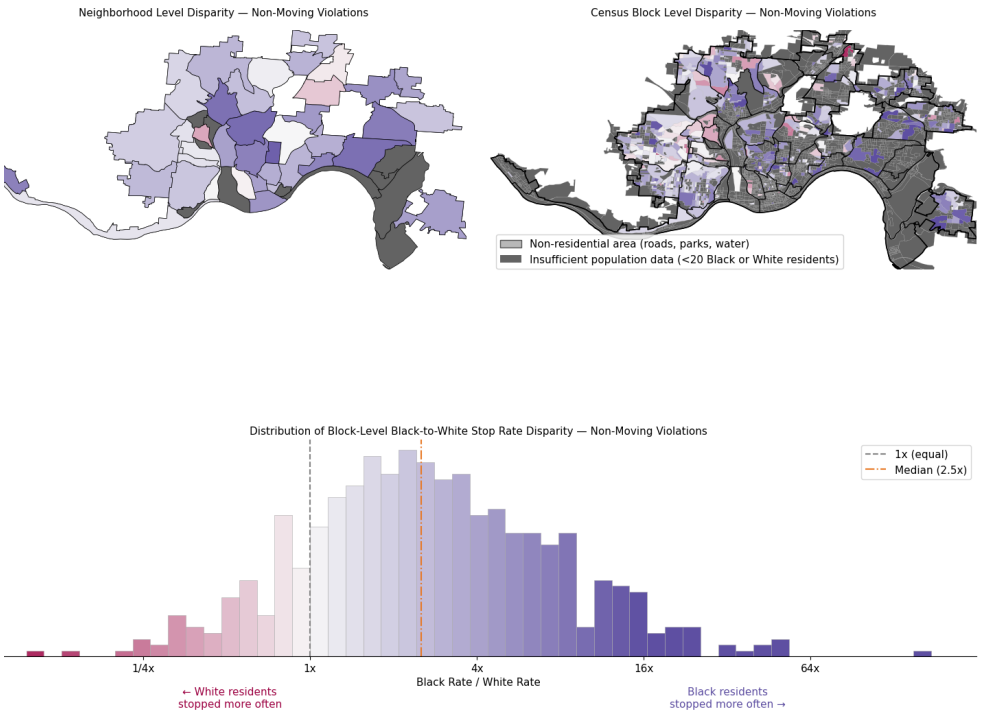


Figure A.9 — Total Crime Rate Per 1,000 Residents (2010–2025)



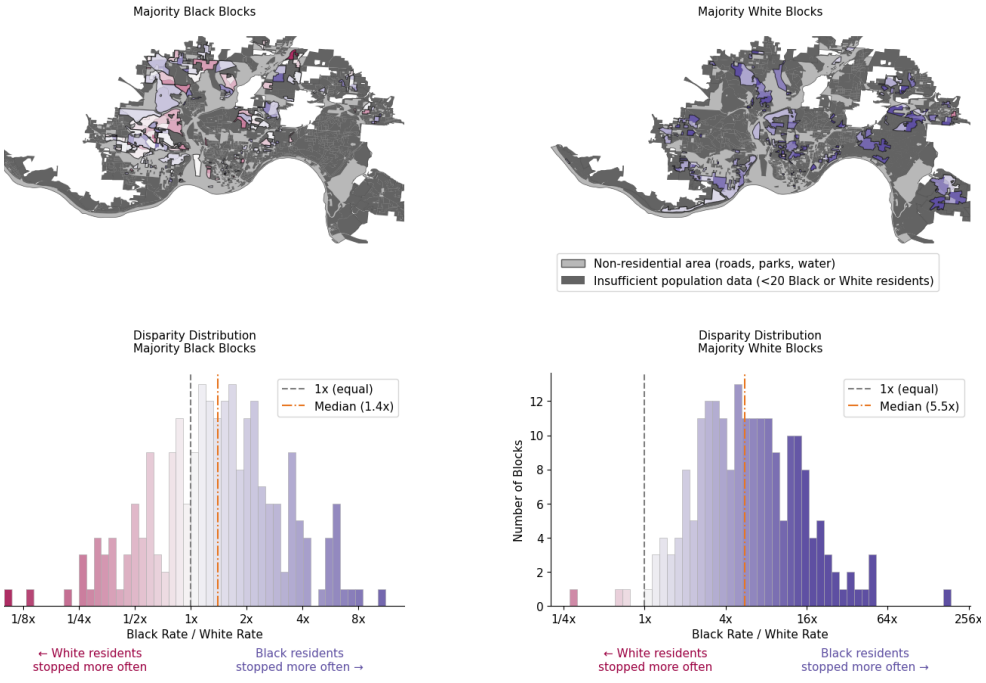
Total crime offenses reported per 100,000 residents per year.

Figure A.10 — Black-To-White Stop Rate Disparity By Neighborhood And Census Block, Motor Vehicle Stops (2011–2023), Non-Moving Violations Only



Replication of Figure 8 in the main text, but restricting the analysis to non-moving violations only, where initial reason was coded as "Equipment Violation", n=60,835 stops. Years were restricted to 2011-2023 because the initial reason field was incomplete for other years.

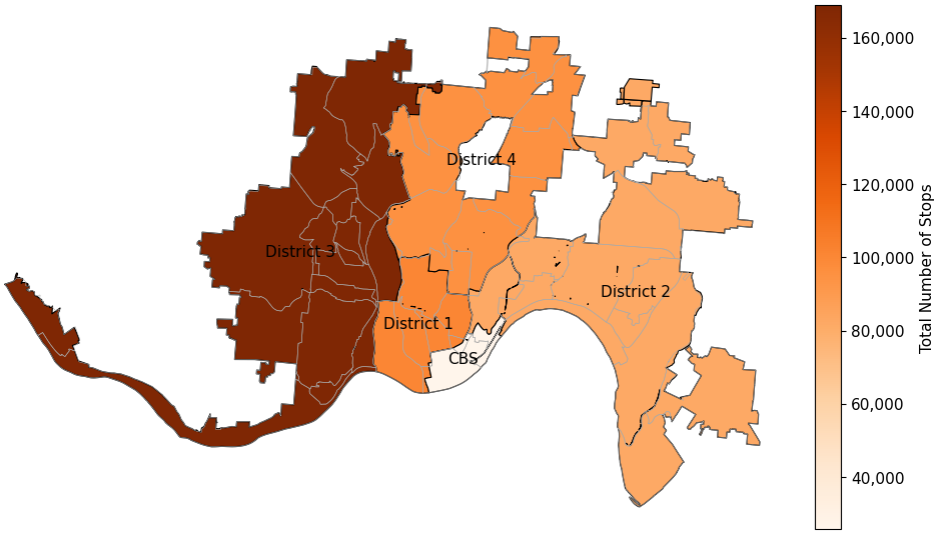
Figure A.11 — Black-To-White Stop Disparity By Block Racial Majority, Motor Vehicle Stops (2011–2023), Non-Moving Violations Only



Replication of Figure 9 in the main text, with the same caveats as Figure A.10.

Appendix B. Supplemetary Figures and Tables — Officer and Supervisor Data

Figure B1 — Total Police Stops By Police District (2009–2025)



Total stops per police district from 2009 to 2025, using current CPD district boundaries sourced from the Cincinnati Open Data Hub. Cincinnati has five police districts (1–4 plus CBS); District 5 was dissolved at the end of 2023 and its area was redistributed across Districts 1, 3, and 4. Stop counts reflect each stop's geographic location within current district boundaries. Gray lines denote neighborhood boundaries. CBS = Central Business Section.

- **Officer:** the police officer's name
- **Personnel ID:** the officer's unique personnel identifier within the Cincinnati Police Department
- **Years:** the years for which the officer has recorded stops from 2020-2025
- **Total Stops:** the total number of stops the officer has made
    - Use in a sentence:
      "[Officer name] stopped x Cincinnati residents."
- **Black Stops:** the total number of Black people the officer has stopped
    - Use in a sentence:
      "[Officer name] stopped x Black residents in Cincinnati."
- **White Stops:** the total number of White people the officer has stopped
    - Use in a sentence:
      "[Officer name] stopped x White residents in Cincinnati."
- **% Black:** the percentage of people stopped by the officer who are Black
    - Formula: (Black Stops) / (Total Stops)
    - Use in a sentence:
      "x% of [Officer name]'s stops were Black people."
- **Black Rate / 1k:** the total number of Black residents stopped by the officer per 1,000 Black residents in the officer's primary CPD district, per year.
    - Formula: ((Black Stops / Black Population of the officer's primary CPD district) × 1,000) / number of years in data
    - Use in a sentence:
      "For every one thousand Black people in [Officer name]'s primary CPD district, they stopped x Black residents."
- **White Rate / 1k:** the total number of White residents stopped by the officer per 1,000 White residents in the officer's primary CPD district, per year.
    - Formula: ((White Stops / White Population of the officer's primary CPD district) × 1,000) / number of years in data
    - Use in a sentence:
      "For every one thousand White people in [Officer name]'s primary CPD district, they stopped x White residents."
- **Disparity Ratio:** takes Black and White city population levels into account to compare their stop rates.
    - Formula: ("Black rate / 1k" / "White Rate / 1k")
    - Use in a sentence:
      "[Officer name] stopped Black residents at x times the rate of White residents."

Table B.2 — Top 10 Officers By Black Stop Rate Per 1,000 Residents (2020–2025)

Officer	Personnel ID	Years	Total Stops	Black Stops	White Stops	% Black	Black Rate/1k	White Rate/1k	Disparity Ratio
DETTMER, BRYAN S.	19713	2020–2025	635	225	371	35.430	33.363	10.755	3.100
MYRES, SAMUEL J.	35601	2022–2025	1,574	1,325	240	84.180	24.595	3.068	8.020
GRAENING, CRAIG A.	31426	2020–2025	133	79	44	59.400	11.714	1.276	9.180
WILLIAMSON, BENJAMIN P.	35812	2020–2025	849	739	96	87.040	9.145	0.818	11.180
LEE, AUSTIN D.	34961	2020–2025	816	716	90	87.750	8.861	0.767	11.550
KENERLY, CHRISTOPHER J.	32948	2024–2025	268	198	45	73.880	7.351	1.151	6.390
NEWMAN, SHAWN M.	31418	2020–2025	116	43	62	37.070	6.376	1.797	3.550
FARWICK, BENJAMIN W.	38021	2023–2025	782	633	99	80.950	6.321	1.935	3.270
SOARD, DENNIS L.	38893	2024–2025	218	162	42	74.310	6.014	1.074	5.600
LUTZ, ZACHARY M.	37255	2022–2025	566	324	221	57.240	6.014	2.825	2.130

The table to the left shows the top 10 officers ranked by the Black stop rate per 1,000 residents per year. All 10 officers in this list stopped Black people at higher rates than White people.

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each office made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only officers with at least 100 total stops between 2020–2025 are included.

Table B.3 — Top 10 Officers By Total Number Of People Stopped (2020–2025)

Officer	Personnel ID	Years	Total Stops	Black Stops	White Stops	% Black	Black Rate/1k	White Rate/1k	Disparity Ratio
MULLIS, CAMERON A.	34964	2020–2025	1,688	1,545	124	91.530	4.649	0.468	9.930
MYRES, SAMUEL J.	35601	2022–2025	1,574	1,325	240	84.180	24.595	3.068	8.020
SHOOK, JOSEPH M.	32264	2020–2025	1,475	635	719	43.050	1.911	2.713	0.700
PARKER, CALAH I.	32276	2020–2025	1,408	559	711	39.700	1.682	2.683	0.630
HALUSEK, ANTHONY R.	34083	2020–2025	1,218	436	713	35.800	1.312	2.690	0.490
WUEST, DANIEL R.	34979	2020–2025	1,207	966	220	80.030	2.907	0.830	3.500
ADAMSON, MICHAEL P.	30630	2020–2025	1,172	492	613	41.980	1.481	2.313	0.640
REED, DUSTIN R.	31417	2020–2025	1,111	334	692	30.060	1.005	2.611	0.380
HENDERSON, SEAN P.	37079	2022–2025	1,088	1,003	79	92.190	4.527	0.447	10.130
GUNN, BENJAMIN J.	37108	2022–2025	1,078	893	174	82.840	4.031	0.985	4.090

The table to the left shows the top 10 officers ranked by the total number of people stopped in descending order.

These 10 CPD officers made the most stops, traffic and pedestrian, of any officers on the police force from 2020-2025.

- ***All 10 CPD officers made over 1,000 stops, individually, during this time period.***
- ***One CPD officer made 1,688 stops since 2020.***

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each officer made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only officers with at least 100 total stops between 2020–2025 are included.

Table B.4 — Top 10 Supervisors By Black Stop Rate Per 1,000 Residents (2020–2025)

Supervisor	Personnel ID	Years	Total Stops	Black Stops	White Stops	% Black	Black Rate/1k	White Rate/1k	Disparity Ratio
DAVIS, JAMES	13156	2020–2024	976	909	55	93.140	3.282	0.249	13.181
NORRIS, BRIAN	13571	2020–2021	273	122	131	44.690	2.854	1.108	2.576
PUTNICK, LUKE M	18768	2020–2023	162	137	21	84.570	2.543	0.268	9.489
FOX, STEVEN	13145	2020–2024	1,770	683	926	38.590	2.466	4.192	0.588
MUMMERT, JASON	18355	2020–2022	548	310	207	56.570	1.866	1.562	1.195
HUDEPOHL, MICHAEL	13187	2020–2020	143	98	36	68.530	1.769	0.815	2.171
HEINE, SHANNON	13175	2020–2021	116	80	32	68.970	0.722	0.362	1.994
ZUCKER, DENNIS	14053	2020–2024	401	195	155	48.630	0.704	0.702	1.003
HEINE, JOHN	10504	2020–2024	309	194	102	62.780	0.701	0.462	1.517
DOWNING, DANIEL	20986	2020–2023	175	135	38	77.140	0.609	0.215	2.833

The table to the left shows the top 10 supervisors ranked by the Black stop rate per 1,000 Residents per year, made by the officers under their command. The two highest rates were 3.28 and 2.90 per 1,000 residents per year.

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each officer made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only supervisors with officers under their command who made at least 100 total stops between 2020–2025 are included.

Table B.5 — Top 10 Supervisors By Total Number Of People Stopped (2020–2025)

Supervisor	Personnel ID	Years	Total Stops	Black Stops	White Stops	% Black	Black Rate/1k	White Rate/1k	Disparity Ratio
FOX, STEVEN	13145	2020–2024	1,770	683	926	38.590	2.466	4.192	0.588
DAVIS, JAMES	13156	2020–2024	976	909	55	93.140	3.282	0.249	13.181
MUMMERT, JASON	18355	2020–2022	548	310	207	56.570	1.866	1.562	1.195
ZUCKER, DENNIS	14053	2020–2024	401	195	155	48.630	0.704	0.702	1.003
HEINE, JOHN	10504	2020–2024	309	194	102	62.780	0.701	0.462	1.517
NORRIS, BRIAN	13571	2020–2021	273	122	131	44.690	2.854	1.108	2.576
SCHUTTE, MARK	21832	2020–2024	191	88	93	46.070	0.318	0.421	0.755
VAN HORN, ROBERT	25403	2022–2024	182	65	99	35.710	0.391	0.747	0.523
DOWNING, DANIEL	20986	2020–2023	175	135	38	77.140	0.609	0.215	2.833
PUTNICK, LUKE M	18768	2020–2023	162	137	21	84.570	2.543	0.268	9.489

The table to the left shows the top 10 CPD supervisors ranked by the total number of stops, traffic and pedestrian, made by the officers under their command.

One CPD supervisor oversaw nearly twice as many total police stops (1,770) by officers under his command than any other supervisor on the force.

District populations were derived from 2020 decennial census data at the census block level, aggregated to the CPD district where each officer made the majority of their stops. Rates per 1,000 residents were then calculated using that district population, divided by the number of years the officer appears in the dataset. Only supervisors with officers under their command who made at least 100 total stops between 2020–2025 are included.

Appendix C. Records Request

Figure C1

Public Records Request Language

Two separate public records requests were submitted to the City of Cincinnati to obtain the contact card dataset used in this analysis. The complete language for each request is included below:

Original Records Request Language:

This request pertains to the following departments: Citizens Complaint Authority; Emergency Communication; Cincinnati Police Department; and the Office of Performance & Data Analytics.

This is a public records request for records mapping police officer badge numbers to the city's contact card dataset maintained by the City's Office of Performance & Data Analytics (OPDA) using data provided by the Cincinnati Police Department (CPD). Specifi cally, this request is seeking records mapping officer badge numbers to the officer ID field found in the Contact Card Dataset.

The dataset can be found at the link provided below.Link to Contact Card dataset:

https://data.cincinnati-oh.gov/safety/CPD-Contact-Cards/svan-pass/about_data

Second Request Language:

This is a public records request for updated records related to the city's Contact Card Dataset maintained by the City's Office of Performance & Data Analytics (OPDA). Specifically, I am seeking an updated version of the dataset titled "Contact_Cards_with_Badge_Number__Officer_Names__and_actual_locations.xlsx" which was provided in response to my records request made on March 3, 2025 (Reference No: C006730-032625). This fi le contained contact card data spanning from 6/3/2024 to 4/3/2025.

I am now seeking an updated version of this file that contains contact card data spanning from June 3, 2024, to the date of this request, June 26, 2025. Additionally, the updated excel sheet should include the following fields which are captured by 534 forms:

1) NARRATIVE (officer narrative—found at the bottom of a completed 534 form—contains the officer's observations and a general description of the stop/interaction),

2) DOB of the individual(s) subject to the officer's stop,

3) GENERAL DESCRIPTION / CLOTHING (officer description of individual subject to stop), and

4) FORCE USE

Appendix D. Supplementary Figures and Tables — Crime Rate and Stop Disparity Analysis

Random Effects Within-Between (REWB) Model

To test whether neighborhood crime rates or racial composition better explain racial disparities in police stops, we merged police-reported crime data with stop disparity ratios across Cincinnati's 50 Statistical Neighborhood Approximations (SNAs). The crime rate analysis in this section covers 2010–2025; Cincinnati's publicly available crime incident data (PDI/STARS) begins in 2010, which is why earlier 2009 is excluded here.

Crime data consists of UCR Part I offenses (aggravated assault, burglary, homicide, larceny, motor vehicle theft, rape, and robbery) drawn from Cincinnati's publicly available PDI and STARS crime incident databases. Cincinnati's publicly available crime incident data (PDI/STARS) begins in 2010, so 2009 could not be included in analyses that require neighborhood-level crime rates. Crime rates per 1,000 residents were calculated using ACS 5-year population estimates, matched to each neighborhood using areal apportionment from census tracts to SNAs.

The stop disparity ratio is calculated as the Black stop rate per 1,000 Black residents divided by the White stop rate per 1,000 White residents. Because this ratio is sensitive to small population denominators — a handful of stops in a neighborhood with very few Black or White residents can produce extreme values — we applied a population filter excluding neighborhood-years where either the Black or White population fell below 100 residents. The final filtered panel is 624 neighborhood-years (n = 800 before filtering). Sensitivity analyses at thresholds of 50 and 500 produced consistent results.

Statistical model. We estimated a Random Effects Within-Between (REWB) model (Bell & Jones, 2015). For each neighborhood *i* in year *t*:

$$\log(disparity_{it}) = \beta_0 + \beta_W \cdot X_{it}^{W} + \beta_B \cdot X_i^{b} + \gamma \cdot pct\_white_i^{b} + \delta_t + \upsilon_i + \varepsilon_{it}$$

where X_{it}^{W} captures the year-over-year change in a neighborhood's crime rate relative to its long-run mean, X_i^{b} captures the neighborhood's long-run mean crime rate relative to the panel average, $pct\_white_i^{b}$ is the neighborhood's residential share of White residents (2020 Decennial Census), δ_t are year fixed effects, and $\upsilon_i \sim N(0, \sigma_v^2)$ is a random intercept per neighborhood. Estimation was via restricted maximum likelihood. Predictors were standardized so coefficients are directly comparable across specifications.

REWB was chosen over a pure neighborhood fixed-effects model because a fixed-effects specification absorbs all time-invariant neighborhood characteristics — including racial composition, which barely moves year-to-year in this panel. A fixed-effects model would therefore be silent on the central question. REWB identifies the within-coefficient that fixed effects identifies while also estimating the between-neighborhood coefficient that fixed effects discards.

Variance decomposition of log(disparity) on this sample: **81.5% between neighborhoods, 18.5%** Intraclass correlation across all seven sub-type REWB models ≈ 0.60.

Hierarchical multiple-testing procedure. Ten crime measures were tested in a pre-specified tree:

Level	Offenses tested	α split	Effective α (per test)	Tested when…
L1	total crime	α	0.05000	— (root)
L2	violent, property	α / 2	0.02500	total crime rejects
L3a	homicide, rape, robbery, aggravated assault	α / (2·4)	0.00625	violent rejects
L3b	burglary, larceny, motor vehicle theft	α / (2·3)	0.00833	property rejects

Ten crime tests arranged in a pre-specified tree. A child is tested only if its parent rejects; sibling groups Bonferroni-split the parent's α. Under the closure principle (Marcus, Peritz, & Gabriel, 1976), this controls the family-wise error rate at α = 0.05 across all ten crime tests. "Effective α (per test)" is the per-test threshold within the sibling group at that level, i.e. the parent's α divided by the number of siblings.

A child is tested only if its parent rejects; sibling groups Bonferroni-split the parent's α. Under the closure principle (Marcus, Peritz, & Gabriel, 1976) this controls the family-wise error rate at α = 0.05 across all ten crime tests, with a non-rejection at any node closing off its subtree. In addition to the hierarchical procedure, we report flat Bonferroni and Benjamini–Hochberg FDR thresholds computed over a 46-test robustness family that pools the ten crime tests with 36 subsidiary tests (three stop-type subsets × twelve outcome/predictor combinations). The two procedures agree on the substantive conclusion.

Stop-type subset construction. The contact cards distinguish motor-vehicle stops, pedestrian stops, field interviews, and search warrants. Three parallel stop-count panels — all stops, traffic stops only, and pedestrian stops only — were built using identical SNA assignment (point-in-polygon geocode) and identical 2020 Decennial Census residential denominators. Each subset enters the REWB specification changing only the numerator. This is the cleanest available test of whether non-residents driving through a neighborhood are inflating the headline % White effect. Subset-level estimates appear in Table 2 of the main text.

An additional caveat. Police-reported crime rates are themselves shaped by policing decisions: neighborhoods that are more heavily policed will, by definition, have more reported crime. This creates a feedback loop in which over-policing generates the crime statistics used to justify further policing. The feedback loop biases crime-rate coefficients upward, meaning that even the weak negative correlations between crime and disparity reported in Table D.1 likely overstate crime's explanatory role — the crime data is partly a product of the policing it is supposed to explain. Victim-reported crime data (e.g., NCVS), which is less susceptible to this problem, is not available at the neighborhood level.

Alternative outcome. To address the possibility that the disparity ratio is mechanically driven by small denominators even after the population filter, we re-ran the main analyses using a second outcome: excess Black stop share = (Black stops ÷ (Black + White stops)) − (Black population ÷ (Black + White population)). This measure is bounded between −1 and +1 and is well-defined even in cells with zero stops of one race. The excess-share version of the stop-type subset analysis gives β = +0.136 / +0.135 / +0.149 across all / traffic / pedestrian stops, with the pedestrian subset again largest. The substantive conclusion is identical.

Table D.1 — Hierarchical REWB: Crime-Rate Predictors Of Black-White Stop Disparity

Level	Node	β (between)	95% CI	raw p	effective α	Decision
1	total crime	-0	[−0.25, +0.05]	0.203	0.05	no evidence of effect
2	violent crime	-0	[−0.28, +0.03]	0.124	—	not tested (parent non-sig)
2	property crime	-0	[−0.24, +0.06]	0.242	—	not tested (parent non-sig)
3	homicide	-0	[−0.31, +0.05]	0.164	—	not tested
3	rape	-0	[−0.26, +0.06]	0.234	—	not tested
3	robbery	-0	[−0.24, +0.07]	0.290	—	not tested
3	aggravated assault	-0	[−0.34, −0.02]	0.032	—	not tested
3	burglary	-0	[−0.30, −0.00]	0.045	—	not tested
3	larceny	-0	[−0.21, +0.10]	0.494	—	not tested
3	motor vehicle theft	-0	[−0.27, +0.05]	0.184	—	not tested
—	pct_white_btwn (covariate)	1	[+0.64, +0.94]	$< 10^{-14}$	—	survives Bonferroni and BH-FDR in the extended family

Decisions under hierarchical testing: 0 of 10 crime tests reject. Nominally suggestive sub-tests (aggravated assault raw p = .032, burglary raw p = .045) also fail flat Bonferroni over the 46-test robustness family (threshold ≈ 0.0011) and BH-FDR. n = 624 neighborhood-years, 2010–2025, pop ≥ 100 filter.

Each row is a REWB model with one crime measure and the % White covariate as predictors, a random intercept per neighborhood, and year fixed effects. The reported test is the between-neighborhood crime coefficient. Tests follow the pre-specified tree above; children are tested only if their parent rejects.

Decisions under hierarchical testing: 0 of 10 crime tests reject. "No evidence of effect" at the root is a statement about what the data can show, not a claim that the true effect is exactly zero. The nominally-suggestive sub-tests (aggravated assault raw p = .032, burglary raw p = .045) also fail flat Bonferroni over the 46-test robustness family (threshold ≈ 0.0011) and BH-FDR.

Table D.2 — Stability Of The % White Coeffcient Across Crime Specifications

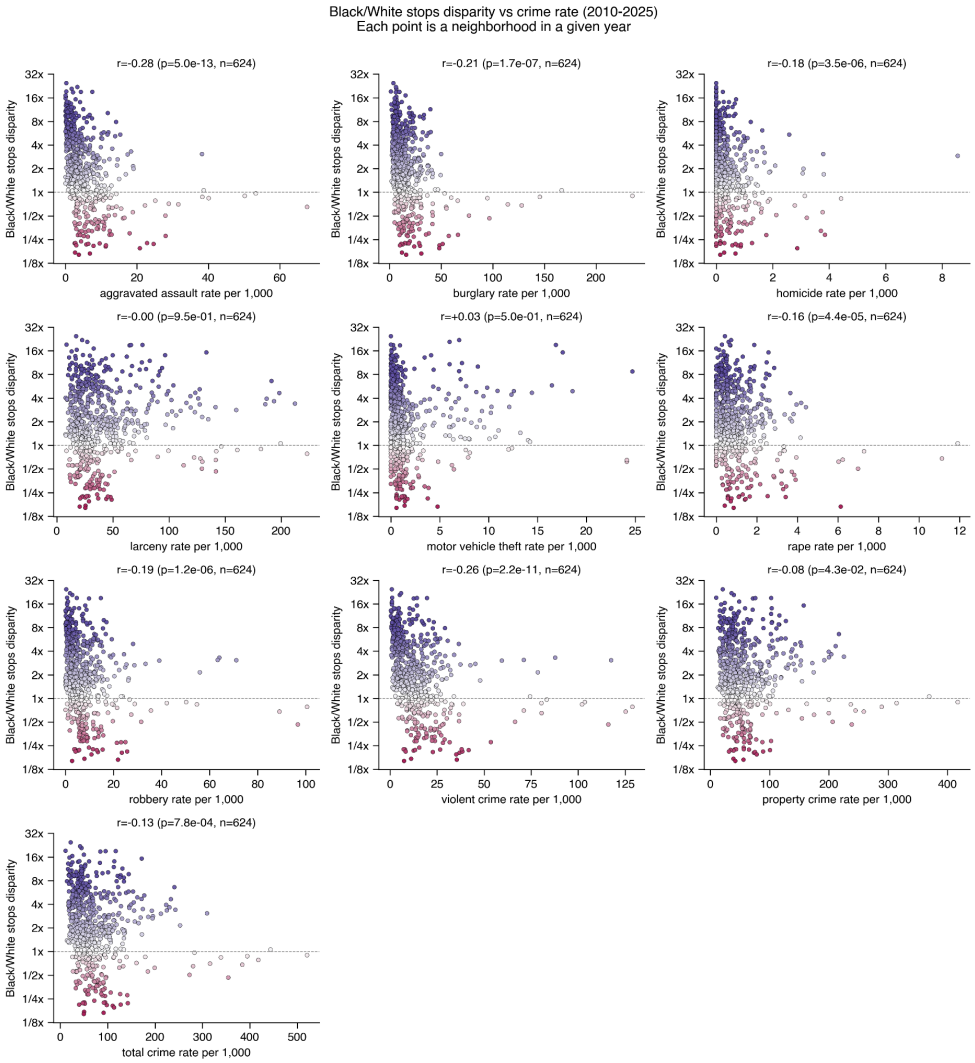
Each row refits the Table D.1 model with a different crime measure — total, violent, property, and each individual offense — and reports the % White coefficient from that model. A skeptic's claim is that % White is a stand-in for unmeasured crime; if so, the % White coefficient should move materially when a different crime variable is swapped in, because each crime measure captures a different slice of the supposedly-hidden signal. The coefficient barely moves.

Level	Crime measure in model	β (pct_white_btwn)	95% CI	p
1	total crime	1	[+0.64, +0.94]	$< 10^{-14}$
2	violent crime	1	[+0.60, +0.91]	$< 10^{-14}$
2	property crime	1	[+0.64, +0.95]	$< 10^{-14}$
3	aggravated assault	1	[+0.56, +0.88]	$< 10^{-14}$
3	burglary	1	[+0.62, +0.92]	$< 10^{-14}$
3	homicide	1	[+0.54, +0.90]	$< 10^{-14}$
3	larceny	1	[+0.64, +0.96]	$< 10^{-14}$
3	motor vehicle theft	1	[+0.60, +0.92]	$< 10^{-14}$
3	rape	1	[+0.61, +0.92]	$< 10^{-14}$
3	robbery	1	[+0.62, +0.93]	$< 10^{-14}$

Range: +0.72 to +0.80 SD (spread 0.08; cross-specification standard deviation 0.03). All ten models reject pct_white_btwn = 0 at $p \approx 10^{-14}$ or smaller. No crime specification — not even total_crime — takes the % White effect away. n = 624 neighborhood-years, 2010–2025, pop ≥ 100 filter.

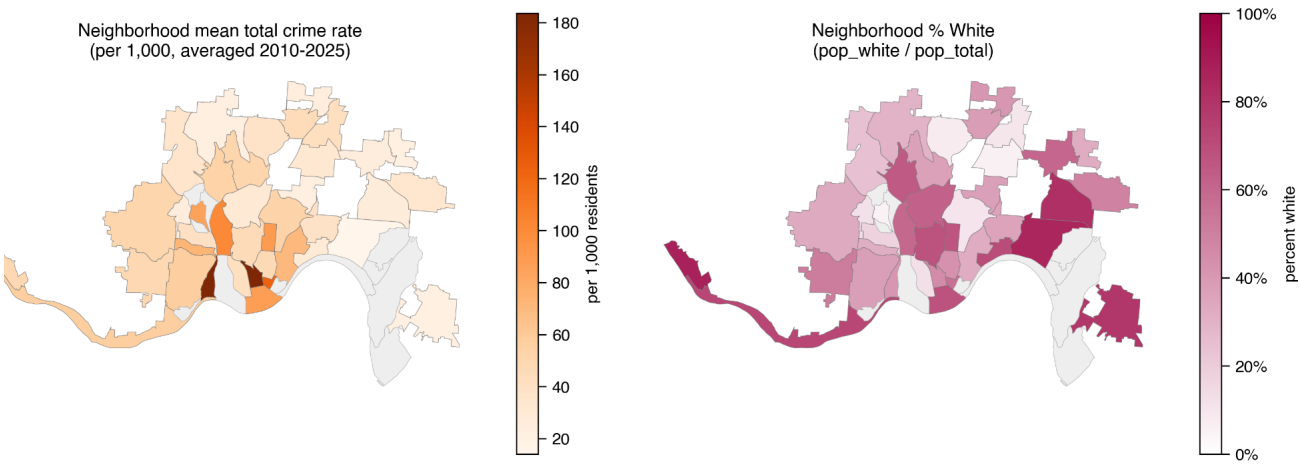
Range: +0.72 to +0.80 standard deviations (spread 0.08; cross-specification standard deviation 0.03). All ten models reject the % White coefficient = 0 at $p \approx 10^{-14}$ or smaller. No crime specification — not even the coarse total-crime aggregate — takes the % White effect away.

Figure D.1 — Bivariate Correlations Between Stop Disparity And Crime Rates By Offense Category (Population ≥ 100 Filter Applied)



Bivariate correlations between Black-to-White stop disparity and crime rates across ten offense categories. Each point represents one neighborhood in one year (n = 624 neighborhood-years, 2010–2025). The y-axis shows the stop disparity ratio on a log scale, where 1x indicates equal stop rates for Black and White residents. The seven primary panels correspond to individual UCR Part I offenses (aggravated assault, burglary, homicide, larceny, motor vehicle theft, rape, robbery); the remaining three panels show composite categories (violent crime, property crime, total crime). While several categories show statistically signifi cant negative correlations in these simple bivariate plots, the regression analyses reported in Table 1 demonstrate that these relationships are largely or entirely explained by the correlation between crime rates and neighborhood racial composition — once % White is controlled for, crime rates no longer significantly predict stop disparity. Neighborhood-years where either the Black or White population fell below 100 residents are excluded. Color gradient refl ects the disparity ratio: purple indicates higher stop rates for Black residents, pink indicates higher stop rates for White residents.

Figure D.2 — Total Crime Rate Vs. Percent White Population By Neighborhood



Poisson regression models

This appendix describes two Poisson regressions we fit in addition to the log-disparity OLS used in the main body. The specifications are taken from Chohlas-Wood, Goel, Shoemaker & Shroff (2018), An Analysis of the Metropolitan Nashville Police Department's Traffic Stop Practices. They complement the main-body analysis by answering two narrower, more mechanical questions than the log-disparity regression does, using a model class that is a better match for the data-generating process.

Motivation

The main body models the log of the Black/White stop-rate ratio as a linear function of standardized neighborhood characteristics. That specification is well-suited to the headline question — how does disparity vary across neighborhoods? — but it throws away two pieces of information that are worth examining directly:

It collapses two separate rates (Black stop rate, White stop rate) into a single ratio before modeling, so it cannot distinguish a disparity driven by high Black stop rates from one driven by low White stop rates.

It conditions on having nonzero stops of both races, which discards sparse cells and treats a neighborhood-year with two Black and one White stops the same as one with two thousand of each.

The two Poisson regressions described below instead model stop counts directly, with population entering as an exposure term rather than a denominator. Model 1 asks whether the total neighborhood stop rate is elevated in neighborhoods with a higher share of non-white residents, after adjusting for reported crime. Model 2 asks whether, within the same neighborhood, Black residents are stopped at a higher per-capita rate than White residents.

Why a Poisson regression ?

The outcome in both specifications is a count of police stops in a neighborhood-year. Counts are nonnegative integers, and their variance grows with their mean — a property that linear regression on rates handles poorly, especially when cell sizes differ by orders of magnitude (Cincinnati neighborhood-years range from single-digit stop counts to several thousand).

A Poisson model with a log link and a population offset parameterizes this cleanly:

$$\log E[s \mid X] = \log p + X\beta$$

where *s* is the stop count, *p* is the at-risk population (here, residential driving-age population), and $\boldsymbol{X\beta}$ is the linear predictor. The log*p* term is an offset: its coefficient is fixed at 1, so the model is equivalent to linear regression on the log stop rate *log(s/p)*, with the correct variance structure for count data.

Three properties make this the right tool for the question:

- **Coefficients are multiplicative on the rate scale.** A coefficient of β on a covariate means the stop rate is multiplied by e^{β} per one-unit increase in that covariate, holding other covariates fixed. So all effects are directly interpretable as rate ratios.
- **Zeros and sparse cells are handled naturally.** A neighborhood-year with zero White stops does not create a log-of-zero problem, unlike the log-ratio outcome used in the main body.
- **Overdispersion is accommodated.** Police-stop counts have variance well above their mean (officer deployment clusters geographically and temporally; stops don't arrive as independent Poisson draws). We use a quasi-Poisson adjustment — the Pearson dispersion $\hat{\Phi} = X^2/df$ to inflate standard errors accordingly. This matches Chohlas-Wood et al, 2018.

Model 1: Between-neighborhood, crime held fixed

$$s_g \sim Poisson\left(p_g \cdot \exp(\mu + \alpha \log c_g + \beta r_g + \gamma_{t(g)})\right)$$

symbol	definition
s_g	total Black-plus-White stop count in neighborhood-year g
p_g	total Black-plus-White residential population in neighborhood-year g
c_g	crime rate per 1,000 residents in neighborhood-year g (total Part I offenses)
r_g	neighborhood racial composition, either proportion non-white or proportion Black, $r_g \in [0, 1]$
$\gamma_{t(g)}$	year fixed effect, absorbing city-wide temporal trends
μ	overall log stop rate at $c_g = 1, r_g = 0$, in the reference year
α	crime-rate elasticity: a 1% increase in the crime rate multiplies the expected stop rate by $(1.01)^{\alpha}$
β	racial-composition effect: moving a neighborhood from 0 to 100% non-white multiplies the expected stop rate by e^{β}, holding crime and year fixed

Parameter of interest: β. A nonzero β after conditioning on $\log c_g$ means that the association between racial composition and stop rate is not fully mediated by reported crime. Conversely, β close to zero (as in Nashville, where $\hat{\beta} = -0.4$, 95% CI [−1.1,+0.4]) would support the interpretation that the concentration of stops in non-white neighborhoods is accounted for by the concentration of crime in those neighborhoods.

Relationships among variables implied by the equation.

- Population and stop count are assumed to scale linearly: doubling the at-risk population doubles the expected stop count, holding rate fixed. This is the offset assumption; it is a modeling choice, not an estimated parameter. We verify in the notebook that relaxing it (fitting $\log p_g$ as a free regressor) leaves $\hat{\beta}$ essentially unchanged.
- Crime enters on the log scale, so stops respond elastically to crime: a 10% increase in reported crime is assumed to produce an $\alpha \cdot 10\%$ increase in stops, regardless of baseline crime level.
- Racial composition enters linearly on the log-rate scale. The scale of β is therefore the log-ratio of stop rates between a hypothetical all-non-white and a hypothetical all-white neighborhood with identical crime rates and year. Intermediate compositions interpolate exponentially: a 30% non-white neighborhood has an expected rate of $e^{0.3\beta}$ relative to an all-white one.
- Year fixed effects are additive on the log-rate scale, so they shift all neighborhoods' expected rates by the same multiplicative factor in a given year — absorbing trends like the citywide decline in total stops from 2014 on without soaking up cross-neighborhood variation.

What Model 1 does not identify. Model 1 is a between-neighborhood association. Its $\hat{\beta}$ can still reflect omitted neighborhood-level confounders — officer deployment intensity, daytime vs residential population mismatch, or the spatial distribution of non-residential driving trips — that are correlated with both racial composition and stop rate but are not captured by reported crime alone. It is not a causal estimate of the effect of racial composition on stops.

Model 2: Within-neighborhood, location held fixed

$$s_{r,g} \sim Poisson\ (p_{r,g} \cdot \exp(\alpha_r + \beta_g + \gamma_{t(g)}))$$

symbol	definition
$s_{r,g}$	stop count of race *r* in neighborhood-year *g*
$p_{r,g}$	race *r* residential population in neighborhood-year *g* (log-offset)
α_r	race fixed effect ($r \in \{White, Black\}$; White = reference)
β_g	β_g neighborhood fixed effect, absorbing all location-level variation
$\gamma_{t(g)}$	year fixed effect

Parameter of interest: $\alpha_{Black} - \alpha_{White}$. Exponentiated, this is the within-neighborhood, within-year Black/White stop-rate ratio. It answers the question "in the same neighborhood, in the same year, are Black residents stopped more often per capita than White residents?"

Relationships among variables implied by the equation.

- Because β_g is a free parameter for every neighborhood, any covariate that is constant within a neighborhood over a given year — crime rate, racial composition, median income, deployment intensity, whatever — is perfectly absorbed. Model 2 therefore cannot estimate the effect of any such covariate; it trades that capacity for the ability to control for all of them at once.
- The race coefficient α_r is additive on the log-rate scale and the same across all neighborhoods and years. This is a strong restriction: it assumes the Black/White rate ratio is constant across neighborhoods. In practice, ratios vary widely across neighborhood-years (see Fig. 5 in the main body), and $e^{\alpha_{Black}-\alpha_{White}}$ should be read as a pooled, population-weighted average of those ratios.
- Population appears only through the offsets $p_{r,g}$, so the fitted rate for each race-neighborhood-year cell is $\exp(\alpha_r + \beta_g + \gamma_{t(g)})$. The neighborhood fixed effect β_g is identified up to the reference category and can be interpreted as the log of that neighborhood's baseline stop rate, averaged across races under the pooling assumption above.

What Model 2 does not identify. Model 2 removes every neighborhood-level and year-level confounder, which makes its headline ratio robust to the denominator critique that motivates most pushback on residential-benchmark analyses. It does not, however, identify the mechanism of the within-neighborhood gap. Candidate mechanisms include differences in exposure to police by time of day, differences in discretion-heavy stop types, officer-level variation in enforcement behavior, or differences in the population on the street versus the population at home. Distinguishing among these is outside the scope of this model.

Estimation details

Both models were fit in Python using a generalized linear model routine with a Poisson family and a log link, with neighborhood population entering as an offset so that the estimated effects describe per-capita stop rates. Because police-stop counts cluster geographically and temporally in ways that violate the Poisson independence assumption, we estimate a dispersion parameter from the Pearson chi-square statistic and inflate the standard errors accordingly, producing quasi-Poisson Wald intervals; this matches footnote 10 of the Nashville paper. Year enters as a set of year dummies in both models, neighborhood as a set of fixed-effect dummies in Model 2, and race as a two-level categorical with White as the reference — so the fitted race coefficient is directly $\alpha_{Black} - \alpha_{White}$.

The estimation sample is restricted to neighborhood-years with both Black and White residential populations exceeding 100, the same stability filter applied in the main body. This drops only a handful of neighborhood-years and leaves 624 in the "all stops" panel. In Model 1, the log-crime predictor is undefined for the rare neighborhood-year that reports zero crime; we clip the crime rate at a small positive floor before logging, which affects at most a handful of cells and does not measurably shift the estimated coefficients.

Relation to the Random Effects Within-Between (REWB) model

The headline regression in the main body is a Random Effects Within-Between (REWB) model in which the outcome is the log of the Black/White stop-rate ratio and every neighborhood-level predictor is decomposed into a between component (the neighborhood's long-run mean) and a within component (the year-over-year deviation from that mean). The reported "effect of neighborhood racial composition on stop disparity" in Table 2 is specifically the between-neighborhood coefficient on proportion White — that is, the standardized association between a neighborhood's long-run racial composition and its long-run log-disparity, holding year fixed.

Poisson Model 1 asks a different question on a different outcome scale. Rather than modeling a ratio, it models the total per-capita stop rate and asks whether non-white neighborhoods are stopped more overall, after adjusting for reported crime. A significant REWB $pct\_white^{b}_{i}$ coefficient tells us that whiter neighborhoods exhibit a larger within-neighborhood Black/White gap; a significant Model 1 β tells us that non-white neighborhoods are stopped more heavily in absolute terms. In Cincinnati both are significant, and they are not redundant: whiter neighborhoods can have both lower total stop rates and higher within-neighborhood Black/White ratios.

Poisson Model 2 adds the third piece. The REWB model does not produce a single, clean estimate of the pooled within-neighborhood Black/White ratio — it works on log-disparity as the outcome, so that ratio is the intercept-like quantity rather than a testable contrast. Model 2 isolates that ratio as a single number with a defensible confidence interval, by modeling race-specific stop counts with neighborhood and year fixed effects. Its race coefficient, exponentiated, is the within-neighborhood Black/White stop-rate ratio that the REWB log-disparity regression treats as a property of the dependent variable rather than as an estimand.

Appendix D References

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Appendix E. Veil of Darkness and the Pedestrian Search-Rate Finding

The test and what it does not address

Grogger & Ridgeway (2006) ask whether an officer's decision to stop depends on being able to visually identify the subject's race. If it does, the Black share of stops at a fixed clock time should be higher in daylight than in darkness, because at 7:30pm in June the officer can see who is present and at 7:30pm in December they cannot. The seasonal shift in visibility at a fixed clock time is the identifying variation.

This is a narrow test of one channel. It is silent on neighborhood-level deployment, dispatch routing, radio descriptions, recognition of known individuals, or any disparity-generating mechanism that does not require real-time visual identification at the stop decision. A null or wrong-sign VOD result therefore does not undermine any of those other channels — it only removes one specific explanation from the menu.

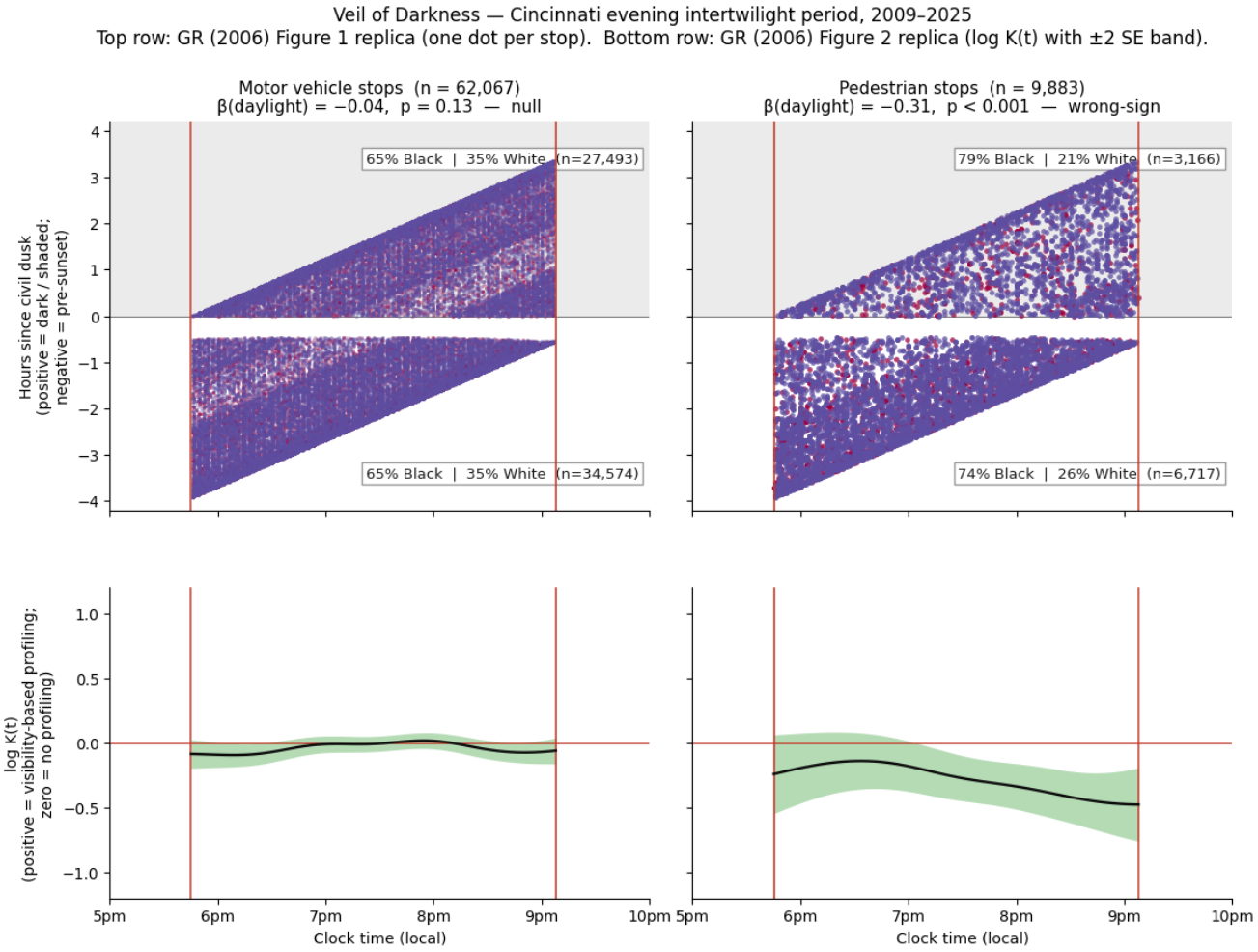
Results

We used Cincinnati contact-card records from 2009 to 2025 during the evening intertwilight period (5:45–9:08pm local time), restricted to Black and White subjects and excluding civil-twilight stops. The specification is a logit model of the probability that a stopped subject is Black, regressed on a daylight indicator with 15-minute clock-time fixed effects, day-of-week fixed effects, and standard errors clustered by date. Following Knode et al. (2024), daylight is the treatment condition: a positive β(daylight) is the signature of visibility-based profiling (more Black stops when officers can see who they are stopping).

- Motor vehicle stops (n = 62,067): β(daylight) = −0.037, p = 0.13. No VOD signal — a clean null on the canonical VOD subject, consistent with the standing literature.
- Pedestrian stops (n = 9,883): β(daylight) = −0.310, p < 0.001. Wrong-sign: the Black share of evening pedestrian stops is higher in darkness (79.3%) than in daylight (73.7%) at the same clock time — opposite to what visibility-based profiling would predict.

Neither subject supports the textbook VOD story. The motor-vehicle result is a null; the pedestrian result points in the wrong direction for the profiling hypothesis.

Figure E.1 — Veil of Darkness fi gure for Cincinnati evening stops, combining the two canonical Grogger & Ridgeway (2006) plots.



Top row — Grogger & Ridgeway (GR) Figure 1 replica. Each dot is one stop; the x-axis is clock time and the y-axis is hours since civil dusk on that stop's date. Dots are colored by race × light state. Stops in the shaded upper band occurred after civil dusk (dark); stops below the zero line occurred before sunset (light). Civil-twilight stops are excluded from the sample, producing the visible gap between bands. Boxed annotations give the Black / White share within each band. Bottom row — GR Figure 2 replica. The smooth curve is log K(t) = logit P(Black | light, t) − logit P(Black | dark, t), estimated by a Nadaraya–Watson Gaussian kernel smoother (bandwidth 0.35h for motor vehicle, 0.45h for pedestrian). The green shaded area is ±2 pointwise SE from a 200-draw cluster bootstrap over stop dates. The red horizontal line at zero is the null (no visibility-based profiling). Red vertical lines mark the evening intertwilight-period bounds. Motor-vehicle column: 65 % Black in both scatter bands and log K(t) wiggles near zero with the SE band covering zero throughout the intertwilight period — the β (daylight) null, and it is null pointwise across the evening, not just on average. Pedestrian column: 79 % Black in the dark scatter band vs. 74 % in light, and log K(t) sits around −0.3 to −0.5 with the SE band excluding zero across most of the intertwilight period — the β (daylight) wrong-sign, and it is stable across the evening rather than a single-slice artifact.

Black-specific search-rate expansion under darkness

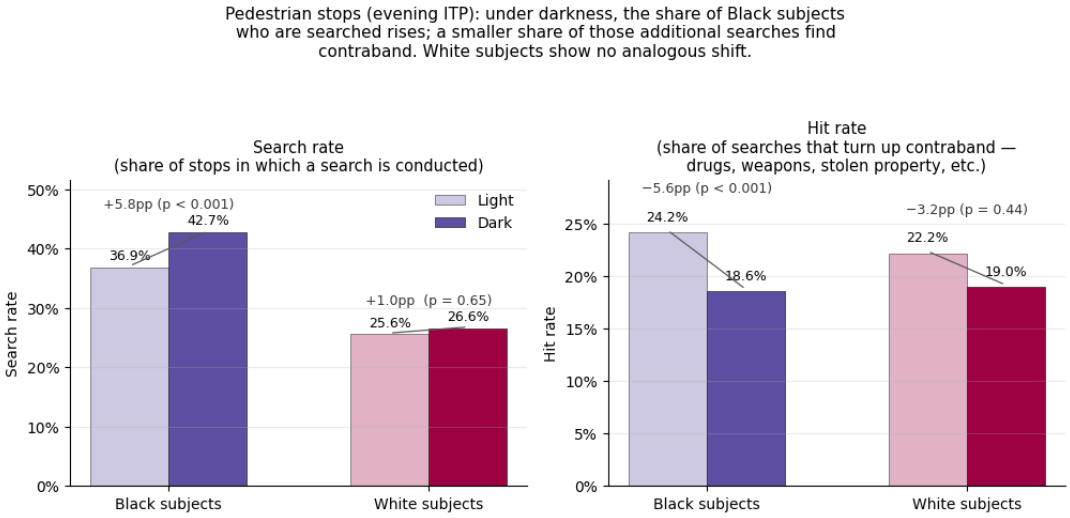
The pedestrian wrong-sign led us to look at stop outcomes by race and light state. That produced the one finding from this analysis that stands on its own terms, independent of the VOD framework:

	Black subjects			White subjects		
	Light	**Dark**	**Δ (p)**	**Light**	**Dark**	**Δ (p)**
n stops	4,952	2,511		1,765	655	
any active action	36.8%	31.2%	**−5.6 pp (<0.001)**	45.8%	37.3%	**−8.6 pp (<0.001)**
searched	36.9%	42.7%	**+5.8 pp (<0.001)**	25.6%	26.6%	+1.0 pp (0.65)
hit rate (given searched)	24.2%	18.6%	**−5.6 pp (<0.001)**	22.2%	19.0%	−3.2 pp (0.44)

Pedestrian stops in the evening intertwilight period (17:45–21:08 local), 2009–2025, Black and White subjects only, non-twilight. "Searched" = a legal basis for a search was recorded (incident to arrest, odor, reasonable suspicion of weapons, plain view, consent, inventory, dog alert, or other probable cause). "Hit rate" = the share of searches in which contraband was recovered (drugs or paraphernalia, weapon, stolen property, currency, or other). Δ is the dark − light difference in percentage points, with p from a two-sided test. Bolded Δ cells are significant at p < 0.05.

"Searched" = the contact card records a legal basis for a search (incident to arrest, odor, reasonable suspicion of weapons, plain view, consent, inventory, dog alert, or other probable cause). "Hit rate" = the share of those searches in which something other than nothing was recovered — i.e., drugs or paraphernalia, a weapon, stolen property, currency, or other contraband. A lower hit rate means a larger share of searches produced no evidence of wrongdoing.

Figure E.2 — Pedestrian Stops in the Evening Intertwilight Period



Left: the share of stops in which officers conduct a search, by race and light state. **Right:** of those searches, the share that turn up contraband. Delta annotations give the light→dark change in percentage points. The key pattern: only the Black search rate rises under darkness, and that rise is accompanied by a drop in the share of searches that find anything.

Three patterns, one of which is the finding:

1. **Citation and arrest rates fall under darkness for both races.** Citation + arrest combined drops 5–9 pp regardless of subject race. Dark pedestrian stops less often result in an enforcement action.
2. **Search rates rise sharply under darkness — but only for Black subjects.** +5.8 pp ($p < 0.001$) for Black vs. +1.0 pp ($p = 0.65$) for White. The pre-existing Black/White search-rate gap widens from 1.44× in light to 1.61× in dark.
3. **A larger share of those additional searches on Black pedestrians turn up nothing.** The hit rate drops 5.6 pp (24.2% → 18.6%, $p < 0.001$) — meaning more Black pedestrians are subjected to searches that find no evidence of wrongdoing. The White hit-rate point estimate moves similarly but the White dark-search cell is small ($n = 174$), so the change is not individually significant.

Read those three together: under darkness, officers search more Black pedestrian subjects, and a significantly larger share of those searches produce no evidence of wrongdoing. The White comparison cell is the natural control — White subjects are present in the same stop sample, under the same darkness, and show no analogous expansion. This is a direct observation from the stop-outcome data; it does not depend on the VOD coefficient or on VOD methodology. It is substantive evidence of darkness-expanded search discretion specifically directed at Black pedestrian subjects.

Interpretation

Neither the motor-vehicle null nor the pedestrian wrong-sign is consistent with the textbook "officer profiles on visible race at the stop decision" story; the Black hit-rate drop under darkness reinforces the same reading. Cincinnati's evening stop disparities therefore do not run through real-time visual identification at the moment of the stop — they run through whatever channels the rest of the report documents (deployment, dispatch, institutional practice). The search-rate finding is a separate, substantive result: darkness is a natural condition that expands officer search discretion on Black pedestrian subjects and not on White subjects, and a larger share of those additional searches find no evidence of wrongdoing.

Limitations

1. **Dark is confounded with winter.** At 7pm, light observations come mostly from April–August and dark observations from November–February. Any seasonal pattern in pedestrian population or officer behavior unrelated to visibility is attributed to "darkness" by this design.
2. **Outcome rates are raw marginals, not adjusted.** The +5.8 pp Black search-rate rise does not control for stop location, officer, time of evening, or age/gender. A fully-adjusted version is a natural next step and could tighten or dissolve the finding.
3. **Contact cards are recorded stops, not all stops.** If recording compliance varies by light state or subject race, everything downstream is biased and the contact-card data cannot detect it on its own.
4. **Post-2023 stop-reason coding break.** The stop-reason field's fill rate drops to roughly 69 % in 2023 and to 0 % from 2024 onward across both the legacy and current data feeds; CPD's own export shows the same pattern, so the break is upstream of our data pipeline. This limits any analysis that slices by stop reason. The β(daylight) and search-rate findings above do not depend on stop-reason coding and are unaffected.

Appendix F. Exploratory Analysis on Officer-Recorded Citizen Attitude

Contact cards include a field[27] where officers record their perception of the stopped person's attitude or demeanor, including emotional observations (i.e. “cooperative” or “annoyed”) as well as physical reactions (i.e. “crying” or “quiet”). These labels are subjective — they reflect the officer's interpretation of the encounter, not an independent measure of behavior.

Figure 22 below shows the disparity ratio for each word – how many times more often it is applied to Black residents versus White residents, adjusted for population[28]. The most striking pattern is how many attitude labels skew toward Black residents. Of the 30 terms most recorded by officers, the large majority are applied more often to Black residents than White residents — including not only words associated with resistance like ”fled/ran” (16x), “annoyed” (9x), “disrespectful” (4.5x), “irritated” (4.3x), but also neutral and compliant terms like "cooperative" (2.4x), "quiet" (1.8x), and "calm" (1.4x). This broad skew largely reflects the underlying stop disparity: because Black residents are stopped far more often per capita, most attitude labels will appear more frequently for Black residents as well.

The words that do skew toward White residents are notable for what they suggest about the nature of those stops. "Intoxicated" (2.35x), “nervous” (1.7x), “crying” (4.19x) and “apologetic” (4.87x) are more commonly recorded for White residents — terms consistent with substance-related or traffic stops where the reason for the encounter is clear and the person's response reflects awareness of a specific violation. This may indicate that White residents are more often stopped in circumstances with a defined legal basis, while Black residents are stopped across a wider range of contexts, consistent with the discretionary policing patterns documented throughout this report.

These patterns should be interpreted with caution. Officer-recorded attitude labels are filtered through individual perception, and research has shown that Black individuals — particularly Black men — are more readily perceived as hostile or noncompliant by observers, including law enforcement officers (Eberhardt et al., 2004; Goff et al., 2014). At the same time, residents who experience frequent, discretionary police contact may understandably express more frustration during stops. The data here cannot distinguish between these dynamics, and both are likely at work.

What the data can show is that officer-recorded attitudes may have real consequences for how stops unfold. Future analysis should examine whether recorded attitude labels predict escalation, searches, or arrests — and whether that relationship differs by race.

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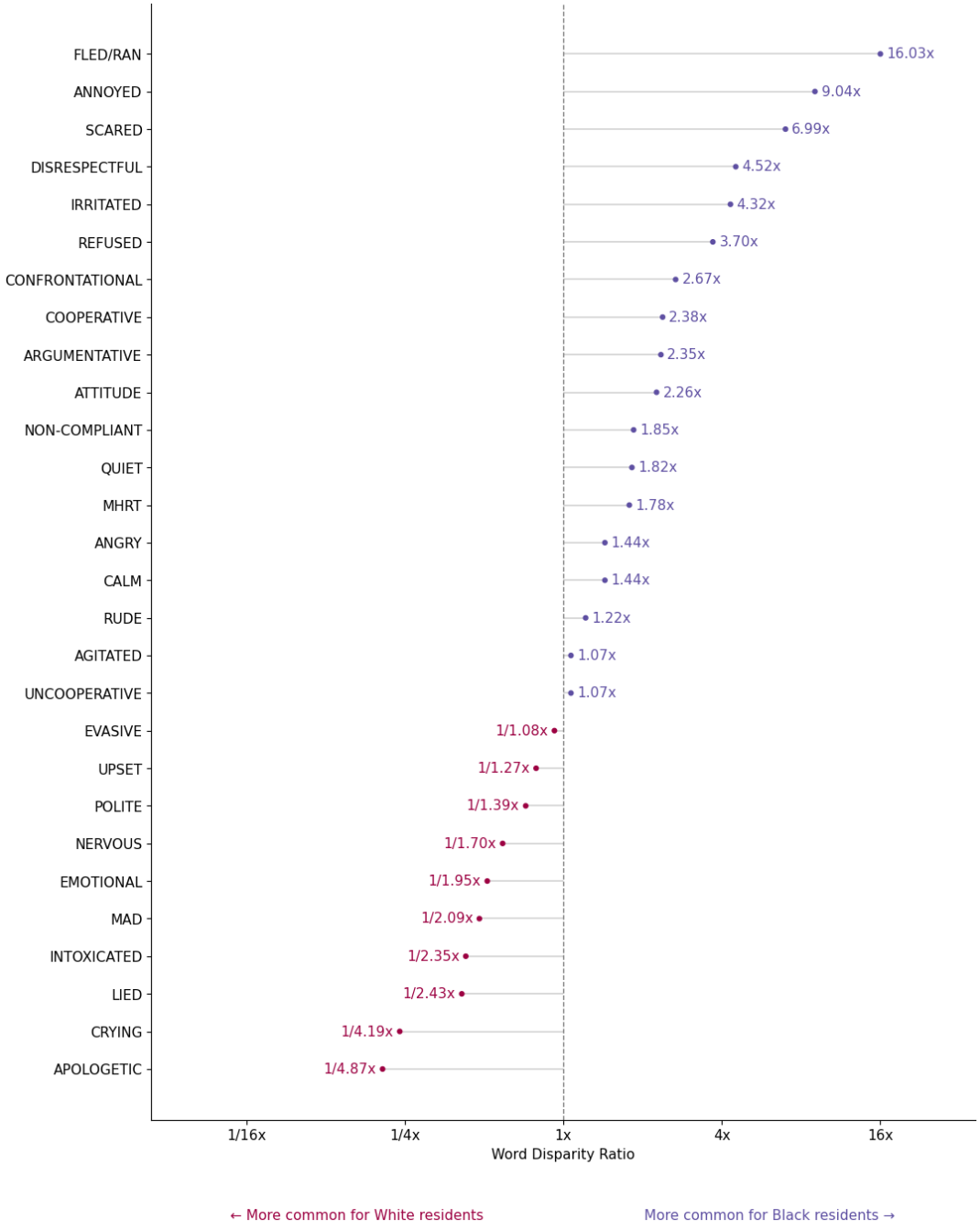
[27] This citizen attitude field is recorded in only 2,426 stops out of 472,666 (0.5%), as shown in Table 1. Findings should be interpreted with this selection bias in mind, knowing the officers who chose to fill in this field may not be representative of all officers, and the stops where attitude was recorded may differ systematically from those where it was not.

[28] A ratio above 1 means the word is used more for Black residents, whereas a ratio below 1 means the word is used more for White residents.

Figure F.1 — Attitude Word Disparity Ratio, Black vs. White Residents (2009-2023)



Each data point shows how much more or less common a given attitude word is in stop records for Black residents compared to White residents, expressed as a ratio of the percentage of stops in which the word appears for each group. A ratio of 1x indicates the word appears equally often; values above 1x (purple) mean the word is more common in stops of Black residents, values below 1x (pink) mean it is more common in stops of White residents. Only words appearing in at least 0.5% of stops for one group and at least 0.1% for both groups are shown. The x-axis uses a log scale so that ratios in both directions are visually symmetric around 1x.