Contact Cards in Cincinnati:
A Review of Racial Bias in Police Stops, 2009–2025

CAMPAIGN ZERO JUNE 15, 2026 REPORT ADDENDUM

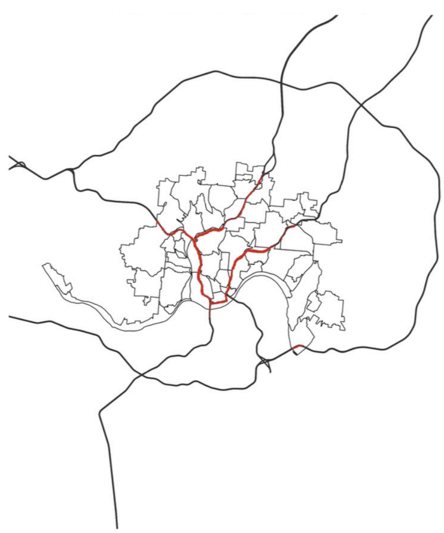
Interstates

We did another analysis of the data where we separated interstate stops from all other vehicle ("surface") stops. Because people don't live on interstate highways, we can't report population-adjusted disparities— we can only report percentage stops.

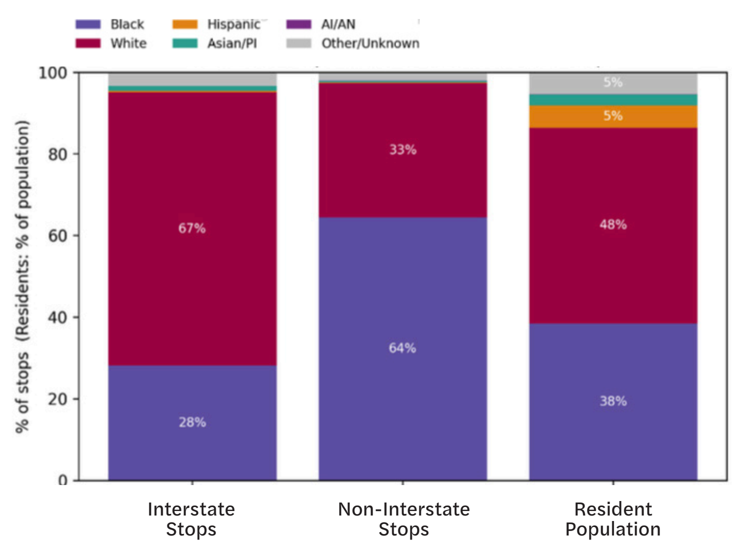
Of the 403,037 motor vehicle stops we analyzed, 47,838 of them (11.9%) were on interstates. Of those, 47,442 (99.2%) were resolvable to correct GPS coordinates using the methods described in the main text (pages 5-7).

What we see for interstate stops is that, uniquely, more White people are stopped (67%) than Black people (28%). The ratio is nearly reversed for all other motor vehicle stops (33% White vs 64% Black).

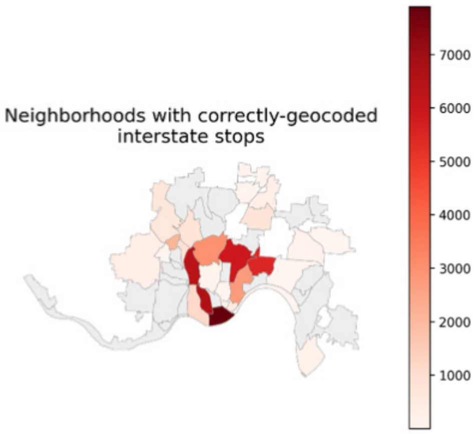
Interstate Stops, Correct Geocode (n=47,442)

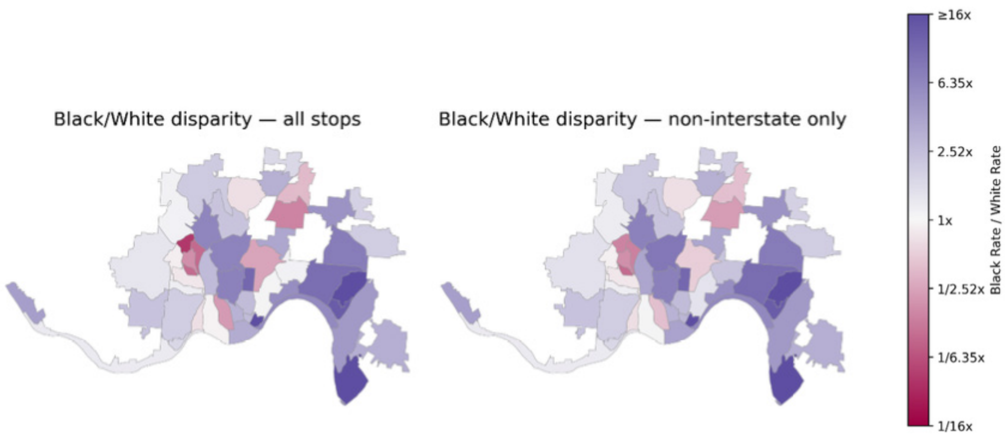


Interstate Stops, Alone vs Non-Interstate Stops

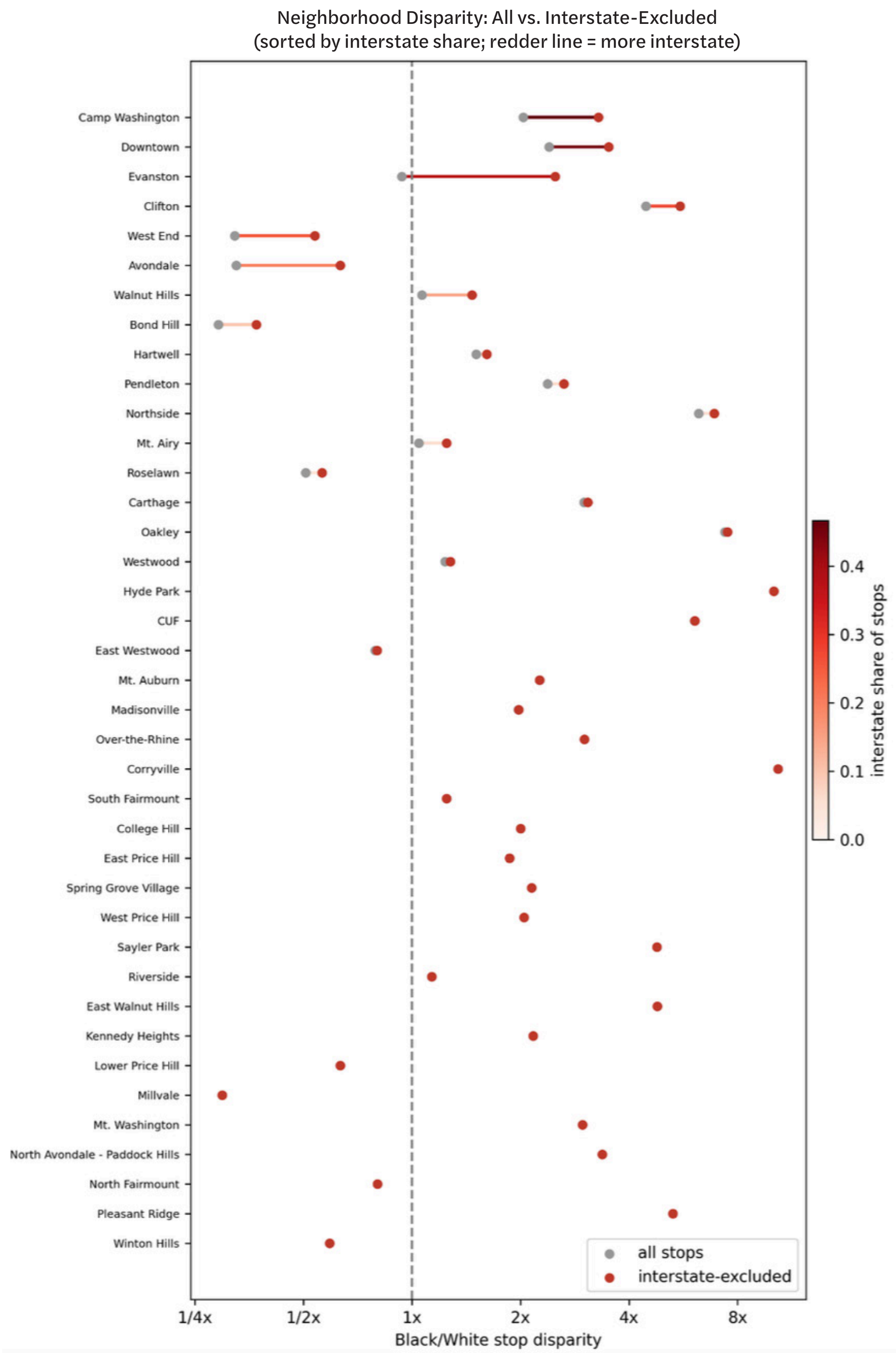


Removing interstate stops from the neighborhood analysis, however, increases neighborhood-level disparities against Black people. Here are the maps (compare to Figure 6 (page 13) and Figure 8 (page 15) of the report):



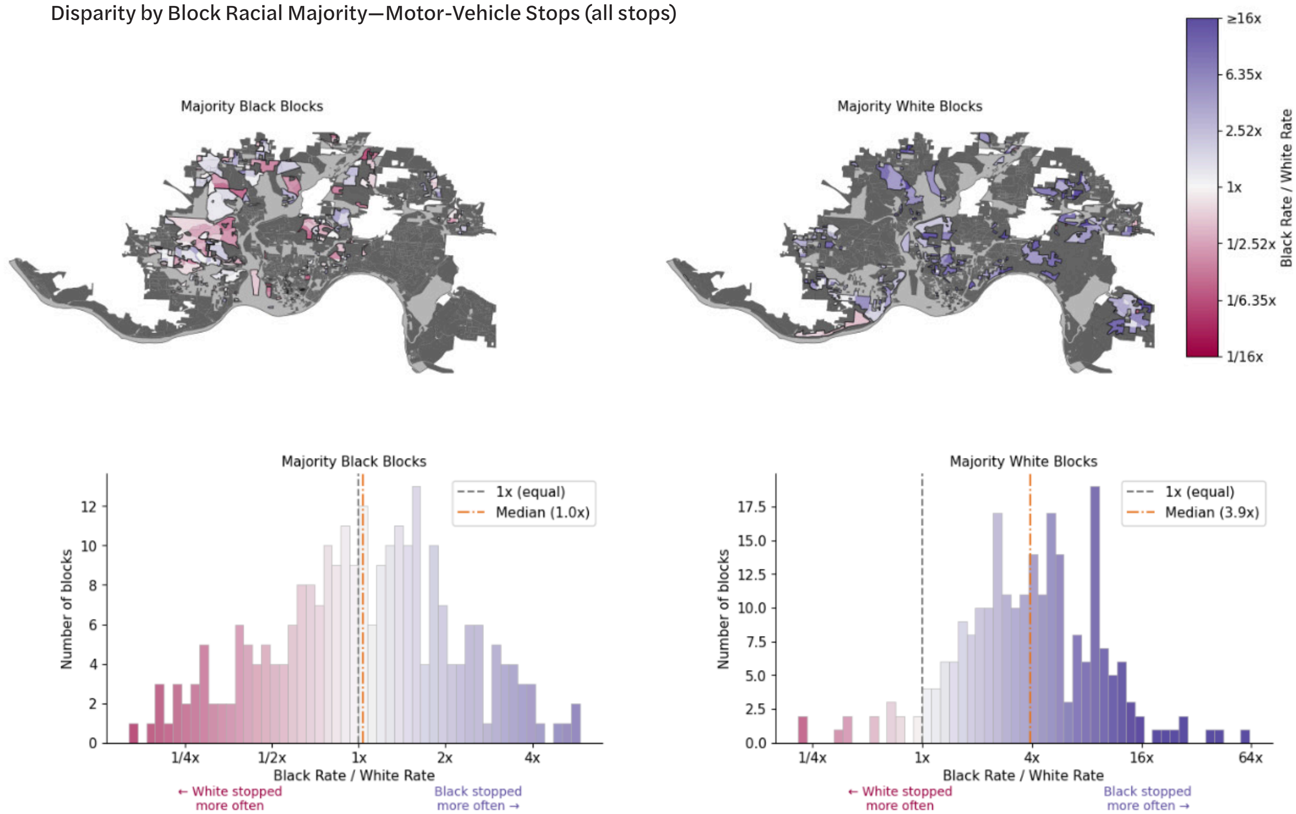


And here are the disparities for each neighborhood including interstates (gray) and excluding them (red). **In nearly every neighborhood, the Black disparity increases or stays the same**.



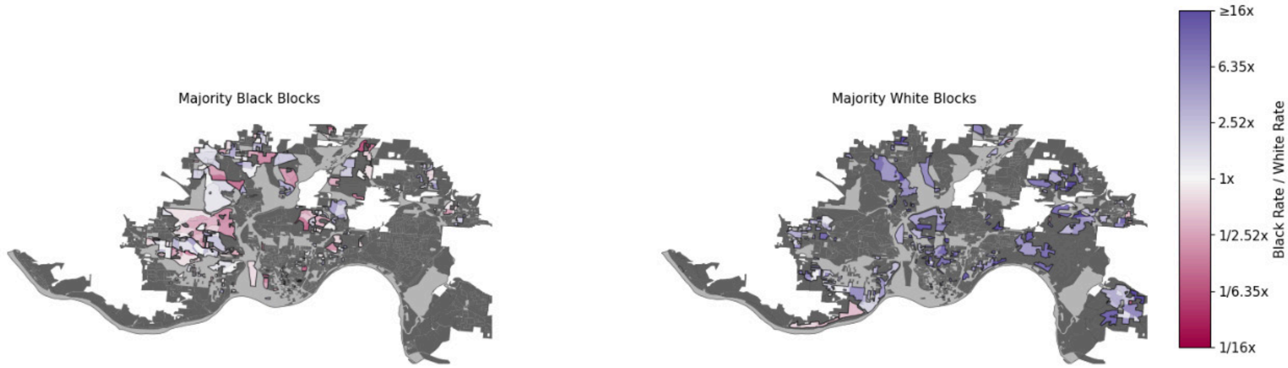
The results of our geographic analyses change very little when excluding interstate stops. For example, the following charts include interstate stops (Figure 9 on page 16 of the report).

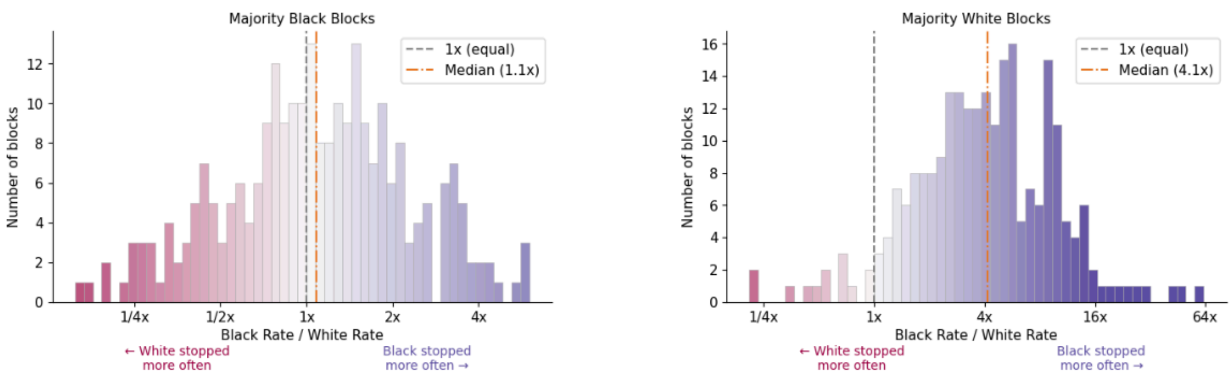
Disparity by Block Racial Majority—Motor-Vehicle Stops (all stops)



While the maps and charts below *exclude* interstate stops:

Disparity by Block Racial Majority—Motor-Vehicle Stops (interstate-excluded)





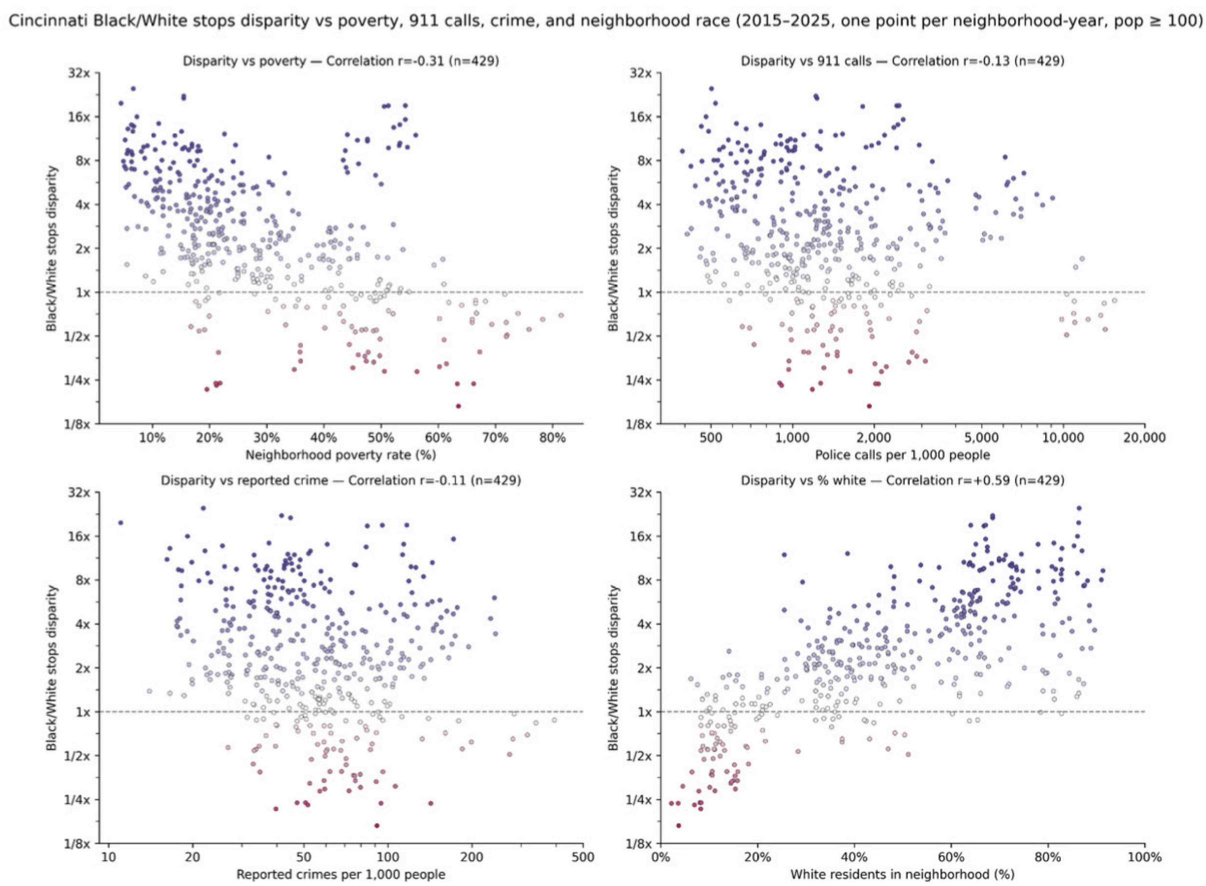
Takeaway: Because more White people than Black people are stopped on interstates, removing them from the disparity analysis makes the median neighborhood disparity higher across all years.

Poverty Rate

We added poverty rates to our neighborhood analysis as a potential predictor of stop disparities, in addition to the crime rates and racial composition of the neighborhoods included in the report.

Poverty rate is a stronger predictor of racial disparities in police stops than crime rates, but poverty is still a weaker predictor than racial composition.

Note: For 911 calls data details, see next section.



When performing regression analyses on stop disparities and neighborhood % White, poverty rate, and crime rate, either alone or together with the other two factors, a striking trend emerges. **The whiteness of a neighborhood is the strongest predictor in all cases**. Poverty rate on its own is a significant predictor, but that vanishes when racial composition is added.

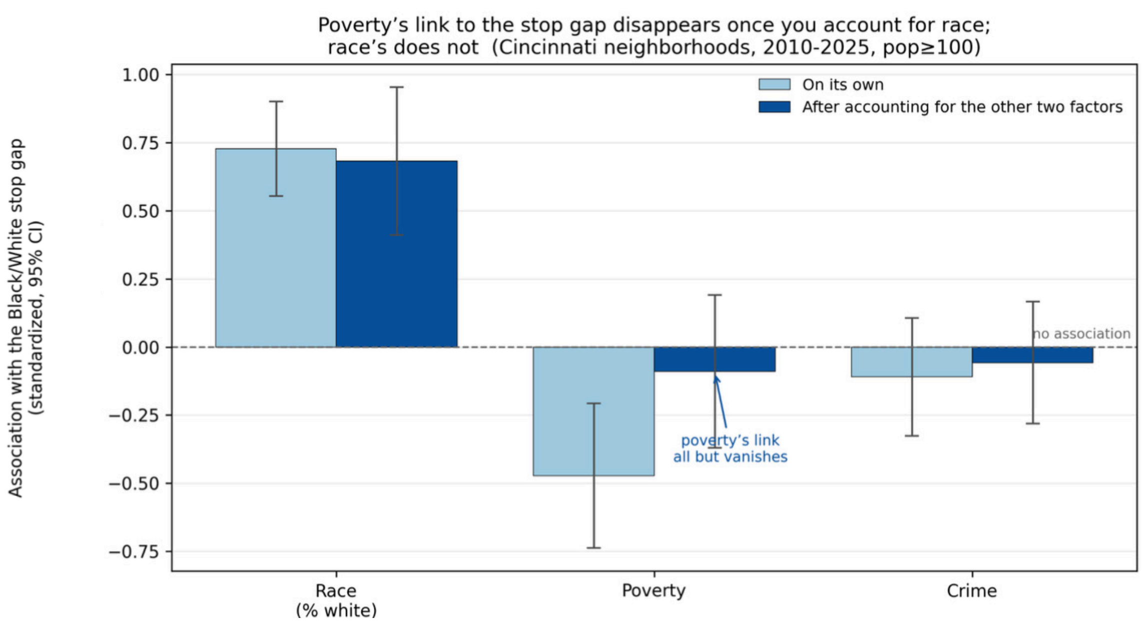
Note: Poverty rate's significance disappearing means that the poverty rate adds no additional information as a predictor of stop disparities than is already captured by using neighborhoods' racial demographics alone.

We fit an Ordinary Least Squares regression:
log(disparity) ~ z(pct_white) + z(poverty_rate) + z(total_crime) + C(year)

- **Unit**: one neighborhood-year (Cincinnati SNAs, 2015–2025), filtered to population ≥ 100 (and population ≥ 500 as a robustness sample).
- **Outcome**: log(disparity): log of the Black/White stop rate ratio
- **Predictors**: the three neighborhood axes, each z-scored (standardized to mean 0, SD 1) so coefficients are directly comparable as standard-deviation effects.
- **C(year)**: year fixed effects, absorbing city-wide year-to-year shifts.
- **Standard Errors**: clustered by neighborhood.

What this tests: Holding the year constant, how does the Black/White stop disparity move with citizen call demand, poverty, and racial composition when all three compete for the same variance?

By running the regression with a single predictor (e.g. poverty rate), the "on its own" (light blue) estimate in the plot below is produced. The "after accounting for the other two factors" (dark blue) estimates how much power that predictor has in predicting stop disparities when the model has access to all three pieces of information (neighborhood demographics, poverty rate, and crime rate).

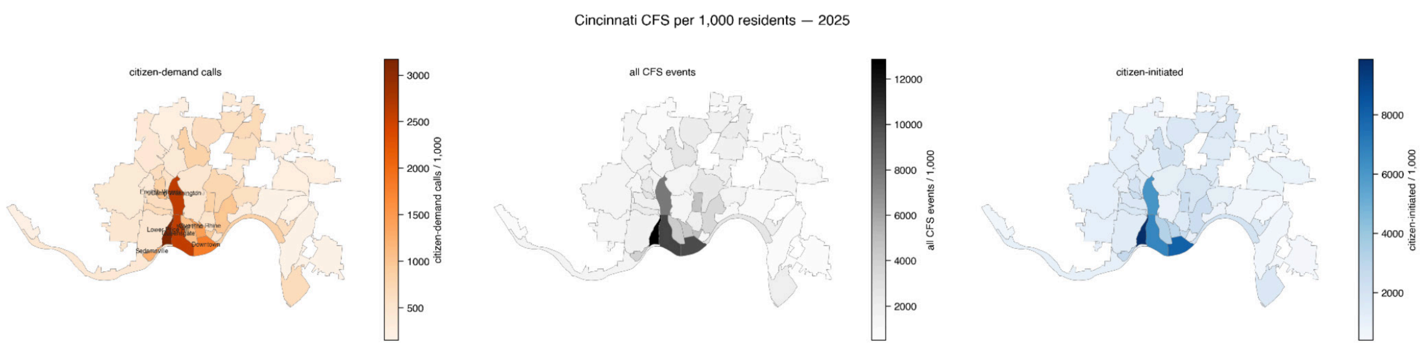


Takeaway: We only find two of these three predictors, neighborhood demographics and poverty rates, to be significantly associated with police stop disparities. Neighborhood demographics are strongest, followed by poverty rate. However, poverty rate becomes insignificant when accounting for the other two factors. This means that the poverty rate as a predictor of stop disparities adds no additional information than is already captured by using percent white alone. **Crime is not significant alone or in combination**.

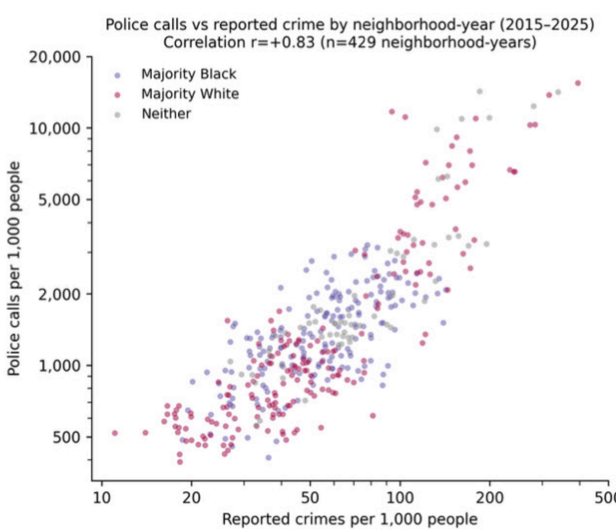
Calls for Service (911 Calls)

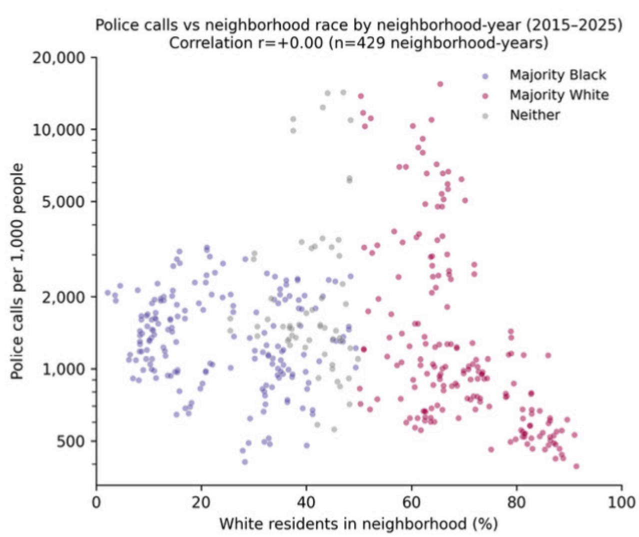
Upon CPD's and the City's request, we analyzed citizen-initiated calls for service (911 calls). We pulled the data from the Cincinnati PDI dataset on the open data portal: https://data.cincinnati-oh.gov/safety/PDI-Police-Data-Initiative-Police-Calls-for-Servic/gexm-h6bt, which has 2015 as the first full calendar year of data available.

The CFS dataset includes officer-initiated "calls". We exclude those from the analysis, as they do not capture citizen demand in the way that was part of this request. A large proportion of the officer initiated "calls" are in fact traffic stops. Including traffic stops here would be circular: it would double-count them as both cause and effect, and diminish the explanatory power of 911 calls as a potential factor that could explain stop disparities.



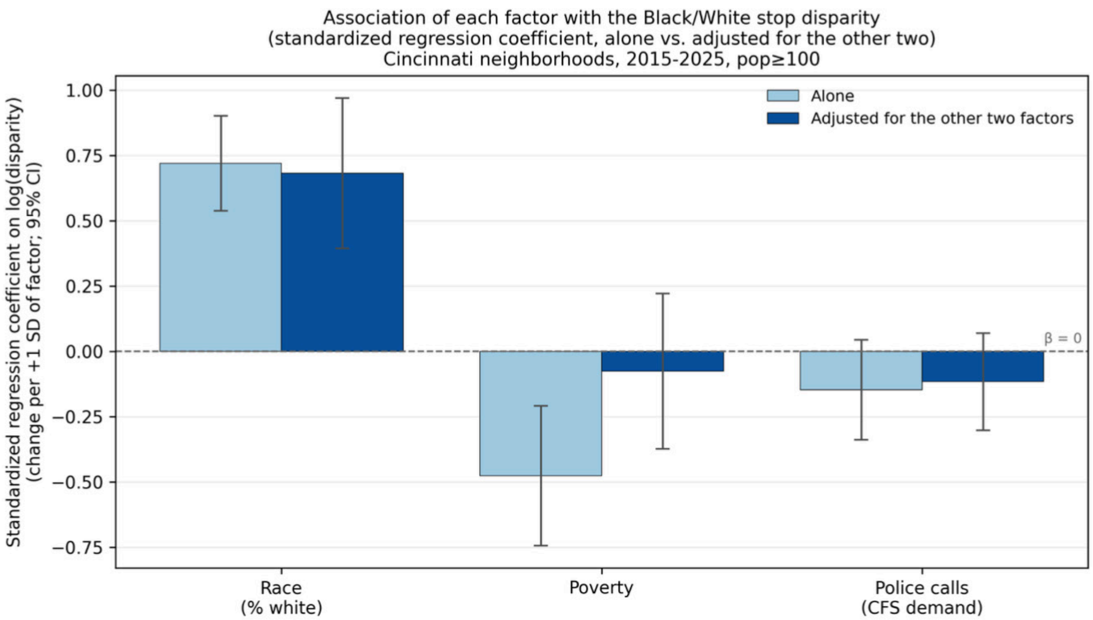
911 calls are very highly correlated with total crime rate (left). In Cincinnati, 911 calls are not correlated with how white the neighborhood is (right). Note for the plot on the right, a neighborhood can have fewer than 50% White residents and may or may not be majority Black, because other racial groups are present, to varying proportions.





It is therefore unsurprising that 911 calls have a very similar correlation with police stop racial disparities, as compared to crime rates (see figure in “Poverty” section).

Repeating the OLS regression above but swapping calls for service in for total crime, very similar results emerge:



Takeaway: Similar to the results of the previous section on poverty rates, we find that the same two predictors, neighborhood demographics and poverty rates, are significantly associated with police stop disparities. 911 call rates have very slightly more predictive power than crime rates, but are still not a significant predictor when neighborhood demographics are taken into account.

Census Populations: People Who Identify as Multiple Races/Ethnicities

The Census treats “Hispanic” as an ethnicity than may or may not be included with all other races (i.e. Black, White, Asian, American Indian / Alaska Native, Native Hawaiian / Pacific Islander). The Census also allows for people to be recorded as having multiple races. For example, one person can be recorded as both White and Hispanic. Another can be recorded as Black and White multi-racial.

Datasets like the contact cards, however, do not allow for multiple races and/or ethnicities. An individual can be recorded as White or Hispanic, but not both. Similarly, an individual cannot be recorded as Black and White multi-racial – they are coded as either Black or White.

Therefore, we have to make a choice in how we map these slightly misaligned datasets. Any choice we make, we must apply consistently to every race/ethnicity in the data. There are 3 options for this:

1. Treat Hispanic as its own “race”, meaning that other races do not include Hispanic populations, and do not include multiracial populations.
    a. In practice: using White “alone” as one category, Black “alone” as another, and “Hispanic, any race” as another, and not including multiracial counts.
2. Allow for multiracial populations, but keep Hispanic separate.
    a. In practice: using the sum of all White non-Hispanic “alone” and White + multiple race categories as “White”, the sum of all Black non-Hispanic “alone” and Black + multiple race categories as “Black”, and “Hispanic, any race” as another. Multiracial counts are included in “White”, “Black”, etc in this version.
3. Allow for multiracial populations, and include Hispanic in those counts.
    a. In practice: using the sum of all White non-Hispanic AND HISPANIC “alone” and White + multiple race categories as “White”, the sum of all Black non-Hispanic AND HISPANIC “alone” and Black + multiple race categories as “Black”. Multiracial counts are included in “White”, “Black”, etc in this version. “Hispanic” can be used as a separate category, but doing so double-counts all the White Hispanic, Black Hispanic, and other Hispanic populations.

All 3 approaches are valid, and also imperfect in their own unique ways. We chose #1 because it means no double-counting of populations, and seems the closest to the contact card data we are trying to harmonize with (where Hispanic is separate and there’s no multiracial option).

Now, for how this impacts the disparities.

Using 2020 Decennial data on 2020 stop counts:

Definition for Black and White	Black population	Black population change vs report	White population	White population change vs report	Black stops/1k	White stops/1k	Black/White Stop Disparity	vs in report
Alone, not Hispanic (in report)	124,654	—	145,100	—	73.1	23.2	**3.15x**	—
Alone plus Hispanic	125,443	+789	147,532	+2,432	72.6	22.8	**3.18x**	+1.0%
Alone plus Hispanic plus multiple race	134,093	+9,439	163,367	+18,267	67.9	20.6	**3.30x**	+4.7%

Using 2024 ACS data on 2024 stop counts:

Definition for Black and White	Black population	Black population change vs report	White population	White population change vs report	Black stops/1k	White stops/1k	Black/White Stop Disparity	vs in report
Alone, not Hispanic (in report)	112,931	—	149,930	—	102.1	29.3	**3.48x**	—
Alone plus Hispanic	113,535	+604	152,591	+2,661	101.6	28.8	**3.53x**	+1.2%
Alone plus Hispanic plus multiple race	125,982	+13,051	176,662	+26,732	91.6	24.9	**3.68x**	+5.6%

In both the 2020 and 2024 tables, we see that adding Black Hispanic populations to the Black category and White Hispanic populations to White category leads to a roughly 1% increase in the overall Black/White stop disparity. This is because in both cases, there are more White Hispanic people in Cincinnati than Black Hispanic people.

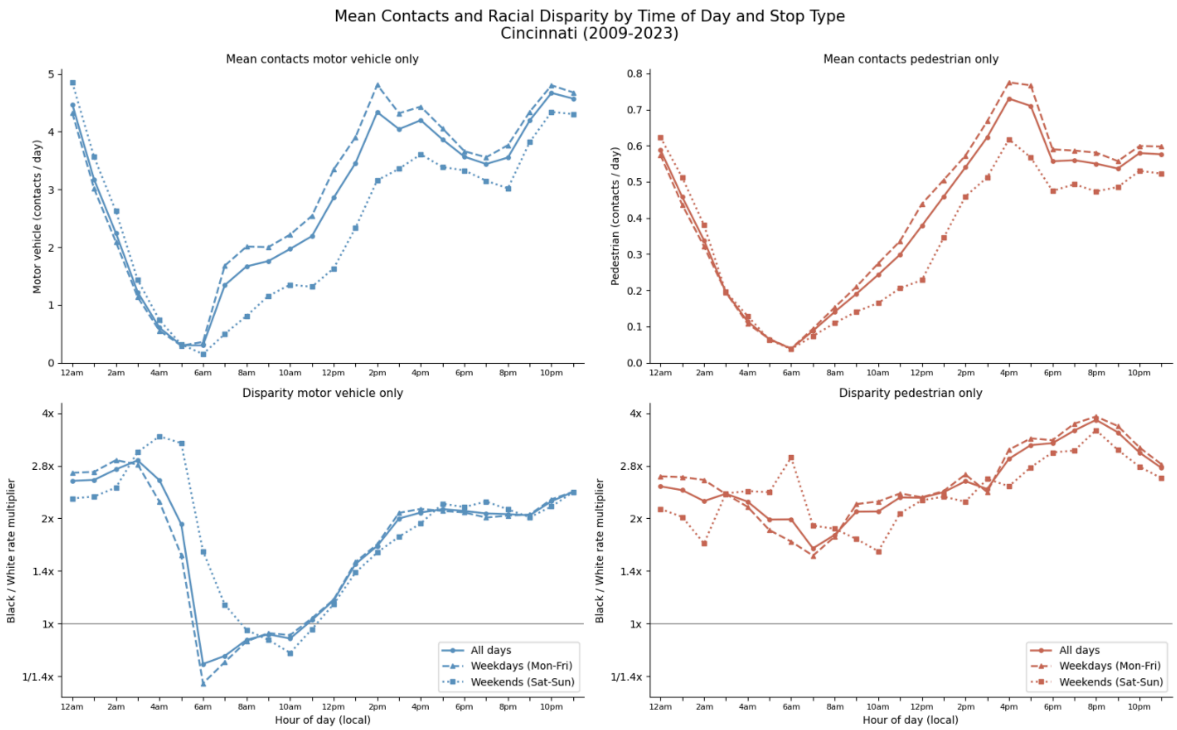
Similarly, adding multiple race populations to the Black and White categories leads to a roughly 5% increase in the overall Black/White stop disparity. Again, this is because there are more people of multiple races that marked White as their first race on the Census compared to those who marked Black as their first race.

Takeaway: If we were to include mixed race / Hispanic people in our analysis, the reported Black / White police stop disparities would worsen.

Census Populations: Using all Years vs 2020 Data

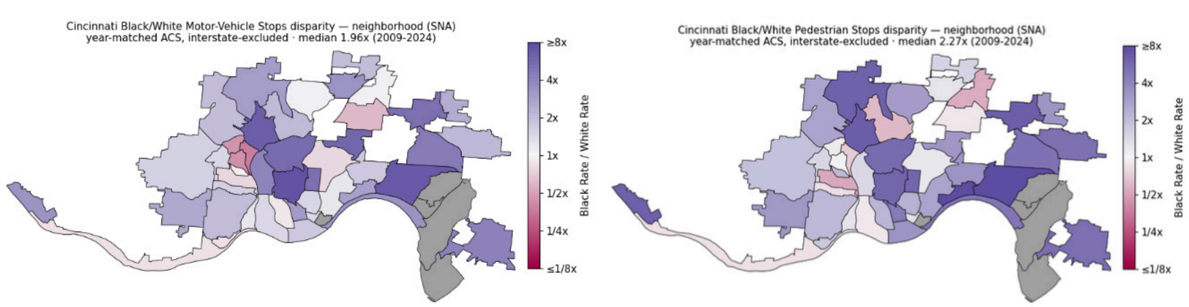
Time of Day Analysis

In the primary report, our time of day analysis was done with 2020 Census population data. Here we reproduce it with ACS 2009-2023 years' population data. Because this analysis is not contingent on year-on-year differences, the results are the same.



Neighborhood-Level Analyses Using Tract Data

The city requested that we perform the neighborhood-level mapping analysis using tract-level data from the 2009-2024 Census ACS population data. The new maps do not include interstate stops, for reasons discussed above.



Block-Level Neighborhood Analyses

The city requested that we perform the block-level neighborhood mapping analysis using neighborhood estimates for all years where Census data is available, not only 2020 Census blocks. Because blocks are only available from the Decennial Census, we use this assignment:

- 2000 Census blocks for 2009 contact card data
- 2010 Census blocks for 2010-2019 contact card data
- 2020 Census blocks for 2020-2025 contact card data

We chose this pattern of assignment because, for example, 2010 census blocks were not known in 2009.

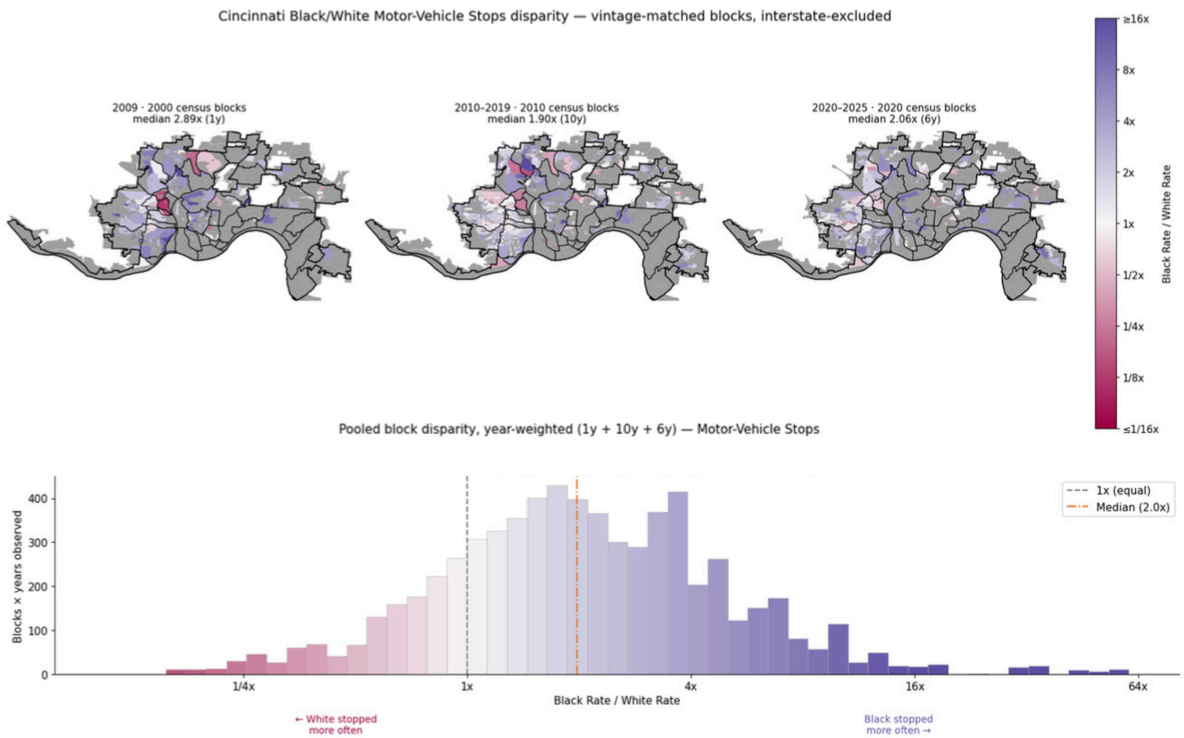
The new maps do not include interstate stops, for reasons discussed above.

Because stop data is now spread across 3 different decades' Census blocks, to mitigate the effects of noise, we implemented an additional filter to only show blocks with 5 or more stops. Therefore, fewer blocks are included in any single decade's map, compared to the 2020-block-only analysis.

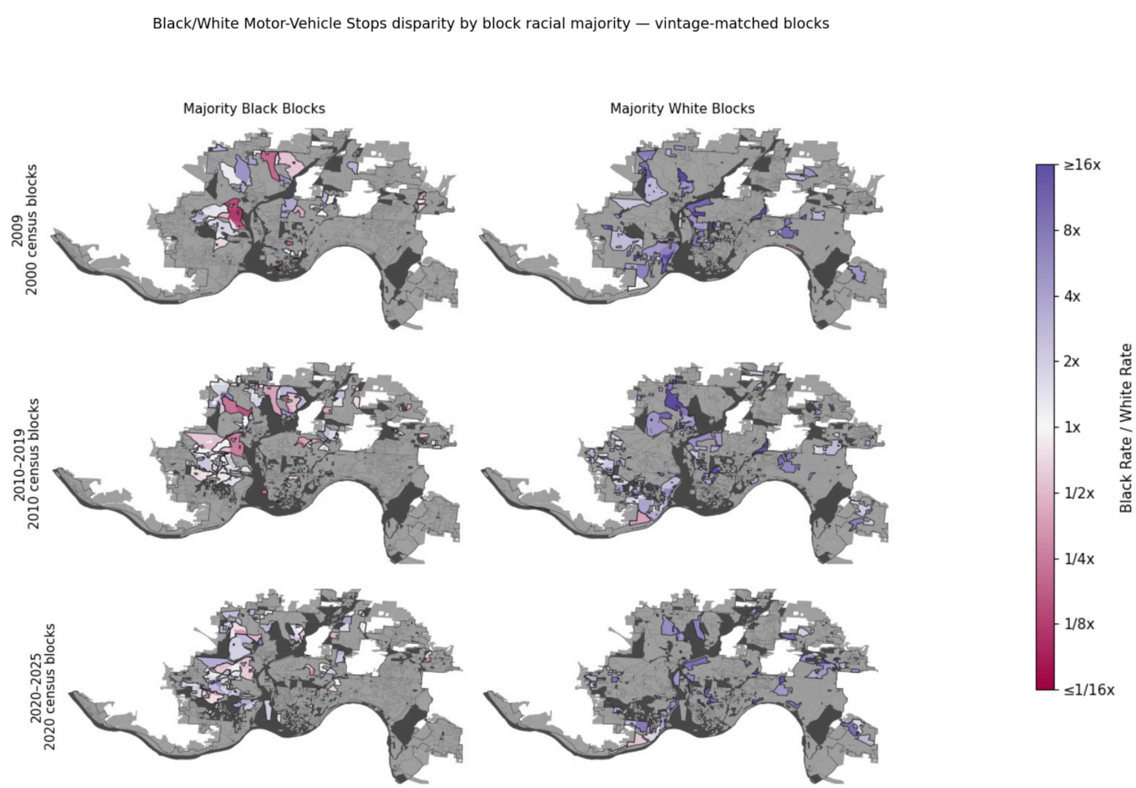
The median block-level motor vehicle stop disparity was 1.9x in the report (figure 8, page 15), and in this version of the analysis is 2.0x. In majority White neighborhoods, it was 1.1x (figure 9, page 16), and here is 1.2x. In majority Black neighborhoods, it was 3.7x (figure 9, page 16), and here is 3.4x.

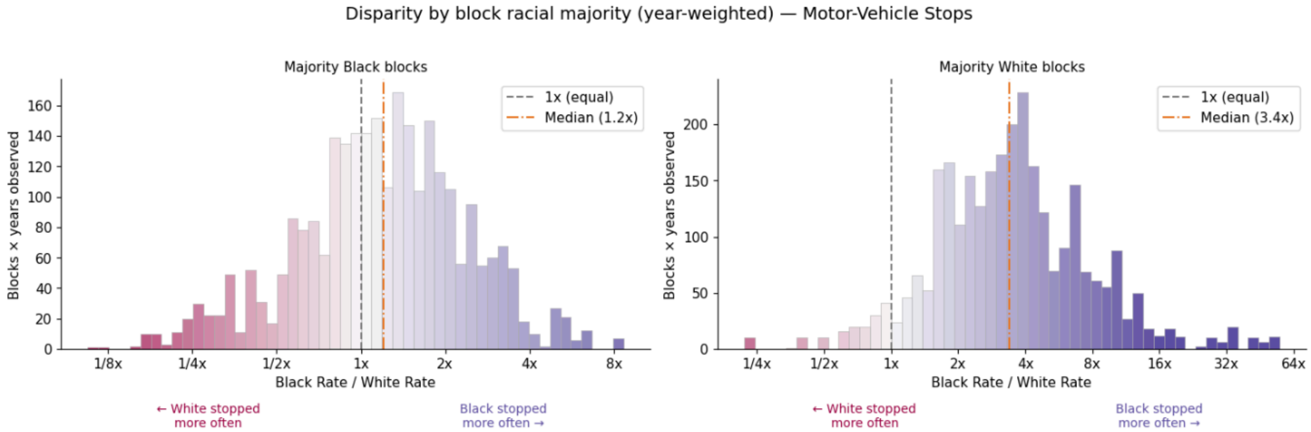
The median block-level pedestrian stop disparity was 2.1x in the report (figure 10, page 17), and in this version of the analysis is 2.0x. In majority White neighborhoods, it was 1.3x (figure 11, page 18), and here is 1.0x. In majority Black neighborhoods, it was 4.5x (figure 11, page 18), and here is 3.3x.

Takeaway: When examining blocks citywide, the report disparities and those reported here are very similar. Examining majority White and majority Black blocks is made more difficult under this analysis because of the lower statistical power when splitting stops into 3 decade bins. However, the main result stands: majority Black blocks show little to no stop disparity, while majority White blocks show disparities higher than the city average, over 3x.

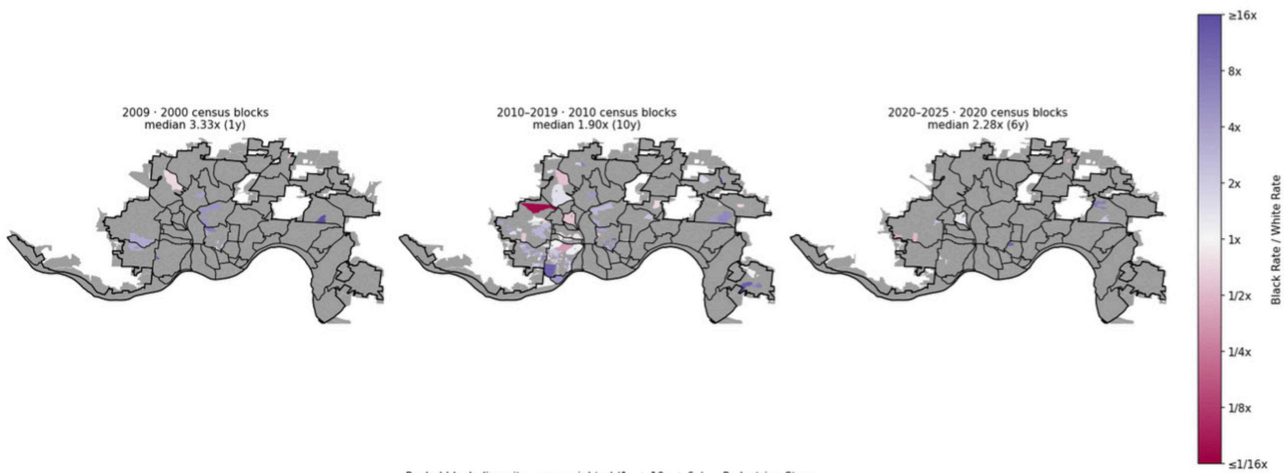


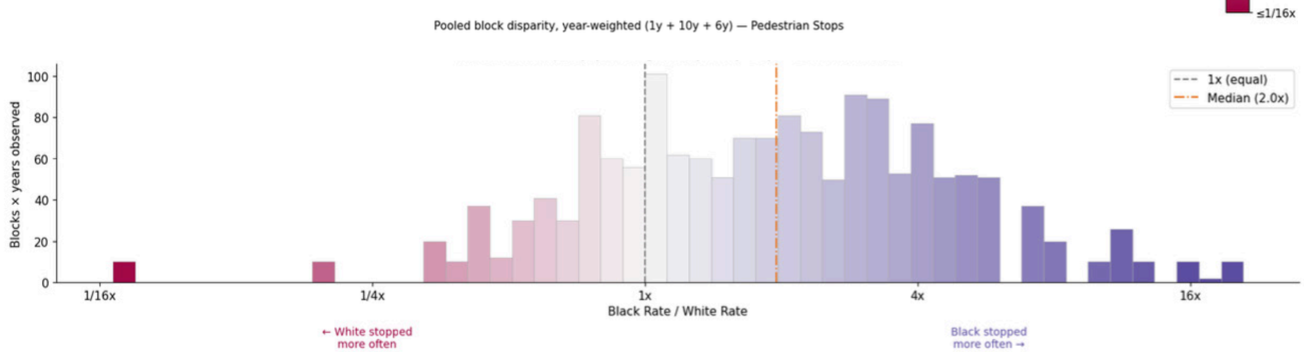
We also reproduced the majority Black/White neighborhood maps and distributions.

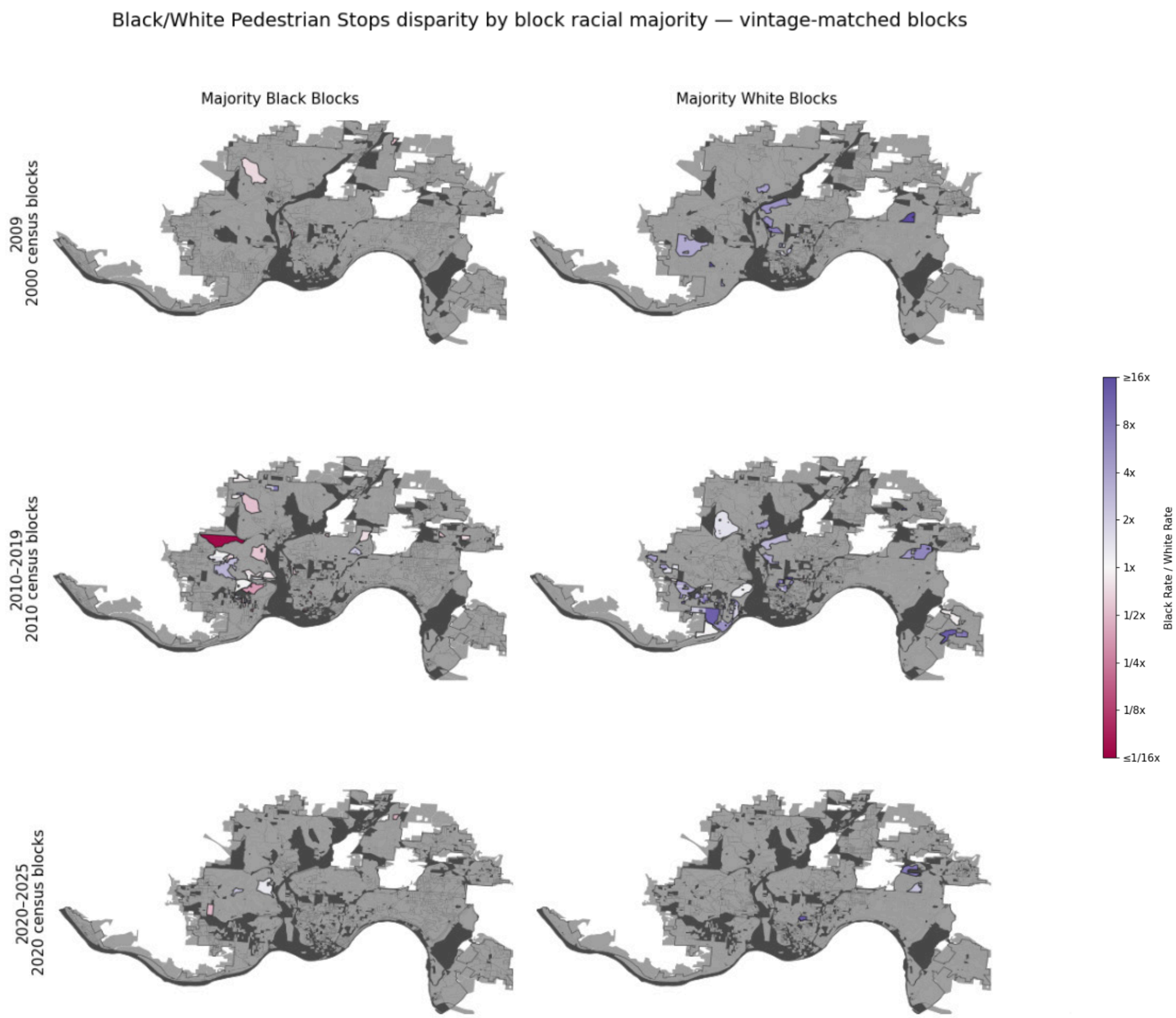


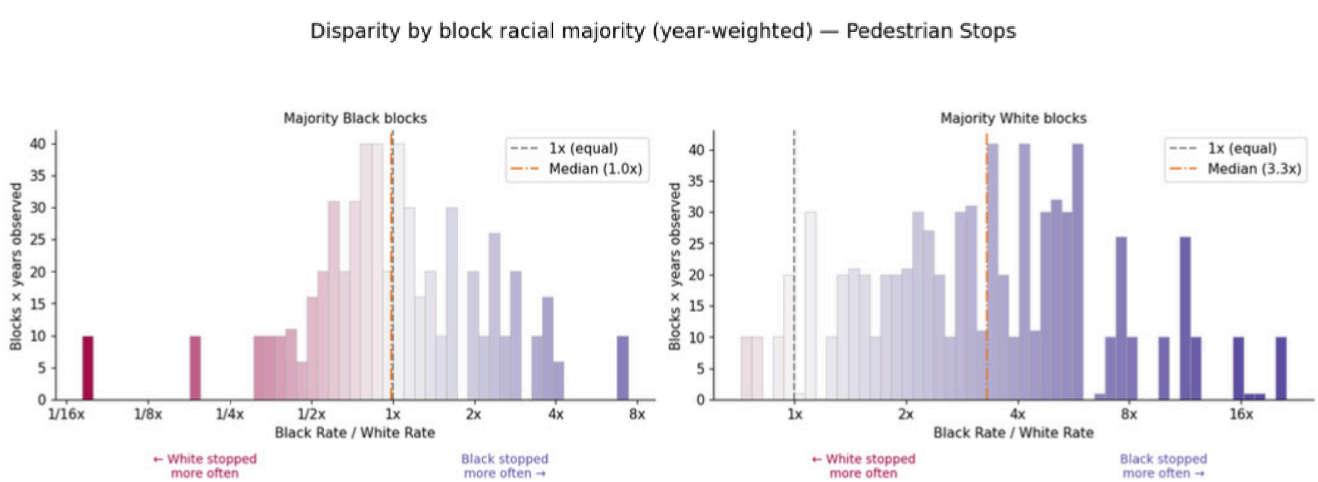


Above: maps and distributions for motor vehicle stops
Below: maps and distributions for pedestrian stops.






Black/White Pedestrian Stops disparity by block racial majority — vintage-matched blocks
Majority Black Blocks
Majority White Blocks
2009
2000 census blocks
2010–2019
2010 census blocks
2020–2025
2020 census blocks
≥16x
8x
4x
2x
1x
1/2x
1/4x
1/8x
≤1/16x
Black Rate / White Rate


Disparity by block racial majority (year-weighted) — Pedestrian Stops
Majority Black blocks
Majority White blocks
Blocks × years observed
1x (equal)
Median (1.0x)
Median (3.3x)
Black Rate / White Rate
1/16x
1/8x
1/4x
1/2x
1x
2x
4x
8x
16x
← White stopped more often
Black stopped more often →

Alternative Benchmarks: Incorporating Additional Information to Calculate Adjusted Disparities

A "benchmark" refers to the reference point used to put a measurement, such as the number of police stops, into context. Benchmarks help answer questions such as, "is this number of stops high or low?" The simplest and most commonly used benchmark is the population.

Rates are calculated by dividing the measurement (e.g., police stops) by the benchmark (e.g., population). Disparities are then calculated by comparing the rates of two different groups, usually as a ratio. In our report, the measurement was police stops, the benchmark was the residential population, and the disparities we reported compared police stop rates for Black and White residents of Cincinnati.

We chose residential population as our benchmark primarily because it centers the experiences of Cincinnati residents. Other benchmarks commonly used in the literature incorporate additional information about the circumstances that may lead to police contact. Population-based disparities therefore capture the overall difference in how frequently police stops occur for different racial groups, regardless of which underlying factors contribute to those differences.

Alternative benchmarks attempt to estimate more precisely the populations exposed to police contact. Broadly speaking, most alternative benchmarks can be understood as pursuing one of two approaches: (1) incorporating police- or justice system-generated data to estimate the populations most likely to come into contact with police, or (2) estimating who was physically present in places where police activity occurs.

Upon request, we implemented two additional benchmarks, one from each of these approaches to more accurately estimating police exposure:

1. Weighting local residential populations by the number of local 911 calls placed
2. Adjusting the daytime population to reflect worker population, using surveys of where people live and work

(1) 911-weighted population benchmark

A 911-calls benchmark applied as a neighborhood-common weight, as suggested by the CPD:

$$\text{Black metric}_A = \frac{\text{Black stops}_A}{\text{Black pop}_A \cdot d_A}, \qquad \text{White metric}_A = \frac{\text{White stops}_A}{\text{White pop}_A \cdot d_A}, \qquad d_A = \frac{\text{reactive calls}_A}{\text{total pop}_A}$$

cancels out of the Black/White stop-rate ratio. Inside a place the weight multiplies both races' denominators identically and divides away:

$$\frac{\text{Black metric}_A}{\text{White metric}_A} = \frac{\text{Black stops}_A/(\text{Black pop}_A\, d_A)}{\text{White stops}_A/(\text{White pop}_A\, d_A)} = \frac{\text{Black stops}_A/\text{Black pop}_A}{\text{White stops}_A/\text{White pop}_A}$$

Therefore, we must weight at the census-block level, then aggregate the exposed population up to the neighborhood:

$$\text{rate}^*_{black} = \frac{\sum_b S_b^{black}}{\sum_b P_b^{black}\, w_b}, \qquad \text{rate}^*_{white} = \frac{\sum_b S_b^{white}}{\sum_b P_b^{white}\, w_b}$$

Taking the ratio, the algebra collapses to

$$\boxed{\text{disparity}^*_N = \text{disparity}_N \cdot \frac{\bar{w}_{white}}{\bar{w}_{black}}} \qquad \bar{w}_r = \frac{\sum_b P_b^r\, w_b}{\sum_b P_b^r}$$

the population-benchmark disparity times the ratio of the average 911 exposure around White residents to that around Black residents, within the neighborhood. The factor is not 1 whenever Black and White residents occupy different blocks with different call activity. If Black residents cluster in higher-911 blocks, $\bar{w}_{white}/\bar{w}_{black} < 1$ and the benchmark shrinks the disparity (more of it is "expected" given exposure); the reverse grows it. If the two races share blocks, the weights cancel again and nothing moves.

(2) Daytime worker-adjusted population benchmark

LODES is the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics dataset, a free Census Bureau download.* We use LODES8 (2020-block geography, state `oh` (Ohio), all-jobs all-segments (`S000`, `JT00`).

* https://lehd.ces.census.gov/data/lodes/

Workplace Area Characteristics (WAC), counts each job at the block where the work happens. It answers "who works here?": the racial mix of the people whose workplace is in a block, whether or not they live nearby. In short: the daytime, on-the-clock crowd a place pulls in. This is our **daytime-worker ambient mix.

Residence Area Characteristics (RAC), the same jobs and the same race columns, but counted at the block where the worker lives. It answers "who lives here and holds a job?": a block's employed residents, regardless of where they actually work. Since most of them commute out each morning, RAC is essentially the working residents who leave a neighborhood during the day. We subtract this when turning a residential headcount into a daytime one.

The LODES daytime denominator only describes who is present during work hours, so applying it to night stops would be meaningless. To make the residential and LODES-weighted disparities directly comparable, we hold the numerator fixed and restrict both the LODES and pure residential population-benchmarked disparities to the same stop set: the weekday daytime window (Mon-Fri 9am-4pm) where the daytime-worker denominator is valid (the same window used for the sec-7 maps). We also excluded stops on federal holidays.

We therefore want a daytime population benchmark:

$$\text{daytime}_i^r = \underbrace{\text{res}_i^r}_{\text{residents (Census P2)}} - \underbrace{\text{RAC}_i^r}_{\text{working residents who commute out}} + \underbrace{\text{WAC}_i^r}_{\text{workers who commute in}} \qquad (\text{clipped at } \geq 0)$$

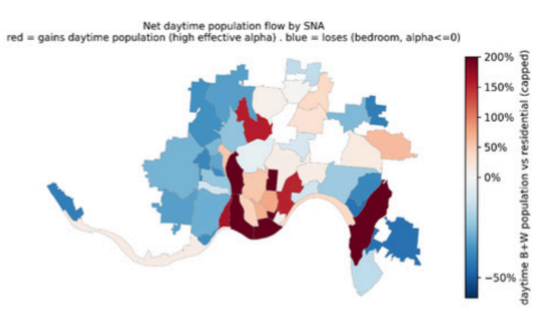
The within-place benchmark disparity:

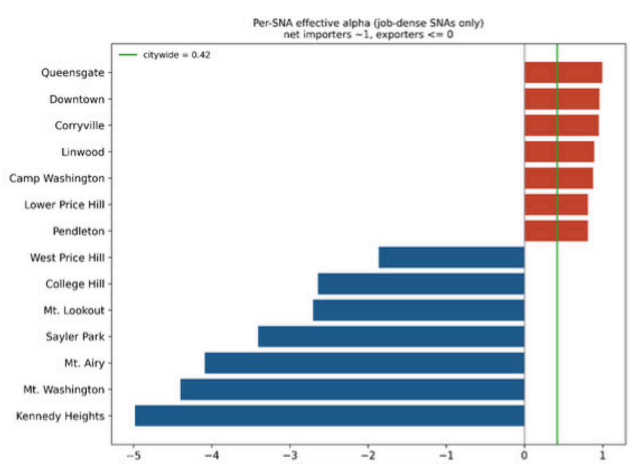
$$\text{disparity}_i = \frac{\text{stops}_i^B / \text{daytime}_i^B}{\text{stops}_i^W / \text{daytime}_i^W}$$

The LODES-ambient-weighted odds ratio (OR), Citywide form:

$$\text{OR}_{\text{ambient}} = \frac{\sum_i \text{stops}_i^B / \sum_i \text{daytime}_i^B}{\sum_i \text{stops}_i^W / \sum_i \text{daytime}_i^W} = \frac{\text{obs}^B / \text{obs}^W}{\text{daytime}^B / \text{daytime}^W}$$

Here we see neighborhood population changes due to LODES commute patterns:





Comparing the Benchmarks

The disparities in the main text of the report (a residential population-based benchmark) are reproduced here in dashed light blue. The 911-exposure adjusted odds-ratio is in orange, and the LODES worker-adjusted odds-ratio is in dotted red. For reference, the dotted gray line is the disparity (residential population-based benchmark) only using stops in the same workday hours as used in the LODES worker-adjusted odds-ratio benchmark.

Both of these alternative benchmarks were requested of us, and we produce them here for reference.

Takeaway: Racial disparities increase when taking daytime worker populations into account, and decrease when taking 911 calls into account. Regardless, racial disparities in police stops still persist, even when using calls for service or daytime worker adjustments.

Black/White stop rates and disparity under three benchmarks — population, 911-exposure (CFS), LODES worker-adjusted (weekday daytime)