Stop and Frisk Around the Country*

David S. Abrams and Priyanka Goonetilleke†

December 31, 2025

Abstract

Like most locally governed activities, police stops are evaluated, if at all, using data from a single municipality. This paper aggregates data on over 8 million pedestrian and vehicle police stops from 16 U.S. cities between 2019 and 2023 to better understand how the widely used police tactic varies by place, time, and race. We find immense variation in the implementation of these policies across cities, something that has not been previously highlighted in the literature. Stop rates vary across cities by almost two orders of magnitude, well in excess of inputs like funding and size of police force vary far less, or outcomes like different measures of crime.

Contraband discovery rates (hit rates) for pedestrian stops are consistently low, with gun hit rates never exceeding 10% of frisks in any city. Consistent with optimizing models of policing, hit rates rise over time as frisk rates fall substantially. However, this result is concentrated in gun contraband, and for other types - mostly drugs - hit rates do not vary much even with vast declines in frisks, suggesting police are not optimizing for other types of contraband. This supports the notion that frisks are consistent with the law, which requires they be based on suspicion that an individual is armed and dangerous. Consistent with prior work, there are substantial racial disparities in all examined cities, with Blacks frisked as much as 10 times more frequently than Whites in some locations. Taken together, these facts point to a standard practice that seemingly has no standards, given the massive variation across the country. This suggests there are potentially large gains in efficiency and fairness from sharing best practices and nationwide data collection on police stops.

*This paper benefited greatly from feedback at the Duke Empirical Crime Roundtable. We thank Daniel Bronfman, Neha Krishna, Louis Li, Max Speil and Nicholas Wu for outstanding research assistance.

†Abrams: University of Pennsylvania. Goonetilleke: Northwestern University

1 Introduction

Across the United States, police departments engage in proactive policing tactics in which officers attempt to preempt criminal activity rather than simply respond to it. The most prominent of these tactics is Stop and Frisk (also known as Stop, Question, Frisk or SQF), which increased greatly in use in the 2000s and has generated controversy and litigation for over two decades (Weisburd & Majmundar 2018). Under this practice, police officers may briefly detain individuals (a "stop") based on reasonable suspicion of criminal activity, and if they suspect the person is armed, conduct a pat-down search (a "frisk") for weapons. While law enforcement officials often cite it as an essential tool for crime prevention and weapon recovery, the practice has faced sustained criticism and legal challenges, particularly regarding racial disparities in its application. The Department of Justice, the ACLU and other organizations have brought cases against numerous departments over their use of stop and frisk policy, leading to cases such as *Bailey v. City of Philadelphia* and *Floyd v. City of New York*.

Because most policing data is recorded at the local level and has historically not been aggregated nationally, there is little work that attempts to get a broad overview of SQF across major U.S. cities. Recently data availability has increased, allowing us to aggregate information on over 8 million stops from 16 large cities from 2019 to 2023 in this paper. This allows for an initial look at how much variation there is in the tactic's use and efficacy.

We find immense variation in the rates of stops and frisks across cities – by nearly two orders of magnitude. These differences are not correlated with differences in crime or poverty rates which differ by at most a factor of three. They also vary far more than do police expenditures or manpower, which differ by at most a factor of four across the cities we examine. We also explore the productivity of frisks and find a great deal of variation along this dimension as well, with success rates in finding any contraband from frisks ranging from roughly 75% in the most effective departments to less than 20% in the least effective ones. We collect a large amount of data on city, crime and police characteristics and do not find strong correlations with stop and frisk rates or productivity. For firearms alone, discovery rates are substantially lower, reaching only 2% in San Diego in 2023.

Much of the economics literature that has explored police stops uses some for of an optimizing model of police behavior, where police are assumed to maximize hit rates - the share of frisks that yield contraband. While nothing in this paper is causal, we find evidence consistent with these models when considering gun hit rates. In particular, as frisks dropped substantially between 2019 and 2023, we find increases in gun hit rates in almost all cities. However, when contraband is not restricted to guns, but may include drugs or stolen property, we find little increase in hit rates over this same time frame. This suggests that police officers are not seeking to optimize non-gun hit rates, consistent with the law, which only allows frisks for officer protection.

We document the well-known phenomenon that stop rates of non-White individuals are substantially higher than those of White subjects, by as much as an order of magnitude in our data. So, too, do we observe low overall discovery rates of contraband across all of the cities we examine, in some cases as low as 2% as in frisks for guns in San Diego.

These facts beg the question of why there is so much variation in stop and frisk tactics. Is this a phenomenon unique to policing or is it a broader feature of services supplied by municipalities, where knowledge diffusion may not be as great or as rapid as in markets with non-government providers? We cannot answer all of these questions in this paper, but begin the journey down this road by presenting new data about stop and frisk policing.

This paper proceeds as follows. Section 2 provides the legal background of stop-and-frisk policing in the United States, outlines a model of optimizing police behavior in conducting these searches, and reviews the relevant literature. Section 3 introduces our data and examines variations in stop-and-frisk practices across cities, analyzing how differences in city characteristics and police force attributes may explain these variations. Section 4 explores police productivity using hit rates, and looks at variation by type of contraband. Section 5 discusses implications of our findings for police policy and practice and concludes.

2 Background and Theory

The legal basis for stop and frisk stems from the 1968 Supreme Court decision of *Terry v. Ohio*. Under this decision, an officer may stop a pedestrian if the officer reasonably suspects that the person is committing, or has committed a criminal offense. To then frisk the individual, the officer must reasonably suspect that the individual is "armed and dangerous" Vehicle stops operate under slightly different rules. A vehicle stop is permitted whenever police have legal grounds to detain the vehicle and its occupants for a traffic violation. While this lower threshold makes vehicle stops easier to justify, the standards for subsequent searches are more stringent. To frisk the driver or any occupant, officers must still establish reasonable suspicion that the person is armed and dangerous. However, to search the vehicle itself, the officer needs probable cause — a higher standard than reasonable suspicion - to believe evidence of criminal activity is concealed within.

While stop and frisk has been used as a policing tactic since before the *Terry* decision, it rose to prominence in the early 2000's. Police departments argued (and continue to argue) that the tactic reduces crime. But there is little good evidence about its efficacy - which we return to below, and most of the studies that exist examine a single location.

2.1 Optimizing Models of Police Stops

Most of the literature on police stops is focused on questions of racial disparities in its application and makes use of Becker's outcome test (Becker 1968). While the focus of this paper is on heterogeneity in the use of stop and frisk along dimensions other than race, a brief review of some of this literature is still relevant, because it may provide a useful framework for considering the police problem. Assume that the objective of police officers is to detect the presence of contraband on pedestrians or vehicle occupants. [1] If a police officer is racially prejudiced against a minority group, he or she would choose to stop and/or search a minority group member with less convincing evidence for the presence of contraband. More generally, a police officer should search individuals at higher rates when the cost of doing so is lower. This means that a comparison of outcomes can indicate differential search costs, where in this case outcomes are the detection of contraband.

However, as argued in the literature, the *infra-marginality* problem may complicate the application of the outcome test. To understand the infra-marginality problem, recall that conceptually. Becker's outcome test is based on the idea that a police officer will search an individual if the suspicion level is above a threshold; for example, an officer prejudiced against non-White people will use a lower suspicion threshold for members of that group than for White individuals. Thus, a comparison of the contraband discovery rate between the *marginal* minority individual and *marginal* White individual is a measure of the officer's prejudice. However, the outcome tests in the literature often compares the *average* contraband finding rates against different groups. The comparison of the group averages may *not* be in the same direction as the comparison of the marginals.

Knowles et al. (2001) (KPT) resolves the infra-marginality problem by presenting an equilibrium "matching pennies" game between police officers and drivers. The equilibrium of the "matching pennies" game is in mixed strategies, and minority drivers will carry contraband with lower probability in this mixed strategy equilibrium if and only if the police officers are prejudiced against them. A feature of the KPT model, however, is that the marginal drivers and the average drivers are the same because in the mixed strategy equilibrium all drivers of the same race are carrying contraband at the same rate, even if the drivers differ in their propensity to commit crimes.

Subsequent work by Anwar & Fang (2006) includes a model of policing behavior

[1] We define contraband in two ways - guns and any type, which may include drugs, weapons or stolen property. Drugs typically account for the vast majority of the general category of contraband.

where officers decide whether to search a driver after observing signals about whether the driver may be carrying contraband, but allow for heterogeneity within racial groups. Since drivers within the same racial group are heterogeneous in their level of suspicion, the infra-marginality problem exists in this setting. Anwar and Fang address this issue by comparing officers of different races and use officers of a given race as a benchmark to assess the relative prejudice of one group of officers against another group of officers.

While the mechanisms underlying the KPT model and the Anwar and Fang model differ substantially, both models assume that the police officers are rational and are trying to optimize an objective that includes finding contraband as one of its components. As such, both models would predict that, if for some exogenous reason the costs of stopping or searching drivers (or pedestrians) were to go up – as they would during a pandemic or amidst a nationwide protest against police brutality – the contraband finding rates against all drivers should go up.

In the KPT model, this prediction emerges through the endogenous response of the drivers who are deciding whether to carry contraband. As the officers' cost of searching vehicles increase, it is necessary for the drivers to increase their probability of carrying contraband to ensure that the officers are indifferent between searching and not searching in the mixed strategy equilibrium. In Anwar and Fang (2006), an increase in officer's search cost will make the officers increase the suspicion threshold of the drivers that they search. This increase in the marginal suspicion threshold will necessarily increase the average search success rate of each group of drivers, *ceteris paribus.*

Both KPT and Anwar and Fang's models (as well as many others, some of which are listed at the end of the next section) are optimizing models of police behavior, in that they assume the goal of police officers is to maximize *something*, usually hit rates. This type of police behavior will lead to a relationship as in the right panel of Figure 1, which simulates the total number of contraband finds against the total number of stops or frisks (in Abrams et al. (2025) this is referred to as the policing production function). The relationship is concave under the optimizing model, because officers seek out those most likely to have contraband first, leading to a higher slope near the origin and then their success rate diminishes as they exhaust the supply of suspects with a high likelihood of carrying contraband. Only as the number of stops/frisks increase will the less suspicious pedestrians/drivers be stopped. Thus, the contraband finding rate will decrease in the total number of stops/frisks, and the total number of contraband "hits" will exhibit diminishing returns with respect to the number of stops/frisks.

This figure is on contrast to that in the first panel of 1 which simulates a *random policing* model where officers either have no information about the likelihood a suspect has contraband or no incentive to prioritize those who do. This leads to a linear relationship between contraband and frisks. An exogenous reduction in frisks would linearly lower the total number of contraband findings, but the hit rate would remain unchanged. By contrast, if police are effective in targeting – probabilistically at least– then a reduction in frisks will then increase the contraband hit rate. We explore these models empirically in Section 4.

It is worth noting that the optimizing model of police stops is most likely to apply where officers have the most information and experience with a set of potential subjects. This corresponds best to officers on a regular beat where subjects are pedestrians. With vehicle stops, there is typically far less information and - particularly in a highway context - there may have been no prior interaction with the individual. In that setting the officer may be making decisions based on seconds of observation. Thus the optimizing model may be less applicable and stops may be closer to random, with respect to contraband finds.

2.2 Related Literature

Three recent papers have sought to empirically test the underlying assumption that police officers face diminishing returns to searches. Feigenberg & Miller (2022) estimates a between-officer Search Productivity Curve (SPC) to determine whether there is an equity-efficiency trade-off using data on traffic stops for speeding violations conducted by Texas Highway Patrol troopers. They find that the relationship between the search rate and unconditional hit rate (hit rate as a proportion of stops) is roughly linear, i.e., that the conditional hit rate is roughly constant across troopers with different search rates.

Meanwhile, Gelbach (2021) further elaborates that a testable implication of the optimizing model of officer search behavior of Anwar & Fang (2006) is that at the *officer level* there should be a negative relationship between search rates and conditional hit rates. He empirically tests this implication for Florida and Harris County Texas and finds mixed results. In Florida the relationship is negative, consistent with officers facing diminishing returns to search. Meanwhile in Harris County the relationship is positive for White and Hispanic drivers which is taken as suggestive evidence that the Becker framework may not be appropriate in this setting.

Under the optimizing models used in the literature diminishing returns applies at the officer level. Due to the rarity of exogenous shifts to policing, these papers use *between-officer variation* as a proxy for within-officer changes. As Feigenberg and Miller (2022) note, in the absence of strict monotonicity, the between-officer SPC may not coincide with the within-officer SPC if for example search rates were correlated with the ability of an officer to identify suspects.

Another recent paper is by Pierson et al. (2020) which collects data from across the country in order to assess racial disparities in police stops. That paper, which focuses only on traffic stops, finds evidence for racial disparities. Unlike the current paper, which focuses on large cities, the bulk of the data for that one comes from state highway patrols.

A predecessor to the current paper is Abrams et al. (2025) where we test outcome-based models of policing using data from Philadelphia and New York City. The focus in that paper is on using the shock to police frisks from the protests following George Floyd's murder in 2020 in order to test whether police optimize in selection of subjects for frisks. The advantage of that approach over the two discussed above is that it allows within-officer comparison. The current paper expands geographically – from 2 cities to 16 – but is also agnostic about the exogeneity of the contraction in frisks with respect to other important inputs that can impact hit rates.

In addition to research on optimizing police behavior, there are a number of papers in the statistics, economics and legal literature that have focused on racial disparities and efficacy of stop and frisk tactics. See e.g. Dharmapala & Ross (2004), Ridgeway (2006), Gelman et al. (2007), Ridgeway & MacDonald (2009), Abrams (2014), Macdonald et al. (2015), MacDonald & Braga (2019), Abrams et al. (2025), and Grossman et al. (2024).

3 Stop and Frisk Around the Country

3.1 Data Assembly

In order to better understand how stop and frisk policing is carried out, we attempted to obtain data on both pedestrian and vehicle stops from the 20 largest U.S. cities. We sought information on prevalence of stops and frisks and contraband discovery rates. Many of the cities have data available for download on data portals. We contacted all of the other cities, some repeatedly. Eventually we obtained some data from all cities other than Phoenix, Jacksonville, Indianapolis, Denver and Oklahoma City. [2] Our data includes 3,030,0478 pedestrian stops and 9,677,390 vehicle stops over all cities and years.

One contribution of this paper is in aggregating datasets from sixteen large cities around the country, including the East and West coasts, the Midwest and Texas. In most locations this includes both pedestrian and vehicle stops, which may result from substantially different processes (see brief discussion in Section 2). Our primary data consists of suspect-stop level records from each city and we restrict the time period to 2019 through 2023. This yields 1,815,760 pedestrian and 6,293,349 vehicle stops for the primary analysis. Eleven cities provided data for both pedestrian and vehicle stops.

[2] We also obtained data from four other cities in large metro areas, Washington DC, Milwaukee, Oakland, and Cincinnati.

Seattle and New York City supplied only pedestrian stop data, while Dallas, Houston, and Fort Worth provided only vehicle stop records, thus the number of cities varies by the measure used. These records document whether a frisk or search occurred and if contraband was discovered. [3] In bringing together these datasets we are able to shed light on the vast differences in policing practices - decisions that are locally made.

We supplement our analysis with contextual data about each city and its police departments. Since this data tends to be less dynamic we capture it for just one year of the time range covered by the stop and frisk data. For cities reporting to the Uniform Crime Report (UCR) in 2023 we use UCR data on yearly incidents by crime type. We choose this year to be long enough after the onset of COVID-19 that these figures were less likely to be impacted by the pandemic.; As Los Angeles, Oakland, San Francisco, and San Jose did not report during this period, we obtained crime incident data directly from their police department websites and city databases.[4]. Demographic and income data is drawn from the 2019 through 2023 American Community Survey Single-Year Estimates[5]. Police budget data is drawn from each city's 2022 fiscal year plan, while police staffing levels are taken from the 2023 Uniform Crime Reports (UCR).[6][7]

3.2 How Much Stops and Frisks Vary

Figure 2, which shows daily pedestrian frisk rate and stop rate per million residents in 2023, immediately conveys a striking feature of the data. While all of the cities presumably have similar aims for their stop and frisk programs, there is immense variation in their usage of it. This may also be seen in the top two rows of Table 1 which shows summary statistics of for both 2019 and 2023. There is immense variation in population-adjusted stop rates - spanning nearly two orders of magnitude. In 2019

[3] Most cities specify the type of contraband, allowing us to identify firearm recoveries, although Austin, Cincinnati, Dallas, Fort Worth, and Houston's data lack sufficient detail to make this classification.

[4] https://data.lacity.org/ https://data.oaklandca.gov https://www.sanfranciscopolice.org/stay-safe/crime-data/crime-dashboard https://www.sjpd.org/records/crime-stats-maps/police-dashboards

[5] https://www.census.gov/data/developers/data-sets/acs-1year.html

[6] Retrieved from https://policefundingdatabase.org/

[7] Retrieved from https://costofpolice.org/

(Appendix Table A.1), Washington D.C. and San Diego had the highest stop rates at 312 and 195 per million residents, respectively, while New York City recorded just 4.65 - almost two orders of magnitude lower. [8] While New York appears to be an outlier in 2019, in 2023 Milwaukee, another city that has been subject to independent monitoring, had a stop rate almost half that of New York City. [9] Even taking outliers aside, a visual inspection of Figure 2 shows the great variation in both stop and frisk rates and that it is not simply due to 1 or 2 outliers. Turning back to Table 1 we see the ratio of standard deviation to median stop and frisk rates is above 1 in both 2019 and 2023. While the level of variation is not quite as large for vehicle stops, these general patterns hold there, too (see Figure 3 and Appendix Table A.2).

Vehicle stops (Table A.2) also show dramatic variation across cities and over time. In 2019, Philadelphia conducted a striking 846.41 vehicle stops per million residents daily—more than ten times the number in Chicago, which had the fewest stops. While the median number of stops reported in Table 1 declined by nearly half from 2019 to 2023, there still remains an order-of-magnitude difference between the highest- and lowest-stop cities in 2023.

Nearly all cities conduct more vehicle stops than pedestrian stops, though the ratio varies considerably across cities. In 2023, for instance, Philadelphia and Cincinnati each recorded more than ten vehicle stops for every pedestrian stop, while Milwaukee's ratio exceeded 40 to 1. The only departures from this general pattern were Chicago, San Diego, and Washington in 2019, and Oakland in 2023, each of which recorded more pedestrian than vehicle stops.

For all cities besides Chicago, the proportion of vehicle stops that involve a frisk is much lower. This may reflect the difference in standards between the two types of stops. As mentioned above, the legal justification for a stop includes a traffic violation

[8] A recent report of the Independent Monitor in NYC contained an audit using body worn camera footage to estimate that stops were undercounted by about 40% (Denerstein 2024). Even accounting for this underreporting, NYC's use of stops remains substantially lower than other cities - reflecting policy changes following federal litigation (Floyd v. City of New York).

[9] But note that monitor reports in Milwaukee have also shown that reported numbers are likely substantial undercounts (The Crime and Justice Institute 2024)

and does not require any reasonable suspicion of a crime. Meanwhile, to search the vehicle, the officer needs probable cause to believe that there is evidence of criminality hidden within, while to frisk the driver or occupants, the same standard applies as in a pedestrian stop.

Several of the figures and tables show comparisons between the years 2019 and 2023. These years are chosen because the data is available for most of the cities and they avoid the pandemic, which had a substantial impact on police stops (Abrams et al. 2022, Abrams 2021). But it is also useful to examine trends over the full time period of study and we present those for police stops in Figure 4 and frisks in Figure 5. One can see that stops and frisks, whether pedestrian or vehicle, declined over this time period, with the greatest drop happening in 2020, except for vehicle frisks (or searches) which overall had a greater decline in 2021 and then an increase in 2022. The trend for pedestrian stops shows a continued decline after 2020 although of substantially smaller magnitude. For vehicle stops there was even a small increase in 2023. Both pedestrian and vehicle frisks/searches saw an increase in 2022 and then small changes in 2023. These temporal patterns reflect various factors, including changes in potential targets (number of people or vehicles on the streets) as the pandemic waxed and waned. They are also doubtless impacted by costs of stops and frisks as attitudes toward policing have been fairly dynamic over this time period, growing more critical after George Floyd's murder and less so in more recent years.

Figures 6 and 7 show how stops and frisks evolved between 2019 and 2023 for pedestrians and vehicles, respectively. The arrows indicate for each city how the pair of daily stops and frisks moved over this time interval. In almost all cases (with the exception of Oakland) both stops and frisks declined, as expected from the change in the median just discussed. It is hard to tell with precision but most have a slope lower than 45 degrees suggesting that stops declined more than frisks. Indeed this is borne out in Table 1, which shows that pedestrian stops fell by an average of just under 60% while frisks fell around 45%. Thus it is unsurprising that the frisk rate, the ratio of frisks to stops rises from a mean of 37% in 2019 to 43% in 2023.

There appears to be greater heterogeneity in the changes to vehicle stops and frisks or searches. While all cities show a decline in both, some cities, like Austin and Washington DC, had an immense drop in stops but little decline in frisks. Others, like Houston and Cincinatti saw the opposite - a modest decline in stops but a large one in frisks or searches. Figure 8 shows that the ratio of frisks to searches actually declined for vehicles between 2019 and 2023, but only after an initial jump in 2020.

We analyze contraband discovery using two measures. The first, "Guns," specifically tracks firearm discoveries. The second measure, "Overall," encompasses drugs, weapons, and stolen property, with drugs being the most commonly found item. Hit rates for contraband also vary tremendously - by over a factor of four across cities (Appendix Table A.1). General contraband hit rates range from 18% (Washington DC) to 74% (San Francisco), while gun hit rates are consistently lower, between 2% and 9%. As

Figures 9 and 10 show how gun and overall hit rates evolved for pedestrian and vehicle stops. Both pedestrian and vehicle gun hit rates rose substantially in 2020 as stops and frisks fell and then rose even further in 2021. Vehicle gun hit rates continued to rise through 2023, and in that year were very similar to pedestrian gun hit rates which had remained about the same for two years. The pattern is similar for overall hit rates, although there vehicle hit rates rose faster and then declined slightly after 2021, whereas pedestrian hit rates increase steadily although less so through the full time period. We return to hit rates in Section 4.

3.3 Correlates of Stop and Frisk

These stark differences suggest that local policies and enforcement practices play a central role. Differences in data collection exist across jurisdictions, but all departments report having official policies governing stops and frisks, making it unlikely that reporting practices fully explain the observed disparities. While we cannot rule out this possibility, substantial experience of one of the authors with several of these departments indicates that such reporting differences are not likely to account for most of the variation. Departments do vary in the details of their data collection practices—for example, how forms are formatted and what software is employed—but the mandate to report stops and frisks is fairly consistent across cities. Indeed, all departments report having official policies governing pedestrian stops, vehicle stops, and racial profiling.

The huge amount of variability across cities in stop and frisk practices may instead be due to heterogeneity in city characteristics. To investigate potential drivers of this variation, we begin by examining census data in Table A.3, including population, racial composition, poverty rates, and income per capita. City size varies appreciably, from around 300,000 in Cincinnati to over 8 million in New York. But given that most policing measures that we examine are per capita, we would not expect this level of variation in the stop and frisk practices which we observe. Other demographic data varies even less. Poverty rates vary from 8% in San Jose to 22% in Milwaukee. Income per capita ranges from just under $30,000 in Milwaukee to over $88,000 in San Francisco. The variation in these characteristics does not seem substantial enough to explain the magnitude of variation in policing measures.

We next present crime and policing statistics in Tables 2 and A.4. We focus on serious crimes that are more likely to influence police department policies: overall violent crime, murder, rape, aggravated assault, and robbery. We first examine violent crime rates (aggregating murder, rape, aggravated assault, and robbery), reported as annual rates per million residents, where we find meaningful variation across cities. Oakland, the city with the highest violent crime rate, reports approximately four times the rate as San Diego, the city with the lowest. We see greater cross-city variation when we look at individual crime categories. From lowest to highest cities, murder rates vary by a factor of 13, rape by a factor of 4, aggravated assault by a factor of 8, and robbery by a factor of 11. While this amount of variation is still substantially less than what we saw in the use of stop and frisk, it is substantial and worth investigating whether it might correspond to the large variation in stops and frisks. Perhaps cities with high crime rates respond by increasing frisks substantially. Or perhaps cities with very low frisk rates have substantially higher rates of violent crime.

We examine these hypotheses below but first present one other data set that might be expected to be related to police tactics, that on the police labor force (Table A.5). Expenditures on policing per capita vary by less than a factor of three, with the lowest level in Fort Worth and highest in Oakland. Officers per resident vary by roughly a factor of four. But officers per murder vary by over an order of magnitude.

We now turn to a correlation analysis in Table 3 to assess whether the variation in stop-and-frisk activity across cities can be explained by demographics, police resources, or crime rates. The table uses Spearman rank-based correlation calculations to be robust while handling data with such high variance. Cells in the brightest red (green) shades have the largest negative (positive) correlations.

Surprisingly, neither department budgets nor police staffing levels show strong correlations with the number of stops or searches/frisks (first 4 columns of Table 3). This holds whether we measure resources per capita or relative to violent crime rates. This suggests that resource availability is not the primary driver of variation in stop-and-frisk practices across cities. Further, there is no clear relationship between crime rates and the frequency of stops and frisks. Thus, the large variation in crime rates does not explain the dramatic differences in stop-and-frisk implementation across cities.

Next, we examine whether city characteristics can explain the observed variation in hit rates across departments. As we would expect, better-resourced police departments show higher pedestrian firearm hit rates, with correlations at or above 0.7 for both police budget and sworn officers per capita. However, this correlation weakens for vehicle hit rates of both guns and contraband, and flips sign for pedestrian contraband. This suggests that the observed correlation may be spurious, or that searches yielding pedestrian firearms operate through fundamentally different processes than the other categories. Surprisingly, cities with higher violent crime rates do not have a strong correlation with hit rates. Only robberies show any apparent correlation, but again, only for firearms and potentially contraband in vehicles.

To illustrate the inability of these factors to explain the observed variation in stop and frisk implementation, consider a direct comparison of Washington DC and

Philadelphia in 2019 (Appendix Table A.1). The two cities have very similar racial compositions and crime rates. Philadelphia is a substantially poorer city with an average income over 50% lower and 7 percentage points more of its population below the poverty line in 2023. Yet in 2019, Washington DC conducts almost 3.5 times the number of frisks as Philadelphia and maintains a higher firearm hit rate.

We can also see the reverse, that differences in these characteristics are not necessarily associated with differences in the use of stop-and-frisk. For example, consider Washington DC and San Diego in 2023. Despite Washington DC experiencing substantially higher rates of violent crime - more than double the overall rate of violent incidents with 10 times more murders — and having access to greater resources — nearly double the per capita budget and approximately four times the officer-to-population ratio — the difference in frisk rates between the two cities is remarkably small, with Washington DC conducting roughly 10% fewer pedestrian frisks than San Diego in 2023. Moreover, the effectiveness of these frisks, as measured by pedestrian firearm recovery rates, is notably different, with Washington having over four times the gun hit rate in 2023. This disparity in productivity could indicate either a significant difference in officer ability to identify individuals likely to be carrying contraband, or alternatively, a fundamental difference in departmental objectives.

Of course, one interpretation of the correlation data is that the low hit rate correlations are to be expected in equilibrium. If, as in the KPT model, potential offenders adjust contraband carry rates to the probability of frisk, and that is correlated with e.g. department budgets, then we would expect to see no correlation. However, we still would expect to see a correlation with overall rates of stops or frisks.

Finally, in Figures 12 and 13, we look at the racial breakdown of stop and frisk across cities (see also Appendix Tables A.6 and A.7). Each bar in the figures shows the median of the ratio of the non-White group indicated to the White group for the given metric. For example, the first bar in Figure 12 indicates that the median stop rate of Black individuals per same-race residential population is 3.42 times higher than that of White individuals per same-race residential population. Black individuals are consistently overrepresented among stopped pedestrians relative to their population share, with stop rates at least three times that of White pedestrians across all cities. The magnitude of this disparity varies substantially by location. In Washington and New York City, Black pedestrians are stopped at rates over fifteen times higher than White pedestrians, while Austin and Philadelphia show smaller disparities with ratios of 3.7 and 3.5, respectively. This disparity becomes even larger when looking at the number of frisks, as each city frisks Black pedestrians who are stopped at a higher rate than White pedestrians. This is particularly extreme in Washington D.C. where the rate of frisk conditional on being stopped is 25% for Black pedestrians and only 11% for White pedestrians. As a result, the proportion of Black pedestrians frisked in Chicago is 35 times higher than White pedestrians.

The disparities between Hispanic and White pedestrians are substantially less pronounced. Washington D.C. stops Hispanic pedestrians 4 times more frequently than White pedestrians, while Austin's ratio is nearly 1:1. However, the rate of frisks conditional on being stopped is higher for Hispanic pedestrians in all cities, with frisk rates generally closer to those of Black pedestrians than White pedestrians.

Although a formal outcome-based test of racial discrimination would require examining marginal hit rates, the observed patterns in average hit rates across racial groups highlight the importance of understanding the objective of police officers in conducting such a test. For example in Washington D.C., 19% of Black pedestrian frisks recover any contraband, relative to 17% for White pedestrians. However, 10% recover a firearm relative to just 5% of White pedestrian frisks. We see similar patterns in other cities such as Los Angeles, New York, and Oakland with Black pedestrians having relatively similar contraband hit rates but higher firearm hit rates compared to White pedestrians. This divergence suggests that the conclusions of outcome-based tests of racial discrimination may vary substantially depending on how success is defined — appearing neutral when considering overall contraband recovery, but indicating potential differences when firearm recoveries are examined specifically.

4 Policing Productivity

In this section we discuss what we can learn about police productivity based on hit rates. We begin by assuming optimizing police behavior, consistent with the optimizing models discussed in Section 2. Under these models we would expect the relationship between successful frisks and the number of frisks to resemble the concave function in Figure 1. In prior work (Abrams et al. 2025), we explore this relationship in Chicago and Philadelphia using the exogenous shock that led to an abrupt and large decline in police stops following George Floyd's death.

Here we take a slightly different approach to understanding how police productivy varies as frisk rates do. We examine a substantially longer time period, which means these results must be interpreted as correlations, not casual. But we have the advantage relative to prior work of being able to compare a large number of big cities. These results are presented in the four panels of Figure 11, each of which plots the hit rate against the daily number of frisks or searches for 2019 and 2023. Each arrow points to the 2023 observation for a given city.

An initial big picture look at the different panels reveals far more horizontal or almost horizontal lines for *any contraband* hit rates (right panels) compared to *gun* hit rates (left panels), which have almost none. A horizontal arrow means that a decline in frisks or searches (sometimes substantial) is associated with no change in hit rate. That is, even as the frisk rate declines substantially, by 50% or more in several cases, there is no increase in hit rate. If this were a causal relationship it would be at odds with the optimizing model of policing. By contrast, the vectors on the gun hit rate panels have varying slopes but are largely oriented in the northwest direction. This means that hit rates are rising as frisk rates are falling, consistent with the optimizing model. Why might these differences arise and are they meaningful given the lack of identification?

We tackle the second question first in considering what other changes might occur that could impact hit rates and frisk rates over a four year period. Two major factors immediately come to mind - contraband carry rates and the cost of frisks. It is likely that both gun and drug carry rates have increased over the four years examined. There is evidence Valek et al. (2024), Miller et al. (2022) that gun ownership rates increased substantially during the pandemic. While data about drug use and carrying tends to be less precise, there has been a general trend in recent years toward decriminalization of some types of drugs, which would lower the cost to individuals of carrying. At the very least, one would not expect a decline in drug carry rate, and hence overall contraband, since this comprises the bulk of this category. If this is correct, then for both guns and any contraband one would expect the 2023 hit rate to be an upper bound on what it would counterfactually be had there been no change in carry rates, assuming lack of full adjustment of police to the new carry rates. That is, if anything the vectors in figure 11 have higher magnitude of slope than they might were carry rates held constant.

What about the cost of frisks? This is necessarily more speculative, but based on anecdotal news reports, it seems unlikely that they declined over this time period, at least in 2021 and 2022. Scrutiny of police increased substantially after George Floyd's death and there were numerous efforts to modify police priorities across the country. Attitudes toward police declined at least through 2022 (Brenan 2025) but seem to have rebounded beginning in 2023 or 2024. Additionally, there were a number of reforms, both legislative and administrative, aimed at reducing police discretion. The net effect in our comparison of 2019 and 2023 is that attitudes toward police are likely to be more negative in the latter time period, increasing the personal cost of making a stop or frisk.

This is our preferred explanation of why there was a decline in frisk rates of all kinds between 2019 and 2023 and an increase in gun hit rates. As the costs of frisks rose over this time period, fewer individuals exceeded the cost to frisk and hence the rate declined. Additionally, the marginal person frisked had higher probability of carrying a firearm and the hit rate rose. But given the lack of identification noted above we don't argue for a clear causal relationship.

We now turn to the question of why there is such a marked difference in the pattern of changes to gun and any contraband hit rates. The horizontal arrows for many contraband hit rates suggest a less targeted approach to non-gun contraband discovery. Given that the law only allows for pedestrian frisks when there is reasonable suspicion that the individual is *armed and dangerous*, one should expect other types of contraband discovery to be more or less random. If officers are not searching for non-gun contraband, the discovery rate should be uncorrelated with frisk rate. This is an important distinction not always considered in the literature.

It is also worth noting that there is some difference between pedestrian and vehicle all contraband hit rate changes (top right and bottom right panels, respectively). While the number of cities is too small to make much out of this, there are 6 that move in the NW direction for vehicle stops and only 2 for pedestrian. This may well also be due to differences in legal standards. A frisk of a driver or pedestrian requires reasonable suspicion that the person is armed and dangerous, and thus non-weapon contraband is incidental. So it should not be surprising that most of the vectors in the top right panel are gorizontal. But a different standard holds for searches of the vehicle itself. There the officer needs probable cause, a higher standard than reasonable suspicion, that evidence of criminal activity is concealed within. Thus a vehicle search for any contraband may be better described by an optimizing behavior model, whereas a search of a driver or pedestrian would only be so for weapons.

5 Conclusion

This paper has assembled and analyzed one of the most comprehensive datasets on stop-and-frisk policing to date, covering over eight million stops across sixteen of the nation's largest cities. In doing so, it makes several contributions to the literature. First, it expands the geographic scope beyond the handful of cities most often studied, allowing for direct comparisons across regions with very different policing contexts. Second, by comparing two types of hit rates, gun and any, it shows how the difference in legal standards relates to the relevance of the optimizing policing models. While firearm discovery seems to align with optimizing models of police behavior, non-firearm contraband discovery appears largely random. This comports with the law, but also calls into question common empirical strategies that treat all contraband alike.

Perhaps the most notable finding is the immense variation across cities in their use of stop and frisk tactics. This leads to several potential hypotheses. In this paper we have attempted to test some of the most obvious ones, namely that the use is related to city characteristics, like crime or poverty rates. We found no strong or consistent correlation. We next tested the hypothesis that stop and frisk usage is related to other policing characteristics, such as the size of the police force per capita, or expenditures on it. We again did not find any strong or consistent relationship.

Having eliminated some of the more obvious hypotheses, we turn to other possibilities. One is that data collection practices on police stops varies so much across cities that the data is not comparable. There is certainly some truth to this, but it is unlikely to explain over an order of magnitude variation in stop rates and massive variation in hit rates. Audit studies in some of the cities examined (New York and Milwaukee) show that stops are undercounted, by an estimate of around 40% in New York. While large, it could only explain a small amount of the large variation we observed.

California mandates uniform collection of vehicle stops that should at least enforce some data uniformity across those cities for vehicle stops. We note that their variation in vehicle stops exceeds that for pedestrian stops. Thus, while data collection issues may contribute to some of the observed differences across cities, there is still an immense amount that remains.

The substantial variation across cities in the use of stop and frisk policing seems like a mystery. One might expect that cities to copy successful practices employed in other locations. This is after all the promise of federalism. If there is competition across cities then we would expect this to happen on various dimensions. So one possibility is that competition across cities is weak, particularly in light of declining mobility rates in the U.S.

Another possibility is that stop and frisk doesn't matter. This doesn't mean that policing doesn't matter. Perhaps the best established finding in the law and economics of crime is that police deter crime (Chalfin and McCrary 2017, Klick and Tabarrok 2005, Di Tella and Schargrodsky 2004). But there is far less evidence about whether the activity police engage in impact crime. Perhaps it doesn't matter to crime rates whether police engage in stop and frisk or just stand around on street corners. Perhaps stop and frisk does not appreciably increase the ability to solve crimes, capture suspects, or even recover a meaningful amount of contraband. If this is true, then we might expect exactly the kind of consistency we see across cities, which is to say, no consistency at all!

References

Abrams, D. S. (2014), 'The Law and Economics of Stop-and-Frisk', *Loyola University Chicago Law Journal* **46**(2), 369–379.
URL: *https://lawecommons.luc.edu/luclj/vol46/iss2/5/*

Abrams, D. S. (2021), 'COVID and crime: An early empirical look', *Journal of Public Economics* **194**, 1–16.
URL: *https://doi.org/10.1016/j.jpubeco.2020.104344*

Abrams, D. S., Fang, H. & Goonetilleke, P. (2022), 'Police Frisks', *AEA Papers and Proceedings* **112**, 178–183.

Abrams, D. S., Fang, H. & Goonetilleke, P. (2025), Do Cops Know Who to Stop? Assessing Optimizing Models of Police Behavior with a Natural Experiment.
URL: *https://www.nber.org/papers/w31594*

Anwar, S. & Fang, H. (2006), 'An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence', *The American Economic Review* **96**(1), 127–151.
URL: *http://www.nber.org/papers/w11264*

Becker, G. S. (1968), 'Crime and Punishment: An Economic Approach', *The Journal of Political Economy* **76**(2), 169–217.
URL: *http://www.journals.uchicago.edu/doi/abs/10.1086/259394*

Brenan, M. (2025), 'Racial Divide on Policing Narrows 5 Years After Floyd Death'.
URL: *https://news.gallup.com/poll/690959/racial-divide-policing-narrows-years-floyd-death.aspx*

Denerstein, M. (2024), Twenty-Second Report of the Independent Monitor Underreporting of Terry Stops by the NYPD, Technical report.

Dharmapala, D. & Ross, S. L. (2004), 'Racial Bias in Motor Vehicle Searches: Additional Theory and Evidence', *Contributions to Economic Analysis & Policy* **3**(1), Art. 12.
URL: *http://www.degruyter.com/view/j/bejeap.2003.3.issue-1/bejeap.2004.3.1.1310/bejeap.2004.3.1.1310.xml*

Feigenberg, B. & Miller, C. (2022), 'Would Eliminating Racial Disparities in Motor Vehicle Searches have Efficiency Costs?', *Quarterly Journal of Economics* **137**(1), 49–113.

Gelbach, J. B. (2021), Testing Economic Models of Discrimination in Criminal Justice.
URL: *https://ssrn.com/abstract=3875678*

Gelman, A., Fagan, J. & Kiss, A. (2007), 'An Analysis of the New York City Police Department's "Stop-and-Frisk" Policy in the Context of Claims of Racial Bias', *Journal of the American Statistical Association* **102**(479), 813–823.
URL: *http://www.tandfonline.com/doi/abs/10.1198/016214506000001040*

Grossman, J., Nyarko, J. & Goel, S. (2024), 'Reconciling Legal and Empirical Conceptions of Disparate Impact: An Analysis of Police Stops Across California', *Journal of Law and Empirical Analysis* **1**(1).

Knowles, J., Persico, N. & Todd, P. (2001), 'Racial Bias in Motor Vehicle Searches: Theory and Evidence', *Journal of Political Economy* **109**(1), 203–229.

MacDonald, J. & Braga, A. A. (2019), 'Did Post-Floyd et al. Reforms Reduce Racial Disparities in NYPD Stop, Question, and Frisk Practices? An Exploratory Analysis Using External and Internal Benchmarks', *Justice Quarterly* **36**(5), 954–983.
URL: *https://doi.org/10.1080/07418825.2018.1427278*

Macdonald, J., Fagan, J. & Geller, A. (2015), The Effects of Local Police Surges on Crime and Arrests in New York City.

Miller, M., Zhang, W. & Azrael, D. (2022), 'Firearm Purchasing During the COVID-19 Pandemic: Results From the 2021 National Firearms Survey', *Annals of Internal Medicine* **175**(2), 219–225.

Pierson, E., Simoiu, C., Overgoor, J., Corbett-Davies, S., Jenson, D., Shoemaker, A., Ramachandran, V., Barghouty, P., Phillips, C., Shroff, R. & Goel, S. (2020), 'A large-scale analysis of racial disparities in police stops across the United States', *Nature Human Behaviour* **4**(7), 736–745.
URL: *http://dx.doi.org/10.1038/s41562-020-0858-1*

Ridgeway, G. (2006), 'Assessing the Effect of Race Bias in Post-traffic Stop Outcomes Using Propensity Scores', *Journal of Quantitative Criminology* **22**(1), 1–29.
URL: *http://link.springer.com/10.1007/s10940-005-9000-9*

Ridgeway, G. & MacDonald, J. M. (2009), 'Doubly Robust Internal Benchmarking and False Discovery Rates for Detecting Racial Bias in Police Stops', *Journal of the American Statistical Association* **104**(486), 661–668.
URL: *http://pubs.amstat.org/doi/abs/10.1198/jasa.2009.0034?ai=s0amp;mi=3b2vtyamp;af=R http://pubs.amstat.org/doi/abs/10.1198/jasa.2009.0034*

The Crime and Justice Institute (2024), City of Milwaukee Settlement Agreement Six-Month Report on Non-Compliant Items, Technical report.
URL: *http://mkemuralmap.com/reynaldo-hernandez/.*

Valek, R., Ward, J. A., Jones, V. & Crifasi, C. K. (2024), 'Political violence, racial violence, and new gun ownership: results from the 2023 National Survey of Gun Policy', *Injury Epidemiology* **11**(1).

Weisburd, D. & Majmundar, M. K. (2018), *Proactive policing: Effects on crime and communities*, National Academies Press.

6 Figures and tables

Figure 1: Total Contraband vs Frisks

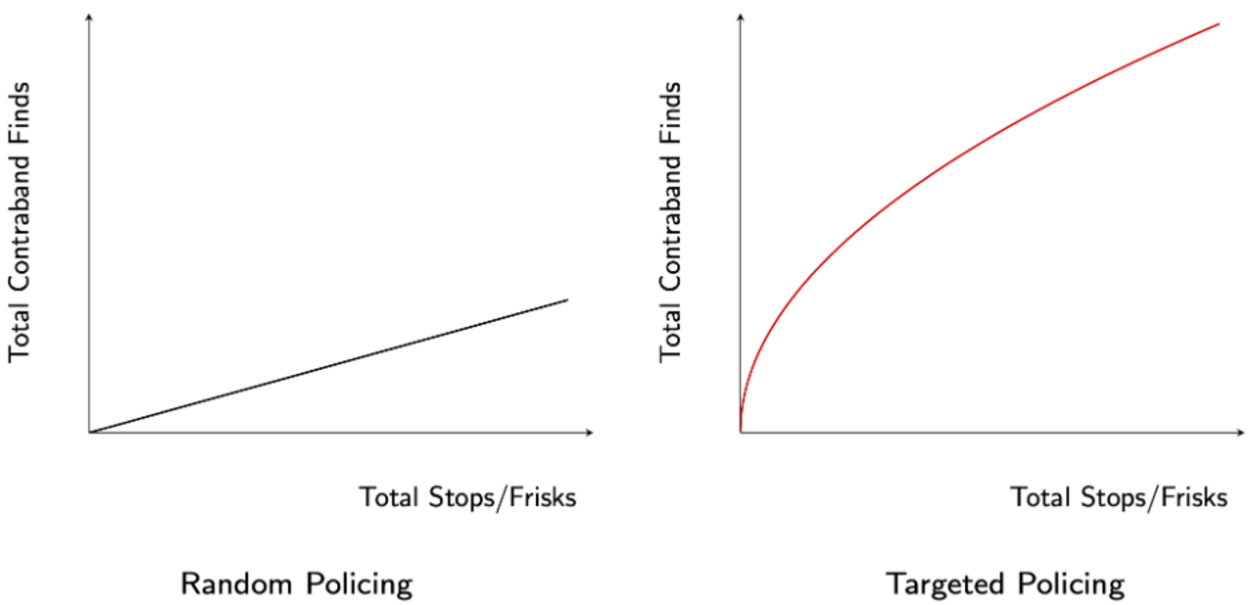


Figure 2: Daily Pedestrian Frisks vs. Stops per Million Residents, 2023

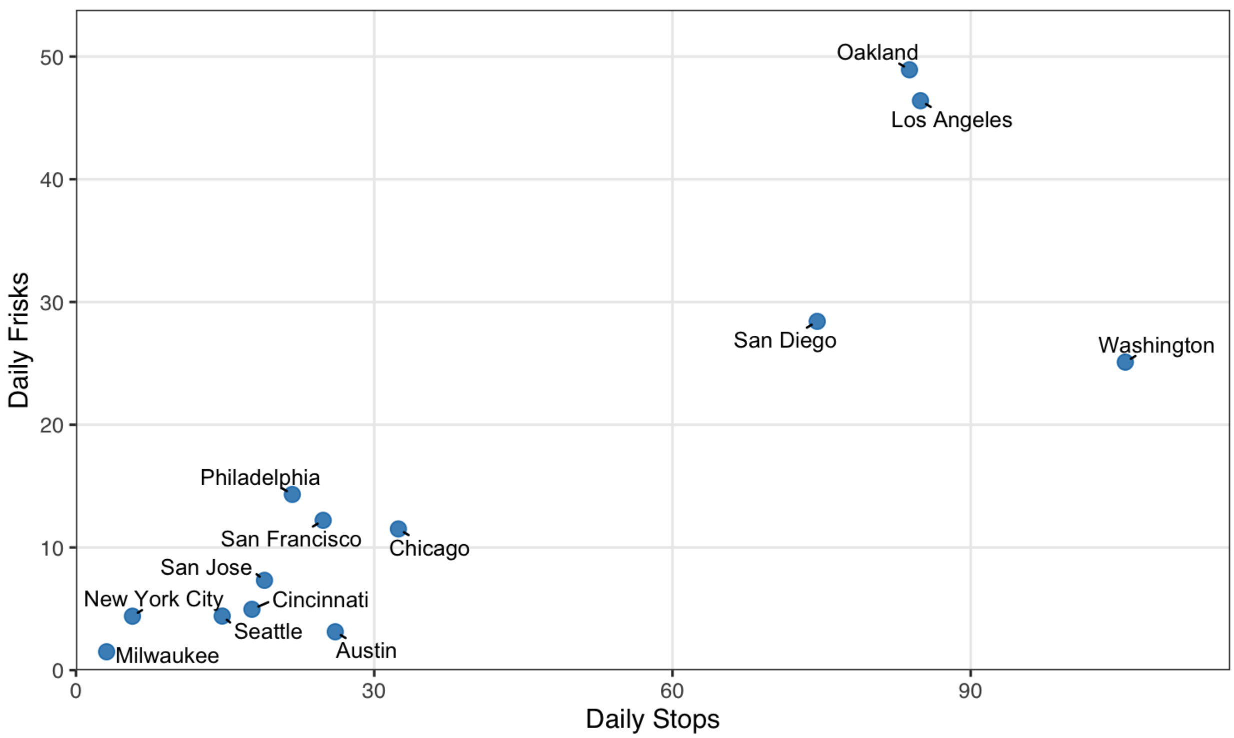
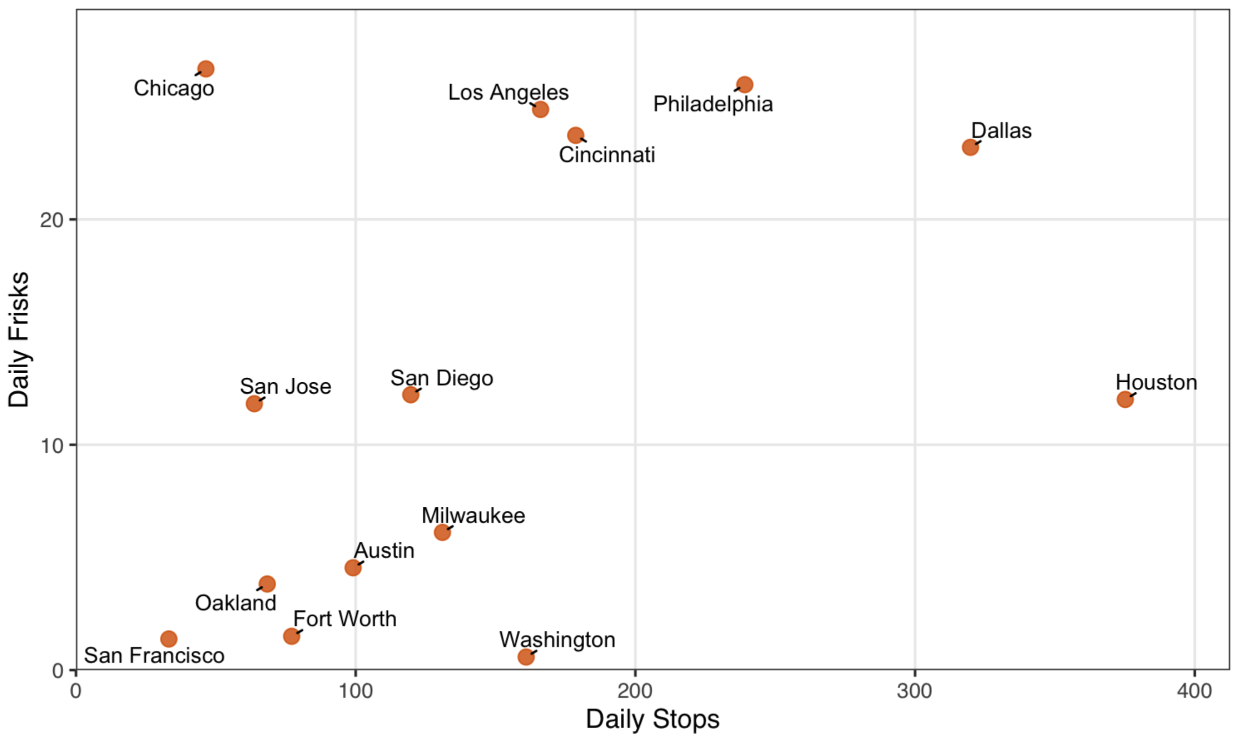
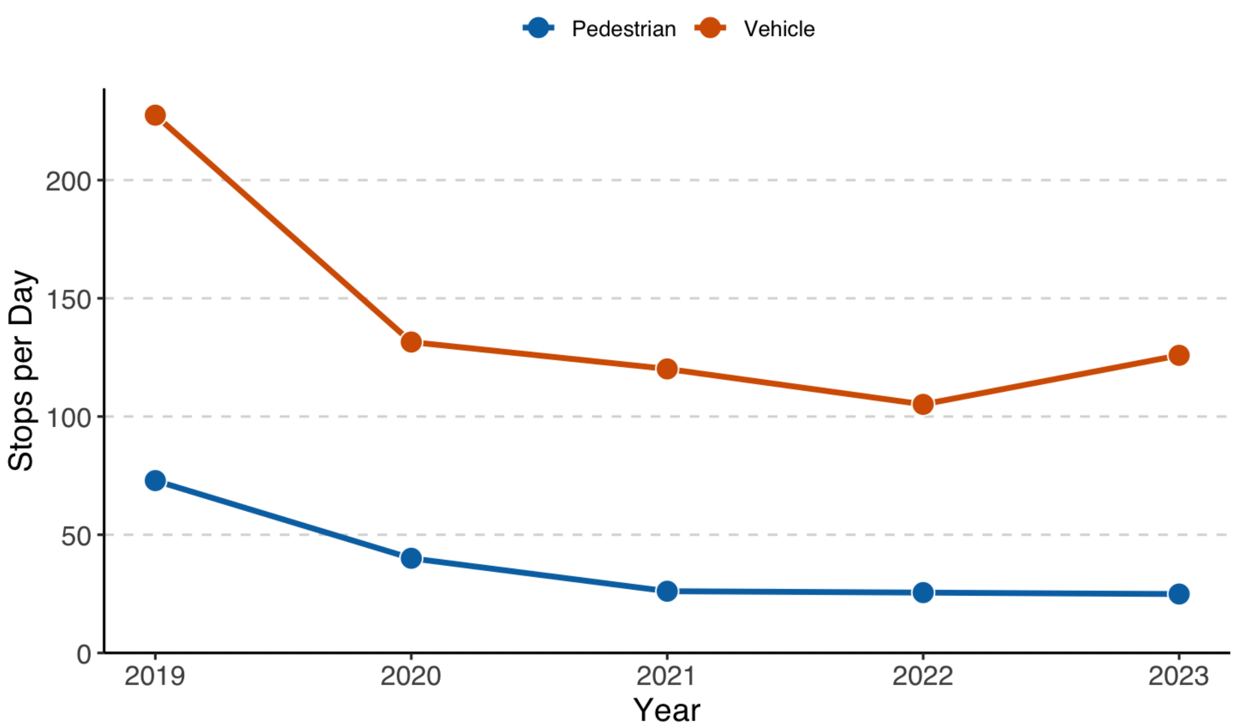


Figure 3: Vehicle Frisks vs. Stops, 2023



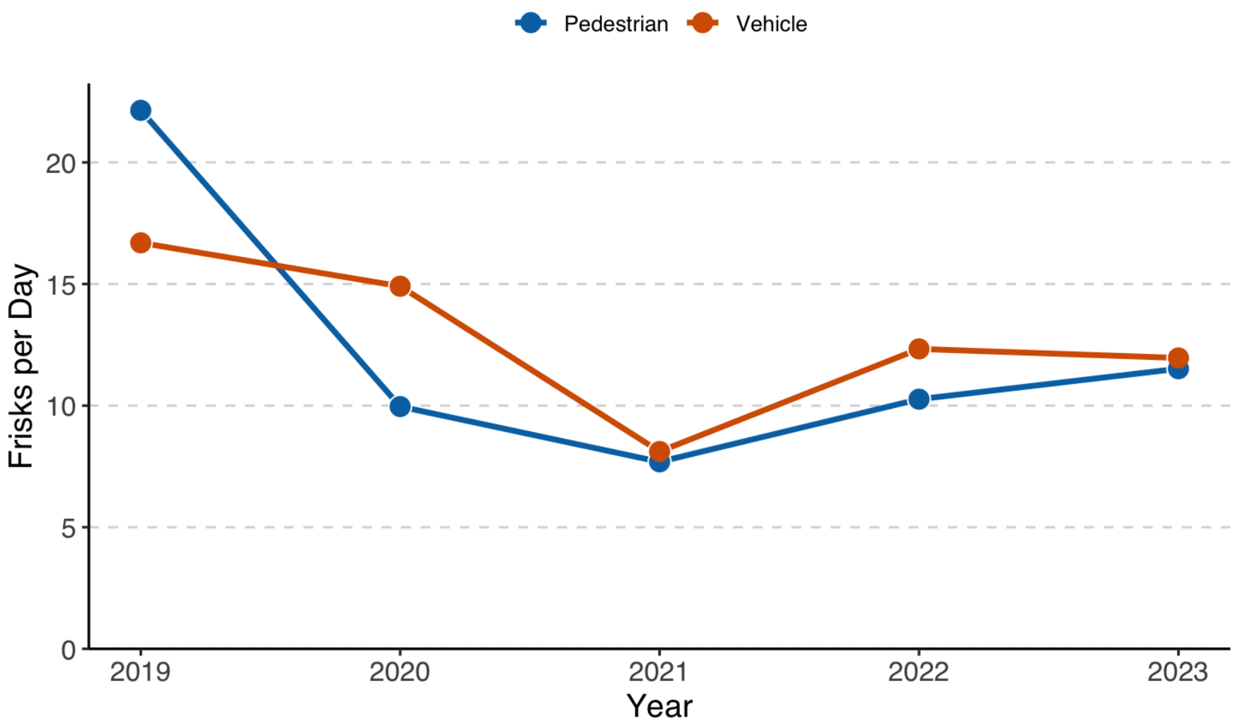
Stops and frisks are daily per million residents.

Figure 4: Median Daily Stops for Pedestrian and Vehicle Stops, 2019–2023



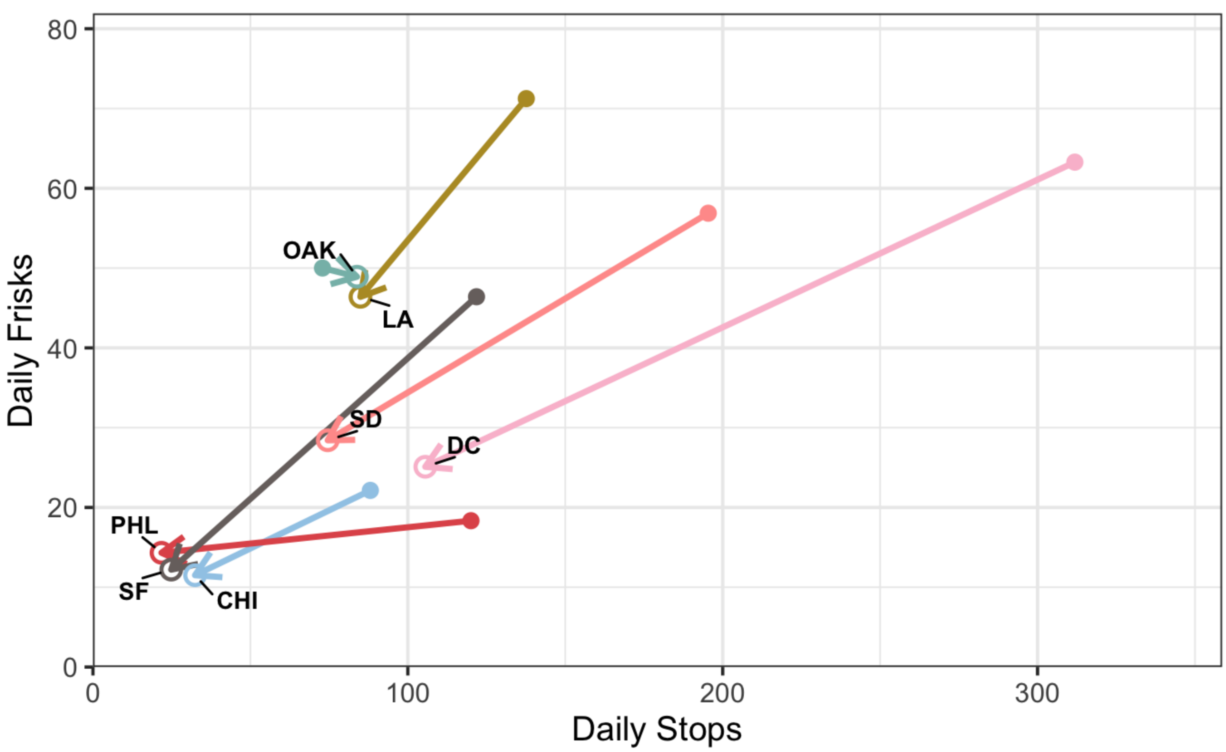
Stops are daily per million residents.

Figure 5: Median Daily Frisks for Pedestrians and Vehicles, 2019–2023



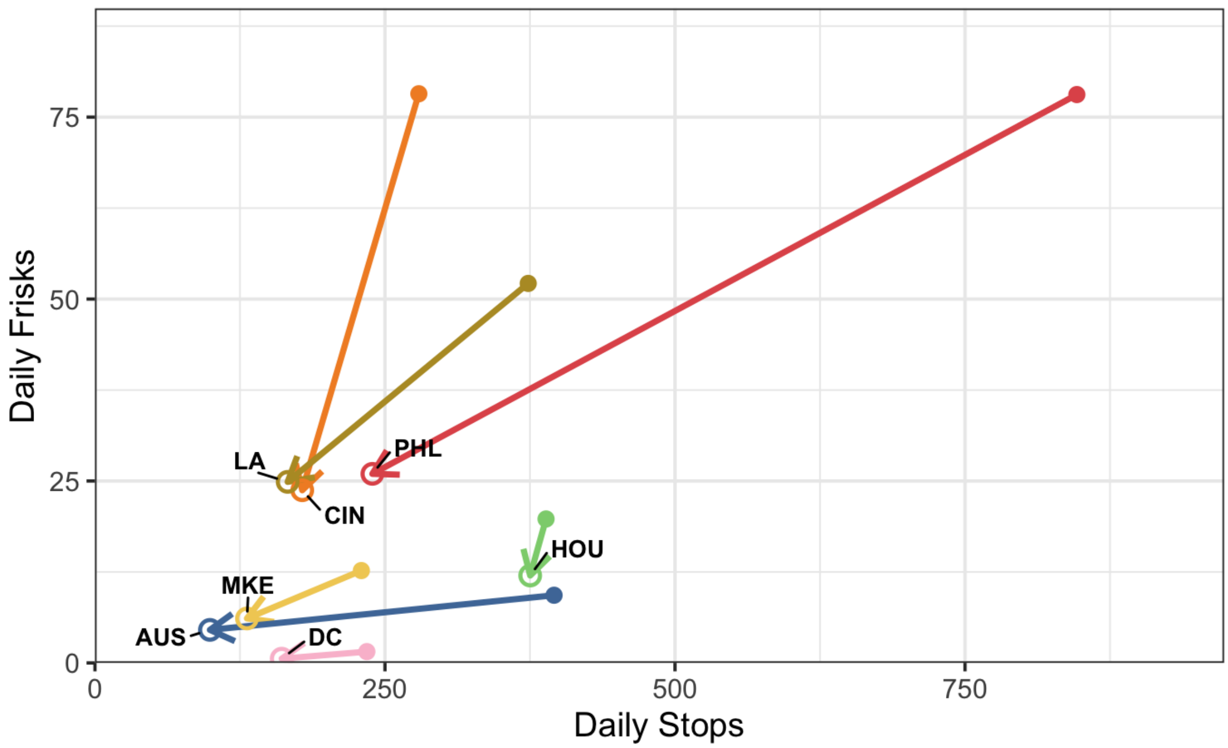
Frisks are daily per million residents.

Figure 6: Pedestrian Frisks vs. Stops in High-Stop Cities, 2019–2023



Stops and Frisks are daily per million residents.

Figure 7: Vehicle Frisks vs. Stops in High-Stop Cities, 2019–2023



Stops and Frisks are daily per million residents.

Figure 8: Mean Frisk Rates for Pedestrian and Vehicle Stops, 2019–2023

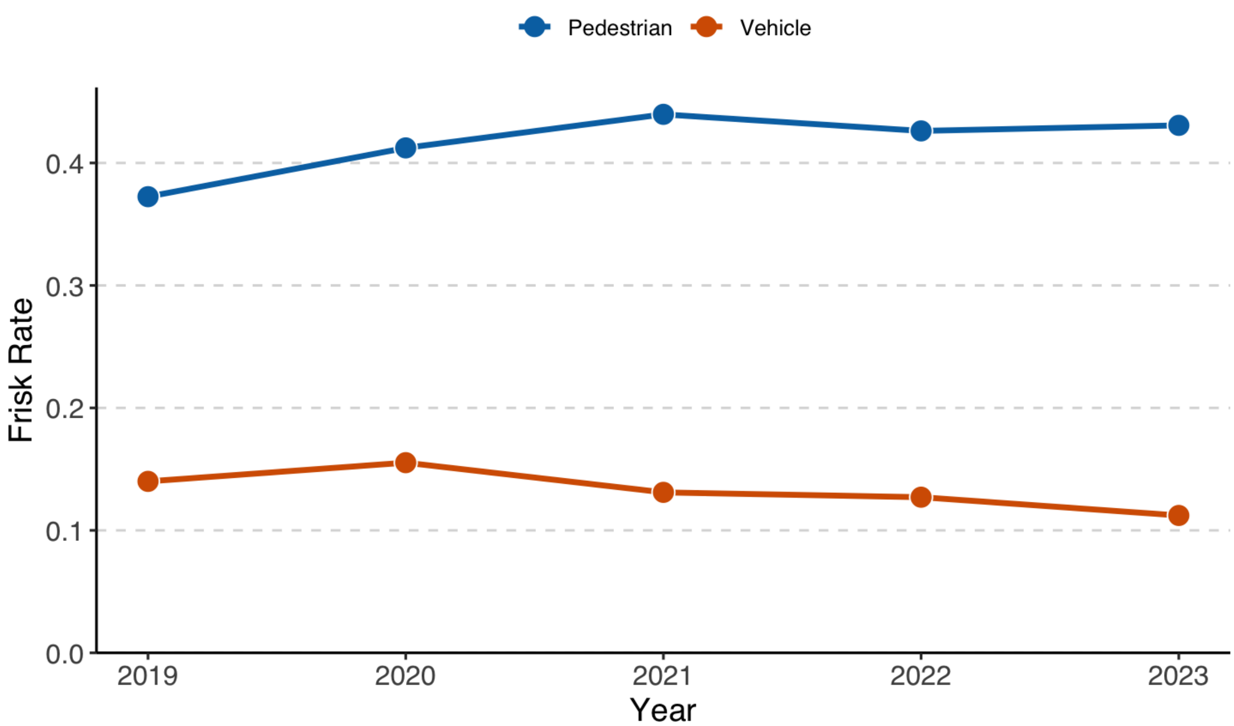


Figure 9: Mean Gun Hit Rates for Pedestrian and Vehicle Stops, 2019–2023

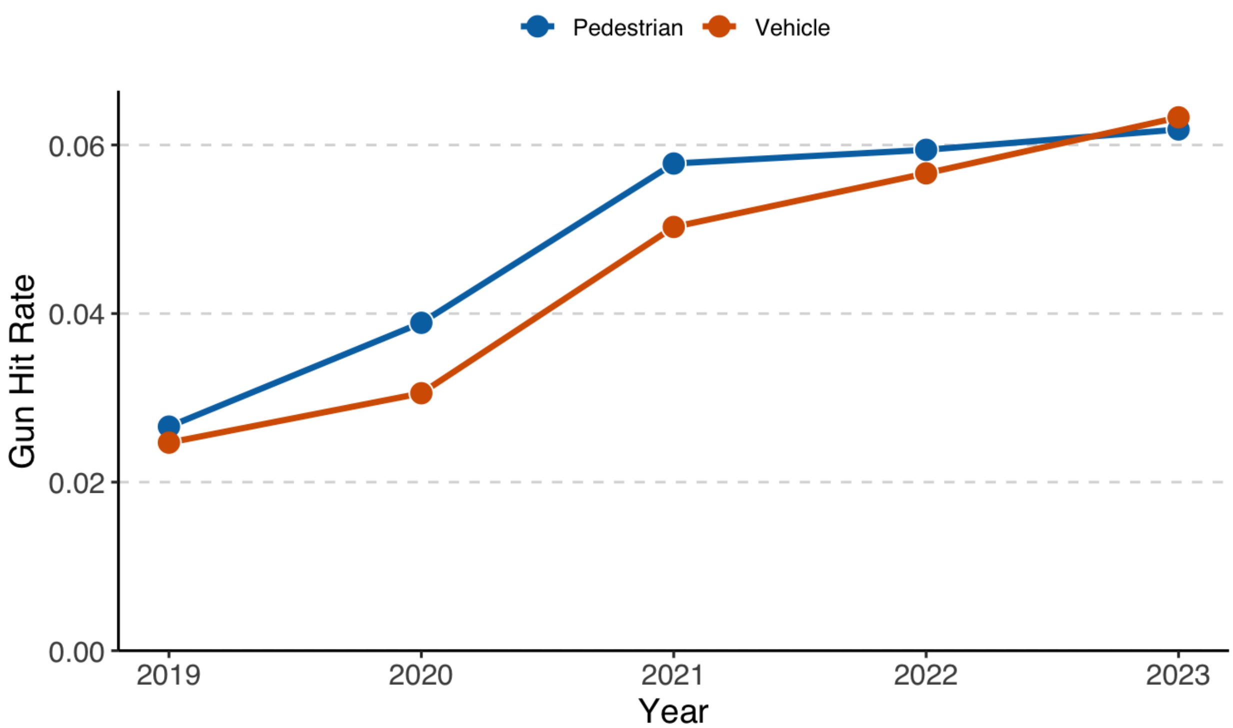


Figure 10: Mean Contraband Hit Rates for Pedestrian and Vehicle Stops, 2019–2023

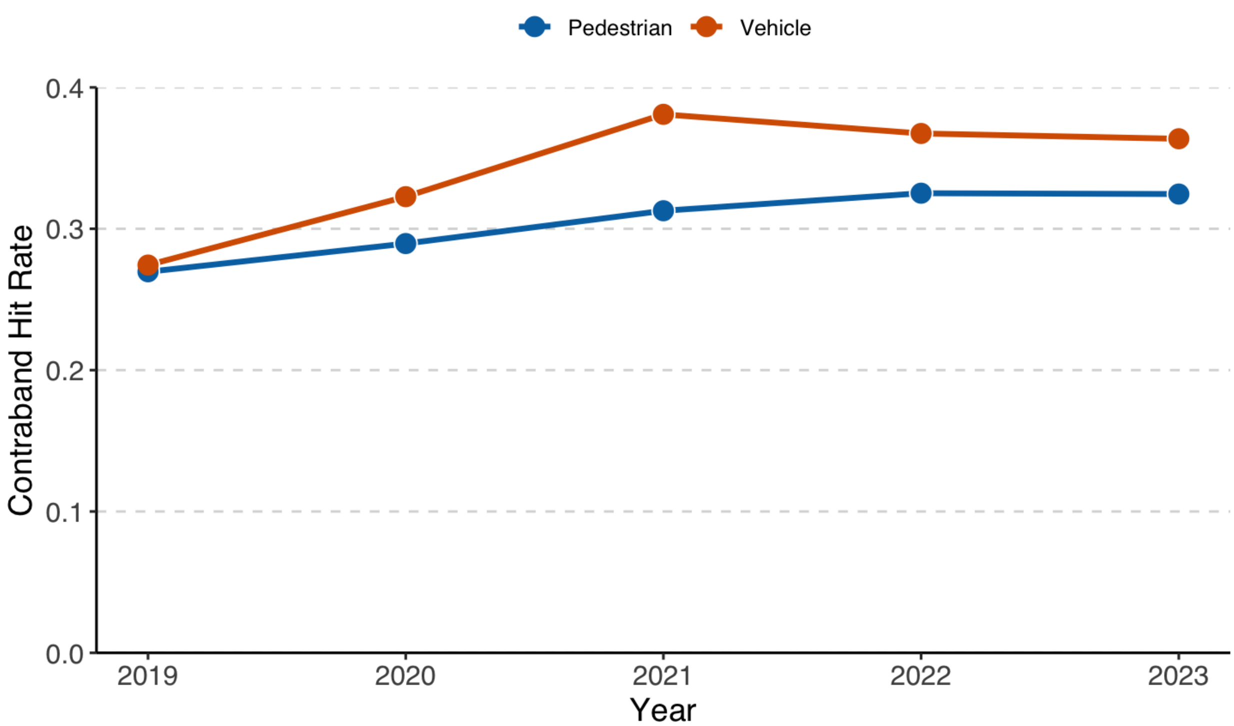


Figure 11: Pedestrian and Vehicle, Gun and Contraband Hit Rates, 2019–2023

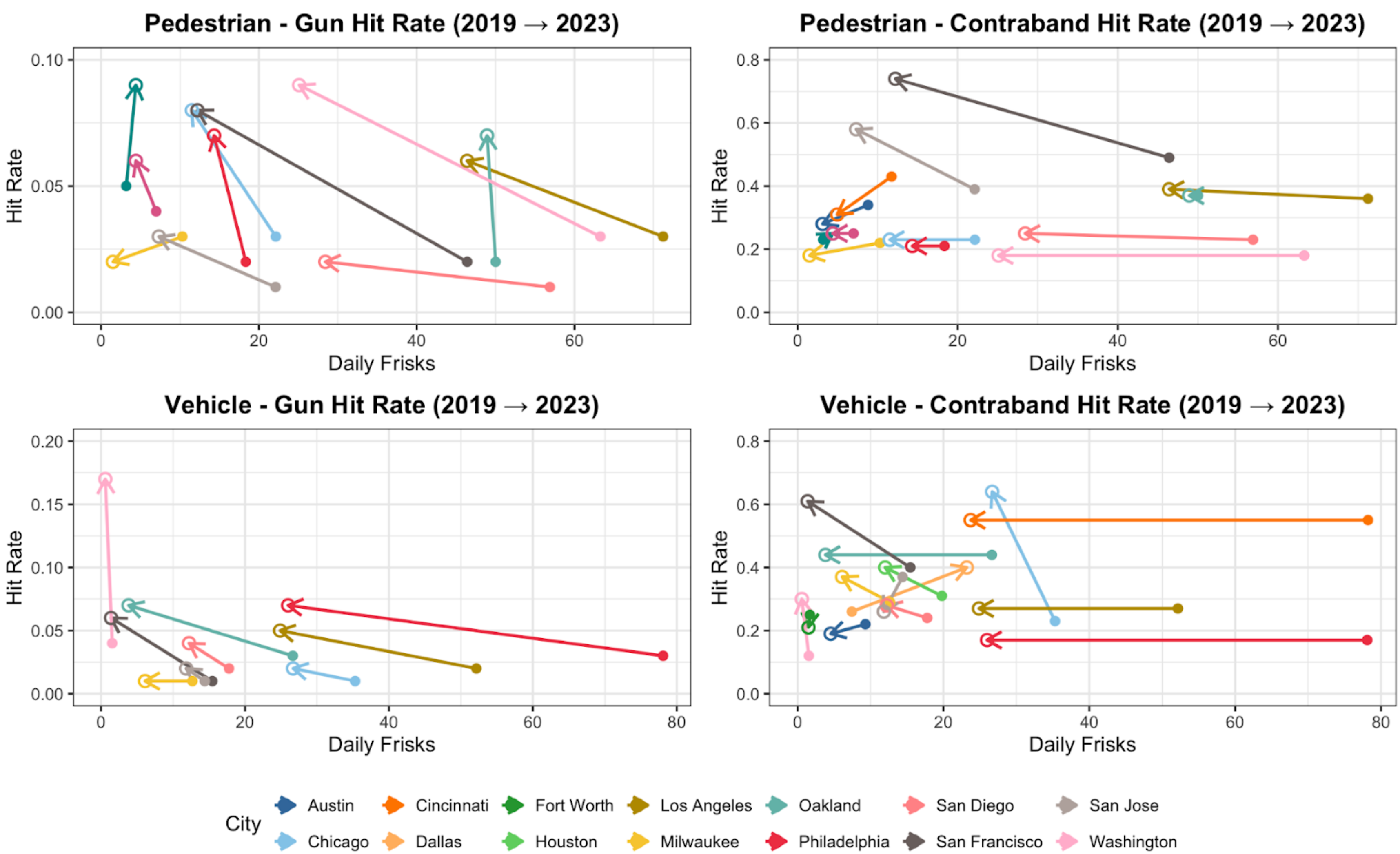
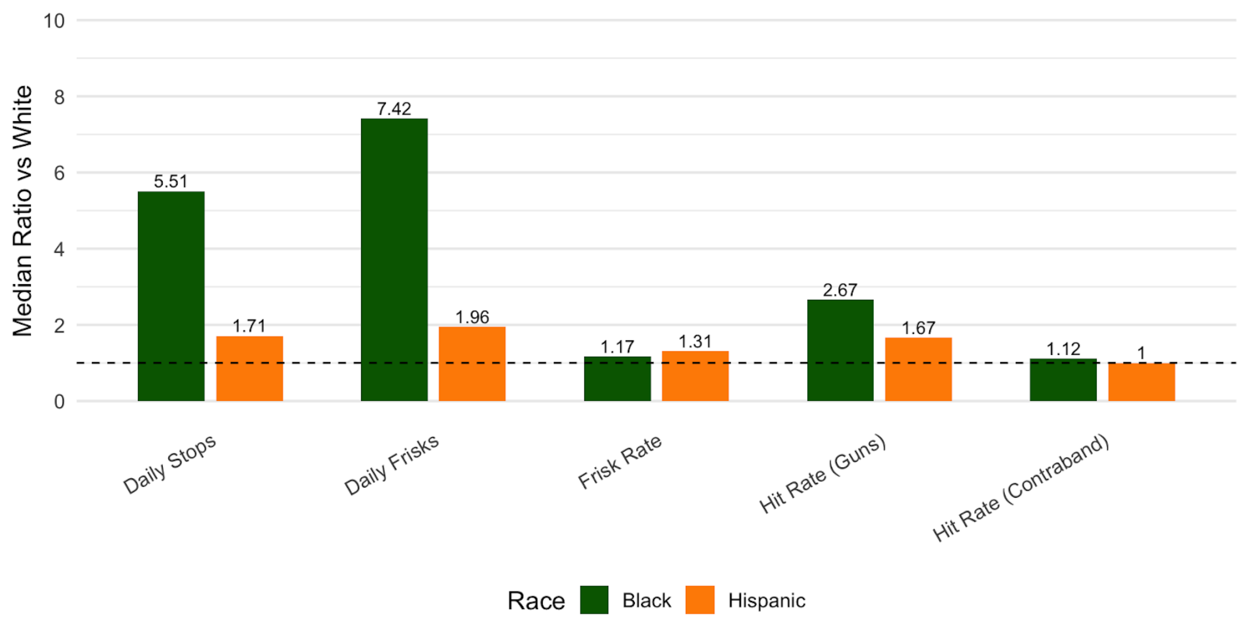
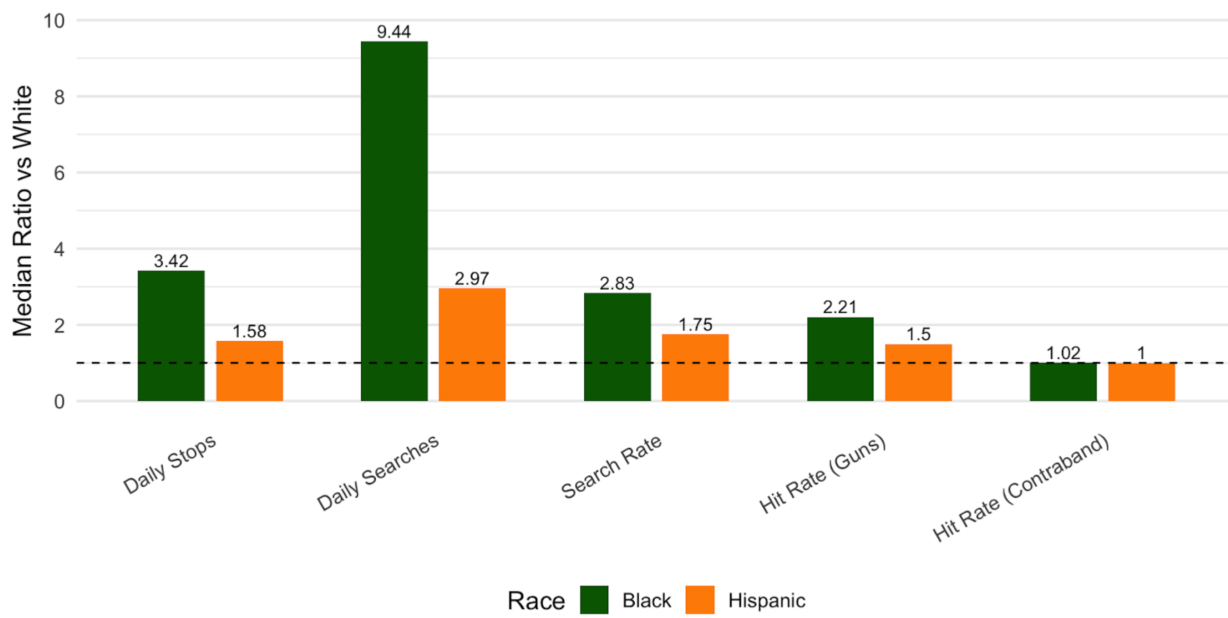


Figure 12: Median ratios of Black and Hispanic demographic groups relative to White individuals for pedestrian stops.



Values represent the median ratio across all cities for each statistic. Daily stops and frisks are reported per million residents of the racial group. "Black" includes Hispanic and non-Hispanic Black individuals, while "Hispanic" refers to White-Hispanic individuals.

Figure 13: Median ratios of Black and Hispanic demographic groups relative to White individuals for vehicle stops.



Values represent the median ratio across all cities for each statistic. Daily stops and frisks are reported per million residents of the racial group. “Black” includes Hispanic and non-Hispanic Black individuals, while “Hispanic” refers to White-Hispanic individuals.

Table 1: Stop and Frisk Summary Statistics (2019 vs. 2023)

	Mean		Median		SD		CV	
Variable	2019	2023	2019	2023	2019	2023	2019	2023
Pedestrian Data								
Stops	96.1	39.6	72.9	24.9	81.2	33.2	0.85	0.84
Frisks	30.1	16.4	22.1	11.5	23.0	15.5	0.76	0.95
Frisk Rate	0.37	0.43	0.38	0.49	0.18	0.18	0.48	0.41
HR Guns	0.026	0.061	0.030	0.070	0.011	0.025	0.44	0.41
HR Overall	0.27	0.32	0.23	0.25	0.13	0.16	0.48	0.49
Vehicle Data								
Stops	259	148	227	125	198	99	0.76	0.66
Searches	26.5	12.7	16.6	11.9	24.7	9.8	0.93	0.77
Search Rate	0.14	0.11	0.09	0.07	0.15	0.14	1.05	1.22
HR Guns	0.024	0.063	0.025	0.055	0.010	0.048	0.42	0.76
HR Overall	0.27	0.36	0.25	0.34	0.11	0.15	0.42	0.40

Stop and frisk data are daily per million residents. CV is the coefficient of variation SD/Mean. For pedestrian data, $n = 13$ except for gun hit rates where $n = 11$. For vehicle data, $n = 14$ except for gun hit rates where $n = 8$.

Table 2: Summary Statistics for City-wide Correlation Variables (2023)

	Mean	Median	Std Dev	CV
% Below Poverty Level	15.0	15.0	4.10	0.273
Per Capita Income ($1,000s)	54.7	49.9	17.3	0.316
Police Budget per Capita	527	488	133	0.251
Sworn Officers per Capita	2,550	2,320	1,180	0.462
Officers per Violent Crime	0.348	0.341	0.164	0.470
Violent Crimes	8,040	6,820	3,650	0.454
Murder	166	130	123	0.740
Rape	357	326	147	0.411
Aggravated Assault	4,780	4,300	2,250	0.470
Robbery	2,730	2,160	2,020	0.740

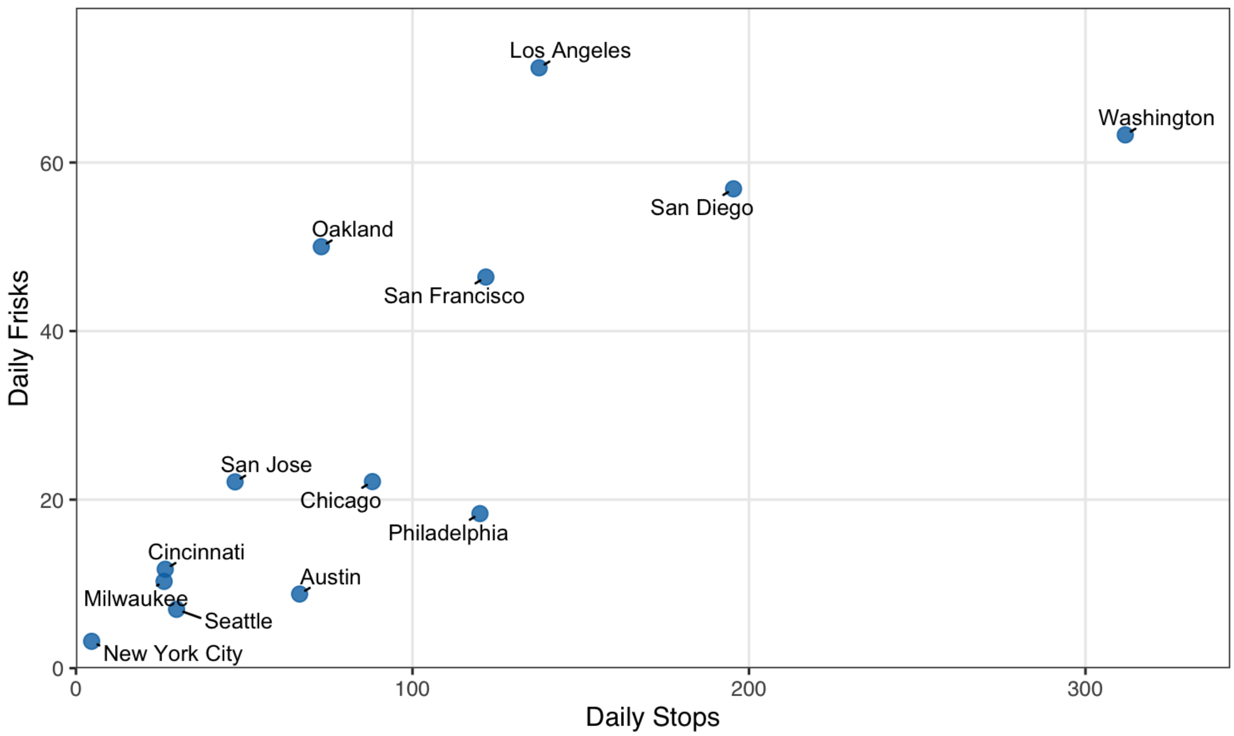
All crime variables, police budget, and officer counts are per million residents. Per Capita Income is measured in $1,000s. CV = Std Dev / Mean.

Table 3: Correlations between Stop and Frisk Metrics and City Characteristics (2023)

	Stops		Searches/Frisks		Gun Hit Rate		Contraband Hit Rate	
	Pedestrian	Vehicle	Pedestrian	Vehicle	Pedestrian	Vehicle	Pedestrian	Vehicle
% below poverty level	-0.27	0.55	-0.16	0.48	0.19	-0.08	-0.43	0.28
Per capita income	0.25	-0.54	0.08	-0.47	0.29	0.42	0.41	0.16
Police budget per capita	0.07	-0.43	0.09	-0.24	0.72	0.45	0.02	0.50
Sworn officers per capita	0.07	0.32	-0.01	0.28	0.72	0.30	-0.54	0.32
Officers per violent crime	0.21	0.13	0.04	0.36	0.58	0.22	-0.20	0.07
Violent crimes	-0.14	0.29	0.05	-0.13	0.33	0.42	-0.33	0.40
Murder	0.06	0.36	0.00	-0.07	0.35	0.42	-0.59	0.19
Rape	-0.18	-0.29	-0.25	-0.08	-0.10	-0.52	0.05	0.20
Aggravated assault	-0.44	0.59	-0.18	-0.01	-0.14	0.13	-0.31	-0.05
Robbery	0.20	-0.07	0.29	-0.08	0.67	0.63	-0.22	0.57
Police perception	-0.08	0.01	-0.34	-0.41	0.64	0.29	-0.31	-0.36
Precipitation	-0.20	0.04	-0.19	0.11	0.06	0.00	-0.11	0.17

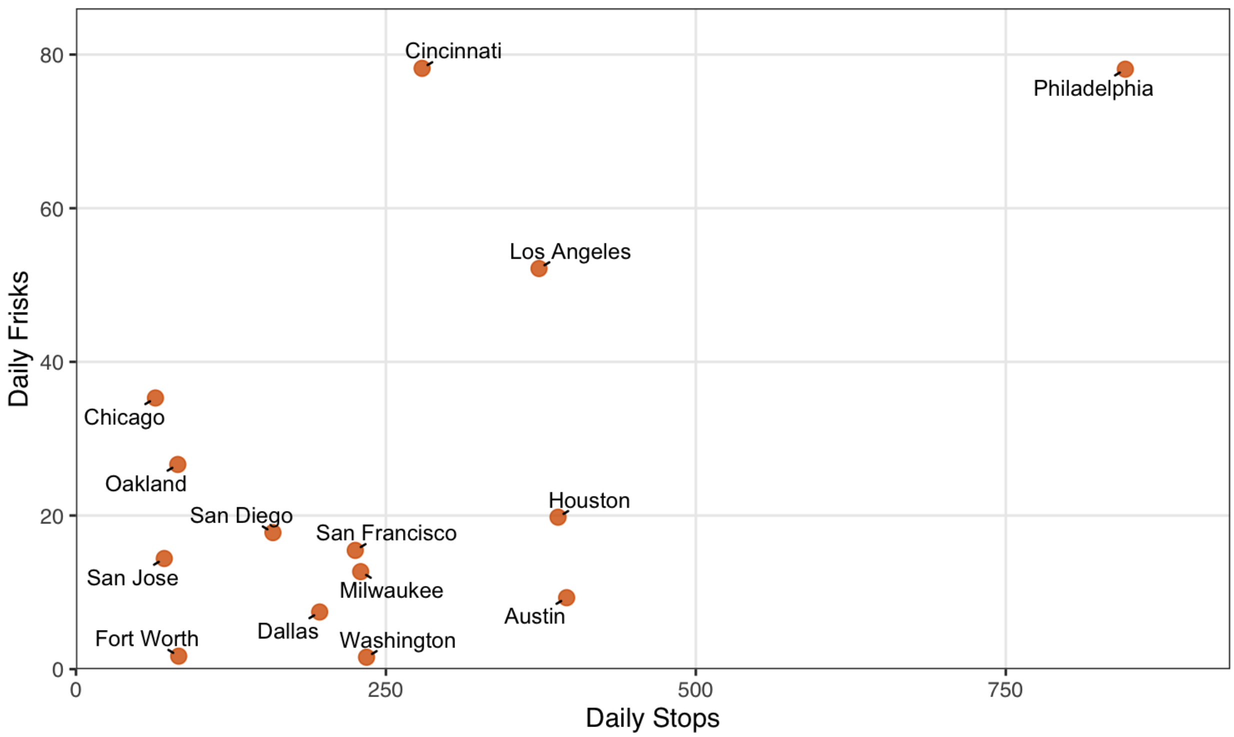
A Additional Figures and Tables

Figure A.1: Pedestrian Frisks vs. Stops, 2019



Stops and frisks are daily per million residents.

Figure A.2: Vehicle Frisks vs. Stops, 2019



Stops and frisks are daily per million residents.

Table A.1: Pedestrian Stop and Frisk Summary Statistics 2019 vs. 2023

	Daily Stops		Daily Frisks		Frisk Rate		HR Guns		HR Overall	
City	2019	2023	2019	2023	2019	2023	2019	2023	2019	2023
Washington	311.84	105.55	63.28	25.10	0.20	0.24	0.03	0.09	0.11	0.18
San Diego	195.41	74.56	56.88	28.42	0.29	0.38	0.01	0.02	0.23	0.25
San Francisco	121.81	24.86	46.41	12.21	0.38	0.49	0.02	0.08	0.49	0.74
Philadelphia	120.05	21.76	18.34	14.32	0.15	0.66	0.02	0.07	0.12	0.21
Los Angeles	137.62	84.95	71.24	46.40	0.52	0.55	0.03	0.06	0.36	0.39
Oakland	72.90	83.84	50.01	48.92	0.69	0.58	0.02	0.07	0.14	0.37
Chicago	88.09	32.43	22.14	11.51	0.25	0.35	0.03	0.08	0.13	0.23
San Jose	47.28	18.96	22.11	7.32	0.47	0.39	0.01	0.03	0.48	0.58
Seattle	29.88	14.71	6.98	4.41	0.23	0.30	0.04	0.06	0.25	0.25
Austin	66.46	26.08	8.80	3.13	0.13	0.12	—	—	0.34	0.28
Cincinnati	26.52	17.70	11.74	4.96	0.44	0.28	—	—	0.43	0.31
Milwaukee	26.18	3.08	10.30	1.50	0.39	0.49	0.03	0.02	0.22	0.18
New York City	4.65	5.68	3.19	4.40	0.69	0.78	0.05	0.09	0.23	0.25
Mean	96.05	39.55	30.11	16.35	0.37	0.43	0.03	0.06	0.27	0.32
SD	81.20	33.24	23.01	15.50	0.18	0.18	0.01	0.03	0.13	0.16
CV	0.85	0.84	0.76	0.95	0.48	0.41	0.44	0.41	0.48	0.49

Stops and Frisks are daily per million residents. CV is SD/Mean.

Table A.2: Vehicle Stop and Frisk Summary Statistics 2019 vs. 2023

	Daily Stops		Daily Searches		Search Rate		HR Guns		HR Overall	
City	2019	2023	2019	2023	2019	2023	2019	2023	2019	2023
Philadelphia	846.41	239.13	78.10	25.98	0.09	0.11	0.03	0.07	0.14	0.17
Austin	395.76	99.08	9.30	4.54	0.02	0.05	—	—	0.22	0.19
Houston	388.84	375.17	19.78	12.01	0.05	0.03	—	—	0.31	0.40
Los Angeles	373.48	166.11	52.15	24.88	0.14	0.15	0.02	0.05	0.21	0.27
Cincinnati	279.18	178.68	78.21	23.73	0.28	0.13	—	—	0.59	0.55
Washington	234.36	160.95	1.55	0.58	0.01	< 0.01	0.04	0.17	0.12	0.30
Milwaukee	229.63	131.02	12.69	6.11	0.06	0.05	—	—	0.29	0.37
San Francisco	225.26	33.20	15.46	1.38	0.07	0.04	0.03	0.06	0.40	0.61
Dallas	196.54	319.83	7.44	23.20	0.04	0.07	—	—	0.26	0.40
San Diego	158.86	119.70	17.77	12.22	0.11	0.10	0.02	0.04	0.24	0.28
Fort Worth	82.84	77.12	1.69	1.50	0.02	0.02	—	—	0.25	0.21
Oakland	82.10	68.38	26.64	3.82	0.32	0.06	0.03	0.07	0.20	0.44
San Jose	71.21	63.76	14.40	11.82	0.20	0.19	0.01	0.02	0.37	0.26
Chicago	64.09	46.45	35.30	26.68	0.55	0.57	0.01	0.02	0.23	0.64
Mean	259.18	148.47	26.46	12.75	0.14	0.11	0.02	0.06	0.27	0.36
SD	197.53	98.67	24.71	9.79	0.15	0.14	0.01	0.05	0.11	0.15
CV	0.76	0.66	0.93	0.77	1.05	1.22	0.42	0.75	0.42	0.40

Stops and Frisks are daily per million residents. CV is SD/Mean.

Table A.3: City Demographics (2023)

	Population ('000s)	White (%)	Black (%)	Hispanic (%)	Below Poverty Level (%)	Per Capita Income ($)
New York City	8,184	31	20	28	18	50,764
Los Angeles	3,821	28	8	47	16	46,699
Chicago	2,628	32	27	30	17	48,954
Houston	2,304	23	23	44	19	41,579
Philadelphia	1,551	33	38	16	20	37,973
San Diego	1,378	40	5	30	11	56,642
Dallas	1,305	28	23	42	16	45,146
Austin	979	46	7	33	12	64,182
Fort Worth	974	36	19	35	12	38,088
San Jose	970	21	3	32	8	63,575
San Francisco	809	37	5	16	12	88,336
Seattle	754	59	6	9	10	83,303
Washington	679	37	40	12	13	78,479
Milwaukee	559	31	36	22	22	29,800
Oakland	437	27	19	30	14	60,823
Cincinnati	309	50	35	5	20	40,759
Mean	1,728	34.9	19.6	26.9	15.0	54,694
SD	1,952	10.0	13.0	12.6	4.1	17,265

Table A.4: Violent Crime Statistics by City (2023)

	Violent Crimes	Murder	Rape	Aggravated Assault	Robbery
Oakland	17,272	289	440	8,089	8,454
Milwaukee	14,292	387	490	10,557	2,858
Houston	10,719	158	339	7,254	2,968
Washington	10,495	389	292	4,231	5,583
Philadelphia	9,847	293	299	5,868	3,387
Seattle	7,677	101	188	5,154	2,234
Cincinnati	7,361	236	662	4,372	2,091
San Francisco	6,865	63	318	3,083	3,401
Dallas	6,765	217	280	4,673	1,595
New York City	6,589	47	137	4,400	2,005
Chicago	6,103	190	473	1,308	4,132
San Jose	5,362	28	458	3,873	1,003
Los Angeles	5,467	57	282	3,607	1,521
Austin	4,877	83	334	3,524	936
Fort Worth	4,813	94	563	3,441	715
San Diego	4,153	32	157	3,090	874
Mean	8,041	166.5	357	4,783	2,735
SD	3,647	123.3	147	2,247	2,024

Annual incidents per million residents.

Table A.5: Police Department Statistics by City (2022/2023)

	Police Budget per million residents ($M)	Officers per million residents	Officers per Murder	Police Budget % of Total Budget (%)
Oakland	769	1,627	5.6	42.8
Washington	736	4,922	12.7	4.7
San Francisco	703	2,310	36.6	9.8
Chicago	647	4,487	23.6	34.8
New York City	625	4,071	85.9	7.6
Cincinnati	543	2,960	12.5	38.0
Milwaukee	502	2,894	7.5	45.9
San Jose	496	1,109	39.8	30.3
Philadelphia	470	3,510	12.0	13.8
Seattle	479	1,413	14.0	22.5
Los Angeles	446	2,333	40.9	22.7
Dallas	434	2,335	10.8	36.9
San Diego	430	1,289	40.4	34.0
Houston	415	2,245	14.2	16.9
Austin	453	1,520	18.4	37.9
Fort Worth	290	1,708	18.1	34.0
Mean	527	2,546	24.6	27.0
SD	133	1,175	20.4	13.2

Police budget data is from 2022. Police staffing data is from 2023.

Table A.6: Pedestrian Stop and Frisk Summary Statistics by Race (2023)

(a) Black

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
San Diego	301.28	124.49	0.54	0.02	0.27
Los Angeles	268.98	161.44	0.49	0.08	0.36
Washington	223.60	56.38	0.25	0.10	0.19
Oakland	218.51	130.60	0.68	0.08	0.35
San Francisco	176.61	94.84	0.37	0.13	0.69
San Jose	88.78	32.82	0.33	0.03	0.72
Austin	81.39	11.76	0.14	—	0.27
Chicago	76.34	30.23	0.40	0.09	0.25
Philadelphia	39.25	26.84	0.41	0.08	0.22
New York City	19.23	15.32	0.60	0.10	0.25
Milwaukee	6.76	3.33	0.80	0.03	0.20
Mean	136.16	62.91	0.46	0.07	0.35

(b) Hispanic

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
San Diego	73.86	31.32	0.42	0.02	0.25
Los Angeles	98.86	54.75	0.55	0.05	0.41
Washington	42.47	6.42	0.15	0.04	0.12
Oakland	74.63	47.05	0.63	0.07	0.34
San Francisco	35.04	18.28	0.52	0.06	0.81
San Jose	33.06	13.28	0.40	0.03	0.57
Austin	11.60	2.91	0.25	—	0.20
Chicago	25.05	8.28	0.33	0.06	0.19
Philadelphia	16.67	11.34	0.68	0.06	0.23
New York City	4.06	3.07	0.76	0.07	0.27
Milwaukee	1.14	0.58	0.51	—	0.15
Mean	37.85	17.30	0.47	0.05	0.32

(c) White

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
San Diego	75.41	24.69	0.33	0.01	0.24
Los Angeles	48.81	21.75	0.45	0.03	0.38
Washington	14.33	1.61	0.11	0.05	0.17
Oakland	50.59	24.05	0.48	0.03	0.47
San Francisco	20.46	8.92	0.44	0.04	0.81
San Jose	19.01	7.30	0.38	0.03	0.58
Austin	22.05	2.64	0.12	—	0.32
Chicago	11.42	2.14	0.19	0.04	0.23
Philadelphia	11.06	6.05	0.55	0.03	0.16
New York City	1.02	0.59	0.58	0.03	0.21
Milwaukee	0.95	0.36	0.38	—	0.04
Mean	24.28	9.19	0.36	0.03	0.33

Daily Stops and Frisks are reported per million residents of the racial group. Frisk Rate is the proportion of stops involving a frisk. Hit Rates are the proportions of frisks yielding contraband or a gun. Black is defined as Hispanic and non-Hispanic Black. Hispanic is defined as White-Hispanic.

Table A.7: Vehicle Stop and Frisk Summary Statistics by Race (2023)

(a) Black

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
Dallas	553.64	54.59	0.10	—	0.44
Houston	548.23	29.95	0.05	—	0.38
Los Angeles	425.03	103.66	0.24	0.07	0.30
Philadelphia	408.27	54.12	0.13	0.07	0.17
San Diego	340.56	62.46	0.18	0.07	0.29
Cincinnati	329.70	57.20	0.17	—	0.55
Austin	202.57	16.19	0.08	—	0.22
San Jose	178.22	43.69	0.25	0.03	0.31
Milwaukee	222.50	14.55	0.07	0.02	0.38
Oakland	131.74	9.72	0.07	0.09	0.42
Fort Worth	115.70	3.86	0.03	—	0.22
Chicago	114.19	68.79	0.60	0.03	0.63
San Francisco	105.28	9.24	0.09	0.08	0.56
Mean	282.74	40.62	0.16	0.06	0.37

(b) Hispanic

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
Dallas	296.57	19.21	0.06	—	0.37
Houston	235.52	5.77	0.02	0.04	0.45
Los Angeles	185.29	31.68	0.17	—	0.25
Philadelphia	200.54	19.28	0.10	0.06	0.16
San Diego	142.09	17.56	0.12	0.04	0.26
Austin	57.41	3.54	0.06	—	0.13
San Jose	114.06	27.15	0.24	0.02	0.24
Milwaukee	107.44	2.01	0.02	—	0.29
Oakland	80.02	4.63	0.06	0.06	0.47
Fort Worth	80.19	1.63	0.02	—	0.22
Chicago	42.70	23.10	0.54	0.02	0.64
San Francisco	48.20	2.13	0.04	0.03	0.67
Mean	132.50	13.14	0.12	0.04	0.35

(c) White

City	Daily Stops	Daily Frisks	Frisk Rate	HR Guns	HR Overall
Dallas	221.44	8.41	0.04	—	0.36
Houston	536.86	10.31	0.02	—	0.42
Los Angeles	106.15	4.33	0.04	0.07	0.33
Philadelphia	117.43	5.28	0.04	0.04	0.16
San Diego	99.58	6.26	0.06	0.02	0.30
Cincinnati	109.22	6.06	0.06	—	0.52
Austin	110.52	3.66	0.03	—	0.22
San Jose	46.52	5.44	0.12	0.01	0.31
Milwaukee	73.56	1.14	0.02	—	0.37
Oakland	32.88	1.38	0.04	—	0.47
Fort Worth	65.89	0.52	0.01	—	0.15
Chicago	6.46	2.60	0.40	0.03	0.62
San Francisco	28.18	0.93	0.03	0.03	0.53
Mean	119.59	4.33	0.07	0.03	0.37

Daily Stops and Frisks are reported per million residents of the racial group. Frisk Rate is the proportion of stops involving a frisk. Hit Rates are the proportions of frisks yielding contraband or a gun. Black is defined as Hispanic and non-Hispanic Black. Hispanic is defined as White-Hispanic.