# An Analysis of the Metropolitan Nashville Police Department's Traffic Stop Practices

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**EXECUTIVE SUMMARY**

For the last several years, Nashville has made considerably more traffic stops per capita than the national average, with stops disproportionately involving black drivers. Here we examine the Metropolitan Nashville Police Department's (MNPD) traffic stop practices in 2017, drawing on an extensive dataset of records provided by the department. Black drivers were stopped 44% more often per driving-age resident when compared to white drivers; this gap is particularly pronounced among stops for non-moving violations (68%), such as broken tail lights and expired registration tags. These disparities stem, in part, from a strategy that concentrates traffic stops in high-crime areas. In particular, after controlling for location, disparities among non-moving violation stops drop from 68% to 37%. This policy of concentrating stops in high-crime areas may be predicated on the belief that traffic stops are an effective tactic for reducing burglaries, robberies, and other criminal activity. We find, however, no immediate or long-term impact of traffic stops on serious crime. We further find that only 1.6% of stops result in a custodial arrest—often for license violations or drugs. These findings suggest that the MNPD could reduce traffic stops without an associated rise in serious crime, while bringing Nashville's traffic stop rates more in line with similar cities around the country. In particular, the MNPD could substantially reduce racial disparities by curtailing stops for non-moving violations. Notably, a small proportion of active MNPD officers conduct the majority of non-moving violation stops, potentially facilitating any effort to reduce such stops.

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Like all police departments, the Metropolitan Nashville Police Department (MNPD) uses a wide range of enforcement tools to ensure public safety. Traffic stops are one such tool. These interactions typically involve an officer pulling over a motorist, issuing a warning or citation, and—more rarely—conducting a search for contraband or making a custodial arrest. The prevalence and nature of traffic stops vary widely across American cities, but they are generally the most common way police departments initiate contact with the public [6].

In the past several years, the MNPD made more traffic stops per capita than many similarly sized American cities—in some cases, over ten times as many (Figure 1). Local community groups have also raised concerns that the MNPD's traffic stop practices disproportionately impact black drivers. In 2016, Gideon's Army published a report, "Driving While Black," documenting racial disparities in MNPD traffic stops between 2011 and 2015 [4]. Notably, there were more stops of black drivers per year than the number of black driving-age residents in Nashville. The MNPD, in response, argued that such disparities resulted from higher deployment to areas with greater incidence of crime and requests for police services.

Our goals in this report are three-fold. First, we aim to quantify racial disparities in the MNPD's current traffic stop practices. In particular, we focus on stops in 2017, a year in which the MNPD's traffic stop rates had dropped by almost 50% from their peak during the years covered by the Gideon's Army report. Second, we seek to assess the extent to which any observed racial disparities may be driven by concerns for public safety. Finally, and most importantly, we strive to provide concrete, data-driven insights to improve both the equity and efficacy of the MNPD's policing strategies. Our analysis builds on a long line of empirical research examining traffic stops [2, 3, 8, 13–20, 22].

To conduct our analysis, we used several datasets provided to us by the MNPD, including traffic stop records and crime reports. We also incorporated information from the U.S. Census to construct population benchmarks for Nashville neighborhoods. Though we focus on 2017, our dataset covers traffic stops occurring between 2011 and 2017, permitting comparisons with historical trends.

Last year, the MNPD conducted approximately 246,000 traffic stops, or roughly one stop for every two driving-age residents. We start by comparing stop rates for black motorists and non-Hispanic white motorists. We focus on these two groups, which comprise about 85% of Nashville's population, in part for ease of exposition and in part to mitigate statistical difficulties with analyzing groups that comprise a smaller share of the local population.[1] We find that the stop rate for black drivers in Nashville in 2017 was 44% higher than the stop rate for white drivers, where stop rates are computed relative to the driving-age population. Further, certain types of stops exhibited far greater disparities than others. Among moving violations (e.g., speeding or reckless driving), the stop rate for black drivers was 24% higher than white drivers; in contrast, among non-moving violations (e.g., broken tail lights or expired registration tags), the stop rate for black drivers was 68% higher than for white drivers. Moreover, stops for non-moving violations were relatively common, comprising 45% of all traffic stops in Nashville in 2017.

These differences in stop rates are striking. It bears emphasis, though, that such differences may result from a variety of complex factors, and are not necessarily the product of racial bias [1, 5, 9, 13, 19]. In particular, we find that the observed disparities are in part attributable to deployment patterns, particularly the MNPD's concentration of stops in high-crime neighborhoods, which, in Nashville, tend to have disproportionately large minority populations.

One reason—and arguably the primary rationale—for carrying out large numbers of traffic stops in high-crime areas is a belief that this enforcement strategy has broader benefits for public safety. One might posit that traffic stops deter future crime or lead to apprehending those responsible for past incidents. Though plausible, we find little evidence of such a connection between traffic stops and serious crime levels in Nashville. Over the 2011–2017 time period, crime levels for Part I offenses[2] remained steady despite substantial reductions in stop rates over the same period. Further, week-to-week changes in area-specific stop rates were uncorrelated with changes in local crime levels.

Traffic stops might also benefit public safety by facilitating the arrest of those individuals charged for past crimes but who may have been difficult to otherwise track down. We find, however, that only 1.6% of traffic stops lead to a custodial arrest, often for license violations or drug possession. An additional 5.8% of traffic stops end in a misdemeanor citation (resulting in a non-custodial arrest), typically for driving without a valid license.

These findings suggest that the MNPD could curtail traffic stops without increasing serious crime. Given the substantial disparities in non-moving violations, one might first focus on reducing these stops. In particular, we note that a 90% reduction in non-moving violation stops would bring Nashville more in line with per capita traffic stop rates in similar cities across the U.S. (Figure 1), and we estimate this change would reduce stop rate disparities between black and white drivers from 44% to 28%. This reduction in proactive policing would be sizable, though not unprecedented. For example, the New York Police Department reduced pedestrian stops from nearly 700,000 in 2011 to 11,000 in 2017, a reduction of more than 95%[3] with no associated increase in crime. Further, the MNPD itself has nearly halved its use of traffic stops over the last several years, while crime rates have held steady.

Such a reduction may be facilitated by the fact that a relatively small set of officers carry out the bulk of non-moving violation stops, allowing the MNPD to work directly with that group to redirect enforcement activity. For example, 50% of these stops were conducted by 125 individuals, or 17% of all officers who conducted at least one traffic stop in our observation period. It is unclear why stops are concentrated among such a relatively small group. We note, however, that officers in many jurisdictions are given considerable discretion to enforce traffic laws as they see fit, which may in turn result in the observed pattern.

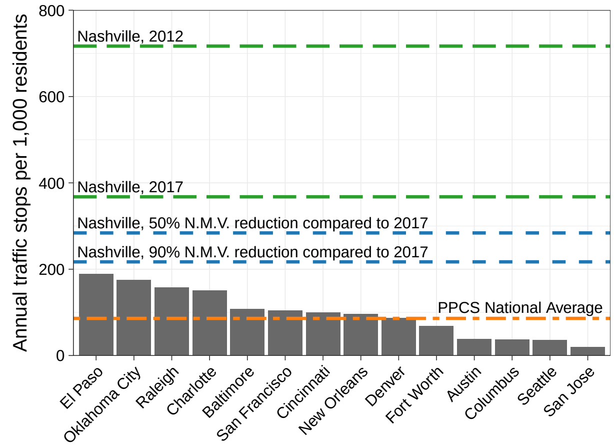



**Figure 1:** *Per capita traffic stop rates in Nashville compared with the national average and activity in other American cities between approximately 2011–2016.*[4] *This figure is intended for approximate comparison, not to suggest optimal levels of policing. Traffic stop rates for comparison cities were calculated using data compiled by the Stanford Open Policing Project (OPP). All OPP cities with populations between approximately 500,000 and 1 million were included for comparison. Cincinnati, New Orleans, and Raleigh have populations under 500,000, but were added for additional context. Green reference lines display historical stop rates for Nashville, blue lines display stop rates for hypothetical reductions in non-moving violation stops, and the orange line displays the 2015 Police-Public Contact Survey (PPCS) national average*[5] *[6].*

[1] In 2017, the driving-age population in Nashville was 58% white, 27% black, 9% Hispanic, and 6% Asian and other groups.

[2] Part I offenses are murder, rape, robbery, assault, burglary, larceny, and motor vehicle theft.

[3] https://www.nyclu.org/en/stop-and-frisk-data

[4] Several cities in this chart do not have data over the entire 2011–2016 period. In addition, some cities only share data on stops that ended with a citation. As a result, strict comparisons should be avoided; this chart is intended to demonstrate the notable difference between Nashville traffic stop rates and other proxies for what could be considered typical behavior.

[5] Note that PPCS reports number of *individuals* stopped per 1,000 drivers, whereas these city-level stop rates consider number of *stops* per 1,000 residents—which could include multiple stops per individual, and multiple residents per driving-age resident. Assuming each car is driven by exactly one person, we can approximate a similar statistic using license plate data available to us for MNPD stops. Using this new statistic, we find that Nashville's driving-age

## Background

Police departments may conduct traffic stops for many reasons, including traffic safety, crime reduction, and public engagement and education. Traffic stops and traffic safety have a clear connection, given that certain driving behaviors (e.g., speeding or DUI) directly threaten the safety of motorists and pedestrians. Conducting traffic stops may therefore increase compliance with laws designed to minimize the risk of serious or fatal traffic collisions. Some departments also consider traffic stops to be an effective tool in fighting crime. Under this premise, a traffic stop may directly impede the commission of a crime in progress; less directly, the presence of officers may discourage criminal activity in the areas being patrolled. Traffic stops may also impact crime levels through the discovery of people with outstanding arrest warrants, or by recovering weapons or other contraband. Furthermore, officers may also conduct stops to make contact with members of the public and remind them of traffic laws, inform them about policing programs, or provide educational materials. Finally, we note that some jurisdictions rely on minor infractions like traffic stops to generate revenue [7], a controversial practice that has recently come under scrutiny. Regardless of these broader policy aims, individual officers may simply be enforcing traffic or criminal codes without explicit attention to longer-term objectives.

Government practices which disproportionately burden (or benefit) one racial group in comparison to another are often undesirable, but such practices may be justified by legitimate policy considerations. In the case of traffic stops, it is theoretically possible that such activity has a net benefit for drivers themselves, by deterring unsafe behavior on the road, or by acting as an educational and community relations strategy for police officers to engage with the public. In the specific case of stops for non-moving violations, arguably the primary objective is crime suppression and detection, as the benefits for traffic safety are likely attenuated. Despite such potential benefits, research has shown that police stops also impose a substantial burden on residents. Police stop practices may create stress for stopped individuals, result in fines and fees which are difficult for some residents to pay, and threaten police-community relations [10, 21]. As police rely on residents to report crime and cooperate with investigators, any erosion of trust between residents and law enforcement is a particular concern.

## Data

Our analysis primarily used three datasets provided by the MNPD, restricted to 2017 unless otherwise noted. Traffic stop records were used in every part of the study. We used arrest and crime incident records to gauge the efficacy of traffic stop enforcement. We also used shapefiles of MNPD geographies, along with publicly available data from the U.S. Census, when calculating per capita stop rates by race and location.

Traffic stop records were provided by the MNPD for the period 2011–2017, during which MNPD conducted 2.57 million traffic stops. However, as noted previously, traffic stops in Nashville have seen a marked decline since their peak in 2012: the MNPD conducted almost 450,000 traffic stops that year, but fewer than 250,000 stops in 2017. The traffic stop dataset includes many relevant attributes, including the date and time of the stop; the reason for the stop (chosen from among several standardized responses, described below); the zone and reporting area of the stop (two MNPD-specific geographies); the race of the stopped driver; information about the officer who conducted the stop; whether weapons or other contraband were found, a custodial arrest was made, or a misdemeanor citation was issued; and narrative details about the incident.

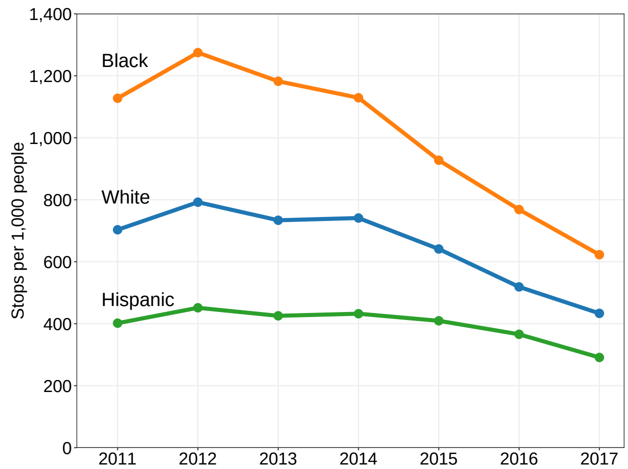


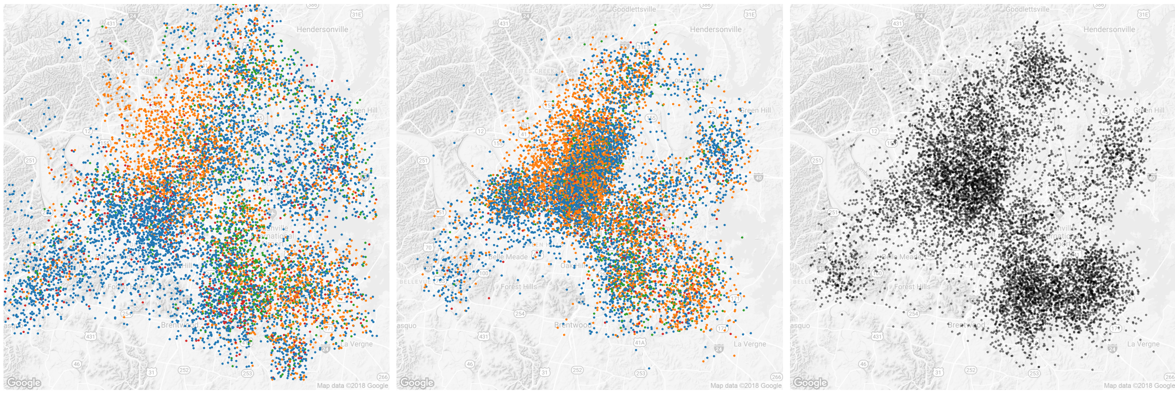

**Figure 2:** *While stop rates (for all types of traffic stops) of both black and white drivers have been decreasing since 2012, the stop rate for black drivers has remained consistently higher than the stop rate for white or Hispanic drivers.*

Almost all traffic stops in 2017 were categorized with one of four stop reasons. Moving violations were the most common, constituting 51% of all traffic stops. These violations include illegal driving behavior such as speeding, talking on a cellphone while driving, or reckless driving. The next most common categories were equipment violations (27%), registration violations (9%), and safety violations (9%), comprising 45% in aggregate. A manual review of the narrative details for 100 records marked as safety violation stops found that they most often involved equipment violations (like broken headlights or tail lights).[6] Throughout this report, we refer to stops for these latter three reasons—equipment, safety, and registration violations—as *non-moving violation stops*. The remaining 4% of stops are marked with other stop reasons, including investigatory stops, seatbelt violations, and child restraint violations. We note that regardless of the type of stop, officers may issue a verbal or written warning instead of a citation. In Nashville, warnings are a frequent occurrence—in 2017, roughly three out of every four traffic stops ended in a warning alone.

We use the MNPD's incident-record dataset to investigate the relationship between reported crime and the en-

stop rate in 2012 was still about 8 times higher than the national average.

[6] We note that the narrative details of all other types of stops were more closely aligned with their marked reasons.



**(a)** Population. **(b)** Non-moving violation stops. **(c)** Reported crime.

**Figure 3:** *The distribution of Nashville's residential driving-age population (3a) and locations of non-moving violation stops (3b), colored by race (white, black, Hispanic, and other). Non-moving violation stops are concentrated in neighborhoods where reported crimes (3c) are the most dense, which, in Nashville, also have disproportionately large minority populations.*

forcement of traffic violations. The MNPD receives over 80,000 incident reports annually, with over 100,000 reported crimes, for a total of approximately 725,000 reported crimes between 2011 and 2017.[7] These records contain a date and time; a reporting area, marking the location of the alleged crime; and the Federal Bureau of Investigation's National Incident-Based Reporting System categorization. In the case of drug-related incidents, we also have drug type and quantity.

Finally, we combine MNPD shapefiles with public U.S. Census records to generate population benchmarks for each MNPD geographic unit. The MNPD uses three geographic divisions of increasing resolution: precincts (8), zones (65), and reporting areas (2,003). We translated American Community Survey (ACS) estimates[8] to MNPD geographies by distributing population from each block group proportionally according to the area of each MNPD geography that overlaps. To calculate per capita stop rates, we then compare stop counts in each geography with the driving-age residential population recorded by the Census in that area.[9]

## Racial disparities in stop rates

Since 2012, the per capita traffic stop rate has decreased substantially for both black and white drivers. However, the stop rate for black drivers has been consistently higher than for white drivers across all years (Figure 2).[10] In 2012, the stop rate disparity was 61% (1,275 stops per 1,000 black driving-age residents vs. 792 stops per 1,000 white driving-age residents), and this disparity dropped to 44% by 2017 (623 vs. 433 stops per 1,000). These stop rate disparities are particularly pronounced for non-moving violation stops, though they have also been declining over time. Among stops for non-moving violations, the disparity dropped from 82% in 2012 (578 vs. 317 stops per 1,000) to 68% (309 vs. 184 stops per 1,000) in 2017.

Such disparities may arise from a variety of factors, including a deployment strategy that concentrates officers in high-crime areas. We next examine this possibility in several different ways. Given the substantial disparities associated with stops for non-moving violations, we focus this analysis on that subset, though we note that qualitatively similar patterns hold for the full set of stops.

First, we visually investigate the geographic distribution of residents and non-moving violation stops, disaggregated by race. As shown in Figures 3a and 3b, non-moving violation stops occur largely in predominantly black neighborhoods. In particular, there are relatively few such stops in the predominantly white neighborhoods on the southwestern side of Nashville. Figure 3c further shows that the geographic distribution of non-moving violation stops is quite similar to the geographic distribution of reported crimes throughout the city. These maps thus provide some indication that the racial disparities in non-moving violation stops are at least partly attributable to such stops being made in high-crime areas—which, in Nashville, tend to be predominantly black.

[7] These figures exclude non-crime incidents, which MNPD marks as "matter of record."

[8] Due to data availability, we use ACS block-group estimates for 2013–2016. When analyzing 2011 and 2012 traffic stop data, we benchmark to 2013 estimates; we similarly use 2016 ACS estimates as a benchmark for the 2017 traffic stop data.

[9] To our knowledge, driving-age population estimates by race are not available at the block-group level. We accordingly estimate these figures as follows: for each block group, we compute the fraction of driving-age residents, and scale the population of each race group by that fraction. Citywide estimates are computed by aggregating these block-group level estimates. We note that these driving-age benchmarks are only a proxy for the number of drivers, and do not account for daytime populations, or the amount of time drivers spend on the road. In rare cases, we exclude extreme instances of areas with high daytime populations as outliers.

[10] Throughout this period, we find lower stop rates for Hispanic drivers, consistent with a national analysis of police stops by Pierson et al. [13], and with results from the Police-Public Contact Survey (PPCS), which is based on a nationally representative sample of approximately 50,000 people who report having been recently stopped by the police [6, 11].

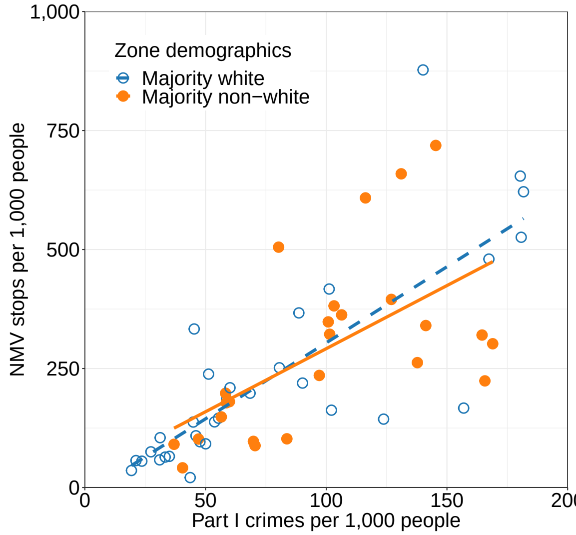



**Figure 4:** *Per capita stops for non-moving violations (NMV) vs. per capita Part I crimes for the year 2017, by police zone. Each circle represents a police zone, colored by whether the zone population is majority white (open circles, dashed line), or majority non-white (shaded circles, solid line). Zones with similar levels of reported crime have similar stop rates, regardless of the zones' racial compositions.*

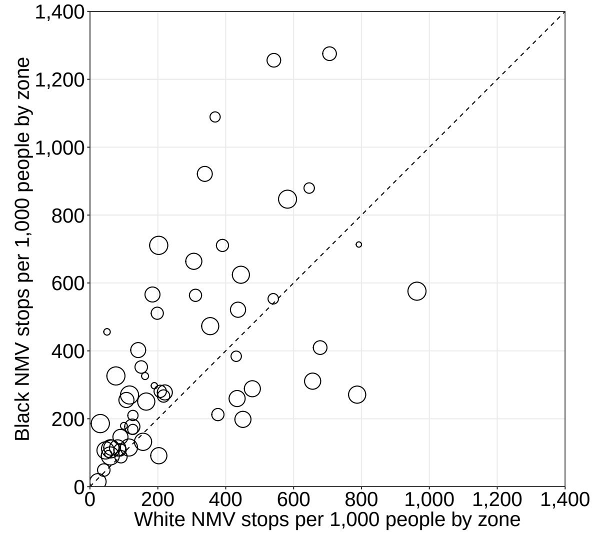



**Figure 5:** *Black versus white per capita stops for non-moving violations (NMV). Each circle represents a police zone, sized by number of stops (black and white) made in each zone in 2017. More points lie above the reference line than below, indicating that within-location stop rates are higher for black drivers than for white drivers.*

To more rigorously quantify this pattern, we next compare non-moving violation stop rates in predominately white and predominately non-white zones, controlling for reported Part I crime. As shown in Figure 4, we see stop rates and crime rates are positively correlated, meaning that officers are making more stops in zones with higher crime rates. Also, among zones with similar crime rates, stop rates in predominately white zones are similar to stop rates in predominately non-white zones. It thus appears that stops are concentrated in neighborhoods where crimes are most frequently reported, regardless of the demographic composition of the zone.

We add quantitative detail to this result by fitting the following Poisson regression model:

$$s_g = \text{Poisson}\left(p_g \cdot e^{\mu + \alpha \log(c_g) + \beta r_g}\right),$$

where $s_g$ is the stop count in zone $g$, $p_g$ is the number of driving-age residents in zone $g$, $c_g$ is the number of crimes per capita in zone $g$, and $r_g$ is the racial composition (proportion non-white) of zone $g$. Under this model, a positive value of $\beta$ would indicate that zones with predominately minority populations were being stopped at higher rates than predominately white zones with similar crime rates. We find, however, that $\beta$ is not statistically significantly different from 0 ($\hat{\beta} = -0.4$, 95% CI: (-1.1, 0.4)).[11] That is, we do not find statistically significant evidence that predominately white and predominately black zones are differentially policed after adjusting for reported crime.[12]

Instead of looking at patterns across zones, we can also look at patterns within zones. Figure 5 shows that in the majority of zones, the per capita non-moving violation stop rate for black drivers is higher than for white drivers. This visual pattern is corroborated with a statistical model that estimates zone-level disparities:

$$s_{r,g} \sim \text{Poisson}\left(p_{r,g} \cdot e^{\alpha_r + \beta_g}\right),$$

where $s_{r,g}$ is the stop count of drivers of race $r$ in zone $g$, and $p_{r,g}$ is the driving-age population of race $r$ in zone $g$. We include coefficients for each race group, denoted by $\alpha_r$, and for each zone, denoted by $\beta_g$. Comparing the coefficients $\alpha_{\text{white}}$ and $\alpha_{\text{black}}$, we find that after controlling for location at the zone-level, the non-moving violation stop rate for black drivers is 37% higher (95% CI: (18%, 59%)) than for white drivers.[13][14]

In summary, our analysis of stop rate disparities suggests three high-level trends. First, though racial dispari-

[11] Confidence intervals for Poisson regression in this study use a dispersion parameter that allows variance to scale proportional to the mean, accounting for overdispersion.

[12] We also fit this model restricting to zones with similar crime profiles. Specifically, for each predominately non-white zone, we selected its nearest-neighbor, matching on reported Part I crime rate, using the `MatchIt` package in `R`. Under this matched subset, $\hat{\beta} = -0.5$ with CI (-1.5, 0.4), in line with the model fit on all zones.

[13] Comparing the coefficients $\alpha_{\text{white}}$ and $\alpha_{\text{hispanic}}$, we find that after controlling for location at the zone-level, the non-moving violation stop rate for Hispanics drivers is 40% lower (95% CI: (55%, 22%)).

[14] Using moving violation stops instead of non-moving violation stops, we found that black-white stop rate disparities for moving violations exhibit a small—but not statistically significant—reduction, from 24% to 18% (95% CI: (0%, 41%)).

ties have been declining over the last several years, black drivers are still stopped more often than white drivers, and this gap is particularly large for the subset of stops for non-moving violations. Second, this pattern is in part driven by the concentration of stops in high-crime neighborhoods, with such activity uncorrelated with zone-level demographics after controlling for crime. Finally, such an enforcement pattern does not account for all the observed disparities. In particular, black drivers are stopped more often than white drivers even within most zones. It is unclear what may be driving this remaining disparity. At least in theory, it may arise from differences in violation rates (e.g., if black drivers are disproportionately more likely to have broken tail lights), differences in enforcement (e.g., implicit bias), heterogeneity in population or crime within zone, or some combination of these factors.

## Stop efficacy

As described above, the observed racial disparities in stop rates appear to result in part from the concentration of non-moving violation stops in high-crime areas—in line with the MNPD's explanation. However, unless there are discernible benefits of such a policing strategy, we would still characterize these disparities as problematic. Here we examine one potential benefit—and ostensibly the primary rationale—for such policing practices: that traffic stops are an effective means for reducing more serious crime.

We analyze the efficacy of these stops by measuring two different outcomes: crime levels, and rates of custodial arrest, misdemeanor citation, and contraband recovery. Traffic stops may influence crime levels through direct or indirect mechanisms. For example, traffic stops could directly impede crime by catching criminals (e.g., burglars) driving to or from from the scene of a crime. On the other hand, traffic stops may also indirectly discourage crime in a neighborhood through the active and visible presence of an attentive officer in the area. Some traffic stops will also end with a custodial arrest, a misdemeanor citation, or the recovery of contraband or weapons, potentially preventing future criminal activity or apprehending those involved in past crimes.

**Effects on crime.** If changes in traffic stop enforcement are connected to changes in crime, one would expect to see crime rates change as stop enforcement changes. We examine this potential relationship on two time scales: first, over a longer, multi-year time frame; and second, over many shorter, week-long time frames. We begin by comparing the citywide per capita traffic stop rate with per capita crime rates over the last several years, shown in Figure 6. The crime rates for both Part I crimes and violent crimes are roughly steady over the entire time frame. However, the rate of traffic stops begins to decrease quite substantially in 2014. Between 2014 and 2017, overall traffic stop rates, as well as stop rates for non-moving violations, dropped by more than 40%. Consequently, at least on this time scale, traffic stops do not appear to reduce more serious crime.

In theory, it is possible that other long-term trends—like an improving economy—mask any crime-prevention benefit from traffic stops. That is, crime might have been even lower had traffic stops not declined. To address this concern, we now examine how crime responds to stops on shorter time scales and at higher geographic resolution, where such confounding is less likely. In particular, we consider stops and crime occurring over the course of a week in individual *reporting areas* (RPAs), the MNPD's most granular unit of geography.

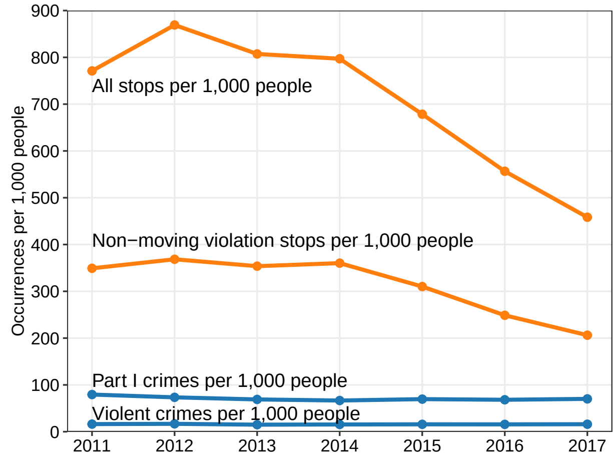
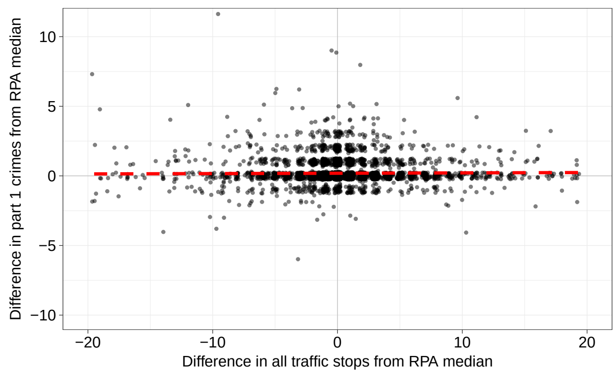



**Figure 6:** *This time series of annual stops and crimes per capita suggests the absence of a long-term connection between traffic stops and crime levels. MNPD substantially reduced traffic stops over the second half of the seven year period without any substantial rise in crime.*

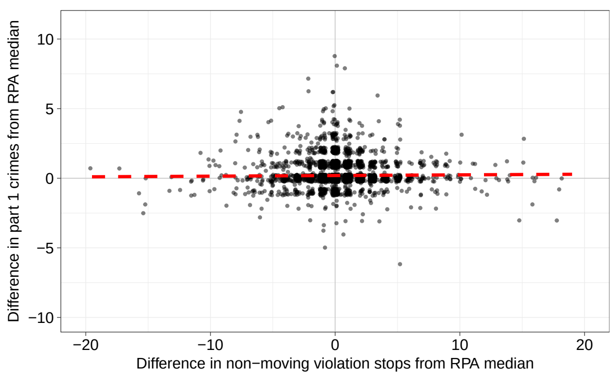
The MNPD generally holds weekly CompStat meetings on Fridays to make deployment decisions for the following week, creating and communicating these directives over the next 1–2 days based on current crime trends. Accordingly, we consider weeks starting on Sunday and ending on the following Saturday. After controlling for information available at CompStat meetings, we consider deployment to be as-if randomly assigned. In practice, it is possible that officer assignments are changed mid-week in response to a serious crime outbreak; further, we cannot fully account for all information available to commanders at the CompStat meetings. Nevertheless, we believe this assumption is a reasonable, though admittedly imperfect, starting point for such an analysis.

We first visually examine the short-term relationship between stop levels and crime levels. In Figure 7, each point represents a week in an RPA in 2017, and the axes represent departures from each RPA's median level of crime or median number of traffic stops.[15] As the flat red trend line indicates, we find that weekly crime levels within an RPA have almost no relationship with that week's traffic stop levels. For example, an RPA could have a week with the median number of stops for that RPA, another week with ten fewer stops than the median, and another with ten more stops than the median. Despite these variations in stop enforcement, we would still expect crime to occur at the median level for that RPA in all three weeks. This lack of correlation persists when exam-

[15] Outliers that were far from the median, representing roughly 0.05% of all points, were removed from the analysis. Points are downsampled and jittered for the purposes of visualization, but the trend line is constructed from every unjittered point in the domain.




**(a)** Part I crimes vs. all traffic stops.




**(b)** Part I crimes vs. non-moving violation stops.

**Figure 7:** *Part I crimes versus both all traffic stops, and also non-moving violation stops specifically, for MNPD reporting areas (RPAs) in 2017. Each point corresponds to a specific week in one RPA, where crime and stop levels are both measured by that week's difference from the RPA's 2016 median. Changes in crime levels are effectively uncorrelated to changes in traffic stop levels, as indicated by the flat slope of the red trend line.*

ining more specific crime types, such as violent crimes or burglaries, when considering non-moving violation stops specifically, and when including the effect of the previous week's crime levels or traffic stop enforcement (as discussed below).

To more quantitatively examine the short-term relationship between non-moving violation stops and crime levels, we fit a Poisson regression model. Specifically, given a crime count $y_{g,t}$ in RPA $g$ in week $t$, we aim to estimate the relationship with normalized[16] stop counts $s_{g,t}$ in the same RPA and week. We include the RPA's population $p_g$ as a baseline, normalized counts of the previous week's crimes and stops, coefficients $\delta_g$ for each geography, and $\theta_{m[t]}$ for the month in which week $t$ occurs. Accordingly, we fit the following regression model:

$$y_{g,t} \sim \text{Poisson}(p_g \cdot e^{\alpha \cdot s_{g,t} + \beta \cdot y_{g,t-1} + \gamma \cdot s_{g,t-1} + \delta_g + \theta_{m[t]}}).$$

[16] Stop and crime counts are normalized for each RPA by subtracting the mean count for that RPA and dividing by the standard deviation of that count.

| Custodial arrest charge | Per 1,000 stops: All stops | NMV stops |
|---|---|---|
| Suspended/revoked licenses | 3.7 | 5.0 |
| Minor marijuana possession | 0.7 | 0.8 |
| Other drug crimes | 2.2 | 2.4 |
| DUI | 4.6 | 2.0 |
| FTA/parole violation/warrant | 1.9 | 2.2 |
| Driving violation | 0.8 | 0.7 |
| Public misconduct | 0.7 | 0.7 |
| Another crime (burglary, assault) | 0.6 | 0.7 |
| **Misdemeanor citation charge** | | |
| Suspended/revoked licenses | 47.1 | 53.9 |
| Minor marijuana possession | 3.3 | 3.7 |
| Other drug crimes | 2.0 | 2.0 |
| FTA/parole violation/warrant | 3.8 | 4.5 |
| Driving violation | 0.3 | 0.1 |
| Public misconduct | 0.3 | 0.2 |
| Plate alteration | 0.6 | 1.0 |
| Another crime (burglary, assault) | 0.2 | 0.2 |

**Table 1:** *Custodial arrest and misdemeanor citation rates for traffic stops.*[18] *For example, 5 out of every 1,000 non-moving violation stops resulted in a custodial arrest for a suspended or revoked license. Note that 1 out of every 1,000 stops and 0.8 out of every 1,000 non-moving violation stops also included a weapons charge.*

The fitted model suggests that stops do not decrease crime ($\hat{\alpha} = 1.03$, 95% CI: $(1.01, 1.04)$), confirming our intuition from the graphical representation in Figure 7.[17]

**Arrests, citations, and contraband.** Stops may additionally have an impact on future crime via the custodial arrest of individuals or the recovery of contraband, including illegal weapons. For example, during a non-moving violation stop, an officer may detain a suspect—who might otherwise be difficult to locate—with an open warrant for a string of recent robberies. It is possible that these custodial arrests prevent future crimes. It is also plausible that contraband recovery, like the recovery of drugs, thwarts the sale and consumption of illegal materials. Finally, weapon recovery by the MNPD may make it harder for individuals to follow through with violent impulses.

Overall, however, both custodial arrests and contraband recoveries were infrequent occurrences. As noted in Table 1, arrest rates were highest for suspended or revoked licenses, or for drug crimes.[19] Custodial arrests which might be suspected to have a direct impact on future

[17] The fitted model results in a small *positive* coefficient on stop levels, indicating—counterintuitively—that crime increases 3% for every one standard deviation increase in stop activity. The point estimate is statistically significant when using robust standard errors; however, the estimated effect is not statistically significant under an alternative over-dispersed Poisson model. It is also possible that the result is driven by an unmeasured confounding variable that correlates both with stop activity and crime rates.

[18] When a custodial arrest leads to multiple charges, we count only the most severe charge per incident, using the following hierarchy: serious crime (assault, burglary, theft, sex offense, child crimes), drug crimes (non-marijuana charges, or possession of at least 0.5 oz of marijuana), DUI, minor marijuana possession (less than 0.5 oz), FTA/parole violation/warrant (also includes probation violations and FTB), public misconduct (public intoxication, disorderly conduct, vandalism, trespassing), driving violations, plate alterations, license charges (suspended/revoked license, driving with no license).

[19] Only 51% of non-moving violation stops that led to a custodial arrest matched a corresponding arrest record. Values reported in Table 1 are over the subset of these matched arrests. The coverage for all stops that led to custodial arrest was 56%. The coverages

crime (e.g., those arrests which are not solely for holding an invalid license, for minor marijuana possession, for public misconduct, or for driving violations) occur in 0.7% of non-moving violation stops. A larger percentage (6.6%) of non-moving violation stops led to misdemeanor citations. However, the majority of these citations were for license-related charges: 82%[20] of non-moving violation stops that led to a misdemeanor citation included only a license-related charge, and no other charge. An additional 0.7% of non-moving violation stops resulted in the recovery of other contraband (typically drugs), but did not include a custodial arrest. Altogether, 2.2% of non-moving violation stops resulted either in a custodial arrest or the recovery of contraband.

Quantifying the benefits of such stop outcomes is beyond the scope of this report. We note, however, that it is possible that other police activity may be a more effective use of time. For example, 16% of investigatory stops—which require that officers have reasonable and articulable suspicion of criminal activity—resulted in a custodial arrest or contraband recovery, a rate almost eight times higher than the corresponding rate for non-moving violation stops. This difference suggests the MNPD may be able to more effectively achieve the arrests and contraband recoveries from non-moving violation stops with other enforcement efforts.

## Officer-level differences in stop activity

As one might expect, there are significant differences in stop rates across officer assignments. For example, officers assigned to flex units—whose duties allow for more proactive policing—conduct about twice as many non-moving violation stops per officer (217 stops per officer in 2017) as patrol units (109 per officer). Such differences ostensibly reflect the discretion that flex officers have in carrying out proactive policing duties. Similarly, officers working evening shifts make more such stops than those working during the day, likely in part because certain non-moving violations—like broken lights—are more visible at night.

More surprisingly, however, we find that a relatively small number of officers conduct the vast majority of non-moving violation stops. For example, as shown in Figure 8, the 10 most active flex and patrol officers made 9,399 stops, or approximately 9% of all non-moving violation stops over the year; further, half of all non-moving violation stops were conducted by 17% of active officers—125 officers in total.[21] We find similar patterns when we disaggregate by assignment. For example, among patrol officers working the night shift, 15% made 50% of stops.

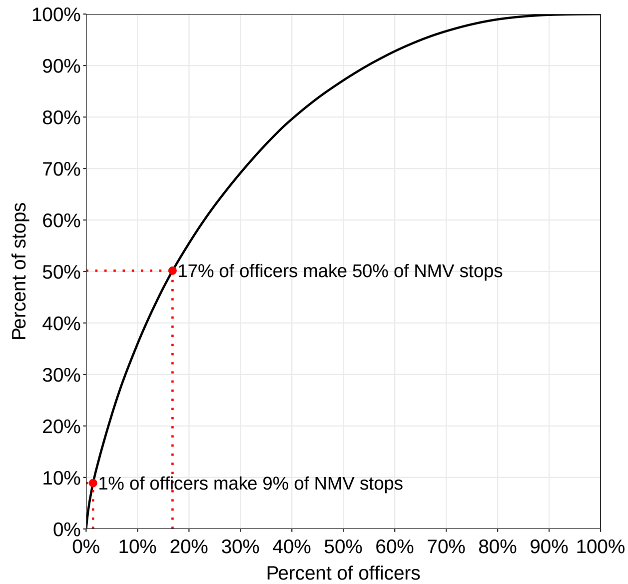



**Figure 8:** *The distribution of the number of non-moving violation stops across MNPD officers in 2017, illustrating that a small number of officers conduct the majority of such stops.*

It is unclear why such a small group of officers carries out the majority of stops. As in many jurisdictions, it is possible that the MNPD gives officers wide leeway to engage in proactive policing, which in turn may result in the observed heterogeneity. It is also possible that these officer-level differences are part of an intentional policing strategy, though we are unaware of any such policy directives. Regardless of the underlying reason, the relatively small number of officers involved makes it easier for the department to understand and appropriately address their behavior as necessary.

## Discussion

Based on an extensive analysis of the MNPD's 2017 traffic stop data, we find that black drivers were stopped substantially more often than white drivers; these disparities were particularly pronounced among stops for non-moving violations, such as broken tail lights and expired registration tags. The racial disparities in these non-moving violation stops are in part attributable to the concentration of stops in high-crime areas, which in Nashville often coincide with predominantly black neighborhoods. The defensibility of such a policing strategy, however, rests on its effectiveness in ensuring public safety. In this case, we found that traffic stops—including stops for non-moving violations—had no discernible effect on serious crime rates, and only infrequently resulted in the recovery of contraband or a custodial arrest.

for all stops and for non-moving violation stops that led to misdemeanor citations were 89% and 91%, respectively.

[20] This number considers as a baseline only the 91% of non-moving violation stops that matched an arrest record, since for the remaining 9% we do not have data on charges. Implicit in this computation is an assumption that the remaining 9% have similar charge distributions as the 91%. We can set a lower bound on this estimate by assuming that none of the 9% were license-only charges, and an upper bound by assuming that all of the 9% were license-only charges. With this, we conclude that the number of non-moving violation misdemeanor citations that were charged with only a license-related charge lies between 74% and 84%.

[21] For this analysis, we consider "active" officers to be flex and patrol officers who conducted at least one stop during 2017, to avoid counting those assigned to administrative duties. These general patterns hold when when we use a more stringent definition of "active". For example, among flex and patrol officers who carried out at least 10 non-moving violation stops in 2017, 19% were responsible for half of stops.

These results suggest that the MNPD could safely reduce overall stop rates. In particular, curtailing stops for non-moving violations could reduce racial disparities, partially addressing community concerns about its policing practices. However, in order to bring Nashville's stop rates to the level of similar American cities, the MNPD would have to significantly reduce the number of such stops it carries out (Figure 1). A reduction of even 50% in non-moving violation stops would still leave the city's overall stop rate twice as high (or higher) than other peer cities. A more substantial 90% reduction in such stops would put Nashville on par with peer cities with the highest stop rates. These reductions would have significant impact on the day-to-day lives of Nashville residents. Assuming the MNPD reduced non-moving violation stops by 90%, and changed nothing else, roughly 100,000 stops—52,000 stops of white drivers, 40,000 stops of black drivers, 6,000 stops of Hispanic drivers, and 2,000 stops of drivers of other races—would be avoided each year. The disparity between overall black and white stop rates would also drop substantially, from 44% to 28%.

The remaining disparities largely result from differences in stop rates for moving violations. In particular, black drivers were stopped for moving violations (which comprised half of all traffic stops) 24% more often than white drivers last year. We expect that reducing such stops will not adversely impact crime levels, though they could have other unintended consequences. For example, one concern is the possible effect of traffic stop reductions on traffic safety. This may be an issue in Nashville, where traffic accidents per capita increased by roughly 60% between 2011 and 2017. As such, reductions in moving violations require balancing the potential impacts on traffic safety with broader community concerns. In contrast, most non-moving violation stops are for minor traffic infractions, like a broken tail light, a broken license plate light, or an expired registration. We thus expect one could safely reduce non-moving violation stops by continuing to enforce the most serious such offenses (e.g., broken headlights) while eliminating stops with a less immediate connection to traffic safety. Finally, we note that reductions in traffic stops may also reduce opportunities for officers to engage the public, although there are arguably other more appropriate channels for community contact.

Our analysis illustrates the power of a data-driven approach to public policy. Looking forward, more extensive data could yield further insights. For example, we found inconsistencies in how police searches were classified in the data we analyzed, making it difficult to carry out statistical tests for racial bias in search decisions [12, 13, 19]. Additionally, inconsistent incident identification numbers made it difficult to fully link traffic stops to arrest records. Finally, many of the categories that the MNPD uses for traffic stops are relatively coarse. For instance, equipment violations can include both plate light violations and headlight violations, despite their potentially different impacts on traffic safety. Finer classification would improve the department's capacity to monitor changes in enforcement over time, and would be useful information to help the MNPD safely curtail traffic stops. We hope our analysis, and these suggestions for future data collection, help both the MNPD and the broader Nashville community design more effective and equitable policing strategies.

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