The Impact of Partisan Politics on Policing Practices and Personnel Composition: Evidence from North Carolina's Sheriff's Offices

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Abstract

We study the impact of partisan leadership on traffic stop policing behaviors and personnel turnover in North Carolina. Using a difference-in-differences design that leverages sheriff turnovers, we find that offices with a Democrat-to-Republican sheriff turnover rather than a Democrat-to-Democrat transition experience an increase of black drivers' share in traffic stops by 3.2 percentage points, a 13.5% increase compared to baseline. A shift of focus from traffic safety to potential investigation in conducting traffic stops is also found: the share of traffic stops for moving traffic violations decreased by 8.8 percentage points, a 16.6% decrease compared to the baseline. The change of the relative focus on different types of traffic stops results in racially disparate impact and contributes to 18% of the increased black drivers' share associated with Democrat-to-Republican sheriff turnovers. Democrat-to-Republican turnovers increase the search rate for black drivers in moving traffic violation stops without a decrease in hit rates. With such policy preferences changes, officers not aligned with new sheriffs' party affiliation are 7.2 percentage points more likely to leave the public sector than their aligned peers, leading to a 6.2 percentage point increase in the share of Republican officers in D-to-R sheriff's offices. These results suggest that partisan leadership can impact frontline policing racial disparities and the representation of law enforcement officers.

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1 Introduction

The criminal justice system in the United States is deeply related to and influenced by partisan politics due to the political process of personnel selection. Although leaders of local law-enforcement agencies are often elected, the impact of political preferences on frontline policing is not well-understood. This paper studies the impact of the political party affiliation of leaders on one of the most frequent interactions Americans have with law-enforcement officers: traffic stops.

We examine the impact of partisan leadership on racial disparities in traffic stops. Racial disparities in traffic stops are well-documented. Black drivers are more likely to be stopped than White drivers, especially before sunset; during the stop process, Black drivers are twice likely to be searched than White drivers (Pierson et al., 2020). A vast literature studies to what extent the racial disparities come from racial bias and has established evidence of racial discrimination at the officer level (Antonovics and Knight, 2009; Goncalves and Mello, 2021). We start from a different point in the hierarchy of law-enforcement agencies and ask if leaders matter in determining racial disparities of frontline traffic stops.

This paper focuses on sheriff's offices in North Carolina. We focus on sheriff's offices instead of police departments since sheriffs are elected through partisan elections and hence allow direct identification of party affiliations. We exploit party turnovers of sheriffs which are induced by elections to examine the impact of the party affiliation of sheriffs on offices' traffic stop behaviors. One central challenge in estimating the relationship between party affiliation of local law-enforcement leaders and traffic stop behaviors is that localities with leaders from different parties may have unobserved differences that make officers adopt different traffic stop strategies. Time trends that affect local law-enforcement practices such as crime rate changes and gentrification development may also evolve differently across such localities.

We adopt a difference-in-differences research design to overcome these challenges. Our control group is counties that experience Democrat-to-Democrat (henceforth D-to-D) sheriff turnover that does not necessarily involve a leader turnover; our treatment group is counties that experience Democrat-to-Republican (henceforth D-to-R) sheriff turnover. We analyze turnovers from the 2010, 2014, and 2018 elections. For each election, we examine traffic stops in an election cycle defined as from 3 years before the election to 1 year after the election. This definition of election cycle allows us to stack up data from 3 election cycles without having overlapping timing periods.

Using our differences-in-differences framework, we find that Republican sheriffs' leadership alters the racial composition of stopped drivers. Republican sheriffs increase the probability that a stopped driver is Black by 3.2 percentage points, a 13.5% increase compared to the probability in the baseline. We find that the increase in the black driver's share comes from two parts. We divide stops into safety stops, where drivers violate moving regulations, and investigation stops, in which drivers violate non-moving regulations such as broken tail lights. The first part of the increase in the black driver' share comes from the decrease in the share of safety stops associated with the D-to-R transitions, leading to a racially disparate impact since Black drivers account for a less proportion of safety stops than in investigation stops. The change in the share of safety stop accounts for 18% of the increase. The second part comes from the change of black drivers' share within safety and investigation stops. In particular, we find statistically significant evidence that black drivers' share increases among safety stops.

We test three mechanisms that may contribute to the change in the black driver's share within safety stops. First, patrolling location and time policies. We find no strong evidence that the increased share of Black drivers can be explained by Republican sheriffs shifting their patrolling focus to different neighborhoods or different times of the day. Second, officers' discretionary decisions on whom to stop. Among officers who perform traffic stop duties both before and after the elections, we do not find evidence that officers who were more likely to stop black drivers before the election responds to the Republican leadership by increasing the probability of stopping a black driver. Third, personnel policies. Although we find that D-to-R transitions are associated with assigning more new officers to the traffic stop team than D-to-D transitions, we do not find evidence that new officers are more likely to stop black drivers than officers who had performed traffic stops before the elections. We also do not find evidence that Republican sheriffs assign officers who are less likely to stop black drivers out of the traffic stop team.

On search behaviors, we find that the search rates for black drivers increase within safety stops without a decrease in the hit rate, providing evidence consistent with Feigenberg and Miller (2022): law-enforcement organizations are able to change search rates without sacrificing hit rates.

The demographic composition of sworn officers in law-enforcement agencies has long been considered an important factor shaping racial disparities in law-enforcement practices (McCrary, 2007; Ba et al., 2022). Motivated by the empirical pattern that D-to-R transitions are associated with more personnel turnover within traffic stop teams, we turn to analyze the impact of partisan leadership on the composition of officers with a data set that contains officers' demographic such as party affiliation, race, gender and age and officers' working history within the public sector in North Carolina. The dataset matches law-enforcement officers between pension records and voter registration snapshot files.

We find that two years after the election, compared to D-to-D transitions, D-to-R transitions lead to a 6.2 percentage points increase in the share of Republican officers in sheriff's offices, a 17.5% change with respect to the baseline, while the share of voters registered as Republicans only increase by 0.6 percentage points (1.9% with respect to the baseline mean) in D-to-R counties relative to D-to-D counties. Other demographic compositions of officers, including race, gender, and age, do not respond to the party turnover of sheriffs.

We examine how much of the composition change can be explained by leaving and entering of officers. We find that partisan leadership only affects the composition of officers through the leaving margin. With a triple differences design, we find that Democrat officers are cumulatively 7.2 percentage points more likely to leave the public sector than Republican officers after experiencing a D-to-R rather than a D-to-D sheriff turnover, a 36% increase compared to the baseline. On the entering margin, we find that newly elected Republican sheriffs hire more officers into offices one year after the election, but the newly hired officers are not more likely to be Republicans than the previous hires.

Overall, this paper contributes to our understanding of sources of racial disparities in the criminal justice system and the importance of policy preference in the public sector labor market. Previous literature has found partisanship influences sentencing: compared to Democratic-appointed judges, Republican-appointed judges give longer sentences to Black offenders than non-Black offenders with similar crimes (Cohen and Yang, 2019). We provide evidence that the political preferences of leaders matter in determining racial disparities in frontline policing, where literature has identified the importance of voters the leaders face (Facchini et al., 2020), the race of the leaders (Bulman, 2019), and the racial composition of the police force (McCrary, 2007). Very recent literature identified the heterogeneity of racial bias at the officer level (Goncalves and Mello, 2021), and suggest that officers with different levels of bias have varied traffic stop behaviors responding to short-term political events (Grosjean et al., 2022).

The impact of partisanship on law enforcement is not without ambiguity *ex ante*. Although survey evidence shows that party affiliation of the general public is correlated with attitudes toward policing policies such as body cams and police force size (Hansen and Navarro, 2021), the political preferences of the law-enforcement leaders across parties may not be so dissimilar. Thompson (2020) finds no effect of the party affiliation of sheriffs on compliance with federal requests to detain unauthorized immigrants and suggests that the similar compliance rate may be due to sheriffs sharing similar immigration enforcement views across parties.

We also contribute to the literature that emphasizes the importance of political turnover in personnel in public organizations. Political turnover is often associated with personnel changes on account of patronage. Colonnelli et al. (2020) finds that supporters of the party in power in Brazil are more likely to be hired and are negatively selected on their competence. Akhtari et al. (2022) finds that local mayor election turnovers in Brazil are linked to new personnel turnovers in schools and are further accompanied by lower student test scores. We provide evidence that policy preference alignment matters in linking political and personnel turnover, a prediction since Besley and Ghatak (2005). Our evidence is in line with recent literature focusing on US federal employees. Bolton et al. (2020) finds that presidential turnovers are associated with higher departure rates of senior federal employees, especially in agencies holding different views from the presidents. Spenkuch et al. (2022) further uncover partisan cycles for federal appointees and provide evidence that procurement officers of opposite party affiliations from the presidents perform worse in terms of cost overruns and delays. In contrast to the federal government setting, we present evidence that in local agency settings where public servants are well protected from politicians' personnel decision power, party affiliation misalignment between local politicians and officials still matters for personnel composition.

2 Background

Law-Enforcement Agencies in North Carolina.

Sheriff's offices are the top law enforcement agencies at the county level. Sheriffs have jurisdiction throughout the county. Police departments in municipal governments are in charge of law enforcement in incorporated areas. The main functionality of sheriff's offices includes management of jails and detention centers, crime investigation, immigrants detention, highway patrol, and document application such as gun permits. In this paper, we focus on the traffic stop and search. Each of the one hundred counties in North Carolina has one sheriff's office. Voters directly elect sheriffs. The elections are partisan; they occur every four years in November. There are no term limits for sheriffs. The newly elected sheriffs are sworn in on the first Monday in December after the election. The deputies take their oath on the same day. All of the elected sheriffs since 1998 are affiliated with either the democratic party or the republican party. We use party turnovers of sheriffs' which were induced by the election results as the main variation of change of political control.

Police chiefs, on the other hand, are appointed by municipal councilors. Law-enforcement officers in police departments and sheriff's offices in the same county can be seen as in the same law-enforcement labor market. We thus examine police officer turnover as well.

Traffic stop.

Law-enforcement officers stop drivers for two main reasons. First, the driver exhibits reckless driving, such as speeding. Second, officers stop drivers for nonmoving violations. This includes equipment failures such as broken tail lights, vehicle regulation violations such as expired registration, and suspicion in relation to ongoing investigations. Following Baumgartner et al. (2018), we call the first type a traffic safety stop and the second type an investigatory stop. In practice, officers use vehicle regulation violations as a pretext to stop drivers in pursuit of potential criminal investigations or searches for drug possession (Baumgartner et al., 2018). The relative focus on the two types is a salient policy issue in North Carolina. For example, in 2013, the police chief in Fayetteville announced that the police department would minimize the number of traffic stops due to nonmoving violations. In 2022, the Mecklenburg county sheriff's office announced they would no longer stop drivers for nonmoving violations. [1] During the traffic stop procedure, an officer decides whether to search the vehicle. This is a decision in that officers have much discretionary power. By law, officers can search a vehicle as long as the officers have probable cause to

[1] See https://www.usatoday.com/story/news/nation/2021/04/15/police-reform-fayetteville-burlington-nc-traffic-stops-policing/7225318002/ for a coverage about Fayetteville police department and see https://www.foxnews.com/us/north-carolina-sheriffs-office-stops-pulling-drivers-non-moving-traffic-violations for a coverage about Mecklenburg county sheriff's office. Fliss et al. (2020) used a synthetical control method and found that the policy in Fayetteville leads to a reduction of traffic crashes and injuries and the share of traffic stops of black drivers.

believe that a law has been broken. Regardless of whether a search is conducted, a traffic stop can lead to four actions: no action, warning, citation, and arrest.

Recruiting Process and Sheriff's Power on Hiring and Firing Decisions.

Recruitment is run by each sheriff's office itself. The specific process may vary from county to county. A typical recruiting process involves three parts. First, basic requirements include citizenship, an education degree (typically a high-school diploma), and a driver's license. Second, physical, written tests and interviews. Third, medical tests and background investigations include credit, criminal, court, police, military, and personal history. During the process, it is plausible that the sheriff would gather information about an applicant's political party affiliation and information about the applicant's past behavior in other law enforcement agencies.

Whether sheriffs in North Carolina can fire employees based on political considerations was in debate. Several court cases were filed from fired officers. North Carolina supreme court issued decisions regarding the sheriff's personnel decision power in 2016. The supreme court held that deputy sheriffs could be dismissed by a sheriff's political considerations. The state law also documents that each sheriff has "the exclusive right to hire, discharge, and supervise the employees." Based on the information above, we assume that the sheriff's power to discharge employees exists in the period we consider but was controversial. One worth noting feature is that since the budget of sheriff's offices is determined by county commissioners, the sheriffs cannot freely expand the agency size. On the other hand, county commissioners cannot change employees' salaries in sheriff's offices unless the pay change applies to all county government employees. Sheriffs can adjust employees' salaries as long as it does not exceed the budget.

3 Data

Traffic Stop Records.

The traffic stop and search records are available upon request in North Carolina. The data set contains the driver's race, ethnicity, gender, and age. Unique officer IDs are included in the data. We use the IDs to identify officers who stop performing traffic-stop tasks after elections.[2] The IDs are not linked to other information about officers, such as names, races, or ages. The data set includes the time and the name of the location of each stop. The name of the location can be a county, a city/town, a census-designated place (CDP), or some names used by locals. Sixty percent of the stops only record the location at the county level. This significantly restricts our analysis of officers' patrolling location decisions.

Each stop is associated with one of the twelve stop purposes: speed limit violation, stop light/sign violation, driving while impaired, safe movement violation, vehicle equipment violation, vehicle regulatory violation, seat belt violation, investigation, other motor

[2] The officer ID is only unique within the law enforcement agency. We cannot track officers across agencies.

vehicle violation, and checkpoint. Following Baumgartner et al. (2018), we exclude the sample associated with the checkpoint because such stops are recorded only when searches are conducted. We classify stops into two types: safety and investigation. Safety stops include ones associated with speed limit violations, stop light/sign violations, driving while impaired, and safe movement violation. Investigation stops include ones associated with vehicle equipment violations, vehicle regulatory violations, seat belt violations, investigation, and other motor vehicle violations.

Sheriff Election Records.

Sheriff's election results since 2008 are publicly available on the North Carolina State Board of Elections website. Party affiliation and the names of the elected sheriffs are used to determine if a county went through sheriff turnovers and party turnovers. Vote shares of the winners are used to assess the competitiveness of the elections.

Voter Registration Snapshot Files.

Voter registration snapshot files are publicly available in North Carolina. They can be accessed from the North Carolina State Board of Elections website [3]. We select voter registration records during the years 2008-2020. We use voter registration snapshot files at the beginning of each year except for 2008 due to data availability. We collect name, race, ethnicity, gender, age, party affiliation, registration status (active or not) and registration location (county) from the voter registration snapshot files.

Public Pension Plan Records.

Public pension records are available upon request in North Carolina. The data set contains the employer and salary history of the universe of workers in the public sector in North Carolina since 2008. For people who have been collecting pension benefits in 2020, we can trace their lifetime work history within the North Carolina public sector. We use employer names, employee categories, and job classifications to identify law-enforcement officers in sheriff's offices and police departments.

Matching between voter snapshot and public pension data.

We use first name, middle name, last name, age, and commuting zone to match voter registration records with public pension records. County information in public pension records is derived from employer names. Both public pension records and voter registration snapshot files contain unique IDs for each person across the years. From the matching process, we derive the gender, race, ethnicity, voter registration status, and party affiliation of the public sector workers. We drop observations where one ID in a data set is matched to multiple IDs in the other one. When voter registration records for a worker cannot be found in all years, we extrapolate the demographic information from the nearest year. Our matching rate for sworn officers in sheriff's offices and police departments are respectively 73.25% and 66.25%.

[3] Voter snapshot files can be downloaded from this link: https://dl.ncsbe.gov/?prefix=data/Snapshots

4 Impact of Partisan Leadership on Traffic Stop and Search Behavior

4.1 Research Design

Our goal in this section is to identify the causal effect of sheriff's party affiliation on traffic stop practices. We adopt a difference-in-differences design, comparing counties that experience elections resulting in Democrat-to-Democrat (D-to-D) sheriff transitions with counties that experience Democrat-to-Republican (D-to-R) sheriff transitions. We define an election cycle from three years before an election to one year after. Since new sheriffs are sworn in on the first Monday of December, we define an election year from December to November.

Table 1 reports the sheriff election results from 2010 to 2018. Only four elections involve Republican-to-Democrat (R-to-D) type turnover. We do not consider elections with R-to-D or Republican-to-Republican (R-to-R) turnover in this paper due to statistical power concerns. We define the control group as the county-election-cycles (henceforth county-cycles) that experience D-to-D elections. The treatment group includes county-cycles that experience D-to-R type elections.

Panel D of Table 1 shows the winners' vote share distribution. All D-to-R elections have winner's vote shares of less than 80%. To match on the winners' vote shares, we confine samples to the county-cycles where the winner's vote shares are less than 80%. Panel B shows the number of county-cycles in each election type after we apply this restriction. Our analysis of personnel turnover includes the county-cycles in Panel B.

To analyze officers' traffic stop behaviors for certain stop purposes or race groups, we need the yearly number of traffic stops in each office to not be too small for the sheriff's offices. We exclude the county-cycles where a sheriff's office conduct less than 50 stops in at least an election year within the election cycle. The resulting number of county-cycles of each election type are presented in Panel C of Table 1.

Summary Statistics.

Table 2 presents the summary statistics of traffic stops and searches in the county-cycles we include in our traffic stop behavior analysis (Panel C in Table 1). We report descriptive shares on race, gender, and traffic stop types. The driver is female in 35% of the stops, black in 25% of the stops, Hispanic in 7% of the stops, and white in 65% of stops. Due to the small share of Hispanic drivers, in the following analysis, we divide the drivers into black and non-black groups. [4] Officers search drivers in 6.7% of stops and find contraband in 2.2% of stops. Black drivers, once stopped, are more likely to be searched than white drivers (7.9% compared to 6.1%). The difference in the search rates between black and white drivers is much smaller than that seen in Feigenberg and Miller (2022).

Dividing stops into safety and investigation types, the driver is 28% black in investiga-

[4] Other races, including Asians, Native Americans, and Other/Unknown, account for around 2% of stops and are included in the non-black group.

tion stops and 24% in safety stops. Officers are more likely to search in investigation stops than in safety stops (8.5% and 5.1%, respectively). The conditional hit rates (number of searches with found contraband divided by the total number of searches) are similar across two types of stops, around 31%.

4.2 Estimation Specifications

To estimate the causal effect of sheriff's party affiliation on traffic stop practices, we estimate an ordinary least square regression with a difference-in-differences type specification:

$$Y_{cle} = \sum_{e=-2}^{1} \beta_e D_{cl}^{D-to-R} \cdot \eta_e + \delta_{le} + \delta_{cl} + \epsilon_{cle} \quad (1)$$

where Y_{cle} is a variable at county-year level for county c in election year e in cycle l. Treatment group status in each election cycle is denoted by D_{cl}^{D-to-R}, δ_{cl} is county-cycle fixed effects. We separate data into three election cycles, denoted as l. We use election results from 2010, 2014, and 2018. Hence l can take three values, 2010, 2014, and 2018. We treat the year before the election as the baseline year. In tables and figures, the time convention is as follows: we denote the year when the election happened as t and other years as $t-2, t-1, t+1$. In regression specifications, the time convention chronologically in an election cycle is denoted as $e = -1, -1, 0, 1$. Since the new sheriff is sworn in on the first Monday of December, we define an election year starting from December to November. For example, the year t ($e = 0$) in the 2010 election cycle involved observations from December 2009 to November 2010. Hence, δ_{le} uniquely defines the timing of each stop in year e in cycle l. We analyze at the county level instead of the stop level because we are more interested in the causal effect of leadership on law enforcement agency policy practices than in the effect of party turnovers on the population.

The coefficients of interest are β_e, which captures the differences between control and treatment groups across election years within a cycle. All standard errors are clustered at the county level throughout the paper unless stated otherwise.

4.3 Main Results in Traffic Stop Practices

Graphical Evidence.

Our first task is to examine if partisan leadership impacts law enforcement practices toward minority race groups. We plot the raw data in Figure 1 to show the data variation captured by the difference-in-differences specification. We compute the black drivers' share among all stops at the county-year level. We then take the simple averages across counties to aggregate the data into D-to-D, D-to-R, and R-to-R groups. D-to-D counties have higher black driver's shares than D-to-R and R-to-R counties since D-to-D counties are generally more urban areas. Before the election, the black driver's share gap between the three groups stays roughly constant across the years within an election cycle. This gives us confidence that the parallel pre-trend assumption, which is required by difference-in-differences research designs, is satisfied in this setting. One year after the election, however, the black driver's share in D-to-R counties increased while the shares in D-to-D and R-to-R counties barely changed. We present regression results capturing the increase in D-to-R counties next.

Estimation Results.

We call a stop a Black stop if the driver associated with the traffic stop is black. Table 3, column (1) displays the estimates of β_e in equation 1 with the share of Black stops at the county-year level as the outcome variable. Consistent with the pattern we observe in Figure 1, the shares of Black stops increased by 3.2 percentage points in D-to-R counties one year after the election compared to D-to-D counties. Given that the dependent variable mean of D-to-R counties in the year before the elections is 0.24, this amounts to a 13.5% increase in the probability of a Black stop.

The increase in the share of Black stops may come from Republican and Democratic sheriffs adopting different traffic stop policies. Motivated by the policy proposals we see in Fayetteville police departments and Mecklenburg county sheriff's office, and the literature which finds that officers enjoy more discretionary power in investigatory stops (Roach et al., 2022), we examine if the share of safety stops changes after electing a Republican rather than a Democratic sheriff. In Table 3, column (2), we display the estimation results of equation 1 with the outcome variable the share of safety stops. We find that the share of safety stops decreases by 8.8 percentage points after electing a Republican sheriff. Compared to the dependent variable mean in D-to-R counties in the year before the election, this is a 16.6% decrease. We also find a marginally significant decrease in the share of safety stops in the election year in D-to-R counties. In our next steps, we will examine if the election competitiveness or the fact that the incumbent sheriff participated in the election or not can explain the decrease in the year of the election.

Changes in the focus on safety and investigatory stops can have racially disparate impacts. Black drivers' share is higher in safety stops than in investigation stops (see Table 2). Assuming that the black driver's share within the safety and investigatory stops stay constant after the election in each county, the mere change in the share of safety stops can generate changes in the overall black driver share. To gauge how much of the increase in the probability of a Black stop can be explained by the shift in the share of safety stops, we conduct a prediction exercise as follows. With stop-level pre-election data, we compute the share of Black stops in the two stop types (safety and investigatory) in each county. For example, in the 2010 election cycle, we have 22 counties. We would thus have 44 (22×2) numbers. We use these numbers as predictions of the probability of a Black stop for each stop, both before and after elections. We then compute the county-year average of these predicted probabilities and estimate a regression of equation 1 with the predicted probabilities. Table 3, column (3) displays the coefficient estimates. We find that the change in the share of safety stops can explain part of the black driver's share increase but to a limited extent. The predicted probability of a Black stop in D-to-R counties is only 0.6 percentage points higher than in D-to-D counties in the year after the election.

The previous exercise holds the black share constant within the safety and investigation category before and after the elections. We now examine the magnitude of changes in the black driver's share in each group. Table 3, column (4) shows that black driver's share increases significantly, 4.4%, in safety stops and is statistically significant at 95% confidence level. Column (5) shows that the magnitudes of the changes in investigatory stops are also large, 1.6%, but the estimate is not precise. We cannot reject the null of no changes for investigatory stops.

Changes in Levels.

Table 3 focuses on the change in shares; we now turn our attention to the changes in the levels to know if more Black drivers are stopped and fewer safety stops are conducted. Table 4 columns (1), (2), (4), and (5) shows that with the same estimating specification as in equation 1 and using the natural log of the number of stops in race and stop type groups, we cannot reject the null of no change in the number of Black stops, Non-Black stops, Safety stops, and Investigation stops. Although the magnitude of the coefficients is large in columns (1), (4), and (5), we do not have the statistical power to reject the null.

To compare the change of levels across groups, we estimate a triple difference-in-differences specification as follows:

$$\begin{aligned} Y_{cleg} = & \sum_{e=-2}^{1} \gamma_e D_{cl}^{D-to-R} \cdot \eta_e \cdot G_g + \sum_{e=-2}^{1} \beta_e D_{cl}^{D-to-R} \cdot \eta_e \\ & + D_{cl}^{D-to-R} \cdot G_g + G_g + \eta_e \cdot G_g + \delta_{le} + \delta_{cl} + \epsilon_{cle}, \end{aligned} \tag{2}$$

where G denotes groups and can be one of two sets: black and non-black, and safety and investigation. Other notations are defined similarly in equation 1. We report the estimates of γ_e and β_e in equation 2 in column (3) and (6). Black stops marginally significantly increase more than non-black stops by 16%; Safety stops significantly decrease more than investigation stops by 41% in the year after elections. A notable pattern in Table 4 is that across all kinds of stops, the number of stops decreases in the year of the election compared to the year before the election. We currently do not have a good explanation for the significant decrease. We have two candidate hypotheses. First, D-to-R counties experience more competitive elections. Second, D-to-R counties are likelier to have incumbents not participate in the elections. Both situations may make sheriffs decrease the number of stops by shirking their effort or by focusing on other tasks which voters might care more about. Exploring the two mechanisms is in our next steps. The larger decrease in safety stops in the election year compared to investigation stops might also be related to these two mechanisms.

Taking stock, we have shown that the black driver's share increases by 3.2 percentage points in response to D-to-R transitions compared to D-to-D transitions. The number of stopped black drivers also increases more than non-black drivers in D-to-R counties than in D-to-D counties, although it is only marginally significant. A limited portion, 18 percent, of the change in the shares of black drivers, can be explained by racially disparate impacts from a shift of focus from safety to investigation stops.[5] The most prominent driving force behind the change in the black driver's share is the change of black driver's share within the safety stops, a statistically significant 4.4 percentage points increase. The changes within the safety stops can come from a variety of reasons. Republican sheriffs may focus on neighborhoods different from Democratic sheriffs, which would change the racial composition of the drivers in the patrolling area. New sheriffs may appoint new officers to be in charge of maintaining traffic safety, and the new officers might behave differently from officers who perform traffic stops before the election. In subsequent discussions, we explore three specific mechanisms that might impact the traffic stop practices towards black drivers: *patrolling policies* on patrolling location and time, *personnel policies* on potential personnel reshuffling, and *discretionary changes* in whom to stop from certain types of officers reacting to new leadership.

4.4 Patrol Policies

Race distribution in the driver's population among vehicles at risk of being stopped may depend on location and time due to commuting patterns or other reasons. If Republican sheriffs assign more patrolling focus on specific neighborhoods or a certain time of the day, and the drivers at risk of being stopped in those neighborhoods and the time of the day are more likely to be black drivers, the change of the patrolling focus may induce an increase in the share of black drivers being stopped. To investigate if a such mechanism can explain the increase in black drivers' share in Table 3, we predict the probability of a Black stop using similar techniques we used for Table 3 column (3). For patrolling locations, with stop-level pre-election data, we compute the share of black stops in each location. A location is a place where at least 40 traffic stops were recorded under that place name in the estimation sample. These location names can be cities, towns, census-designated places, or intersections. Note that 60% of the stops only record the county but no finer location data. For patrolling time groups, we compute the share of black stops in each time group x county cell. A day is divided into four time groups by four points: 6 am, noon, 6 pm, and midnight. These shares (location cell or time group x county cell) were used to predict the probability of a black stop for each stop, both before and after elections. We then compute the average of the predicted probabilities at county-year level; use the averages as the outcome variables, and run the regression specified as in equation 1.

Table 5 reports the estimation results. For overall stops, safety stops, and investigation types, we observe small and non-statistical significant coefficient estimates for the post-election interaction term, suggesting that patrolling time and location allocations cannot explain the increase in black drivers' share.

[5] 0.00601 divided by 0.0327 equals 0.1834

4.5 Officer Behavior Change and Personnel Turnover

We consider three hypotheses regarding officers' behavior change and officer reshuffling that may lead to an increase in black drivers' share among stops.

Change of Officer's Discretionary Decisions on Whom to Stop.

The first hypothesis is that officers who were biased against black drivers before the elections respond to the new Republican sheriff's leadership by stopping much more black drivers. This hypothesis is related to a finding in Grosjean et al. (2022): officers who were more likely to give black drivers tickets respond to Trump campaigns by increasing their probability of stopping black drivers.

To understand how officers of different types respond to new Republican leadership, we first examine if the officers who perform traffic stops both before and after the elections (we called them stayers) conduct traffic stops in a different way after the elections. Column (1) in Table 6 shows that the probability of a Black stop increases among stayers in D-to-R counties compared to D-to-D counties after the elections. This suggests that the increase in the probability of a Black stop is not entirely from new officers. The stayers might have changed their discretionary decisions on whom to stop and thus contributed to the increase of the black driver' share.

We examine if officers who were more likely to stop black drivers before elections increase their tendency of stopping black drivers more post-elections in D-to-R counties. We choose not to use the ticketing decision to measure officers' bias against minority groups (as in Grosjean et al. (2022)) because we do not have enough stops for each officer to precisely estimate such ticketing bias. We measure officers' tendency to stop black drivers as follows, with the goal of ruling out the effect of stop location and time on the stopped driver's race. First, we regress Black Stop (a dummy with 1 if the driver is black) on stop location and stop time fixed effects (exact definition as location and time group in Table 5) and compute residuals, using all stops in the estimation sample. Second, for each officer, we compute their Stop Black Tendency before and after elections by taking the simple average of the residual in the relevant period.

To test the hypothesis that officers who were biased against black drivers reacted to Republican sheriff leadership differently from other officers, we regress Stop Black Tendency after the election on the Stop Black Tendency before the election and its interaction term with the D^{D-to-R} dummy variable. To ensure that the tendency measure in our sample is measured appropriately, we include samples where officers conduct at least 10 stops in the year after elections and at least 50 stops before elections (lifetime traffic stops in that county before the election). Column (2) in Table 6 shows the coefficient estimates of the effect of Tendency before the election on the Tendency after the election and the interaction term between the Tendency to Stop Black drivers and D^{D-to-R}. Officers' behaviors are temporally correlated: The correlation between the tendency before and after the election is 0.54. However, such a correlation is not significantly larger in D-to-R counties. We thus do not have strong evidence that officers who were more likely to stop black drivers respond to Republican sheriffs differently from other officers.

Personnel Policies: characteristics of officers conducting stops after elections. The increase of black drivers' share in all stops in D-to-R counties can be achieved by newly elected Republican sheriffs reshuffling the personnel of officers in the traffic stop team. Prior literature found empirical evidence that bias against minority motorist groups exhibits large heterogeneity at the officer level (Goncalves and Mello, 2021). The potential reshuffling may thus make the traffic stop team stop a higher share of black drivers via positively selecting on bias against black drivers.

We first look at the new officers. We investigate whether officers newly assigned to the traffic stop team are more likely to stop black drivers than stayers. To test this, we compute the difference between the black driver's share done by new officers and stayers (black driver's share by New Officers − black driver's share by Stayers) and see if such differences are larger in D-to-R counties. We regress the differences between the black driver's share done by new officers and stayers on the D-to-R dummy variable and compute the robust standard errors. The coefficient estimate is reported in Column (3) of Table 6. We do not find evidence that new officers in D-to-R counties are more likely to stop black drivers than stayers compared to D-to-D counties.

We turn to the characteristics of stayers now. We investigate whether officers who were more likely to stop black drivers before the elections were more likely to be kept on the traffic stop team after the elections. Including all officers who perform at least 50 stops before the elections (lifetime number of stops in the sheriff's office), we regress the Leave dummy variable (one if not perform any stops at $t+1$, 0 otherwise) on the Stop Black Tendency before the elections and its interaction term with D-to-R dummy variable, while controlling for county-cycle fixed effects. In Column (4) we find that the coefficient estimate of Stop Black Tendency is positive and significant, suggesting that in D-to-D counties, officers who are more likely to stop black drivers are more likely to leave the traffic stop team after the elections. The point estimate of the interaction term is large and negative, pointing to the interpretation that compared to D-to-D counties, officers who were more likely to stop black drivers before the election are more likely to stay on the traffic stop team after the election in D-to-R counties. But we do not have the precision to reject the null that the effect of Stop Black Tendency on leaving the traffic stop team is the same in D-to-D and D-to-R counties.

Although we do not find evidence that Republican sheriffs reshuffle officers based on the officers' tendency to stop black drivers, we find that D-to-R transitions are associated with more traffic stop team member turnover than D-to-D transitions. In Columns (5) and (6), we estimate equation 1 with two outcome variables: the share of stops done by new officers each year and the share of new officers among all officers. The definition of the new officers here is different from the one in Column (3). New officers here are defined at the year level. An officer who performed their first-lifetime traffic stop (in that county) is a new officer in that year. We find that D-to-R sheriff's offices have 25 percentage points more stops done by new officers post elections compared to D-to-D sheriff's offices. This is a 130% increase compared to the mean in the year before the election. In terms of the share of new officers among all officers, the share of new officers in D-to-R sheriff's offices is 18 percentage points higher than in D-to-D sheriff's offices, a 50% increase compared to the mean in the year before elections. The traffic stop team turnover we observe here motivates us to dive into the overall personnel turnover analysis in section 5.

4.6 Search Behavior

Thus far we examine if partisan leadership affects officers' decisions on whom to stop. We establish evidence that black drivers are disparately impacted by the Republican leadership. We now turn to officers' decision after stopping a driver: whether to search a vehicle or not. Our goal is to examine if Republican leadership also influences officers' search criteria, especially for black drivers. Following Feigenberg and Miller (2022), we look at the search and any found contraband separately for safety and investigation stops.[6]

We present the effect of partisan leadership on search rates and the share of stops with found contraband, for black and non-black drivers respectively. Table 7 reports results from estimating equation 1 with outcome variables defined within safety stops. Panel A reproduces the results seen in Column (4) of Table 3. In Panel B, we examine the changes in the search rate of black and non-black drivers once stopped. We find different patterns for the two groups of drivers. For black drivers, the share of safety stops with searches significantly increase after the elections in D-to-R counties compared to D-to-D counties. Taking into account the increase of the black driver's share in all stops seen in Panel A, we compute the coefficient size of the interaction term assuming officers maintain the same search rate for black drivers seen in the year before the election. Testing the interaction term coefficient against the null that the black driver's share increases but the search rate stays the same, we can reject the null with the p-value 0.032. For non-black drivers, however, we find no changes in the share of stops with searches after elections in D-to-R counties.

With the increase in searches towards black drivers in mind, we next examine if the higher average search rate leads to changes in the average (conditional) hit rate, defined as the probability of finding contraband conditional on searches. In panel C we find that the share of black searches with found contraband among all stops increases with marginal statistical significance. We test the null hypothesis that the search rate increase as in Panel B but the hit rate stays the same as one year before the election. We cannot reject the null with the p-value of 0.98. The additional searches after elections are not "worse" searches in terms of the probability of finding contraband. For non-black drivers, in Panel C Column (2), we do not find significant changes of the share of searches with found contraband.

Table 8 presents estimation results with investigation stops. We find no changes in search rate and hit rate for both black and non-black drivers in investigation stops.

[6] Feigenberg and Miller (2022) directly drop all investigation stops to ensure that the stopped drivers' population across troopers is similar.

Sheriffs representing different political parties may possess different policy preferences, which may in turn lead to racial disparate impacts. In this section, we focus on traffic stops and searches. We document empirical evidence that black drivers are disparately impacted by officers under Republican sheriffs' leadership than officers under Democratic sheriff's leadership. The probability of a Black stop and the share of stops with searches is higher for black drivers who were stopped for traffic safety reasons. Potential patrolling location and time policy changes, personnel policy changes, and officers' discretionary decision changes cannot explain the racially disparate impact we find. A caveat of the mechanism analysis is that our data do not have rich stop location information. A more detailed analysis of the effect of partisan leadership on patrolling location choices is needed in future research.

In the exploration of whether the officer composition of the traffic stop team can explain the racial disparity, we find that a D-to-R transition is associated with much more traffic stop team member turnover than a D-to-D transition. This motivates us to ask in the next section if party turnover in leadership leads to a reshuffling in the general personnel in the sheriff's offices and impacts how representative the officers are to the civilian population in the jurisdiction, a long-standing concern related to racial disparities in law-enforcement (McCrary, 2007).

5 Impact of Partisan Leadership on Personnel Turnover

5.1 Descriptive Representation of Officers in Sheriff's Offices

Sworn officers in large law-enforcement agencies have shown to be not representative of the civilian population in their jurisdictions (Ba et al., 2022). In North Carolina, officers in sheriff's offices are similar to civilians except for the gender composition. Table 9 compares the demographics of the sworn officers with the civilians in counties sheriff's offices belong to across all of North Carolina in 2010.[7] Compared to civilians, officers are slightly more likely to be Republicans (32% and 36%), less likely to be Black (22% and 19%), and much less likely to be female (54% and 18%). Nearly no Republicans are Black, while around 40% Democrats are Black. Across party affiliations, officers are less likely to be Black than civilians.

5.2 Officer Composition Changes

Sheriffs and deputy sheriffs might find working with people with the same party affiliations easier due to similar policy preferences. Personnel turnovers with respect to the party affiliation dimension may thus respond to sheriff's turnovers while the party affiliation distribution of the civilian population does not change. To examine the effect of change of political leadership on officer composition, we estimate regressions in the same specification as equation 1 with civilian composition and law-enforcement agency officer composition as

[7]The civilians include voters with "active" voter registration status in corresponding counties.

outcome variables.

Timing Convention.

The pension records dataset does not record which months in a year a worker works in a specific agency. Thus, we cannot define the election year as in the previous sections (December to November). The election year in this section is the same as the calendar year. To capture the personnel changes after the elections, we define a cycle ranging from one year before the election to two years after the election. This way, we can capture all personnel changes in the year after the election. Note that if we confine the cycle to one year after the elections, we cannot observe personnel changes in the year after the elections. For example, the exit of an officer from the office in January 2011 in a county that had D-to-R elections in 2010 would not be captured in the composition in 2011 since the pension records would still report the officer working in that agency in 2011. Such an officer exit would be captured by comparing the composition in 2012 with the composition in 2011. The notation convention is the same as in the previous sections: t-1, t, t+1, and t+2 represent one year before, the exact year, one year after, and two years after the elections.

Estimation Results.

Table 10 reports the OLS estimation results with equation 1 using civilian and sworn officers' demographic shares and average age as outcome variables. Results in Panel A show that there is an increasing trend of Republican shares in D-to-R counties. Voters in D-to-R counties are 0.64 percentage points more likely to be registered as Republicans than voters in D-to-D counties two years after the elections.[8] Compared to the mean in D-to-R in the year of elections, this is a 1.9% increase. The off-setting decreasing share comes from the Democrats. D-to-R counties witnessed a 0.79 percentage point decrease in Democrat shares two years after elections compared to D-to-D counties. Race, gender, and age composition, on the other hand, do not exhibit significant changes after elections. The increasing Republican shares in the D-to-R counties are consistent with the party turnover sheriff election results.

We next examine if such civilian composition changes are reflected in the sworn officers' composition. Results in Panel B show that officer composition in D-to-R sheriff's offices changes in the same direction as the civilian trend. Two years after the election, officers in D-to-R sheriff's offices are 6.2 percentage points more likely to be Republicans than in D-to-D offices. Compared to the mean in D-to-R offices in the election year, this is a 17% increase. A much larger increase than the one seen in the civilian changes. The decreasing share goes to the Democrats, a 5.3 percentage point decrease in D-to-R compared to D-to-D counties, not the Unaffiliated officers. The increasing Republican share trend is not seen in police departments. Results in Panel C show that the composition of sworn officers on the party, race, gender and age dimensions in the police departments in D-to-R counties do not exhibit significantly different time trends compared to police departments in D-to-D counties.

[8] The voter registration records we use here is a snapshot of January 1 each year.

5.3 Leaving Margin

The composition changes in the sheriff's offices in Table 10 can be from the leaving or/and entering margins. In this section, we examine the effect of leader changes on incumbent officers' work locations.

Labor Market Mobility in Law-Enforcement Agencies

To gauge the degree of mobility of the local law-enforcement officer labor markets, we report the distribution of work location changes in both sheriff's offices and police departments in table 11. The observation is at the officer-year level. An officer is reported as going to "Other Law" type positions if he or she stopped working at the current law-enforcement agency the next year and was observed to be working as a sworn officer within North Carolina. An officer is reported as going to "Non-Law" type positions if he or she stopped working at the current law-enforcement agency next year and was observed to be working within North Carolina but not as a sworn officer. An officer is reported as "Leave Public Sector" if he or she is not observed to be working in the public sector in North Carolina the following year.

In total, around 8.8% of law enforcement officers leave their original agencies in sheriff's offices at the year level. Decomposing the destination positions, 5.3% of officers leave the public sector. [9] Two percent of deputy sheriffs go to other law enforcement positions; 1.5 percent go to non-law enforcement positions. On the other hand, police officers have a smaller share of people leaving the public sector, but a larger share of officers people go to other law enforcement positions.

Graphical Evidence

Before formally specifying the estimation equations, we provide descriptive evidence exploiting the three variations we will use in the statistical estimation. We select the incumbent officers who worked in the relevant law-enforcement agencies two years before the election into the sample. We follow these officers for the next four years and observe in which year they leave the agency they worked at. Motivated by the composition changes we observe in Table 10, we focus on officers who were Republicans or Democrats two years before the elections. We categorize officers into four groups, based on the counties (D-to-D or D-to-R) and party affiliation (Democrat or Republican). We plot the survival rate of each group across years within the election cycle in Figure 2. The timing convention is as follows: if an officer is observed to be working in the agency at year t but not at year $t+1$, he or she would be considered as left the agency at year t.

Figure 2 shows that the four groups of officers in sheriff's offices share a similar pre-trend in leaving the agency before the elections, up until $t-1$. In the election year, however, Democratic officers in D-to-R counties are significantly more likely to leave the agency than the other three groups of officers. This pattern suggests that some of the composition changes of the political party dimension come from officers whose party preferences are misaligned with the newly-elected leaders leaving the agencies. A different

[9] We cannot differentiate among the leaving reasons, which include firing, retiring, or voluntary leaving.

trend is seen in police departments. Democrat officers in D-to-R counties are *less* likely to leave the agency after the elections. We discuss our interpretation of these trends when we discuss the regression results below.

Estimation Specification

To capture the trend we observe in Figure 2, we adopt the same differences-in-differences framework as in estimating the effect of sheriff party turnover on traffic stop practices but add another layer of differences: the party affiliation of the sworn officers, which includes Democrat (DEM), Republican (REP) and Unaffiliated and others (UNA). We include all D-to-D and D-to-R counties identified in Table 1 Panel B. We estimate an OLS regression with the following specification:

$$
\begin{aligned}
Y_{jle} = & \sum_{p=1}^{2}\sum_{e=-2}^{1}\beta_{pe} D_{cl}^{D-to-R}\cdot Party_{jl}^{p}\cdot\eta_e + \sum_{e=-2}^{1} D_{cl}^{D-to-R}\cdot\eta_e \\
& + \sum_{p=1}^{2}\sum_{e=-2}^{1} Party_{jl}^{p}\cdot\eta_e + \sum_{p=1}^{2} Party_{jl}^{p}\cdot D_{cl}^{D-to-R} \\
& + \sum_{p=1}^{2} Party_{jl}^{p} + \eta_{le} + \delta_{cl} + \epsilon_{jle},
\end{aligned}
\tag{3}
$$

where Y_{jle} denote the outcome variable for individual j in election year e in cycle l. Outcome variables are dummy variables, including leaving the public sector, transferring to other law enforcement positions, and transferring to other non-law-enforcement positions. The data structure is similar to analyzing traffic stops in cycle and year definitions, but the observations are organized as individual panels. We include officers who worked in the agency two years before the elections. We follow where they work for four years and record the first change of workplace to construct the outcome variable. For example, an officer who leaves the public sector in year t would have an outcome equalling 1 in both year t and year $t+1$. The variable $Party_{jl}^{p}$ are dummy variables indicating the party affiliation of the officers in election cycle l (defined as the affiliation at $t-2$). I treat the Republican officer as the baseline group, so $p \in \{1 = UNA, 2 = DEM\}$. Standard errors are clustered at county level. The coefficients of interest are the ones associated with the triple interaction terms (β_e).

Estimation Results

Table 12 reports estimation coefficients of β_{pe} of equation 3. Results in Column (1) show that at the end of the election cycle, Democrat officers in D-to-R sheriff's offices are 7.2 percentage points more likely to leave the public sector than Republican officers in the same agencies, controlling the time trend captured by respectively Democrat and Republican officers in D-to-D sheriff's offices. Compared to the dependent variable mean for Republican officers in $t+1$ in D-to-R counties, this is a large 36 percent increase. Results in Column (2) and (3) shows that the party turnover of sheriffs does not make officers with specific party affiliations more likely to transfer to other agencies.

In Police departments, results in Column (4)-(6) show that the party turnover of sheriffs makes Democrat police officers six percentage points less likely to go to other law-enforcement positions than Republican police officers in the same county at the end of the cycle. This is a 29% decrease compared to the dependent variable mean of Republican officers in D-to-R counties at the end of the cycle.

Taken together, we interpret the results in Table 12 as evidence that policy preference misalignment between sheriffs and officers does affect how sheriffs value the officers and how officers value the work. Democrat officers are more likely to leave the public sector when the newly elected sheriff is a Republican rather than a Democrat. This can be from officers voluntarily retiring or involuntarily leaving the agency. An important observation is that such personnel turnover does not keep the human capital the officers possess within the public sector, as we do not see changes in transitions to other law enforcement agencies or non-law-enforcement agencies.

The personnel turnover pattern in police departments provides some evidence that labor markets for law-enforcement officers include both sheriff's offices and police departments. We interpret the decreasing likelihood for Democrat officers to transition to other law enforcement agencies as a "congestion" effect. There seems to be a steady trend of how many Democrat police officers would transfer to the sheriff's office each year. However, the party turnover of the sheriffs deters some of these Democrat police officers from such transfers, potentially due to the misalignment of their party affiliations.

5.4 Entering Margin

The composition changes of officers associated with the party turnover of sheriffs may come from who *enters* the sheriff's offices. We first examine the number of officers entering the sheriff's offices yearly. We estimate a regression with specification 1 and use the number of entering officers as the outcome variable. Table 13 presents the estimation results. Column (1) shows that D-to-R counties hire more new officers than D-to-D counties after elections. The new officers in D-to-R counties hired after elections, however, are not more likely to be Republicans than the ones hired in D-to-D sheriff's offices. Table 14 reports regression estimation results of equation 1 using shares of new officers with Democratic, Republican, and Unaffiliated and others party affiliations as outcome variables. The political party affiliation distribution among new officers in D-to-R sheriff's offices, compared to D-to-D offices, does not change significantly after elections. On the other hand, in D-to-R counties, police departments are more likely to hire Democrat police officers than in D-to-D counties. In the future, we will check whether the shift from hiring Unaffiliated to Democrat officers reflects the trend of political party affiliation among civilians in the police department's jurisdictions.

6 Tentative Conclusion and Future Steps

This paper finds evidence that partisan leadership matters in determining racial disparities in frontline policing and law-enforcement officer representation.

A Democratic-to-Republican sheriff turnover, compared to a Democratic-to-Democratic turnover, leads to larger racial disparities in stopped driver composition, especially in traffic safety stops as opposed to investigation stops. We provide evidence that the increase in the black driver's share is not driven by Republican sheriffs focusing on patrolling different neighborhoods or at different times of the day from previous sheriffs. The increase is not driven by Republican sheriffs reshuffling officers in the traffic stop teams based on officers' tendency to stop black drivers, although we find evidence that D-to-R transitions are associated with assigning more new officers in the traffic stop team. On officers' search behavior, we find that within safety stops, officers increase the search rate for black drivers while maintaining the same level of hit rate.

Party affiliation misalignment between officers and sheriffs leads to officers leaving the public sector. Democratic officers are much more likely to leave the public sector than Republican officers in D-to-R sheriff's offices, compared to D-to-D offices. The personnel turnover results in a large increase in the share of Republican officers in Democratic-to-Republican offices, while the share of voters registered as Republicans only increase slightly in Democratic-to-Republican counties.

Our next steps include, first, investigating if election competitiveness and incumbents' participation in the election can explain the decreased level of the number of stops in the election year. Second, examining if the decreased share of traffic safety stops leads to worse traffic safety. Third, examining whether the party affiliation of the majority of city councilors can impact the personnel composition of the police departments.

References

M. Akhtari, D. Moreira, and L. Trucco. Political turnover, bureaucratic turnover, and the quality of public services. *American Economic Review*, 112(2):442–93, February 2022. doi: 10.1257/aer.20171867. URL https://www.aeaweb.org/articles?id=10.1257/aer.20171867.

K. Antonovics and B. G. Knight. A New Look at Racial Profiling: Evidence from the Boston Police Department. *The Review of Economics and Statistics*, 91(1):163–177, 02 2009. ISSN 0034-6535. doi: 10.1162/rest.91.1.163. URL https://doi.org/10.1162/rest.91.1.163.

B. Ba, J. Kaplan, D. Knox, M. Komisarchik, R. Mariman, J. Mummolo, R. Rivera, and M. Torres. Who are the Police? Descriptive Representation in the Coercive Arm of Government. 2022.

F. R. Baumgartner, D. A. Epp, and K. S. Shoub. *Suspect Citizens: What 20 Million Traffic Stops Tell Us About Policing and Race*. Cambridge University Press, 2018.

T. Besley and M. Ghatak. Competition and incentives with motivated agents. 95 (3):616–636, 2005. ISSN 0002-8282. doi: 10.1257/0002828054201413. URL http://pubs.aeaweb.org/doi/10.1257/0002828054201413.

A. Bolton, J. M. de Figueiredo, and D. E. Lewis. Elections, Ideology, and Turnover in the US Federal Government. *Journal of Public Administration Research and Theory*, 31(2):451–466, 11 2020. ISSN 1053-1858. doi: 10.1093/jopart/muaa051. URL https://doi.org/10.1093/jopart/muaa051.

G. Bulman. Law enforcement leaders and the racial composition of arrests. 57(4): 1842–1858, 2019. ISSN 0095-2583, 1465-7295. doi: 10.1111/ecin.12800. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecin.12800.

A. Cohen and C. S. Yang. Judicial politics and sentencing decisions. 11(1):160–191, 2019. ISSN 1945-7731, 1945-774X. doi: 10.1257/pol.20170329. URL https://pubs.aeaweb.org/doi/10.1257/pol.20170329.

E. Colonnelli, M. Prem, and E. Teso. Patronage and selection in public sector organizations. *American Economic Review*, 110(10):3071–99, October 2020. doi: 10.1257/aer.20181491. URL https://www.aeaweb.org/articles?id=10.1257/aer.20181491.

G. Facchini, B. Knight, and C. Testa. The franchise, policing, and race: Evidence from arrests data and the voting rights act, 2020. URL http://www.nber.org/papers/w27463.pdf.

B. Feigenberg and C. Miller. Would Eliminating Racial Disparities in Motor Vehicle Searches have Efficiency Costs?*. *The Quarterly Journal of Economics*, 137(1):49–113, 05 2022. ISSN 0033-5533. doi: 10.1093/qje/qjab018. URL https://doi.org/10.1093/qje/qjab018.

M. D. Fliss, F. Baumgartner, P. Delamater, S. Marshall, C. Poole, and W. Robinson. Re-prioritizing traffic stops to reduce motor vehicle crash outcomes and racial disparities. *Injury Epidemiology*, 7(1):3, Dec. 2020. ISSN 2197-1714. doi: 10.1186/s40621-019-0227-6. URL https://injepijournal.biomedcentral.com/articles/10.1186/s40621-019-0227-6.

F. Goncalves and S. Mello. A few bad apples? racial bias in policing. *American Economic Review*, 111(5):1406–41, May 2021. doi: 10.1257/aer.20181607. URL https://www.aeaweb.org/articles?id=10.1257/aer.20181607.

P. Grosjean, F. Masera, and H. Yousaf. Inflammatory political campaigns and racial bias in policing. *The Quarterly Journal of Economics*, page qjac037, 2022. ISSN 0033-5533, 1531-4650. doi: 10.1093/qje/qjac037. URL https://academic.oup.com/qje/advance-article/doi/10.1093/qje/qjac037/6710386.

M. A. Hansen and J. C. Navarro. Gender and Racial Gaps in Support for Policing and Correctional Reforms: Are the Gaps a Consequence of Political Partisanship?

Crime & Delinquency, page 001112872110647, Dec. 2021. ISSN 0011-1287, 1552-387X. doi: 10.1177/00111287211064788. URL http://journals.sagepub.com/doi/10.1177/00111287211064788.

J. McCrary. The effect of court-ordered hiring quotas on the composition and quality of police. *American Economic Review*, 97(1):318–353, March 2007. doi: 10.1257/aer.97.1.318. URL https://www.aeaweb.org/articles?id=10.1257/aer.97.1.318.

E. Pierson, C. Simoiu, J. Overgoor, S. Corbett-Davies, D. Jenson, A. Shoemaker, V. Ramachandran, P. Barghouty, C. Phillips, R. Shroff, and S. Goel. A large-scale analysis of racial disparities in police stops across the united states. *Nature Human Behaviour*, 4(7):736–745, 2020. ISSN 2397-3374. doi: 10.1038/s41562-020-0858-1. URL http://www.nature.com/articles/s41562-020-0858-1.

K. Roach, F. R. Baumgartner, L. Christiani, D. A. Epp, and K. Shoub. At the intersection: Race, gender, and discretion in police traffic stop outcomes. *Journal of Race, Ethnicity, and Politics*, 7(2):239–261, 2022. doi: 10.1017/rep.2020.35.

J. L. Spenkuch, N. Kellogg, G. Xu, and B. Haas. Ideology and Performance in Public Organizations. page 68, 2022.

D. M. Thompson. How partisan is local law enforcement? evidence from sheriff cooperation with immigration authorities. *American Political Science Review*, 114(1):222–236, 2020. doi: 10.1017/S0003055419000613.

Figures

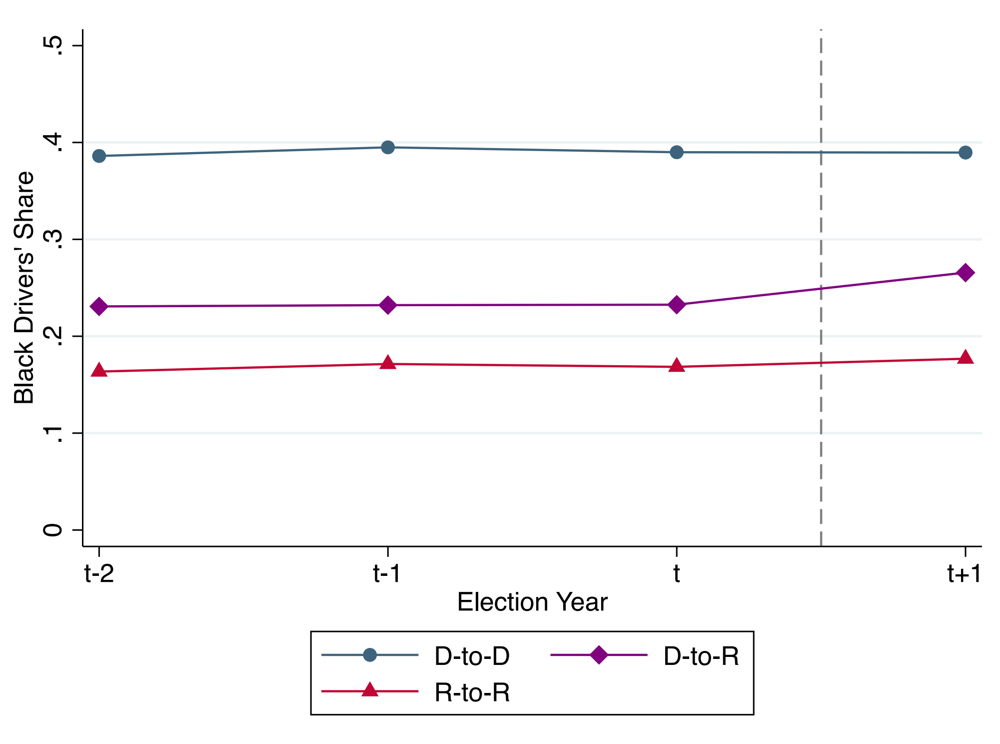
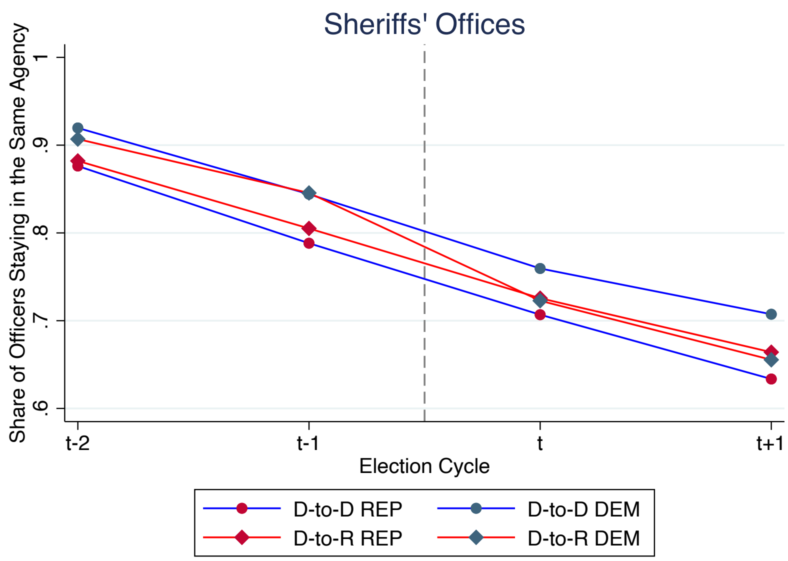


Figure 1: Black Drivers' Share Among All Stops

Notes: This figure plots the raw data pattern of the share of Black drivers among all stops from 2008 to 2019. We compute the share of stops with Black drivers at the county-year level. We compute the D-to-D/D-to-R/R-to-R mean in different cycle years by taking the simple average of the county-year means, where D-to-D, D-to-R, and R-to-R respectively means the counties experience Democrat to Democrat, Democrat to Republican, and Republican to Republican sheriff transitions. Year t represents the year the election was held. The election cycles, with four years within each of them, do not overlap with each other in calendar years.

(a) Survival Rate of Deputy Sheriffs



(b) Survival Rate of Police Officers

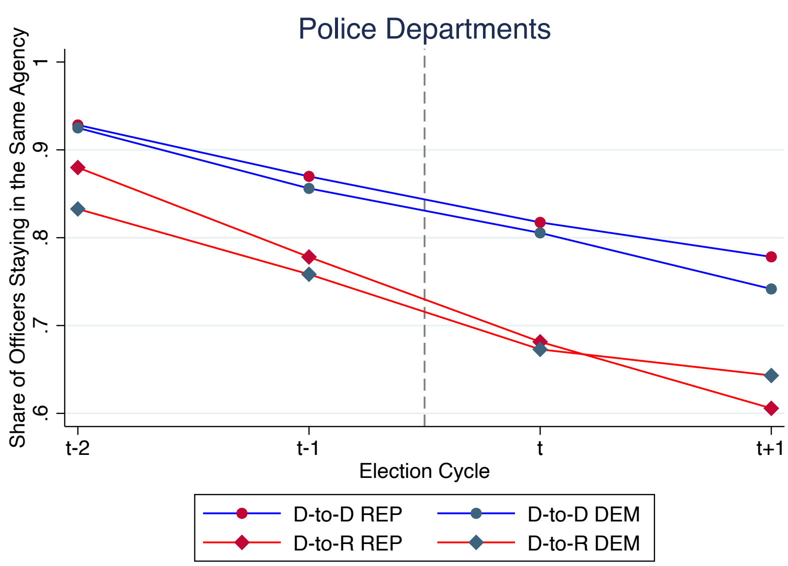


Figure 2: Time Trend of Leaving the Working Agencies Based on Officers' Party Affiliation

Notes: The two figures depict the share of officers staying in the same law-enforcement agency across years within an electoral cycle. We measure the shares based on whether the officer worked in the same agency in the next calendar year. We combine three electoral cycles, ranging from 2008 to 2019. The data structure is an individual panel. We include individuals who worked in the agency two years before the elections and tracked their working locations for the following four years. Since we do not know the exact month the officers stopped working in the agency, we cannot define the election year as we did in the traffic stop dataset. The election year here is defined according to the calendar year. Year t is the calendar year the sheriff's elections were held. The dashed line is drawn between $t-1$ and t, representing the timing of the election in November of that year. The newly elected sheriffs are sworn in at the end of the same November or the beginning of December.

Tables

Table 1: Sheriff Election Results in North Carolina

Panel A: All Sheriffs' Offices						
Election Year	R-to-R Turnover	R-to-R No Turnover	R-to-D	D-to-D Turnover	D-to-D No Turnover	D-to-R
2010	10	24	0	15	46	5
2014	5	33	1	14	37	10
2018	13	32	3	16	27	9
Panel B: Offices with Winners' vote share $<$ 80%						
2010	8	17	0	13	26	5
2014	3	16	1	8	21	10
2018	5	12	3	6	8	8
Panel C: Offices with Winners' vote share $<$ 80% and number of stops $>$ 50 every year						
2010	3	14	0	4	14	4
2014	3	12	0	6	15	6
2018	3	7	3	4	3	5
Panel D: Winners' vote share distribution in all D-to-D and D-to-R elections						
	2010		2014		2018	
Winner's vote share	D-to-D	D-to-R	D-to-D	D-to -R	D-to-D	D-to-R
$<=$0.6	13	3	11	8	5	7
$0.6-0.7$	15	1	8	1	7	0
$0.7-0.8$	11	1	10	1	2	1
$>= 0.8\& < 1$	4	0	4	0	6	0
1	18	0	18	0	23	1

Notes: D refers to the Democratic party, and R refers to the Republican party. North Carolina has 100 sheriff's offices, one for one county. Panel A presents the party turnover distributions in all elections from 2010 to 2018. Panel B drops elections in which the winner's vote share is smaller than 80%. This criterion is chosen to match the vote share support of D-to-R elections. Panel C drops elections that are dropped in Panel B and further drops the ones in which the county had at least one year that had fewer than 50 traffic stops in that four-year cycle (from 3 years before the election to 1 year after the election). Panel D presents the winner's vote share distribution in all D-to-D (turnover and no turnover) and D-to-R elections. An election with the winner's vote share being one means there was only one candidate in that election. We include county-cycles in Panel B for general personnel analysis. We include county-cycles in Panel C in the traffic stop and search behavior analysis.

Table 2: Summary Statistics of Traffic Stops and Searches

	Stops by Motorists' Group			Stops by Types		All
	Black	Hispanic	White	Safety	Investigation	
Share Black	1.000	0.000	0.000	0.238	0.278	0.257
Share Hispanic	0.000	1.000	0.000	0.068	0.070	0.069
Share White	0.000	0.000	1.000	0.669	0.634	0.652
Share Female	0.361	0.239	0.359	0.357	0.343	0.350
Share Safety Stops	0.478	0.511	0.530	1.000	0.000	0.517
Share Investigatory Stops	0.522	0.489	0.470	0.000	1.000	0.483
Search Rate	0.079	0.087	0.061	0.051	0.085	0.067
Unconditional Hit Rate	0.024	0.017	0.021	0.016	0.027	0.022
Observations	84,595	22,600	214,132	169,809	158,730	328,539

Notes: This table presents summary statistics for all county-cycles in Panel C in Table 1. Safety stops include stops due to Speed Limit Violations, Stop Light/Sign Violations, Driving While Impaired, and Safe Movement Violations. Investigation stops include stops due to Vehicle Equipment Violations, Vehicle Regulatory Violations, Seat Belt Violations, Investigation, and Other Motor Vehicle Violations.

Table 3: Impact of Partisan Leadership on the Probability of a Black Stop and a Safety Stop

	(1) $\frac{\text{All Black Stops}}{\text{All Stops}}$	(2) $\frac{\text{All Safety Stops}}{\text{All Stops}}$	(3) $\frac{\text{Predicted Black stops}}{\text{All Stops}}$	(4) $\frac{\text{Black Safety Stops}}{\text{All Safety Stops}}$	(5) $\frac{\text{Black Investigation Stops}}{\text{All Investigation Stops}}$
t-2 x D-to-R	0.00814	-0.00733	-0.00186	0.0146	0.00722
	(0.0173)	(0.0288)	(0.00308)	(0.0141)	(0.0182)
t x D-to-R	0.000788	-0.0330*	0.00242	0.00947	-0.00321
	(0.00823)	(0.0187)	(0.00146)	(0.00925)	(0.0131)
t+1 x D-to-R	0.0327**	-0.0880***	0.00601**	0.0443**	0.0160
	(0.0150)	(0.0234)	(0.00236)	(0.0203)	(0.0216)
County-Cycle	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	244	244	244	244	244
Dep. mean	0.2413	0.5281	0.2419	0.2198	0.2640

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t - 1$. In Column (3), we predict whether a stop is a Black stop based on county-stop-type information. Since we have 61 counties and two stop types (safety and investigatory), we have 122 prediction values. The prediction values are the share of black drivers in each (stop type $\times$ county cell) in pre-election years.

Table 4: Impact of Partisan Leadership on the Number of Stops by Race and Stop Purposes

	(1)	(2)	(3)	(4)	(5)	(6)
			ln(Number of Stops)			
	Black	Non-Black		Safety	Investigation	
t-2 x D-to-R	-0.219	-0.206	-0.203	-0.205	-0.194	-0.206
	(0.173)	(0.147)	(0.145)	(0.145)	(0.184)	(0.180)
t x D-to-R	-0.441**	-0.509***	-0.499***	-0.575***	-0.425**	-0.417**
	(0.178)	(0.169)	(0.168)	(0.171)	(0.176)	(0.173)
t+1 x D-to-R	0.175	-0.00503	0.00547	-0.147	0.242	0.252
	(0.288)	(0.279)	(0.276)	(0.282)	(0.283)	(0.281)
t-2 x D-to-R x Black			-0.0208			
			(0.0944)			
t x D-to-R x Black			0.0482			
			(0.0584)			
t+1 x D-to-R x Black			0.159*			
			(0.0918)			
t-2 x D-to-R x Safety Stops						0.0132
						(0.127)
t x D-to-R x Black x Safety Stops						-0.167**
						(0.0804)
t+1 x D-to-R x Safety Stops						-0.409***
						(0.110)
County-Cycle	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	244	244	488	244	244	488
Dep. mean	5.2468	6.5417	5.2468	6.1667	6.0525	6.1667

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$. Black is a dummy variable being 1 if the driver is Black, and 0 otherwise. Safety Stops is a dummy variable being 1 if the stop purpose is a moving violation, and 0 otherwise.

Table 5: Patrol Location and Time Policy

	(1)	(2)	(3)	(4)	(5)	(6)
			Predicted Black stops			
			Stops			
	All		Safety Stops		Investigation	
	Location	Time	Location	Time	Location	Time
t-2 x D-to-R	0.00307	-0.00125	0.000880	-0.00234	0.00331	0.00317
	(0.00476)	(0.00453)	(0.00395)	(0.00497)	(0.00672)	(0.00417)
t x D-to-R	-0.000966	0.000437	0.000549	0.00184	-0.00301	-0.000249
	(0.00369)	(0.00347)	(0.00415)	(0.00370)	(0.00411)	(0.00419)
t+1 x D-to-R	0.00505	-0.00212	0.00685	-0.00288	0.000816	-0.00327
	(0.00439)	(0.00410)	(0.00451)	(0.00417)	(0.00512)	(0.00460)
County-Cycle	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	244	244	244	244	244	244
dep_mean	0.2417	0.2401	0.2396	0.2352	0.2444	0.2462

Notes: This table reports estimation results examining whether potential patrol policy changes in location and time can explain the increase in the black driver's share in D-to-R counties compared to D-to-D counties after elections. This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t - 1$. For outcome variables used in regression estimations reported in Columns (1), (3), and (5), we predict whether the stop is a Black stop by the share of Black stops in pre-election years in each location. Locations are places where at least 40 traffic stops were recorded under that place name in the estimation sample. For outcome variables used in regression estimations reported in Columns (2), (4), and (6), we predict whether a stop is a Black stop based on stop-time group and county information. For stop-time groups, we divided a day into four groups by four points: 6 am, noon, 6 pm, and midnight. The prediction values are the share of black drivers in each (stop-time group $\times$ county cell) in pre-election years. For outcome variables in Columns (3) and (4), the denominator is the number of all safety stops at the county-year level, and the nominator is the prediction of the probability of a Black stop for all safety stops at the county-year level. Outcome variables in Columns (3) and (4) are similarly defined but replace the safety stops with investigation stops.

Table 6: Officer Behavior Change and Personnel Turnover

	(1) $\frac{\text{Black Stops by Stayers}}{\text{All Stops by Stayers}}$	(2) Tendency to Stop Black Drivers post-election	(3) Black Stop share differences b/w New officers and Stayers	(4) Leave	(5) $\frac{\text{Stops by New Officer}}{\text{All Stops}}$	(6) $\frac{\text{\# of New Officers}}{\text{\# of all officers}}$
D-to-R			0.0124			
			(0.0674)			
t-2 x D-to-R	0.0485				-0.0750	-0.0126
	(0.0316)				(0.0696)	(0.0484)
t x D-to-R	0.00954				-0.0300	0.0395
	(0.0130)				(0.0510)	(0.0569)
t+1 x D-to-R	0.0434**				0.250***	0.184***
	(0.0189)				(0.0803)	(0.0606)
Stop Black Tendency		0.544***		0.434**		
		(0.101)		(0.170)		
D-to-R x Stop Black Tendency		0.0857		-0.255		
		(0.184)		(0.366)		
County-Cycle	Yes	Yes	No	Yes	Yes	Yes
Year	Yes	No	No	No	Yes	Yes
Election cycle	No	No	No	Yes	No	No
N	242	637	58	1453	244	244
Dep. mean	0.2478	-0.0081	-0.0134	0.6946	0.1518	0.3662

Notes: This table reports estimation results examining two hypotheses. First, whether officers who were more likely to stop black drivers before the elections respond to new Republican leadership differently from other officers. This hypothesis is tested in Columns (1) and (2). Second, whether the potential reshuffling of officers contributes to the increase of the share of black drivers. This is tested in Columns (3) and (4). Column (5) and (6) documents an empirical pattern: D-to-R counties are associated with higher turnover in traffic stop team than D-to-D counties after elections. Clustered standard errors at the county level are in parentheses in all Columns except Column (3). Robust standard errors are reported in Column (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep. means are computed from D-to-R counties before the election. Stayers are officers who conduct traffic stops both before and after elections. In Column (2), we compute Stop Black Tendency for stayers both pre and post elections in each cycle. We first regress Black Stop on stop location and stop time fixed effects (exact definition as location and time group in Table **??**) and compute residuals, using all stops in the estimation sample. Stop Black Tendency is then computed as the mean of the residuals for each officer in the relevant time period. We regress Stop Black Tendency after the election on the Stop Black Tendency before the election and its interaction term with the D^{D-to-R} dummy variable. We include samples where officers conduct at least 10 stops post-elections and at least 50 stops before elections (lifetime traffic stops in that county before the election). In Column (3), new officers are defined as those who only conducted traffic stops after elections. The outcome variable is $\frac{\text{Black Stops by New Officers}}{\text{All Stops by New Officers}} - \frac{\text{Black Stops by Stayers}}{\text{All Stops by Stayers}}$, measured at $t+1$, defined at the county-cycle level instead of county-year level. In Column (4), Leave is a dummy variable defined at the officer-cycle level. Leave is 1 if an officer conducts at least one stop before the elections, but does not conduct any stops in the year after the elections, 0 otherwise. To ensure that the Stop Black tendency is estimated with enough stops, we include officers who conduct at least 50 stops before the elections. In Columns (5) and (6), New Officer is defined at the officer-year level. New officers are the ones who conduct their lifetime-first traffic stops in that county in that year.

Table 7: Effect of Partisan Leadership on Traffic Stop Search Behaviors by Drivers' Race Among Safety Stops

Panel A: Stop	(1) Black Stops / All Safety Stops	(2) Non-Black Stops / All Safety Stops
t-2 x D-to-R	0.0146	-0.0146
	(0.0141)	(0.0141)
t x D-to-R	0.00947	-0.00947
	(0.00925)	(0.00925)
t+1 x D-to-R	0.0443**	-0.0443**
	(0.0203)	(0.0203)
County-Cycle	Yes	Yes
Year	Yes	Yes
N	244	244
dep_mean	0.2198	0.7802
Panel B: Search or not	**Black Searches / All Safety Stops**	**Non-Black Searches / All Safety Stops**
t-2 x D-to-R	0.00846	0.000676
	(0.00770)	(0.0122)
t x D-to-R	0.00190	-0.00778
	(0.00335)	(0.00928)
t+1 x D-to-R	0.0252**	0.00959
	(0.00974)	(0.0134)
N	244	244
Dep. mean	0.0146	0.0521
Search rate at $t-1$	0.0818	0.0661
coeff of $t+1 \times D-to-R$ if search rate is the same as $t-1$ but stop share changes as Panel A	0.0036	-0.0029
p-value for test H0: est. coeff. = when search rate is the same as $t-1$ but stop share changes as Panel A	0.0323	0.3567
Panel C: Finding Contraband or not	**Black Contraband / All Safety Stops**	**Non-Black Contraband / All Safety Stops**
t-2 x D-to-R	0.00632	0.00940
	(0.00574)	(0.00612)
t x D-to-R	-0.000251	-0.00570
	(0.00255)	(0.00574)
t+1 x D-to-R	0.0117*	0.00551
	(0.00592)	(0.00677)
N	244	244
Dep. mean	0.0052	0.0192
Hit Rate at $t-1$	0.3718	0.3996
coeff of $t+1 \times D-to-R$ if hit rate is the same as $t-1$ but search rate changes as Panel B	0.0093	0.0038
p-value for test H0: est. coeff. = when hit rate is the same as $t-1$	0.9868	0.7267
County-Cycle FE	Yes	Yes
Year FE	Yes	Yes

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$. Contraband refers to searches that found contraband successfully. Black (Non-Black) stops refer to stops involving Black (Non-Black) drivers, Black (Non-Black) Searches and Black (Non-Black) Contraband are defined similarly. The search rate is defined as the number of searches divided by the number of stops. The hit rate is defined as the number of searches with found contraband divided by the number of searches. We consider safety stops in this table.

Table 8: Effect of Partisan Leadership on Traffic Stop Search Behaviors by Drivers' Race Among Investigation Stops

	(1)	(2)
Panel A: Stop	Black Stops / All Investigation Stops	Non-Black Stops / All Investigation Stops
t-2 x D-to-R	0.00722	-0.00722
	(0.0182)	(0.0182)
t x D-to-R	-0.00321	0.00321
	(0.0131)	(0.0131)
t+1 x D-to-R	0.0160	-0.0160
	(0.0216)	(0.0216)
County-Cycle	Yes	Yes
Year	Yes	Yes
N	244	244
dep_mean	0.2640	0.7360
Panel B: Search or not	Black Searches / All Investigatory Stops	Non-Black Searches / All Investigatory Stops
t-2 x D-to-R	-0.00376	0.0161
	(0.00620)	(0.0102)
t x D-to-R	-0.00356	0.00745
	(0.00776)	(0.0107)
t+1 x D-to-R	0.00179	0.00119
	(0.00758)	(0.0143)
N	244	244
Dep. mean	0.0347	0.0690
Search rate at $t-1$	0.1346	0.0922
coeff of $t+1 \times D-to-R$ if search rate is the same as $t-1$	0.0021	-0.0014
but stop share changes as Panel A		
p-value for test H0: est. coeff. = when search rate is the same as $t-1$	0.9619	0.8525
but stop share changes as Panel A		
Panel C: Finding Contraband or not	Black Contraband / All Investigatory Stops	Non-Black Contraband / All Investigatory Stops
t-2 x D-to-R	0.000283	0.00632
	(0.00384)	(0.00661)
t x D-to-R	-0.00133	0.00255
	(0.00390)	(0.00760)
t+1 x D-to-R	0.00209	-0.00242
	(0.00428)	(0.00966)
N	244	244
Dep. mean	0.0119	0.0256
Hit Rate at $t-1$	0.3887	0.3683
coeff of $t+1 \times D-to-R$ if hit rate is the same as $t-1$	0.0006	0.0004
but search rate changes as Panel B		
p-value for test H0: est. coeff. = when hit rate is the same as $t-1$	0.9751	0.5335
County-Cycle FE	Yes	Yes
Year FE	Yes	Yes

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$. Contraband refers to searches that found contraband successfully. Black (Non-Black) stops refer to stops involving Black (Non-Black) drivers, Black (Non-Black) Searches and Black (Non-Black) Contraband are defined similarly. The search rate is defined as the number of searches divided by the number of stops. The hit rate is defined as the number of searches with found contraband divided by the number of searches. We consider only investigation stops in this table.

Table 9: Compare Officers and Civilians

	Sworn Officers in Sheriff's Offices				Civilians			
	DEM	REP	UNA	ALL	DEM	REP	UNA	ALL
Democrat	1.00	0.00	0.00	0.43	1.00	0.00	0.00	0.46
Republican	0.00	1.00	0.00	0.36	0.00	1.00	0.00	0.32
Unaffiliate and Others	0.00	0.00	1.00	0.21	0.00	0.00	1.00	0.22
Black	0.38	0.01	0.11	0.19	0.41	0.02	0.11	0.22
White	0.58	0.97	0.84	0.78	0.54	0.96	0.81	0.73
Hispanic	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
Female	0.22	0.12	0.17	0.18	0.58	0.51	0.50	0.54
Age	43	39	38	40	51	50	43	49
Observations	3,116	2,643	1,563	7,322	2,579,581	1,793,911	1,269,386	5,642,878

Notes: This table compares the demographics between sworn officers in the sheriff's offices and the civilian population in North Carolina in 2010. The civilian population includes observations whose status is "active" in the 2010 voter registration snapshot file. DEM, REP, UNA, and ALL represent Democrats, Republicans, people with Unaffiliated and other party affiliations, and all people. We report the average age for the age row. In all other cells, the numbers are the share of officers/voters satisfying the conditions.

Table 10: Civilian and Sworn Officers' Composition before and after the sheriff's elections

	(1) DEM	(2) REP	(3) UNA	(4) Black	(5) White	(6) Other Race	(7) Female	(8) Age
Panel A: Civilian								
t-1 x D-to-R	0.00152	-0.000249	-0.00127*	-0.000997	0.00135	-0.000354	0.000882	0.144**
	(0.000991)	(0.000720)	(0.000717)	(0.000677)	(0.000818)	(0.000392)	(0.000618)	(0.0578)
t+1 x D-to-R	-0.00388**	0.00195**	0.00192	0.000148	0.000421	-0.000569	0.000629	-0.0268
	(0.00164)	(0.000972)	(0.00124)	(0.000496)	(0.000839)	(0.000588)	(0.000441)	(0.0333)
t+2 x D-to-R	-0.00792***	0.00641***	0.00151	0.00120	-0.00126	0.0000640	-0.0000605	-0.0637
	(0.00286)	(0.00226)	(0.00165)	(0.00128)	(0.00180)	(0.00135)	(0.000793)	(0.0632)
N	420	420	420	420	420	420	420	420
Dep. mean	0.4169	0.3249	0.2582	0.1761	0.7817	0.0422	0.5334	52.4535
Panel B: Sworn Officers in Sheriff's Offices								
t-1 x D-to-R	0.0253	-0.0262	0.000911	-0.000284	0.00290	-0.00262	-0.00385	0.505
	(0.0215)	(0.0295)	(0.0178)	(0.00793)	(0.00743)	(0.00442)	(0.00729)	(0.343)
t+1 x D-to-R	-0.0363	0.0470*	-0.0107	-0.00579	0.00367	0.00211	0.00695	-0.0261
	(0.0251)	(0.0263)	(0.0200)	(0.0145)	(0.0187)	(0.00988)	(0.00971)	(0.324)
t+2 x D-to-R	-0.0533**	0.0623*	-0.00898	-0.00952	0.00570	0.00382	0.0236	-0.293
	(0.0216)	(0.0371)	(0.0259)	(0.0152)	(0.0193)	(0.0126)	(0.0150)	(0.517)
N	420	420	420	420	420	420	420	420
Dep. mean	0.3409	0.3560	0.3031	0.1154	0.8556	0.0290	0.1589	39.6239
Panel C: Sworn officers in Police Departments								
t-1 x D-to-R	-0.00134	-0.0402	0.0415	-0.00730	0.00691	0.000385	0.00236	-1.055**
	(0.0148)	(0.0325)	(0.0282)	(0.00813)	(0.00825)	(0.00360)	(0.0106)	(0.511)
t+1 x D-to-R	-0.0198	0.0150	0.00476	0.00611	-0.00492	-0.00119	-0.0101	-0.740
	(0.0298)	(0.0223)	(0.0256)	(0.00557)	(0.00634)	(0.00389)	(0.00920)	(0.587)
t+2 x D-to-R	0.0170	0.0184	-0.0354	0.0138	-0.0116	-0.00220	-0.0115	0.303
	(0.0274)	(0.0259)	(0.0237)	(0.00998)	(0.0106)	(0.00832)	(0.0125)	(0.483)
N	368	368	368	368	368	368	368	368
Dep. mean	0.2682	0.4173	0.3145	0.0623	0.8967	0.0410	0.0641	38.4782
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Cycle FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year t. Outcome variables in columns (1)-(7) are the share of civilians/officers with the specific demographic feature. Outcome variables in columns (1)-(3) in the same county should add up to one; the same for columns (4)-(6). The outcome variable in column (9) is the average age. Outcome variables in Panel A are computed from voters with "active" registration records in voter snapshot files. Outcome variables in Panel B and C are computed from officers reported to be working in the relevant agency that year. The number of observations in Panel C differs from Panel A and B because some counties do not have any police departments.

Table 11: Transition Matrix of Law-Enforcement Officers

	Other Law	Non-Law	Leave Public Sector
Sheriff's Offices	0.020	0.015	0.053
Police Dept.	0.030	0.014	0.040

Notes: Data cover from 2008 to 2019. We provide percentages of officers (at officer-year level) who leave the sheriffs' officers/police departments, and transition to law-enforcement positions in North Carolina (Other Law), non-law-enforcement positions in the public sector in North Carolina (Non-Law), and positions not covered by the pension system in North Carolina (Leave Public Sector).

Table 12: Personnel Turnover: Leaving Margin

	Sheriffs'Offices			Police Department		
	Leave Public	Other Law	Non Law	Leave Public	Other Law	Non Law
	(1)	(2)	(3)	(4)	(5)	(6)
t-2 x D-to-R x DEM	0.0191	-0.00930	-0.000805	0.0105	0.0104	0.0104
	(0.0144)	(0.00951)	(0.00455)	(0.0143)	(0.0166)	(0.00698)
t-2 x D-to-R x UNA	-0.000928	-0.0208**	0.000147	0.000585	-0.0153	0.00973
	(0.0148)	(0.00963)	(0.00573)	(0.0185)	(0.0180)	(0.00714)
t x D-to-R x DEM	0.0457**	-0.00130	0.0115	0.0226	-0.0349**	0.00161
	(0.0209)	(0.0102)	(0.00877)	(0.0173)	(0.0156)	(0.00913)
t x D-to-R x UNA	0.0261	-0.000360	0.00101	0.0329**	-0.0294	0.00226
	(0.0245)	(0.00993)	(0.00856)	(0.0155)	(0.0188)	(0.00687)
t+1 x D-to-R x DEM	0.0726***	-0.00899	0.00534	0.0124	-0.0603**	-0.00762
	(0.0260)	(0.0155)	(0.00954)	(0.0227)	(0.0265)	(0.00902)
t+1 x D-to-R x UNA	0.0393	-0.00426	0.000494	0.0196	-0.00586	-0.00894
	(0.0264)	(0.0178)	(0.0111)	(0.0179)	(0.0181)	(0.00738)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cycle FE	Yes	Yes	Yes	Yes	Yes	Yes
N	32068	32068	32068	30260	30260	30260
Dep. mean	0.2000	0.1051	0.0308	0.1619	0.2063	0.0235

Notes: This table examines the effect of party turnover of leaders on incumbent officers' work locations. The table reports estimation coefficients from an OLS regression with specification as in equation 3. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at the officer-year level. t refers to the year of election in that election cycle. Outcome variables denote the work location status. An officer who leaves the sheriffs' officers/police departments, and transitions to law-enforcement positions in North Carolina (Other Law), non-law-enforcement positions in the public sector in North Carolina (Non-Law), and positions not covered by the pension system in North Carolina (Leave Public Sector). in year t will have 0 for the relevant outcome variables in $t-2$ and $t-1$ and would have 1 for t and $t+1$. Dep. mean computed from Republican officers in D-to-R counties at the end of the cycle, year $t+1$. The omitted baseline group is the election year t, DEM-to-DEM counties, and Republican officers. DEM represent Democrat officers, and UNA represent officer with unaffiliated and other party affiliations.

Table 13: Personnel Turnover: The Number of Entering Officers

	Sheriffs'Offices	Police Department
	(1)	(2)
t-2 x D-to-R	0.889	0.470
	(1.492)	(1.426)
t x D-to-R	1.731	-0.933
	(1.100)	(0.957)
t+1 x D-to-R	3.402*	-1.047
	(2.004)	(1.004)
Year FE	Yes	Yes
County-Cycle FE	Yes	Yes
N	420	372
Dep. mean	5.2609	6.4000

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Outcome variables are the number of entering officers at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$. We dropped county-cycles that did not hire any officers in the election cycle.

Table 14: Personnel Turnover: Political Party Composition of Entering Officers

	Sheriffs'Offices			Police Department		
	(1)	(2)	(3)	(4)	(5)	(6)
	DEM	UNA	REP	DEM	UNA	REP
t-2 x D-to-R	-0.0100	0.0731	-0.0622	0.101	-0.170**	0.0613
	(0.0703)	(0.0615)	(0.0804)	(0.0632)	(0.0771)	(0.0730)
t x D-to-R	0.0180	-0.0719	0.0609	0.101*	-0.161***	0.0538
	(0.0837)	(0.0541)	(0.0651)	(0.0591)	(0.0554)	(0.0791)
t+1 x D-to-R	0.00717	-0.0126	0.0109	0.100**	-0.142*	0.0127
	(0.0671)	(0.0532)	(0.0606)	(0.0452)	(0.0792)	(0.0801)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Cycle FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2938	2938	2938	2492	2492	2492
dep_mean	0.2645	0.3058	0.4298	0.1719	0.3516	0.4766

Notes: This table reports estimation coefficients from an OLS regression with specification as in equation 1. Clustered standard errors at the county level are in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Outcome variables are the share of entering officers with a specific political party affiliation at the county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$. We dropped county-cycles that did not hire any officers in the election cycle.