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

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Preliminary. New Version Coming Soon!

Abstract

We study the impact of partisan leaders on traffic stop behaviors and personnel turnover in North Carolina. Using a difference-in-differences design which exploits sheriff turnovers, we find that offices with a Republican-to-Democrat rather than Democrat-to-Democrat sheriff turnover have an increase of black drivers' share in traffic stops by 3.6 percentage points, a 15.5% increase compared to baseline. The overall search rate increased by 3.7 percentage points, a 50% increase, especially in the Non-Black driver group, while the overall *hit rate* does not decrease. With such policy preferences changes, officers that are not aligned with new sheriffs' party affiliation are 11 percentage points more likely to leave the public sector than those that are aligned, which is consistent with suggestive evidence that officer selection contributes to an increased share of Black drivers being stopped.

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1 Introduction

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

One of the most important issues in frontline policing is racial disparities. Black drivers are more likely to be stopped than White drivers, especially before the 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 comes from racial bias and has established evidence of racial discrimination at officer level (Antonovics and Knight, 2009; Goncalves and Mello, 2021). We start from a different point in the hierarchy of law-enforcement agencies and asks if leaders matter in determining racial disparities of frontline traffic stops.

This paper studies traffic policing in sheriffs' offices in North Carolina. We focus on sheriffs instead of police chiefs since sheriffs are elected through partisan elections and hence allows direct identification of party affiliations. We exploit party turnovers of sheriffs induced by elections to examine the impact of 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 makes 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 differences-in-differences research design to overcome these challenges. Our control group are counties that experience Democrat to Democrat (henceforth D-to-D) sheriff election turnover that involves a person turnover but not party turnover; our treatment group are counties that experience Democrat to Republican (henceforth D-to-R) sheriff turnovers. We analyze turnovers from 2010, 2014, and 2018 elections. For each election, we examine traffic stops in a election cycle defined as from 3 years before election to 1 year after elections. This definition of election cycle allow us to stack up data from 3 election cycles without having overlapping timing periods.

Using our differences-in-differences framework, we estimate the effect of having a republican sheriff rather than a democrat sheriff on the probability that a stopped driver is Black (henceforth a Black stop). We find that Republican sheriffs increase the probability of a Black stop by 3.6 percentage points, a 15.5% increase compared to the probability in the baseline year, while no increase of the overall stop intensity (number of stop per vehicle) is found. We also find that Republican sheriffs increase the overall search rate (number of search divided by number of stops) by 3.75 percentage points, a 50% increase comparing to the baseline search rate. The increase of search rate concentrates on Non-Black drivers. Such increase of search rate is often concerned with lower *hit rate* (the proportion of searches that find contraband). We find no evidence of decrease of hit rate, providing evidence consistent with Feigenberg and Miller (2022): law-enforcement organizations are able to equalize search rates while not sacrificing hit rates.

We decompose the policing practices changes along two dimensions, stop purposes and stop officers, to better depict Republican sheriffs' policy goals and their methods to attain the goals. Decomposing Black stop share changes into changes of shares from different stop purposes, we find suggestive evidence that Republican sheriffs do not have the same policy goals across driver racial groups. After the election, Black drivers in D-to-R counties, compared to D-to-D counties, are more likely to be stopped due to investigation and safe movement violation while Non-Black drivers are more likely to be stopped due to vehicle equipment violations. To reach their policy goals, sheriffs can reshuffle officers, assigning officers who share similar policy goals to conduct more stops; sheriffs can also directly affect how officers practice policing. To identify these two channels. We divide officers into two groups: stayers, who conduct traffic stops both before and after elections, and non-stayers, who only conduct traffic stops either before or after elections. We find that share of stops done by non-stayers do not change with the D-to-R transition. We find that changes in search rate and share of stops finding contraband comes from stayers suggesting officers adapt to new leadership. On the other hand, we also find that the number of Black stops done by non-stayers as a share of total stops increase more in D-to-R counties after elections, an indication of selection effects. With this suggestive evidence of selection on officers, we zoom out to the overall sheriffs' offices employees and examine if party turnover of sheriffs is associated with personnel turnover based on public servants' party affiliation.

Political preference of a sheriff may affect not only traffic stop practices but also other organization policies, which may in turn induce disutility of working for officers with different policy preferences. We test the effect of such misalignment on personnel by examining if officers with the opposite party affiliation to the new sheriffs are more likely to leave sheriffs' offices post-election. We match pension records to voter snapshot files in North Carolina to identify party affiliation of all employees in sheriffs' offices. We adopt a triple differences design, looking at the effect of a D-to-R rather than a D-to-D transition on Democrat officers relative to Republican officers.

We find that Democrat officers are cumulatively 11 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. Sub-group analysis shows that only officers who are eligible for pension benefit react to the election turnovers, suggesting that officers trade off between monetary return and policy preferences. On entering margin, we find that newly elected republican sheriffs bring more republican officers into offices in the election year, when the new officers take oath with the sheriffs. But this pattern is not seen in the year after, when the offices actually hire more officers due to the leaving of the Democrat officers. The lack of party favoritism in the year after elections suggests that party affiliation of sheriffs may not play an important role in ordinary hires. These personnel turnovers might have implications to other law-enforcement practices that we do not capture in this paper.

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 crime (Cohen and Yang, 2019). We provide evidence that 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). A very recent literature identified the heterogeneity of racial bias at the officer level (Goncalves and Mello, 2021), and suggest that officers with different level of bias have varied traffic stop behaviors responding to short-term political events (Grosjean et al., 2022). We provide suggestive evidence that officers responds to new leaderships by changing their policing practices and sheriffs achieve their policy preferences by reshuffling officers, pointing to interaction of leaders and subordinate.

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) found no effect of party affiliation of sheriffs on complying with federal requests to detain unauthorized immigrants, and suggest that the similar compliance rate may be due to sheriffs share similar immigration enforcement views across parties.

We also contribute to the literature that emphasize the importance of political turnover in the personnel in public organizations. Political turnover are 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 mayor election turnovers in Brazil is linked to new personnel turnovers in schools and is 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 a recent literature focusing on the US federal employees. Bolton et al. (2020) finds that presidential turnovers are associated with higher departure rate 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. 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

2.1 Law-Enforcement Agencies in North Carolina

Sheriffs offices are the top law enforcement agencies in counties. They perform duties in unincorporated areas within counties. Police departments in municipal governments are in charge of law-enforcement in incorporated areas. The main functionality of sheriffs' offices includes management of jails and detention centers, crime investigation, immigrants detention, high way 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 office; all sheriffs in North Carolina are directly elected by voters. The elections are partisan; they occur every four years in November, and there is no term limits. The newly elected sheriffs are sworn in on November 30, and the deputies would also take their oath on the same day. This feature guides our analysis of officer turnover starting from the election year, not one year after elections. All of the elected sheriffs since 1998 are affiliated with either democratic party or republican party. We use sheriffs turnovers induced by elections as the main variation of change of control. In particular, we focus on sheriffs turnovers that involve party turnovers.

Police chiefs, on the other hand, are appointed by municipal councilors. Although sheriffs do not directly mange police departments, we also discuss police officer turnover when discussing law-enforcement officer turnover in sheriffs' offices. Law-enforcement officers in both police departments and sheriffs' offices in the same county can be seen as in the same law-enforcement labor market.

Recruiting Process of Sheriff's Office Employees. Recruiting in sheriffs' offices is run by each office themselves. Specific process may vary from county to county. A typical recruiting process involves three parts. First, basic requirements checks such as citizenship, education degree (typically high-school diploma) and driver license. Second, physical, written tests and interviews. Third, medical tests and background investigation including credit, criminal, court, police, military, and personal. In these processes, it is plausible that sheriff would gather information about an applicants' political party affiliation and information about the applicants past behavior in other law enforcement agencies.

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

3 Data

We use traffic stop and search data and sheriff elections records to analyze the effect of sheriffs turnover on traffic stop and search behaviors. To analyze the effect of sheriffs turnover on officer turnover, we combine voter snapshot, public pension records, and sheriff elections records.

Traffic Stop and Search Records. Traffic stop and search records are available upon request in North Carolina. The data set contains driver's race, ethnicity, gender and age. Unique officer ID is included in the data and we use this ID to identify officers who left sheriffs' offices or stop performing traffic stop tasks after elections. The ID is not linked to any officer information such as names or ages. The data set also contains rich information on the time and location of the stops. We use these information to flexibly control for time and location patterns of stops and searches. We use data since 2001 to construct experience of officers. In the analysis, we mainly use data 2008-2019.

Sheriff Election Records. Sheriff's election results since 2008 is publicly available on the website of North Carolina State Board of Elections. We hand collect election results in 2006 by searching local newspaper in Newsbank. Party affiliation and the names of elected sheriff is used to determine if a county went through party turnovers. Vote shares of the winners are used to assess the competitiveness of the elections.

Voter Snapshot. Voter snapshot files are publicly available in North Carolina and can be accessed from North Carolina State Board of Elections website [1]. We use voter snapshot files at the beginning of each year except 2008 due to availability. We select voter registration records during the years 2008-2019. We collect name, race, ethnicity, gender and age from the voter snapshot. Importantly, the voter snapshot files provide voter unique ID across years.

Public Pension Plan Records. Public pension records data is available upon request in North

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

Carolina. The data set contains the employer and salary history of the universe of workers in public sector in North Carolina since 2008. For people who have been collecting pension benefits in 2020, we can further trace their life time work history within North Carolina public sector. We use employer names, employee categories, and job classification to identify law-enforcement officers in sheriffs' 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 snapshot files contain unique IDs. From the matching process, we derive the gender, race, ethnicity, and party affiliation of the public sector workers. We drop observations where one ID in a dataset is matched to multiple IDs in the other one. In the cases where voter registration records for a worker cannot be found in all years, we extrapolate the demographics information from the nearest year.

4 Empirical Strategy

Our aim is to identify the causal effect of party turnover on traffic stop practices and personnel turnovers. We adopt a differences-in-difference design exploiting sheriff elections that induce party turnovers. We define a election cycle as from three years before an election to one year after election. Since new sheriffs are sworn in on November 30, I define an election year starting from December to November.

Table 1 reports the sheriff election results from 2010 to 2018. Four elections involving Republican-to-Democrat type turnover. We do not consider elections with Republican-to-Democrat or Republican-to-Republican turnover in this paper due to power concerns. We define the control group as the county-election cycle that experience a Democrat-to-Democrat type election, and the treatment group as ones that experience a Democrat-to-Republican type election. This selection makes every county-cycles involving sheriff turnover but the treatment group additionally experience party turnovers.

4.1 Traffic Stop and Search Behavior

The first goal of this paper is to identify traffic stop policy changes from party turnovers of sheriffs. The traffic stop data quality varies across counties. We define a election cycle as four years ranges from three years before the election to one year after the elections. We drop the county-cycles where at least a year with less than 10 stops is found in that county-cycle. The resulting number of D-to-D and D-to-R county-cycles are presented in table 1 panel B. We use a differences-in-differences type specification:

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

where Y_{cle} is a variable at county-year level for county c in year e in cycle l at county-year level. 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 3 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 denote 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 swear in on November 30, we define a year as starting from December to November. For example, year t ($e = 0$) in election cycle which election was held in 2010 involves observations from December in 2009 to November in 2010. Hence, δ_{le} uniquely defines timing of each stop in year e in cycle l.

The coefficients of interests are β_e which captures the differences between control and treatment groups across years within a cycle. Throughout the paper, we report estimates from ordinary least square estimation. All standard errors are clustered at the county level.

With this specification we first examine if Republican sheriffs conduct more stops per vehicle. We use number of commuters (adjusted by car-pooling) to approximate the number of vehicles on the road in 2010, 2014, and 2018 for each county-cycle. Data on number of commuters comes from American Community Survey (5-Year Data Block Groups & Larger Areas) downloaded from NHGIS.

We next examine if sheriffs focus traffic stops on specific group of drivers. We consider two groups, Black and Non-Black [2] We consider the share of Black and Non-Black stopped drivers among all stopped drivers in each county-year. A traffic stop might result in further searches, to examine if Republic sheriffs conduct different policies on search behavior, we look at for each county-year, search per stop, and searches with Black/Non-Black driver per stop. To understand the effectiveness of the searches, we look at share of searches with contraband, and share of searches with Black / Non-Black drivers and find contraband among all stops as well.

Decompose the Traffic Stop Behavior Changes: Stop Purposes.
Sheriffs may differ in policies about under what situations, a driver should be stopped. For example, some sheriffs may focus more on dangerous driving, while other sheriffs may focus on vehicle equipment violations. Each stop in North Carolina is recorded with the stop purposes. There are ten stop purposes. Four of them are about driving: Speed Limit Violation, Stop Light/Sign Violation, Driving While Impaired, Safe Movement Violation. Other six are: Vehicle Equipment Violation, Vehicle Regulatory Violation, Seat Belt Violation, Investigation, Other Motor Vehicle Violation and Checkpoint. We create dummy variables which takes value 1 if stop purpose is a specific one, 0 otherwise. We also create race-specific dummy variables which takes value 1 if driver is Black / Non-Black and stop purpose is a specific one. We estimate equation 1 with the county-year mean of these outcome variables to see if Republican sheriffs focus on different stop purposes, and whether such emphasis differs across race groups.

Decompose the Traffic Stop Behavior Changes: Officers.
To understand the role of officers in achieving policy goals of new sheriffs. We group officers into two groups. First, stayers are officers who continue performing traffic stop tasks after elections Second, non-stayers, who only conduct traffic stops either before or after the elections. We firs examine if task allocation among these two groups changes differentially across our control and treatment groups. We run a regression with specification **??** and use share of stops conducted by stayers among all stops in a county-year as the outcome. To see which group of officers account for any traffic stop practice changes, we again estimate **??**, this time use the share of Black stops done by stayers / non-stayers among all stops in a county-year, search done by stayers / non-stayers among all stops in a county-year, and

[2] We do not distinguish Hispanic drivers from White drivers since in this context, Hispanic drivers account for a small share of stopped drivers, 7.4%, compared to white drivers, 56%, and Black drivers, 33%

number of stops that find contraband done by stayers / non-stayers among all stops in a county-year.

4.2 Personnel Turnover in Law-Enforcement Agencies

We quantify the effect of change of control in sheriffs' offices on personnel turnovers. We examine if change of party affiliation of sheriffs leads to differential pattern of turnovers of officers with different party affiliations. We adopt the same differences-in-differences framework as in estimating the effect of sheriff party turnover on traffic stop practices, but adding another layer of differences: the party affiliation of the public servants, which includes Democrat (DEM), Republican (REP) and Unaffiliated (UNA). Since we rely on pension records for personnel turnover analysis, we use all D-to-D and D-to-R counties identified in Panel A Table 1. We estimate an OLS regression with the following specification:

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

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 agencies, and transferring to other non law-enforcement agencies. The data structure is similar to the analysis of traffic stops in cycle and year definitions, but the observations are organized as individual panel. We include officers who worked in the agency three years before the elections. We follow where they work for four years and record the first change of work place to construct the outcome variable. For example, an officer who leaves the public sector in year t would have 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 $p \in \{1 = UNA, 2 = DEM\}$. We also include officers' demographics including gender, age age square, experience and experience square (X_{jl}). Age and experience are measured in t. Standard errors are clustered at county level. The coefficients of interest are the ones associated with interaction terms (β_e).

We also conduct analysis on the entering margin. Since we do not observe the candidate pool of law-enforcement officers, we cannot replicate a triple differences-in-differences strategy. We thus conduct a differences-in-differences strategy at sheriffs' office level, exploiting the time and sheriff party turnover variation.

We first look at the size of the sheriffs' offices. We estimate a regression with specification 1 and use the outcome variable the number of entering officers. For the composition of entering officers, we estimate a differences-in-differences regression at officer level with a specification similar to eq :

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

, where $p = \{REP, UNA, DEM\}$, i.e., we have three dummy variables denoting Democrat, Unaffiliated, and Republican for outcomes.

5 Effect of Partisan Leadership on Traffic Stop and Search Behavior

5.1 Main Results

Graphical Evidence.

We start by presenting the variation in the raw data. In figure 1, we present the share of black drivers among all stops across election years combining all three election cycles. Level differences exist between our control (D-to-D) and treatment (D-to-R) group: control group has higher level than the treatment group since black population is higher in the control group than the treatment group. The key identifying assumption for difference-in-difference is parallel pre-trend, and the level differences between control and treatment stays similar before the election (denoted as t). The increase in treatment group at $t+1$ suggest that republican sheriffs are associated with increased black drivers' share. The regression analyses below test whether the increase is statistically significant.

Regression Results.

We present regression results using specification 1 in Table 3. In panel A, Column (1), the point estimate reveals that Republican sheriff is not associated with conducting more traffic stops per vehicle. Column (2) reports the regression results with a outcome variable being county-year mean of Black stop, which takes 1 if driver is black, 0 otherwise. The point estimate confirms the increase we see in figure 1, and shows that republican sheriffs are associated with a 3.6 percentage points increase of the black drivers' share in traffic stops, significant at 95% confidence interval. The magnitude is large: comparing to the black drivers' share in D-to-R counties in $t-1$ (the omitted year), 0.23, reported as Dep. Mean in Table 3, this is a 15.6% increase. For completeness, we show results about Non-Black race groups in Column (3). By definition, all stops are associated with either Black or Non-Black drivers, so coefficients in Column (2) and (3) should be the same magnitude with opposite sign, which is what we have.

In Panel B, we examine policy differences on search. From column (1) we find that overall, D-to-R transitions leads to 3.75 percentage points increase of search rate, defined as total number of searches divided by total number of stops. Compared to the search rate mean in D-to-R counties in $t-1$, this is a 50% increase. The search rate increase is not universal across race groups. Although Column (2) shows marginal significant increase for share of Black searches among all stops, we find that, after taking into account of the Black drivers' share increase shown in Panel A, we cannot reject the null hypothesis that the Black search rate (number of Black searches divided by number of Black stops) is the same as in the year before election. To conduct this test, we compute the expected coefficient of $t+1 \times D-to-R$ by multiplying the increase of Black drivers' share with the Black driver search rate in D-to-R counties in $t-1$ ($0.036 \times 0.1025 = 0.00342$, and test against the null: coefficient $= 0.00342$.

The increase of the search rate comes from the Non-Black group. Since the Non-Black driver share decreases in D-to-R after election, if the search rate for Non-Black drivers stays the same as in $t-1$, we should expect decrease of share of Non-Black searches with D-to-R after election. Instead, we see a positive and significant coefficient in Column (3), Panel B. After applying the same process to take into account of changes of drivers' share as in testing the Black searches, we can reject the null that the search rate for Non-Black drivers stays the same as in $t-1$ at 95% confidence interval level. Note that with the larger search rate for Black drivers than Non-Black drivers in the baseline, the patterns shown in Panel B suggests that search rate gaps across racial groups decrease with a D-to-R sheriff transition.

Whether changing search rate across racial groups can affect the return in terms of probability of finding contraband is a long discussed topic (Feigenberg and Miller, 2022). We examine whether the large search rate increase found in Panel B is associated with changes of hit rate. We run the same regression specification as in Panel A and B, but put share of stops with found contraband, share of stops with contraband and a Black driver, and share of stops with contraband and a Non-Black driver as outcome variables. We find that share of stops finding contraband significantly increase (Panel C Column (1)). We then try to test if the coefficient implies different hit rate than before. We first compute the average hit rate in D-to-R counties i $t-1$, which is 0.4069. If the hit rate stays the same, but the search rate increase 0.0375 as in Panel B Column (1), then the coefficient for $t+1 \times D-to-R$ should be $0.0375 \times 0.4069 = 0.01525$. We cannot reject that the coefficient is equal to 0.01525. The point estimate is also larger than 0.01525, suggesting that if anything, the hit rate increases instead of decreases. We apply similar processes to Black and Non-Black groups and again find that we cannot reject the null that hit rates stays the same as in $t-1$. The results here are consistent with the findings in (Feigenberg and Miller, 2022), suggesting that law-enforcement offices can increase search rate without sacrificing hit rate. Taken together, the results in Table 3 suggests that Republican sheriffs are associated with enlarging the racial disparities of drivers being stopped, while shrinking the racial disparities on search and keeping the hit rate constant. We next decompose the results from 3 on two dimensions: stop purposes and officers, to better interpret these changes.

5.2 Decomposition of Changes of Traffic Stops

Decomposition on Stop Purposes.

We examine if changes of Black drivers' share among stops comes from Republican sheriffs focusing on different kind of driver behaviors. Stop purposes can be generally categorized into moving and non-moving ones. This is distinction is often emphasized. For example, Mecklenburg sheriff in 2022 announced a new policy to not stop drivers due to non-moving purposes such as expiring registration. If certain driving habits or vehicle regulation violations are related to race, then the changes of share of Black drivers among stopped can come from sheriffs shifting focus on specific reasons of stops. We decompose the stops into ten categories, the finest group of stop purposes in the data. In Panel A of Table 4, we find no significant changes of share of specific purposes among all stops. Note that all coefficients in the same row would add up to zero. In Panel B, we zoom in to Black drivers. The sum of the coefficients for $t+1 \times D-to-R$ would be 0.036, the coefficient for $t+1 \times D-to-R$ in Column (2) of Panel A in Table 3. We find that most of the changes come from Safe Movement and Investigation, although the coefficient for Safe Movement is not statistically significant, while in Panel C, we find that for Non-Black drivers, the stop purposes that got increased shares are Vehicle Equipment Violation and Vehicle Regulatory. The different pattern across racial groups suggests that Republican sheriffs' policy may be race-specific. The different pattern also allows to have some confidence that the increase of Black drivers' share might not come from Republican sheriffs focusing more on moving or non-moving purposes, since in those cases, we should see at least same direction of coefficient signs for both Black and Non-Black drivers. The results that share of Black drivers stopped by investigation increases is worth noticing but do not provide persuasive evidence of existence of discrimination. Despite the possibility that under Republican sheriffs, officers make the association between race and crime more often, it is also likely that Republican sheriffs focus on crimes that link to race through other non-race channels such as geography.

Decomposition on Officers.

Every stop is done by an officer. We examine if the policing practices changes are mainly driven by a group of officers. We divide officers into two groups: stayers, who conduct traffic stops both before and after elections, and non-stayers, who only conduct traffic stops either before or after elections. Following this definition, we modify specification 1 and collapse three years before the election into one pre-election period. In Column (1) Panel A, we find that the share of stops done by stayers at county level do not change with the D-to-R transition. Comparing Column (2) and (3) in Panel A, we find that share of Black drivers' increase comes from the non-stayer group. This suggests that part of the effect of sheriff party turnover comes from *selection* of officers. We then apply the same decomposition on the share of searches, and the share of stops finding contraband in Panel B and C. Contrary to the Black driver share result, we find that the increase of search rate and the share of stops with found contraband mainly comes from the stayer group, suggesting officers changing their policing practices under different leadership. Understanding why stayers seem to change their search but not their stop behavior is an important next step for this project.

Traffic stop duty is only one of sheriffs' offices tasks. If we can see some selection on who conducts traffic stops after the party turnover, we might expect similar selections on other teams. We therefore zoom out to the overall sheriffs' offices employees and examine if party turnover of sheriffs is associated with general personnel turnover based on public servants' party affiliation.

6 Effect of Partisan Leadership on Officer Turnover

6.1 Descriptive Graphs and Statistics

Before directly looking at the relationship between sheriffs turnover and officer turnover, we first provide general trend of officers' party affiliation and officer turnover summary statistics.

Law-Enforcement Officers' Party Affiliation Trend

In figure 2, we present the share of officers in each party affiliation from 2008 to 2019, in both sheriffs' offices and police departments. Across North Carolina, there is a general downward trend for democrats and an increasing trend of unaffiliated. This trend is consistent to the citizens' party affiliation trend. We further categorize counties into four groups: all DEM counties where the sheriffs were all democrats in all years; all REP counties where the sheriffs were all republicans; mix counties where party turnover happened at least once over the years. Comparing police officers and deputy sheriffs part affiliation pattern, we can see obvious sorting on political party affiliation in sheriffs' offices but not in police departments. Comparing the distribution in the all DEM counties and all REP counties, in sheriffs' offices, party affiliation distribution of officers are closer to the distribution of voters than police departments. The sorting pattern in sheriffs' offices gives us confidence that the personnel turnover in sheriffs' offices are more flexible, and may respond to changes of leader control.

Personnel Turnover in Law-Enforcement Agencies

We report the turnover situation in both sheriffs' offices and police departments in table 6. These numbers should be considered together since officers are likely to flow across these agencies. In total, around 8.5% of law enforcement officers leave their original agencies. Decomposing the destination places, 5% deputy sheriffs leave public sector every year. We cannot differentiate the leaving reason, which might include firing, retiring, or voluntary leaving. Around 2 percent of deputy sheriffs go to other law enforcement agencies; 1.8 percent go to non law enforcement agencies. Police officers have smaller share of people leaving public sector on average, but more people go to other law enforcement agency.

6.2 Leaving Margin

We examine the effect of changing sheriffs in D-to-R counties on officer turnover, both leaving margin and entering margin, across officers with difference party affiliations with respect to D-to-D counties. We first discuss the leaving margin.

Graphical Evidence

Before formally specifying the estimation equations, we provide descriptive evidence exploiting the three variation we will use in the statistical estimation. Figure 3 depicts the share of officers not leaving the public sector agency across years in an electoral cycle. We denote the starting year of the cycle as 0, which is two years before the elections. The graph combines data from three cycles; the election year of which are 2010, 2014, and 2018. We adopt a individual panel data structure. We select officers who worked in the agency two years before the elections and follow where they work for four years. Note that we only record the first change of work place in the four years. For presentation purposes, we only include officers with Democratic or Republican affiliation.

In sheriffs offices, before the election, the trend of leaving the public sector is the same across D-to-D and D-to-R counties and across two party affiliations. However, starting in the election year, democrat deputy sheriffs are much more likely to leave the public sector than republican deputy sheriffs in D-to-R counties. On the contrary, in D-to-D counties, republican deputy sheriffs are more likely to leave the public sector than democrats after the elections, but the gap of leaving probability is much smaller than the one in D-to-R counties.

In police departments in the same counties, we do not see any change of trend after the elections, indicating that what we see in the sheriffs' offices are derived from the effect of elections, but not other time trend in those counties.

Regression Results

The estimation coefficients of β_{pe} of equation 4.2 are reported in table 7. We report results using data from sheriffs' offices and police departments respectively in column (1)- (3) and (4)-(6). Democrat and unaffiliated officers in sheriffs' offices are 11 / 5.8 percentage points more likely to leave the public sector than republican officers in D-to-R counties with respect to D-to-D counties in election year and one year after elections (column (1). The effects are big comparing to the mean 0.18, which is evaluated in the year after elections. The coefficient of the democrats in the year after elections is significant at 1 percent level, while the coefficient of the democrats in the election year and the ones of UNA in election year and the year after are significant at 10% level. The fact that we do not see similar trend in police departments suggest that the pattern in the sheriffs offices come from election turnovers, not from specific time trend in those counties. We cannot differentiate the leaving reason.

The action included in this leave public dummy variable includes retiring, firing, and voluntary leaving. To further identify the type of action we captured in the dummy variable of leaving public sector, we delve into sub-group analysis later looking into groups of officers based on their eligibility of retirement. For other transfer actions, we do not observe significant changes across years in sheriffs' offices, but we observe that democrats are less likely to go to other law enforcement agencies in the election year. This is likely due to the fact that democrat officers are less likely to *enter* sheriffs' offices when the newly elected sheriff is a republican.

Subgroup Analysis: Pension Benefit Eligibility Groups.
More democrat officers leaving the office when a new republican sheriff enters the office can come from voluntary leaving, which includes retiring, and from sheriffs firing democrat officers. To differentiate these two channels, we categorize officers into groups based on their eligibility of retirement. The criteria of early and full retirement can be found in Appendix A. In table 8, we report the estimation results of equation **??** separately on officers who are not eligible for retirement benefit and who are eligible for either early or full retirement. The positive, large and significant coefficient in column (2) for the interaction term between democrats/unaffiliated and year $t+1$ clearly shows that the turnover effect we found in table 7 are mainly driven by officers who are eligible for retirement. This is intuitive: their marginal return of staying in the public sector in terms of pension benefit is small in terms of pension benefit. Column (4) and (6) further shows that the same group of officers also are more likely to transfer to non law-enforcement agencies and less likely to transfer to other law enforcement agencies. Our current interpretation is that the personnel flow in police departments also is affected by the sheriffs turnover (column (5) in table 7). Since the police department is already crowded, officers in sheriffs' offices who want to switch jobs to police departments thus can only choose to go to non law-enforcement agencies. In Appendix table 11, we further divide officers into three groups: not eligible for any benefit, eligible for early benefit, and eligible for full benefit. We find that the results of leaving public sector are mainly driven by the group of full benefit, and the result of transfer to other law-enforcement agency is driven by the group with early benefit. This is again consistent with the amount of marginal return of staying in the public sector of these two groups of officers.

Overall, from the analysis of leaving margin of officers in the sheriffs' offices around elections, we find that democrat and unaffiliated officers who are eligible for retirement are more likely to leave the sheriffs' offices when the newly elected sheriff is a republican. This provides compelling evidence that policy preferences non-alignment between sheriffs and officers lead officers to leave the sheriffs' offices, indicating that officers gain utility from working with leaders sharing the same policy preferences.

6.3 Entering Margin

In table 9, we report the estimation results using equation 1 with number of entering officers as the outcome.. In column (1), we see that D-to-R counties hire 3.4 more new officers than D-to-D counties in the year after election, with the dependent variable mean 9.7. This is consistent with the results in table 7. As more officers are leaving D-to-R sheriffs' offices, more new hired are needed. Estimation results of equation 3 are shown in table 10. We find that officers hired in election year in D-to-R counties are more likely to be republicans. This tendency is only shown in the election year but not the year after election. This is consistent with the timing of new sheriffs and deputy sheriffs taking their oath: Nov 30 in the election year. The fact that we do not see more republican being hired in the year after election, but more officers in general are hired suggest that newly elected sheriffs reward their supporters when they first enter the offices. However, when more vacancies needs to be taken in the year after elections, party affiliation of a candidate is not an important factor in determining the hiring decision.

7 Future Steps

We present evidence that partisan leadership affects traffic stop behaviors. A Democratic-to-Republican sheriff turnover, comparing to Democratic-to-Democratic turnover, leads to larger racial disparities in stopped drivers composition, but smaller racial disparities in searched driver. The opposite direction of changes invite further investigation into the distinct channels influencing stopping and searching behaviors separately. Current evidence suggests that stop behavior changes come from sheriffs reshuffling officers while search behavior changes come from officers responding to sheriffs' policies. A crucial next step is to understand why officers who continue conducting traffic stops after sheriff turnovers only change their search but not their stop behavior.

We plan to conduct two robustness checks. First, we will examine if the traffic stop behavior changes are robust to dropping randomly selected counties. Second, we will apply the same research design to traffic stops in the same counties but done by police officers. We expect no traffic stop behavior changes from the police officers.

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Figures

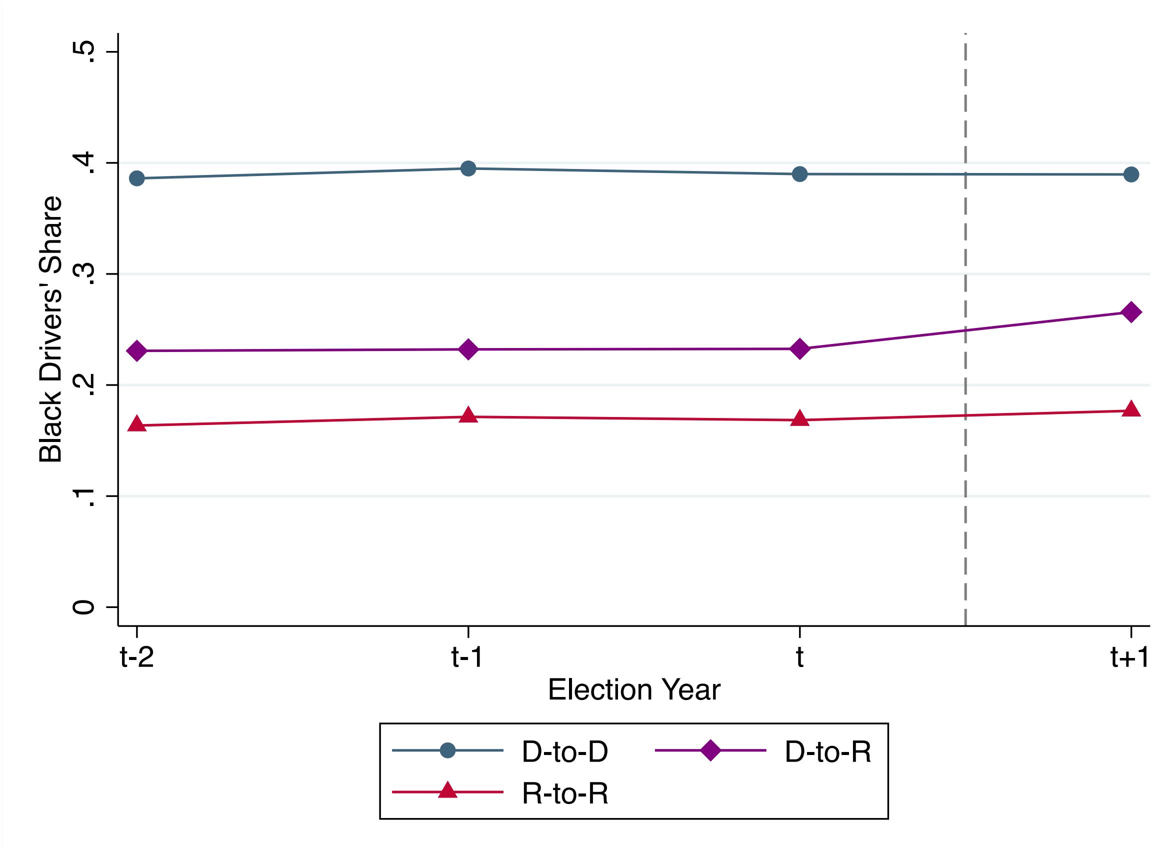
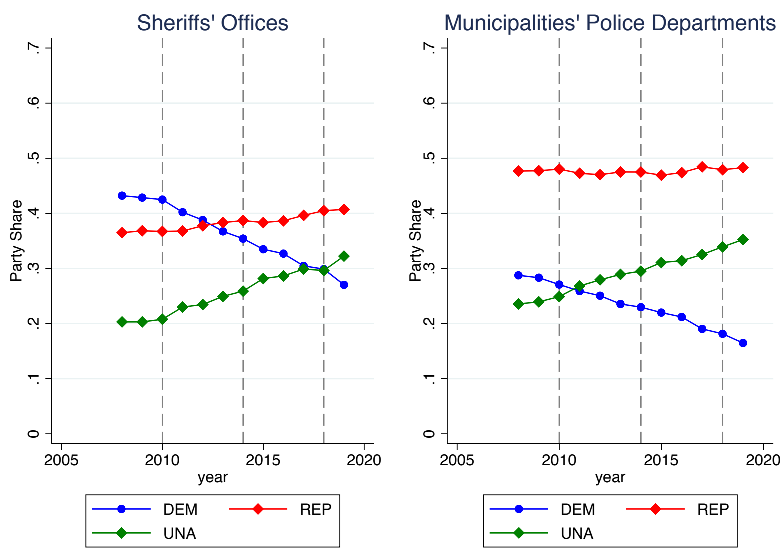


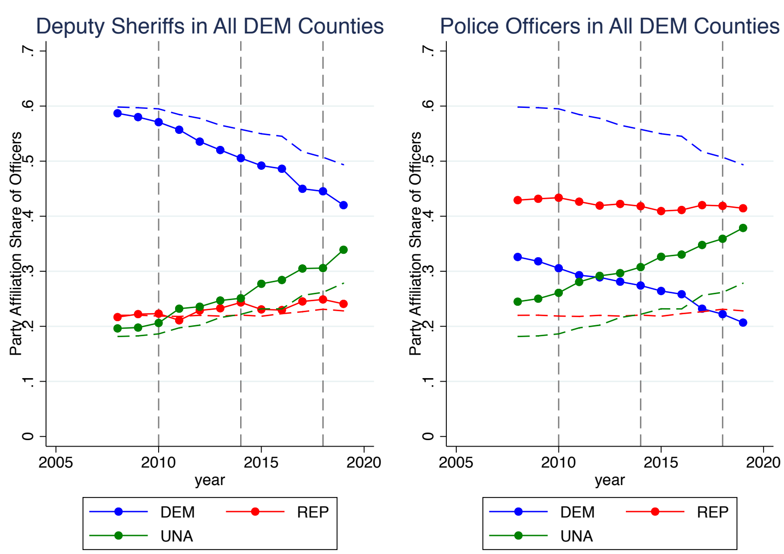
Figure 1: Black Drivers' Share Among Stops

Notes: This figure plots the raw data pattern share of Black drivers among all stops. We first compute the mean of Black stop at county-year level; then we compute the DtoD/D-to-R/RtoR mean in different cycle years by taking the simple average of the county-year means.

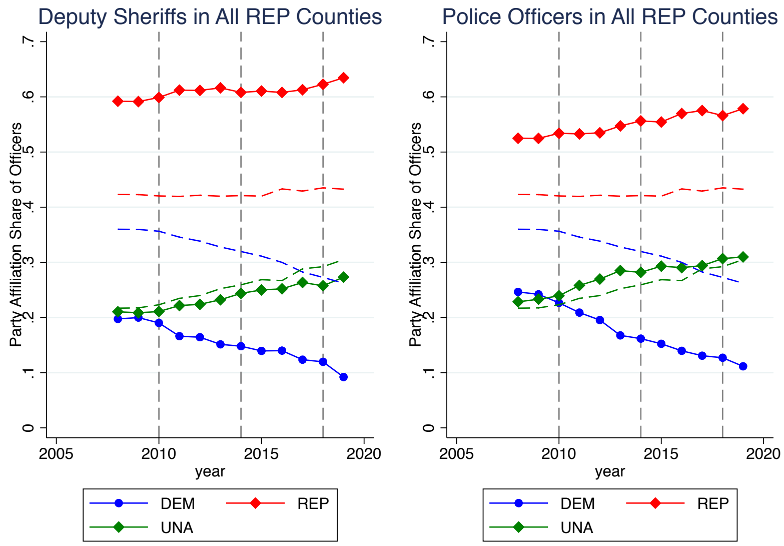
(a) Whole North Carolina



(b) All Democratic Sheriffs



(c) All Republican Sheriffs



(d) Mix Sheriffs

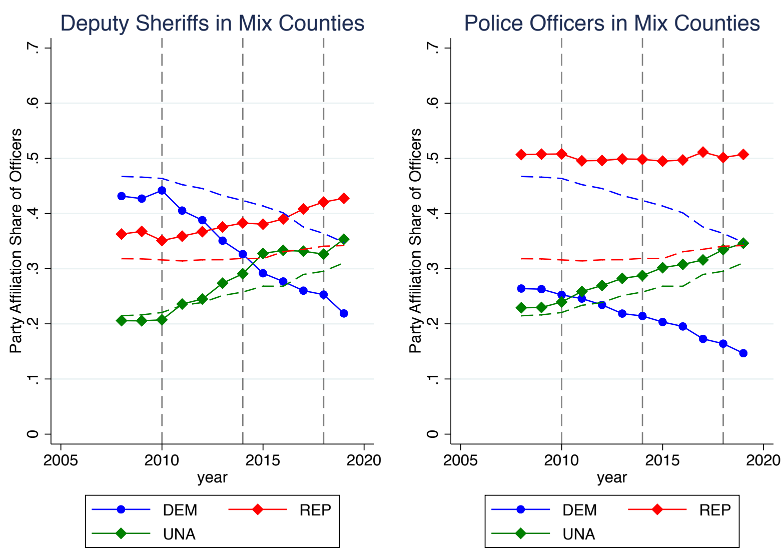
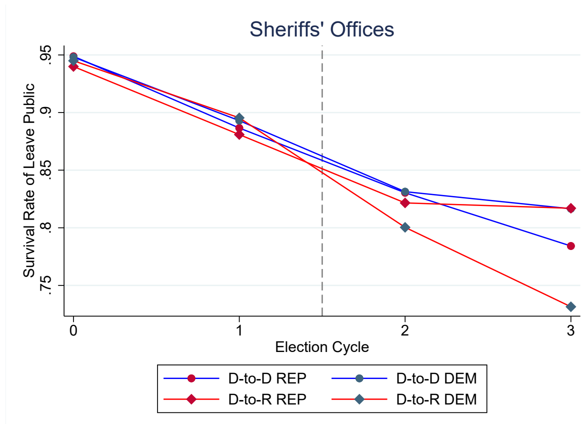


Figure 2: Party Affiliation Trend in Law-Enforcement Agencies

Notes: All fours figures depict the share of party affiliation of law enforcement officers over the years in North Carolina. We look at both sheriffs' offices and Police Departments. The first panel depict the trend over all North Carolina. The second panel looks at counties that have all Democratic sheriffs over the years. The third panel looks at counties with all Republican sheriffs. The final panel looks at counties with party turnovers. The dash lines are the party affiliation share of the voters registered in the same counties

(a) Survival Rate of Deputy Sheriffs



(b) Survival Rate of Police Officers

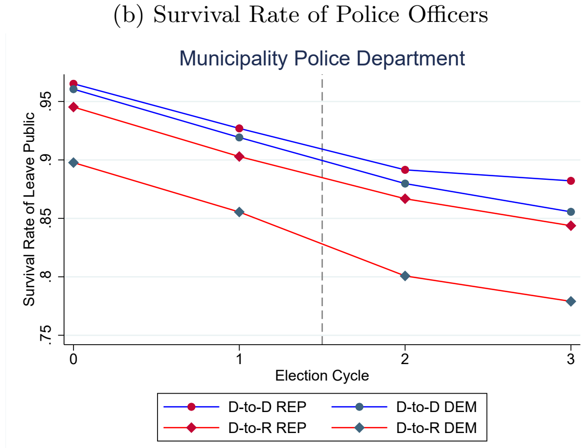


Figure 3: Party Affiliation Trend in Law-Enforcement Agencies

Notes: The two figures depict the share of officers staying in the same agency across years in an electoral cycle. We combine three electoral cycles, ranging years 2008-2019. The data structure is individual panel and we include individuals who were working in the agency two years before the elections.

Tables

Table 1: Sheriff Election Results in North Carolina

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
Panel A: All Sheriffs' Offices						
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 Good Report Quality						
2010	3	20	0	9	28	4
2014	5	26	0	11	29	8
2018	12	24	3	12	17	6

Notes: D refers to the Democratic party, and R refers to the Republican party. North Carolina has 100 sheriffs' offices, one for one county. Panel B drops counties with less than 10 stops in any year within a cycle. The D to D and D to R counties appeared in Panel A all enter into personnel turnover analysis. The D to D and D to R counties appeared in Panel B enter the traffic stop analysis.

Table 2: Effect of Partisan Leadership on Traffic Stop Behaviors

	Stop	Moving Purpose	Non Moving Purpose	Investigation	Search	Find Contraband
t-2 x DtoR	0.00519	-0.00105	0.00640	-0.000157	-0.000953	-0.000135
	(0.0111)	(0.00491)	(0.00837)	(0.00107)	(0.000849)	(0.000435)
t x DtoR	-0.0162	-0.0150	0.000753	-0.00199***	-0.00160**	-0.000504
	(0.0133)	(0.0112)	(0.00670)	(0.000602)	(0.000655)	(0.000354)
t+1 x DtoR	0.00129	-0.00504	0.00606	0.000271	0.000849	0.000443
	(0.0385)	(0.0275)	(0.0123)	(0.00180)	(0.00126)	(0.000536)
N	200	200	200	200	200	200
dep_mean	0.0832	0.0482	0.0292	0.0058	0.0051	0.0020
Weight by number of Vehicle	Stop	Moving Purpose	Non Moving Purpose	Investigation	Search	Find Contraband
t-2 x DtoR	0.00330	0.00201	0.000965	0.000319	-0.000123	-0.0000500
	(0.00652)	(0.00402)	(0.00264)	(0.000537)	(0.000550)	(0.000196)
t x DtoR	-0.00697	-0.00721*	0.000898	-0.000662	-0.000647	-0.000176
	(0.00603)	(0.00389)	(0.00271)	(0.000465)	(0.000470)	(0.000201)
t+1 x DtoR	0.0311	0.0114	0.0185*	0.00117	0.00111*	0.000439*
	(0.0227)	(0.0128)	(0.0108)	(0.000858)	(0.000589)	(0.000246)
N	200	200	200	200	200	200
dep_mean	0.0832	0.0482	0.0292	0.0058	0.0051	0.0020
County-Cycle FE	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes			

Notes: Clustered standard errors at county level in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$, one year before the sheriff election. Vehicle number of each county comes from number of commuters using cars (adjusting for car-pooling). Contraband refers to searches that found contraband successfully. Black stops refer to stops involving Black drivers, similarly for Black Searches and Black Contraband. Non-Black Stops refer to stops involving Non-Black drivers, similarly for Non-Black Searches and Non-Black Contraband. Search rate is defined as number of searches divided by number of stops. Hit rate is defined as number of searches with found contraband divided by number of searches.

Table 3: Effect of Partisan Leadership on Traffic Stop Behaviors

Panel A: Stop	(1) Stop per Vehicle	(2) Black Stops / All Stops	(3) Non-Black Stops / All Stops
t-2 x D-to-R	0.00519	0.00655	-0.00655
	(0.0111)	(0.0139)	(0.0139)
t x D-to-R	-0.0162	0.00659	-0.00659
	(0.0133)	(0.0118)	(0.0118)
t+1 x D-to-R	0.00129	0.0360**	-0.0360**
	(0.0385)	(0.0153)	(0.0153)
N	200	200	200
Dep. mean	0.0832	0.2321	0.7679
Panel B: Search or not	Searches / All Stops	Black Searches / All Stops	Non-Black Searches / All Stops
t-2 x D-to-R	0.00571	-0.00251	0.00823
	(0.0113)	(0.00589)	(0.00902)
t x D-to-R	0.00159	-0.00470	0.00628
	(0.0106)	(0.00551)	(0.00801)
t+1 x D-to-R	0.0375**	0.0128*	0.0247**
	(0.0156)	(0.00720)	(0.0117)
N	200	200	200
Dep. mean	0.0748	0.0221	0.0526
Search rate at $t-1$	0.0748	0.1025	0.0682
coeff of $t+1 \times D-to-R$ if search rate is the same as $t-1$ but stop share changes as Panel A		0.00342	-0.00246
p-value for test H0: est. coeff. = when search rate is the same as $t-1$ but stop share changes as Panel A		0.2010	0.0180
Panel C: Finding Contraband or not	Contraband / All Stops	Black Contraband / All Stops	Non-Black Contraband / All Stops
t-2 x D-to-R	0.00781	0.000895	0.00691
	(0.00686)	(0.00400)	(0.00529)
t x D-to-R	0.00368	-0.00388	0.00755
	(0.00570)	(0.00259)	(0.00477)
t+1 x D-to-R	0.0194**	0.00545	0.0139**
	(0.00881)	(0.00481)	(0.00665)
N	200	200	200
Dep. mean	0.0279	0.0075	0.0204
Hit Rate at $t-1$	0.4069	0.3859	0.4212
coeff of $t+1 \times D-to-R$ if hit rate is the same as $t-1$ but search rate changes as Panel B	0.01525	0.00493	0.01040
p-value for test H0: est. coeff. = when hit rate is the same as $t-1$ but search rate changes as Panel B	0.6445	0.9166	0.6008
County-Cycle FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Clustered standard errors at county level in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All outcome variables are at county-year level. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$, one year before the sheriff election. Vehicle number of each county comes from number of commuters using cars (adjusting for car-pooling). Contraband refers to searches that found contraband successfully. Black stops refer to stops involving Black drivers, similarly for Black Searches and Black Contraband. Non-Black Stops refer to stops involving Non-Black drivers, similarly for Non-Black Searches and Non-Black Contraband. Search rate is defined as number of searches divided by number of stops. Hit rate is defined as number of searches with found contraband divided by number of searches.

Table 4: Stop Purposes Distribution in Race Groups

0.6

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: All Drivers	Speed	Safe Movement	Stop sign	DWI	Equipment	Regulatory	Investigation	Other	Checkpoint	Seat Belt
t-2 x D-to-R	-0.0195	-0.00958	0.00236	0.00103	0.0407**	-0.00519	0.00165	-0.0141	-0.00170	0.00432
	(0.0320)	(0.0217)	(0.00993)	(0.00287)	(0.0160)	(0.0199)	(0.0101)	(0.0103)	(0.0138)	(0.00379)
t x D-to-R	-0.00433	-0.0297	-0.00820	0.00523	0.0208	-0.00000665	-0.00405	0.0110	0.00710	0.00214
	(0.0260)	(0.0187)	(0.0165)	(0.00311)	(0.0173)	(0.0199)	(0.0144)	(0.0168)	(0.0122)	(0.00480)
t+1 x D-to-R	-0.0463	0.000545	-0.0114	-0.00173	0.0277	0.0357	0.00640	-0.0147	0.00797	-0.00423
	(0.0372)	(0.0215)	(0.0136)	(0.00377)	(0.0176)	(0.0217)	(0.0175)	(0.0116)	(0.0151)	(0.00569)
N	200	200	200	200	200	200	200	200	200	200
dep_mean	0.2965	0.1700	0.0592	0.0148	0.1500	0.1179	0.0916	0.0736	0.0131	0.0134
Panel B: Black Stops										
t-2 x D-to-R	0.00304	0.00533	-0.00485	-0.00224	0.0144*	-0.00835	0.00536	-0.0120**	0.00397	0.00197
	(0.0102)	(0.00984)	(0.00531)	(0.00180)	(0.00815)	(0.00734)	(0.00439)	(0.00500)	(0.00588)	(0.00186)
t x D-to-R	0.0143	-0.00383	-0.0103	0.00205*	0.00737	-0.00770	0.00286	-0.00323	0.00319	0.00192
	(0.0125)	(0.00873)	(0.00740)	(0.00118)	(0.00800)	(0.00797)	(0.00737)	(0.00556)	(0.00398)	(0.00208)
t+1 x D-to-R	-0.00515	0.0155	-0.000986	0.000167	0.00873	0.00504	0.0132*	-0.00230	0.00404	-0.00219
	(0.0121)	(0.0105)	(0.00394)	(0.00133)	(0.0104)	(0.0124)	(0.00715)	(0.00474)	(0.00552)	(0.00252)
N	200	200	200	200	200	200	200	200	200	200
dep_mean	0.0640	0.0375	0.0127	0.0020	0.0394	0.0334	0.0181	0.0200	0.0029	0.0022
Panel C: Non-Black Drivers										
t-2 x D-to-R	-0.0226	-0.0149	0.00721	0.00327	0.0264**	0.00316	-0.00371	-0.00207	-0.00567	0.00235
	(0.0255)	(0.0146)	(0.00660)	(0.00285)	(0.0108)	(0.0139)	(0.00889)	(0.00685)	(0.00892)	(0.00297)
t x D-to-R	-0.0186	-0.0259*	0.00210	0.00318	0.0135	0.00769	-0.00691	0.0142	0.00391	0.000216
	(0.0164)	(0.0131)	(0.0108)	(0.00265)	(0.0118)	(0.0143)	(0.0124)	(0.0121)	(0.00971)	(0.00400)
t+1 x D-to-R	-0.0411	-0.0149	-0.0104	-0.00189	0.0190*	0.0307*	-0.00681	-0.0124	0.00393	-0.00205
	(0.0276)	(0.0141)	(0.0128)	(0.00352)	(0.0110)	(0.0162)	(0.0146)	(0.00803)	(0.0105)	(0.00440)
N	200	200	200	200	200	200	200	200	200	200
dep_mean	0.2325	0.1325	0.0465	0.0129	0.1106	0.0846	0.0735	0.0536	0.0101	0.0112

Notes: Clustered standard errors at county level in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t refers to the year of election in that election cycle. Dep. mean computed from D-to-R counties in year $t-1$, one year before the sheriff election. Outcome variables are county-year mean of shares of stop purposes among all stops. The stop purposes are, from Column (1) to Column (10), Speed Limit Violation, Safe Movement Violation Stop Light/Sign Violation, Driving While Impaired, Vehicle Equipment Violation, Vehicle Regulatory Violation, Investigation, Other Motor Vehicle, Checkpoint, and Seat Belt Violation. Panel A looks the overall share, Panel B looks at share of Black stopped by specific purposes among all drivers, while Panel C looks at non-Black drivers.

Table 5: Compare Stops Conducted by Stayers and Non-Stayers

	(1) Stop by Stayer	(2) Black by Stayer	(3) Black by Non-Stayer
Post x D-to-R	0.0321	-0.0271	0.0590*
	(0.0840)	(0.0316)	(0.0298)
N	100	100	100
dep_mean	0.5823	0.1447	0.0881
		Search by Stayer	Search by Non-Stayer
Post x D-to-R		0.0277	0.00727
		(0.0186)	(0.0119)
N		100	100
dep_mean		0.0442	0.0331
		Contraband by Stayer	Contraband by Non-Stayer
Post x D-to-R		0.0136*	0.00126
		(0.00782)	(0.00536)
N		100	100
dep_mean		0.0156	0.0151

Notes: Clustered standard errors at county level in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dep. mean computed from D-to-R counties before election. Stayers are officers who conduct traffic stops both before and after elections. Non-Stayers only conduct stops either before or after the elections. Column (1) report the results using Share of stops done by stayers in a county in a period as the outcome. Column (2) reports the results with outcome as number of Black stops/ searches/ searches with found contraband conducted by stayers divided by total number of stops for a county in a period. In Column (3), the outcome is number of Black stop/ searches, searches with found contraband conducted by non-stayers divided by total number of stops for a county in a period. Post means post-election.

Table 6: Transition Matrix of Law-Enforcement Officers

	Other Law	Non-Law	Leave Public Sector
Sheriffs' Offices	1.97%	1.87%	5.02%
Police Depts	2.94%	1.81%	3.86%

Notes: Data cover from 2008 to 2019. We provide percentages of officers (at officer-year level) who leave the sheriffs' officers / police departments, and go to other law-enforcement positions, public sector positions that have pension coverage in North Carolina other than law-enforcement positions, and did not go to any position that is covered by pensions in North Carolina.

Table 7: 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	0.000397	-0.00368	0.000903	0.00289	0.0101	0.0110
	(0.0153)	(0.00782)	(0.00822)	(0.0161)	(0.0242)	(0.00803)
t-2 x D-to-R x UNA	-0.0140	-0.00814	0.00795	-0.00758	-0.0101	0.0116
	(0.0146)	(0.0106)	(0.00876)	(0.0213)	(0.0162)	(0.00741)
t x D-to-R x DEM	0.0318*	0.00439	0.0141	0.0169	-0.0270*	0.00336
	(0.0175)	(0.0121)	(0.00862)	(0.0183)	(0.0154)	(0.00969)
t x D-to-R x UNA	0.0389*	-0.00869	0.0130	0.0334*	-0.0196	0.000835
	(0.0222)	(0.0127)	(0.00814)	(0.0192)	(0.0140)	(0.00525)
t+1 x D-to-R x DEM	0.114***	0.00291	0.0194	0.000374	-0.0835**	-0.00337
	(0.0423)	(0.0224)	(0.0180)	(0.0306)	(0.0373)	(0.0134)
t+1 x D-to-R x UNA	0.0580*	0.00694	0.0209	0.0389	-0.0281	-0.00843
	(0.0340)	(0.0238)	(0.0166)	(0.0302)	(0.0264)	(0.0130)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27887	27887	27887	31186	31186	31186
Dep. mean	0.1876	0.0668	0.0508	0.1342	0.0911	0.0468

Notes: Standard errors clustered at county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t refers to the year of election in that election cycle. The dependent variable mean is evaluated with the data from the final year in the electoral cycles.

Table 8: Personnel Turnover: Leaving Margin in Subgroups Based on Pension Benefit Eligibility

	Leave Public		Other Law		Non Law	
	Not Eligible	Eligible	Not Eligible	Eligible	Not Eligible	Eligible
	(1)	(2)	(3)	(4)	(5)	(6)
t-2 x D-to-R x DEM	0.000188	0.00230	-0.0184**	-0.00585	-0.00295	-0.0138
	(0.000485)	(0.00285)	(0.00866)	(0.0144)	(0.00723)	(0.00991)
t-2 x D-to-R x UNA	0.000507	0.00755	-0.0148	0.0113	0.00187	0.00376
	(0.000545)	(0.00707)	(0.00988)	(0.0196)	(0.00966)	(0.00661)
t x D-to-R x DEM	0.0186	0.00364	0.0122	-0.0338	0.00999	0.0473**
	(0.0205)	(0.0730)	(0.0163)	(0.0257)	(0.0105)	(0.0189)
t x D-to-R x UNA	0.0382*	0.140	-0.00619	-0.0459**	0.00897	0.0528**
	(0.0226)	(0.122)	(0.0164)	(0.0227)	(0.0109)	(0.0230)
t+1 x D-to-R x DEM	0.0487	0.228**	0.0289	-0.0711**	0.0262	0.0155
	(0.0436)	(0.0911)	(0.0294)	(0.0269)	(0.0204)	(0.0437)
t+1 x D-to-R x UNA	0.0428	0.196*	0.0286	-0.0950***	0.0248	0.00658
	(0.0304)	(0.108)	(0.0294)	(0.0254)	(0.0189)	(0.0386)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20406	3765	20406	3765	20406	3765
dep_mean	0.0843	0.2165	0.0700	0.0276	0.0415	0.0367

Notes: Standard errors clustered at county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t refers to the year of election in that election cycle. The dependent variable mean is evaluated with the data from the final year in the electoral cycles.

Table 9: Personnel Turnover: The Number of Entering Officers

	# of Entering Officers	
	Sheriffs'Offices	Police Department
t-2	0.423	0.193
	(1.518)	(1.000)
t	-0.145	-0.566
	(0.798)	(0.661)
t+1	-0.130	-1.291*
	(1.081)	(0.692)
t-2 x D-to-R	-1.605	-1.685
	(1.757)	(1.830)
t x D-to-R	0.660	-0.0690
	(1.210)	(1.164)
t+1 x D-to-R	3.489**	0.314
	(1.486)	(1.197)
N	291	241
dep_mean	9.7123	9.5802

Notes: Standard errors clustered at county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t refers to the year of election in that election cycle. The dependent variable mean is evaluated with the data from the final year in the electoral cycles.

Table 10: Personnel Turnover: Political Party Composition of Entering Officers

	Sheriffs'Offices			Police Department		
	DEM	UNA	REP	DEM	UNA	REP
t-2	-0.00725	0.0345*	-0.0273	-0.00212	0.0212	-0.0191
	(0.0222)	(0.0199)	(0.0169)	(0.0261)	(0.0345)	(0.0300)
t	0.0388*	0.00658	-0.0456**	-0.0344*	0.0216	0.0127
	(0.0228)	(0.0154)	(0.0210)	(0.0190)	(0.0195)	(0.0220)
t+1	0.0142	0.00695	-0.0230	0.00970	0.0391	-0.0488
	(0.0162)	(0.0174)	(0.0206)	(0.0203)	(0.0270)	(0.0305)
t-2 x D-to-R	0.0423	0.0214	-0.0637	-0.0180	-0.0468	0.0648
	(0.0535)	(0.0580)	(0.0692)	(0.0423)	(0.0646)	(0.0644)
t x D-to-R	-0.0427	-0.0440	0.0869**	0.0330	-0.0632	0.0302
	(0.0591)	(0.0499)	(0.0429)	(0.0599)	(0.0537)	(0.0732)
t+1 x D-to-R	0.0276	-0.0191	-0.00657	-0.0295	-0.00955	0.0391
	(0.0450)	(0.0439)	(0.0447)	(0.0434)	(0.0695)	(0.0845)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2836	2836	2836	2328	2328	2328
dep_mean	0.4193	0.2831	0.2972	0.2121	0.3387	0.4492

Notes: Standard errors clustered at county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. t refers to the year of election in that election cycle. The dependent variable mean is evaluated with the data from the final year in the electoral cycles.

Appendix

A Pension Plans in North Carolina

All law-enforcement officers hired by sheriffs' offices and police departments are in the Local Governmental Employees' Retirement System (LGERS). We make use of the eligibility rules for early retirement (reduced benefit) and service retirement (unreduced benefit) to categorize officers in our sub-group analysis. Employees meeting any one of the following criteria may retire with full retirement benefit.

1. Reach age 65 and complete five years of creditable service
2. Reach age 60 and complete 25 years of creditable services
3. Complete 30 years of creditable service at any age

Employees meeting one of the following criteria may retire with reduced retirement benefit.

1. Reach age 50 and complete 20 years of creditable service
2. Reach age 60 and complete five years of creditable services

Table 11: Subgroup: Elgibility of Pension Benefit

	Leave Public			Other Law			Non Law		
	No	Early	Full	No	Early	Full	No	Early	Full
t-2 x D-to-R x DEM	0.000188	0.00630	-0.00823	-0.0184**	-0.0104	-0.00463	-0.00295	-0.0127	-0.0270
	(0.000485)	(0.00420)	(0.00992)	(0.00866)	(0.0161)	(0.0239)	(0.00723)	(0.00764)	(0.0239)
t-2 x D-to-R x UNA	0.000507	0.0128	-0.0104	-0.0148	-0.0155	0.0508	0.00187	0.00406	-0.0124
	(0.000545)	(0.00935)	(0.00980)	(0.00988)	(0.0168)	(0.0308)	(0.00966)	(0.00957)	(0.0127)
t x D-to-R x DEM	0.0186	-0.0451	0.0190	0.0122	-0.0449	-0.0104	0.00999	0.00199	0.104**
	(0.0205)	(0.0965)	(0.112)	(0.0163)	(0.0369)	(0.00851)	(0.0105)	(0.0171)	(0.0429)
t x D-to-R x UNA	0.0382*	0.00740	0.374**	-0.00619	-0.0710**	0.0128*	0.00897	0.0615*	0.0420
	(0.0226)	(0.142)	(0.184)	(0.0164)	(0.0340)	(0.00750)	(0.0109)	(0.0342)	(0.0331)
t+1 x D-to-R x DEM	0.0487	0.196*	0.235	0.0289	-0.106**	-0.0101	0.0262	-0.00506	0.0525
	(0.0436)	(0.108)	(0.181)	(0.0294)	(0.0451)	(0.0163)	(0.0204)	(0.0484)	(0.0654)
t+1 x D-to-R x UNA	0.0428	0.0720	0.333**	0.0286	-0.129***	-0.0264	0.0248	0.0352	-0.0204
	(0.0304)	(0.131)	(0.162)	(0.0294)	(0.0377)	(0.0341)	(0.0189)	(0.0473)	(0.0491)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20406	2235	1530	20406	2235	1530	20406	2235	1530
dep_mean	0.0843	0.1432	0.3206	0.0700	0.0313	0.0222	0.0415	0.0380	0.0349

Notes: Standard errors clustered at county level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. D-to-R refers to a county which experience a Democrat to Republican sheriff turnover in that election cycle. t refers to the election year in that election cycle