# Do Leadership Transitions Degrade Law Enforcement? Evidence from Sheriff Elections*

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**Abstract**

How disruptive are leadership changes in local law enforcement? While a large body of literature studies the performance effects of electoral turnover among local officials, little is known about county sheriffs. Sheriff elections generate abrupt leadership changes in agencies with substantial authority, raising questions about whether turnover disrupts operations or whether institutional continuity mitigates such effects. This paper investigates whether electoral turnover in law enforcement impacts arrest rates. Using hand-collected data on sheriff elections merged with arrest records, I employ a difference-in-differences design to examine how arrest rates respond, first, to an incumbent sheriff's electoral defeat and, second, to the subsequent transition to new leadership. I find that election losses lead to modest declines in arrests for lower-level offenses, while no significant effects are observed for arrest rates of severe offenses. In contrast, the transition to a new sheriff shows little impact on arrest activity. Analysis of deputy employment data suggests that staffing declines may drive the decrease in arrests following election losses.

**Keywords:** Elections, sheriffs, law enforcement, transition

**JEL classification codes:** K42, D72, H70

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# 1 Introduction

There is a growing body of research examining how leadership transitions among locally elected officials affect the performance of public institutions, though the evidence remains mixed. Some scholars argue that turnover can improve organizational performance and morale when ineffective incumbents are replaced, particularly if elections discipline poor performers (Bazzi et al., 2025; Marx, Pons, and Rollet, 2025). Others emphasize the potential costs of leadership change, noting that newly elected officials may require time to learn institutional procedures, establish authority, and build trust with subordinates, leading to short-term declines in performance (Alt, Bueno de Mesquita, and Rose, 2011; Krause and O'Connell, 2016; Fouirnaies and Hall, 2022). At the same time, leadership transitions may have limited effects when successors are drawn from within the organization—such as deputies or officials with prior administrative experience—suggesting that institutional continuity may mitigate disruption (Boyne et al., 2010; Johnson, 2005).

This debate is especially salient in the context of elected sheriffs, who occupy a distinctive role as the only chief law enforcement officials in the United States chosen directly by voters. Despite their importance, there is limited causal evidence on whether electoral turnover among sheriffs meaningfully alters law enforcement behavior. Sheriffs typically enjoy substantial incumbency advantages (Zoorob, 2019), making unexpected electoral defeats relatively rare. When such defeats do occur, however, the period between the election and the transfer of power may represent a particularly vulnerable phase for law enforcement operations. An outgoing sheriff who has lost reelection may experience diminished morale, which can spill over to deputies and reduce enforcement efforts. Moreover, because sheriff offices function as administrations, an electoral loss often signals impending personnel turnover, as incoming sheriffs frequently appoint new deputies. Anticipation of these changes may further depress enforcement activity. Finally, the arrival of a new sheriff may disrupt existing practices if the incoming official holds different policy priorities or enforcement philosophies. These dynamics suggest that leadership transitions in sheriff offices may produce short-term disruptions with important implications for public safety, making it critical to understand how such transitions shape law enforcement behavior.

In this paper, I examine how sheriff electoral turnover impacts law enforcement by analyzing changes in arrest rates. First, I estimate the impact of incumbent sheriff election losses on arrest rates. Second, I examine how the arrival of a new sheriff following an electoral defeat impacts arrest rates. To conduct my analysis, I constructed a monthly panel of sheriff election results using data compiled by Thompson, 2020, and merged that with arrests from sheriff departments from the National Incident-Based Reporting System from 1995 to 2022. I use a Difference-in-Differences design for both estimations. To estimate the impact of election losses, I compare arrest rates of incumbent sheriffs who lost re-election to incumbent sheriffs who won re-election in stayed in office. To estimate the impact of the new sheriff taking office, I compare arrest rates in counties that elected new sheriffs to arrest rates in counties that either did not have an election in that year or did have an election but the incumbent won re-election, hence there was no new sheriff for that year.

I analysed the impact of election losses and the onset of a new sheriff on arrests for lower-level and higher-level offenses. For lower-level offenses, the results show that election losses lead to decreases in arrests for gambling offenses of approximately 0.02 per 100,000 residents (a 97% decrease relative to the mean) and decreases in arrests for sexual misconduct by about 0.08 per 100,000 (a 15.9% decrease relative to the mean). I find no statistically significant results on arrests for major offenses (such as murder, burglary, etc.) and arrests for the other lower offenses. By contrast, the arrival of a new sheriff is associated with a decrease in arrests for drug-related offenses by roughly 0.39 per 100,000 (a 2.95% decrease relative to the mean) with no statistically significant effects on arrests for major offenses. Overall, the pattern of results suggests that enforcement activity responds more strongly to the electoral outcome—especially the loss experienced by the incumbent—than to the subsequent transition in leadership, implying that the disruption arises from the election itself rather than from administrative turnover.

To examine the mechanisms underlying the decline in arrests following election losses, I analyze how incumbent defeat affects deputy employment within sheriff's offices. As discussed above, an incumbent sheriff's electoral defeat can introduce uncertainty within the department, particularly around staffing and job security, during the period between the election and the transition of power. Using data from the Annual Survey of Public Employment & Payroll, I find evidence of a shift in workforce composition during election years: full-time deputy employment declines by roughly 12 positions, while part-time employment increases by approximately 2,616 positions. These results support the argument that in sheriff transition periods, the office experiences staffing changes, which could explain the decline in law enforcement activity during this period. The smooth transition of leadership in sheriff offices should be paramount to ensure that public safety is not impacted negatively during these periods.

The rest of this paper is structured as follows: Section 2 describes the institutional context of sheriff elections. Section 3 describes the data sources, variable definitions, and measurements, and the descriptive characteristics between treated and control counties. Section 4 describes the empirical and identification strategy used in this paper. Sections 5 and 6 present my results and conclusions.

# 2 Background

## 2.1 Sheriff jurisdiction and roles

Sheriffs' jurisdiction differs from that of municipal police departments. Whereas police chiefs oversee law enforcement within city limits, sheriffs are responsible for countywide policing, including unincorporated areas that lack municipal police departments. Sheriffs also oversee additional statutory responsibilities that police typically do not perform, such as operating county jails, managing court security, serving warrants, and executing civil processes. As a result, sheriff offices function as full administrative agencies with substantial autonomy. They possess broad discretion over hiring, firing, and promotion decisions, both when entering office and in response to deputies' political behavior during re-election campaigns. This discretion creates substantial employment uncertainty during election periods, rendering deputy staffing and job continuity especially volatile (Fanto, 2010; Burke, 2000).

Unlike police chiefs—who are typically appointed by municipal governments—sheriffs are elected by popular vote in the vast majority of counties. Approximately 90% of U.S. counties elect their sheriff (roughly 3,081 out of 3,143 counties), with the exception of Alaska, Connecticut, and Hawaii, where sheriffs have been abolished or assigned largely ceremonial duties.[1] Sheriff elections are partisan and vary in their electoral rules: some counties hold closed elections that restrict participation to registered party members, while others use open elections that permit all eligible voters to participate.

[1] In Rhode Island, sheriffs are appointed by the Governor, while Alaska has no county governments. Connecticut transitioned from a county sheriff system to using judicial marshals, and Hawaii employs deputy sheriffs within the Sheriff Division of the Hawaii Department of Law Enforcement, a state agency (Hoffman, 2000).

## 2.2 Elections Timeline

Sheriff elections typically occur every four years, and most states impose no term limits, allowing incumbents to accumulate substantial political, administrative authority and incumbency advantages. Because general elections take place in the first week of November, a sheriff who loses reelection immediately enters a lame-duck period—lasting from November through December—during which incentives to maintain normal enforcement activity may weaken. This *"November–December"* window is the post-period in the Difference-in-Differences estimation where I estimate the effect of election losses on arrest activity. On the other hand, new sheriffs generally assume office in *January*, and thus I separately estimate the impact of this leadership transition at the start of the election year.[2]

# 3 Data and Sample

For my analysis, I compiled arrests, election results, county population, crime rates, law enforcement employment, and payroll data from multiple sources to generate an unbalanced panel from 1995-2020.

I sourced county-year-month arrest counts from the National Incident-Based Reporting System (NIBRS). These data consist of self-reported arrests submitted by individual sheriff departments in each county.[3] Arrests are categorized into higher-level and lower-level offenses. Higher-level offenses include the 8 index crimes that are typically reported in crime trends and are more severe in nature. These include Murder and Non-Negligent Manslaughter, Robbery, Forcible Rape, Motor Vehicle Theft, Arson, Burglary, and Larceny-theft, which are serious in nature. I group arrests for other crimes that are not considered severe into 5 broad categories, which I refer to as lower-level offenses. These include Assault, Fraud, Gambling, DUI, Drug, and Sexual Misconduct.[4] Finally, I all arrests into arrest rates per 100,000 people using yearly population estimates for each county sourced from the United States Census Bureau.

In addition to arrest data, I obtained incident-level crime data at the monthly level from NIBRS, using the same offense categories as in the arrest analysis. These data allow me to

[2]Since these two events occur very close to together, in the empirical strategy section, I explain how I separate them into two different estimations.

[3]These arrests reflect the number of times an individual is arrested in each county, but not the total number of people arrested.

[4]Appendix Table A1 contains a list of the components of these broad categories and their descriptions.

assess whether the observed changes in arrests following election outcomes are driven by shifts in underlying crime rather than reflecting changes in arrest patterns.

I sourced sheriff election results from Thompson, 2020, which provides comprehensive coverage of sheriff elections across the United States. The dataset includes 7,351 elections across 1,400 counties in 39 states.[5] These are general elections held in November and include indicators for whether a candidate was an incumbent sheriff and whether the election resulted in a win or a loss for the candidate. Because the original data are reported at the yearly level, I aggregated election outcomes to the monthly level so they align with the timing structure of the arrest data.

I compile county-level characteristics from multiple sources. Unemployment rates are obtained from the Bureau of Labor Statistics, county population data from the U.S. Census Bureau, and rural–urban classifications from the Rural–Urban Continuum Codes. These variables are included as controls in all regression specifications.

To examine potential mechanisms driving changes in arrest activity, I incorporate information on deputy sheriff staffing from the Annual Survey of Public Employment and Payroll (ASPEP). These data are reported at the agency-year level and include detailed measures of law enforcement personnel employed by sheriff offices. Specifically, ASPEP provides the number of full-time and part-time deputies, total payroll expenditures for both groups, and the total hours worked by part-time employees. This yearly staffing information allows me to assess whether election outcomes are associated with changes in the size or composition of the sheriff's workforce and whether shifts in employment structure help explain the observed changes in arrest patterns.

## 3.1 Descriptive Statistics

Table 1 presents summary statistics for counties in the treated and control groups. The treated group consists of counties where the incumbent sheriff lost the election, while the control group includes counties where the incumbent won.

Panel A summarizes the main outcomes of the study, with Panel A1 showing arrest rates for lower-level offenses, Panel A2 showing arrest rates for higher-level offenses, and Panel A3 showing the employment, payroll, and hours of work for deputy sheriffs. Because sheriffs lose

[5] Figure 1 shows the counties that are included in the sample

elections less often than they win, the average arrest rates for treated counties are much higher than control counties. Similarly, since election years are less frequent than non-election years (sheriffs are elected every 4 years, meaning the election year is 1, while non-election years are 3), the averages for employment and payroll for treated counties are also higher than those of control counties.

Panel B shows that treated counties are substantially larger: the average population is 236,905 compared with 184,698 in control counties. Rural composition is similar across groups (0.426 vs. 0.445), as is partisan affiliation of the sheriff (49.2% Republican in treated counties vs. 55.2% in control counties).

# 4 Empirical Strategy

## 4.1 The Impact of Election Losses

To estimate the causal effect of election losses on sheriff enforcement behavior, I implement a Difference-in-Differences design. The treatment occurs when an incumbent sheriff loses the election in November, and the post-treatment period corresponds to the lame-duck window of November–December in the election year. The pre-treatment period is defined as January–October of the year prior to the election, which allows me to avoid months when sheriffs actively campaign. Because campaigning may influence enforcement—for example, by increasing arrests to project toughness or decreasing arrests to avoid controversy—using the prior year's January–October window mitigates the risk that pre-election strategic behavior contaminates the counterfactual.

The baseline Difference-in-Differences specification is as follows:

$$Arrests_{cmy} = \beta_0 + \beta_1(Lost_{cmy} \times Post_{my}) + \alpha_c + \tau_{my} + \mathbf{X}_{cmy} + \Phi_c t + \mu_{cmy}, \tag{1}$$

where $Arrests_{cmy}$ is the arrest rate per 100,000 residents in county $c$ in month $m$ in year $y$. $Lost_c$ is an indicator variable that equals 1 when the sheriff in county $c$ lost the election and 0 when the sheriff wins. $Post_{my}$ is an indicator variable equal to 1 after the election (months November and December) and equals 0 in January–October of the year prior to the election. $\alpha_c$ is an indicator for county fixed effects whiles $\tau_{my}$ are year-month fixed effects.

$\mathbf{X}_{cmy}$ represents controls such as population, unemployment rates, and the share of deputies per 100,000 residents in a county. $\Phi_c t$ represents county-specific linear time trends, which allow arrest outcomes to follow distinct secular trajectories across counties. Including these trends accounts for gradual, county-level changes in enforcement activity that may be correlated with electoral outcomes and ensures that identification comes from deviations around these smooth trends rather than from differential pre-existing trends. Standard errors are clustered at the county level. The coefficient of interest $\beta_1$, measures the differential change in arrests for losing sheriffs relative to winning sheriffs during the lame-duck period.

## 4.2 The Impact of the New Sheriff Taking Office

To estimate how arrest patterns respond when a new sheriff assumes office, I estimate a second Difference-in-Differences estimation with the treatment beginning in January.

The corresponding Difference-in-Differences specification is as follows:

$$Arrests_{cmy} = \gamma_0 + \gamma_1(NewSheriff_{cmy} \times PostJan_{my}) + \alpha_c + \tau_{my} + \mathbf{X}_{cmy} + \Phi_c t + \epsilon_{cmy}, \quad (2)$$

where $Arrests_{cmy}$ is the arrest rate per 100,000 residents in county $c$ in month $m$ in year $y$. $NewSheriff_c$ is an indicator variable that equals 1 if county $c$ elects a new sheriff (i.e., the incumbent lost), 0 if it did not (the incumbent won). $PostJan_{my}$ is an indicator variable equal to 1 in January–December of the year after the election and equals 0 in January–December of the election year. Standard errors are clustered at the county level. The coefficient of interest $\gamma_1$, measures the effect on arrest rates when the new sheriff takes office in January.

## 4.3 Identification Assumption

The identifying assumption for the Difference-in-Differences designs is the parallel trends assumption. For the election-loss specification, this assumption requires that—absent an incumbent sheriff losing the election—arrest rates in losing and winning counties would have evolved similarly across the pre- and post-election periods. Likewise, for the new-sheriff specification, the assumption requires that counties receiving a new sheriff in January would have followed similar pre-transition arrest patterns as counties retaining the incumbent.

To assess the credibility of these assumptions, I estimate dynamic versions of both Difference-in-Differences specifications. These event-study models allow the evolution of arrest rates to be plotted month-by-month relative to the election or leadership transition.

#### 4.3.1 Dynamic specification for election losses

$$Arrests_{cmy} = \sum_{\tau=Jan,\tau\neq Oct}^{Dec} \delta_\tau (Lost_{cmy} \times 1[m = \kappa]) + \alpha_c + \tau_{my} + \mathbf{X}_{cmy} + \Phi_c t + \eta_{cmy}, \quad (3)$$

where $1[m = \kappa]$ is an indicator for month $\kappa$ relative to November. The coefficients on the $\delta_\tau$'s capture the difference in arrests between losing-sheriff counties and winning-sheriff counties at each event-time month $\kappa$. I omit October—the month immediately preceding the election—and interpret all event-time effects relative to this pre-treatment baseline. This event-study analysis allows me to visually inspect pre-treatment trends and evaluate whether losing and winning counties exhibit parallel behavior prior to November.

#### 4.3.2 Dynamic specification for the new sheriff taking office

To study changes surrounding leadership transitions, I estimate an analogous dynamic specification centered at January, when the new sheriff assumes office:

$$Arrests_{cmy} = \sum_{s=Jul,s\neq Dec}^{Jun} \theta_s (NewSheriff_{cmy} \times 1[m = s]) + \alpha_c + \tau_{my} + \mathbf{X}_{cmy} + \Phi_c t + \rho_{cmy}, \quad (4)$$

where $1[m = s]$ is an indicator that month $m$ equals calendar month $s$ in the transition year. I omit December—the final month of the outgoing sheriff's tenure—as the reference period. The coefficients $\theta_s$ capture differences between counties receiving a new sheriff in January and those that retain the incumbent, allowing me to examine whether enforcement patterns shift before or after the leadership change.

# 5 Results

## 5.1 Election Loss Effect

Table 2 reports the estimated effects of incumbent sheriff election losses on arrest rates for lower-level offenses. Overall, the results show limited evidence of changes in arrest activity following an election loss. Arrests for gambling offenses decline by approximately 0.016 arrests per 100,000 residents, while arrests for sexual misconduct decrease by about 0.081 per 100,000. By contrast, arrests for assault, fraud, DUI, and drug-related offenses exhibit no meaningful changes following an incumbent's electoral defeat, with point estimates that are small in magnitude and imprecisely estimated. Table 3 presents the corresponding estimates for higher-level offenses. Across all offenses, I find no evidence that election losses affect arrest rates. These results indicate that election losses are associated with modest declines in arrests for a limited set of discretionary offenses, while enforcement of higher-level offenses appears largely unaffected.[6]

## 5.2 New Sheriff Effect

Table 4 reports the estimated effects of a new sheriff taking office on arrest rates for lower-level offenses. Overall, the results show little evidence that the transition to new leadership meaningfully alters arrest activity for lower-level offenses. Estimated effects for assault, fraud, gambling, DUI, and sexual misconduct are small in magnitude and close to zero. The only notable change is observed for drug-related offenses, where arrests decline by approximately 0.39 per 100,000 residents following the arrival of a new sheriff. Table 5presents the corresponding estimates for higher-level offenses. The estimated effects are uniformly small and statistically insignificant. These results suggest that the arrival of a new sheriff has limited effects on enforcement activity, with little evidence of systematic changes in arrests for either lower-level or higher-level offenses.

## 5.3 Event-Study Evidence and Pre-Trends

Figure 2 presents event-study estimates for arrests for lower-level offenses surrounding incumbent election losses. For several offense categories, coefficients in the pre-election period are not tightly centered around zero, indicating potential deviations from parallel trends prior to the election. Importantly, these pre-trends do not appear to be pronounced for the two outcomes that drive the main results—gambling and sexual misconduct—suggesting that the estimated post-election declines in these offenses are less likely to be driven by differential

[6] Appendix Table A2 shows the impact on crime rates, showing that crime rates are not impacted, although arrests change. This means public safety is not compromised however the enforcement behavior of sheriffs changes after the loss.

pre-election trends.

Figure 3 shows analogous event-study estimates for the transition to a new sheriff taking office. As with election losses, several outcomes exhibit nontrivial pre-trends, indicating that arrest patterns were already evolving prior to the leadership transition. For drug-related arrests, which constitute the primary result in this specification, there is evidence of a pre-trend in November preceding the transition, consistent with anticipatory behavior or early adjustments by deputies in advance of the new sheriff's arrival. This indicates that there is no strong enforcement change when a new sheriff takes office.

## 5.4 Mechanisms

To evaluate whether staffing disruptions contribute to changes in arrests following election losses, I estimate a Difference-in-Differences using yearly employment outcomes from ASPEP:

$$Y_{cy} = \lambda_0 + \lambda_1(Lost_{cy} \times ElectionYear_y) + \lambda_2 X_{cy} + \alpha_c + \tau_y + \mathbf{X}_{cmy} + \Phi_c t + \nu_{cy}, \tag{3}$$

where $Y_{cy}$ includes full-time deputies employed, part-time deputies employed, payroll for both full and part-time deputies, and hours worked of part-time deputies.[7] The interaction term $(Lost_c \times ElectionYear_y)$ identifies whether staffing patterns differ in counties where the incumbent lost relative to counties where the incumbent won. Standard errors are clustered at the county level.

Table 6 shows that counties in which the incumbent sheriff loses the election experience a reduction of approximately 12 full-time deputies in the election year. At the same time, part-time payroll increases substantially, by about $2,616. However, this rise in part-time payroll is not accompanied by a corresponding increase in total part-time hours worked. This pattern suggests that the observed increase in part-time employment reflects a shift toward more flexible or temporary staffing arrangements rather than an expansion in total labor input.

[7] ASPEP does not report hours worked for full-time employees.

# 6 Conclusion

This paper examines how sheriff elections influence law enforcement activity by studying two distinct events: the incumbent sheriff's election loss in November and the arrival of a new sheriff in January. Using a monthly panel of election results merged with arrest data, I employed a Difference-in-Differences framework to isolate how political transitions shape enforcement behavior. The results show that losing an election leads to modest but meaningful reductions in arrests for some lower-level, lower-level offenses, with no effects on higher-level offenses. In contrast, the arrival of a new sheriff does not produce measurable changes in arrest patterns, suggesting that the immediate disruption arises not from leadership turnover itself but specifically from the shock of electoral defeat.

To understand the mechanisms behind these patterns, I examine how staffing within sheriff's offices responds to election outcomes. The results indicate that incumbent losses are associated with declines in full-time deputy staffing and increases in the demand for part-time employment, reflected in the increase in payroll. These staffing disruptions may help explain why enforcement activity weakens during the lame-duck period, particularly for offenses that depend more heavily on proactive policing.

Taken together, these findings contribute to a growing literature on the behavioral responses of elected law enforcement officials and reveal the importance of political incentives in shaping public safety outcomes. Sheriffs hold substantial autonomy and discretion, yet face few institutional constraints, making their reactions to electoral pressures especially consequential for local communities. The evidence presented here suggests that electoral losses can disrupt enforcement capacity, raising questions about how political accountability interacts with effective policing.

Future research should explore the persistence of these effects, investigate whether similar dynamics occur in other elected law enforcement roles, and assess how organizational structures might buffer departments from political shocks.

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# Figures and Tables

**Figure 1: Counties represented in the sample**

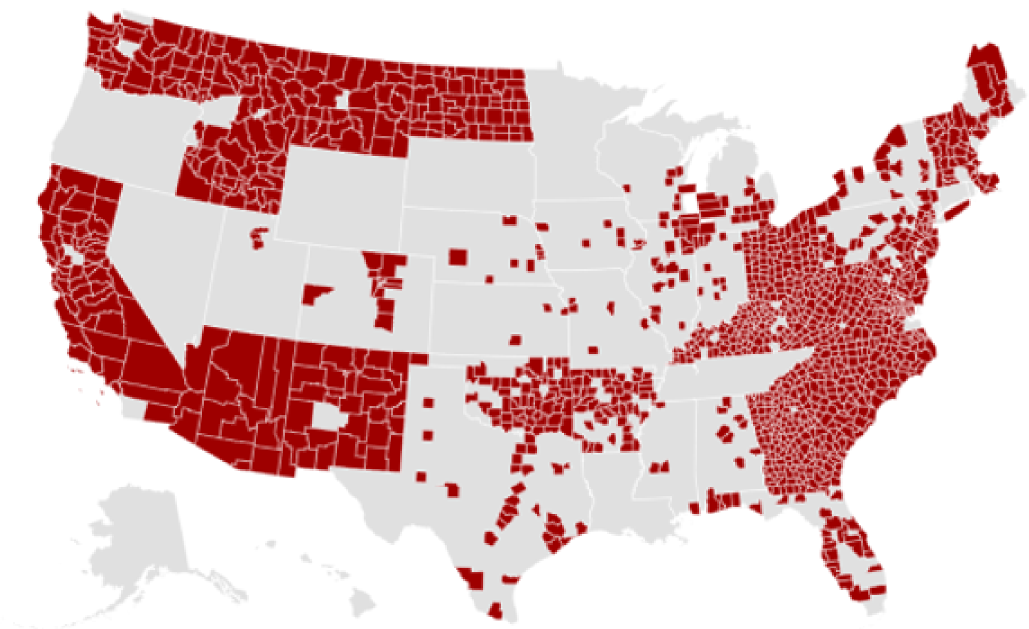
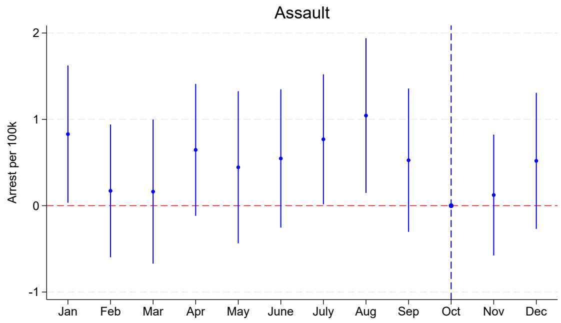
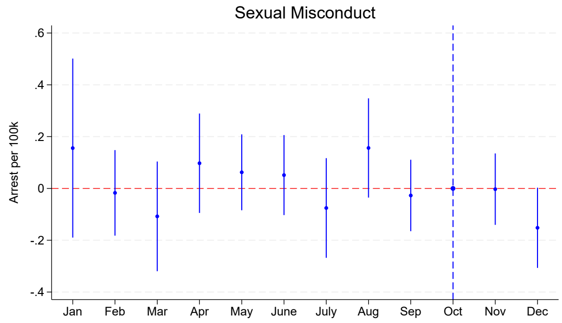


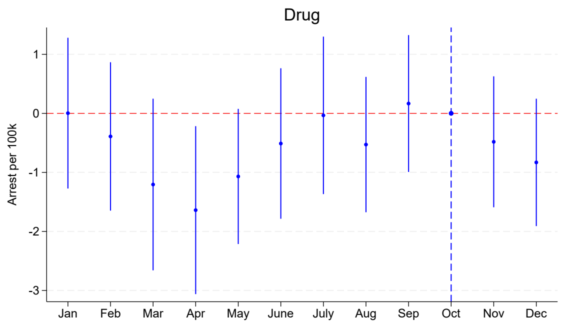
**Figure 2: Event-study graphs on the impact of election losses on arrests for *lower-level offenses***



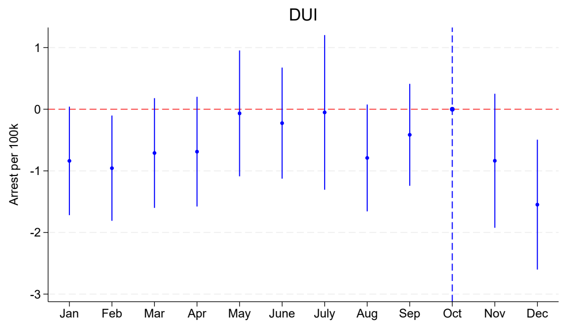

**(a)** Assault



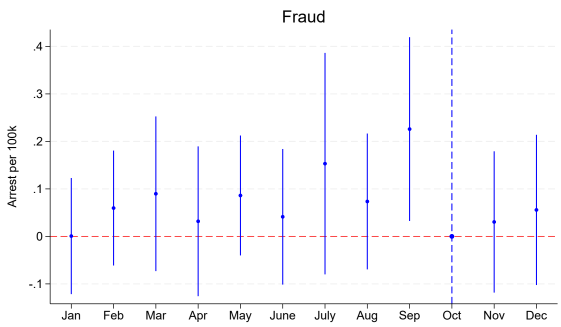

**(b)** Sexual Misconduct



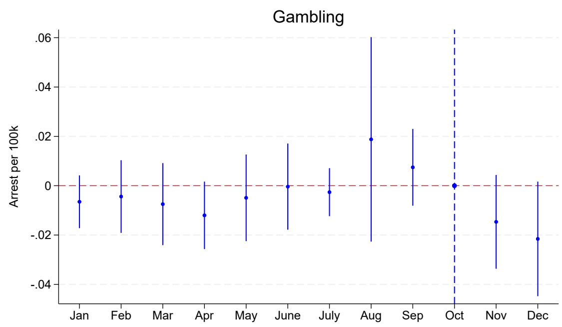

**(c)** Drug




**(d)** DUI



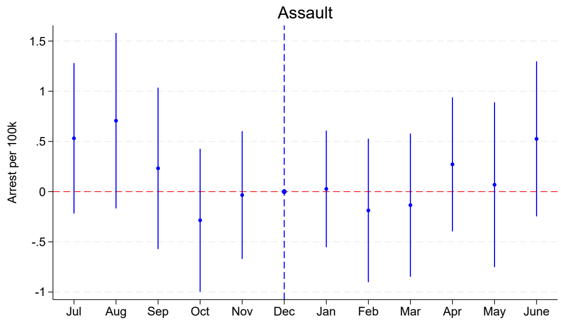

**(e)** Fraud



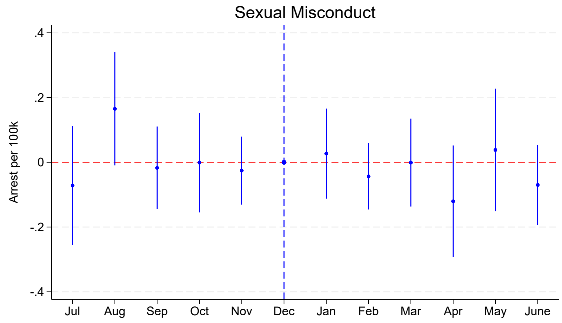

**(f)** Gambling

*Note:* Figure 2 presents the event study plot using equation 3. The graphs present the estimates of the effect of election losses on arrests for lower-level offenses. The treatment month is November, and all estimates are relative to the month before the treatment (October).

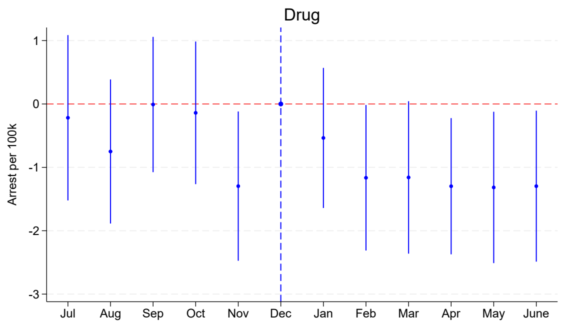
**Figure 3: Event-study graphs on the impact of the new sheriff taking office on arrests for lower-level offenses**



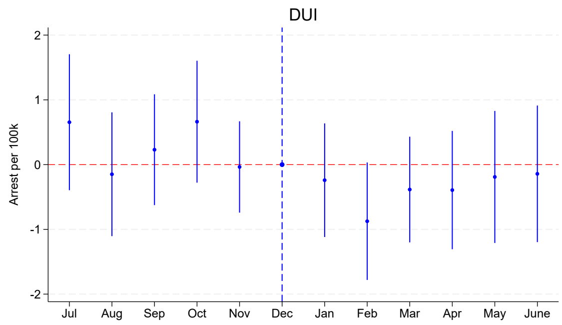

**(a)** Assault



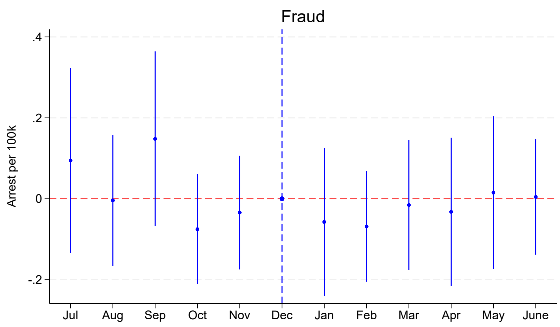

**(b)** Sexual Misconduct



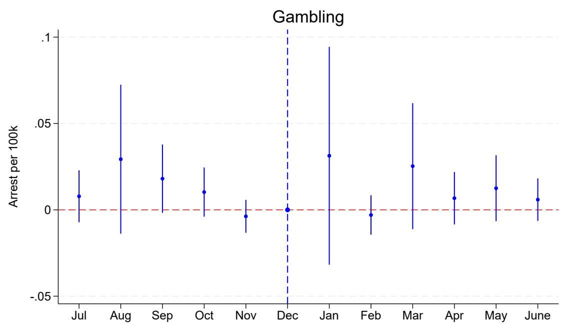

**(c)** Drug




**(d)** DUI




**(e)** Fraud




**(f)** Gambling

*Note:* Figure 3 presents the event study plot using equation 4. The graphs present the estimates of the effect of election losses on arrests for higher-level offenses. The treatment month is January, and all estimates are relative to the month before the treatment (December).

**Table 1: Summary Statistics by Treatment Status**

| | Treated Group (1) | Control Group (2) |
|---|---|---|
| **(A) Panel A: Dependent Variables** | | |
| *(A1.) Arrest per 100k for lower-level offenses* | | |
| Fraud | 0.926 | 0.784 |
| Driving under the Influence | 10.251 | 8.835 |
| Drug | 14.016 | 13.803 |
| Gambling | 0.014 | 0.014 |
| Assault | 16.081 | 13.606 |
| Rape | 0.812 | 0.664 |
| *(A2.) Arrest per 100k for higher-level offenses* | | |
| Murder and Non-Negligent Manslaughter | 0.160 | 0.155 |
| Forcible Rape | 0.315 | 0.242 |
| Robbery | 0.303 | 0.292 |
| Aggravated Assault | 3.162 | 2.872 |
| Larceny-Theft | 6.481 | 5.637 |
| Motor Vehicle Theft | 0.780 | 0.665 |
| Burglary | 2.537 | 2.325 |
| Arson | 0.130 | 0.103 |
| *(A3.) Employment and Payroll* | | |
| Full-time employees | 680.92 | 476.25 |
| Payroll (Full-time employees) | 4,023,080 | 2,741,242 |
| Part-time employees | 25.94 | 23.55 |
| Payroll (Part-time employees) | 27,175.58 | 25,105.55 |
| Hours (Part-time employees) | 1,746.75 | 1,617.04 |
| **(B) County and Sheriff Characteristics** | | |
| Population | 236,905.20 | 184,697.60 |
| Rural/Urban status (1 = Rural) | 0.426 | 0.445 |
| Unemployment rate | 6.710 | 6.686 |
| Deputy sheriff per 100k | 208.371 | 206.976 |
| Party affiliation (1 = Republican) | 0.492 | 0.552 |
| Number of Counties | 1,121 | 279 |
| Incumbent lost frequency | 0.395 | |
| Observations | 39,649 | |

*Notes:* Table 1 provides descriptive statistics for my main sample of counties with elections held between 1995-2020. Panel A presents the main outcome variables, while Panel B presents county and sheriff characteristics by treatment status, with means for the treated group in column 1 and means for the control group in column 2. Since this paper analyses elections, most counties are sometimes in the treatment group (where the incumbent loses) and sometimes in the control group (where the incumbent won the election). However, there are 279 counties where the sheriff never lost an election (pure controls), and the remaining 1,121 counties have been treated at least once.

**Table 2: Impact of election losses on arrest rates of lower-level offenses**

| Arrest per 100k | Assault (1) | Fraud (2) | Gambling (3) | DUI (4) | Drug (5) | Sexual Misconduct (6) |
|---|---|---|---|---|---|---|
| Lost x Post | -0.154 | -0.0292 | -0.0163** | -0.544 | -0.0908 | -0.0810** |
| | (0.202) | (0.0409) | (0.00738) | (0.361) | (0.289) | (0.0378) |
| Outcome Mean | 10.34 | 0.640 | 0.0168 | 7.741 | 12.94 | 0.511 |
| Observations | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |

*Notes:* Table 2 presents the results from equation (1). The dependent variables in columns 1-6 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month, county fixed effects, county-specific linear time trend, and controls. Controls include unemployment rates, population, and deputy sheriffs per 100,000. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 3: Impact of election losses on arrest rates of higher-level offenses**

| Arrests per 100k | Murder and Non-negligenet Manslaughter (1) | Forcible Rape (2) | Robbery (3) | Aggravated Assault (4) | Larceny-theft (5) | Motor Vehicle Theft (6) | Arson (7) | Burglary (8) |
|---|---|---|---|---|---|---|---|---|
| Lost x Post | 0.00815 | -0.0296 | 0.0254 | 0.0484 | -0.192 | 0.0549 | -0.00877 | 0.152 |
| | (0.0255) | (0.0228) | (0.0203) | (0.101) | (0.154) | (0.0460) | (0.0282) | (0.130) |
| Outcome Mean | 0.117 | 0.200 | 0.237 | 2.760 | 4.530 | 0.567 | 0.0882 | 1.942 |
| Observations | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 | 21,807 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y |

*Notes*: Table 3 presents the results from equation (1). The dependent variables in columns 1-8 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month, county fixed effects, county-specific linear time trend, and controls. Controls include unemployment rates, population, and deputy sheriffs per 100,000. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 4: The impact of the *new sheriff taking office* on the arrest rates of lower-level offenses**

| Arrest per 100k | Assault (1) | Fraud (2) | Gambling (3) | DUI (4) | Drug (5) | Sexual Misconduct (6) |
|---|---|---|---|---|---|---|
| NewSheriff x PostJan | -0.0683 | -0.0322 | 0.00463 | -0.271 | -0.390* | -0.0144 |
| | (0.108) | (0.0251) | (0.00473) | (0.171) | (0.199) | (0.0203) |
| Outcome Mean | 10.32 | 0.627 | 0.0198 | 7.530 | 13.22 | 0.476 |
| Observations | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |

*Notes*: Table 4 presents the results from equation (2). The dependent variables in columns 1-6 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month, county fixed effects, county-specific linear time trend, and controls. Controls include unemployment rates, population, and deputy sheriffs per 100,000. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5: Impact of *new sheriff taking office* on arrest rates of higher-level offenses**

| Arrests per 100k | Murder and Non-negligent Manslaughter (1) | Forcible Rape (2) | Robbery (3) | Aggravated Assault (4) | Larceny-theft (5) | Motor Vehicle Theft (6) | Arson (7) | Burglary (8) |
|---|---|---|---|---|---|---|---|---|
| NewSheriff x PostJan | 0.0103 | -0.0112 | 0.0110 | 0.0079 | 0.123 | 0.0144 | -0.0109 | -0.009 |
| | (0.0120) | (0.00907) | (0.00913) | (0.0458) | (0.101) | (0.0213) | (0.0306) | (0.0633) |
| Outcome Mean | 0.128 | 0.170 | 0.237 | 2.628 | 4.851 | 0.566 | 0.103 | 1.981 |
| Observations | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 | 22,044 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y |

*Notes*: Table 5 presents the results from equation (2). The dependent variables in columns 1-8 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month, county fixed effects, county-specific linear time trend, and controls. Controls include unemployment rates, population, and deputy sheriffs per 100,000. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 6: Impact of election losses on deputy sheriff employment and payroll by type of employment**

| Arrests per 100k | Full-time Employees (1) | Payroll (Full-time) (2) | Payroll (Part-time) (3) | Part-time Employees (4) | Hours (Part-time) (5) |
|---|---|---|---|---|---|
| Lost x Election Year | -11.82* | -31,122 | 2,616* | 0.945 | 132.3 |
| | (6.200) | (32,262) | (1,539) | (1.350) | (96.64) |
| Outcome Mean | 555.9 | 3.252e+06 | 25,745 | 24.23 | 1,644 |
| Observations | 8,987 | 8,987 | 8,987 | 8,987 | 8,987 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y |

*Notes*: Table 6 presents the results from equation (3). The dependent variables in columns 1–5 measure staffing outcomes for sheriff's offices: the number of full-time deputies, full-time payroll expenditures, the number of part-time deputies, part-time payroll expenditures, and total part-time hours worked. All regressions include year, county fixed effects, county-specific linear time trend, and controls. Controls include unemployment rates, population, and deputy sheriffs per 100,000. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

# 7 Appendix Tables

**Table A1: Non-index arrest categories and corresponding offense types and descriptions**

| Non-index arrest Category | Component Offense | Description |
|---|---|---|
| Assault | Simple Assault | The intentional, non-felonious attempt or threat to cause physical harm to another person without the use of a deadly weapon and without causing serious bodily injury. |
| | Intimidation | The intentional act of threatening or frightening another person through verbal, written, or physical behavior, without a physical attack or display of a weapon. |
| Fraud | False Pretenses | Obtaining money, goods, or services through intentional misrepresentation or deceit. |
| | Welfare Fraud | Knowingly providing false information or withholding information to obtain public assistance benefits unlawfully. |
| | Wire Fraud | Using electronic communications (telephone, internet, email, etc.) as part of a scheme to defraud another person of money, property, or services. |
| | Credit Card Fraud | Unauthorized or deceitful use of a credit or debit card to obtain goods, services, or funds. |
| | Impersonation | Assuming another person's identity (real or fictitious) to deceive or defraud, including identity theft. |
| Gambling | Betting and Wagering | Participating in or placing unlawful bets or wagers for money or other items of value. |
| | Operation or Promoting Gambling | Running, managing, financing, or publicly encouraging an illegal gambling operation. |
| | Gambling Equipment Violations | Possessing, manufacturing, selling, or using devices or equipment intended for illegal gambling activity. |
| | Sports Tampering | Altering, influencing, or attempting to influence the outcome of a sporting event through illicit means. |
| Driving Under the | Driving Under the | Operating a motor vehicle while impaired by alcohol, drugs, or other intoxicating substances. |
| Influence (DUI) | the Influence (DUI) | Operating a motor vehicle while impaired by alcohol, drugs, or other intoxicating substances. |
| | Drug/Narcotic | Unlawful possession, purchase, distribution, manufacture, sale, or use of controlled substances |
| | Violations | (e.g., heroin, cocaine, methamphetamine, opioids). |
| Drug | Drug Equipment | Possession, sale, manufacture, or use of items intended to prepare, package, consume, or produce illegal drugs |
| | Violations | (e.g., pipes, syringes, scales). |
| Sexual Misconduct | Forcible Fondling | Touching the private body parts of another person forcibly and against their will, for sexual gratification. |
| | Forcible Sodomy | Oral or anal sexual intercourse with another person forcibly and against their will. |
| | Sexual Assault With an Object | Penetration of another person's genital or anal opening with any object, forcibly and against their will. |
| | Incest | Non-forcible sexual intercourse between persons who are legally too closely related to marry (e.g., parent–child, siblings). |

**Table A2: Impact of election losses on lower-level crime rates**

| Incidents per 100k | Fraud | Drug | Gambling | Sexual Misconduct | Assault |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Lost x Post | -0.246 | 0.102 | -0.00382 | -0.0473 | -0.223 |
| | (0.191) | (0.412) | (0.00380) | (0.0526) | (0.342) |
| Outcome Mean | 8.313 | 16.85 | 0.0135 | 1.961 | 30.10 |
| Observations | 37,414 | 37,414 | 37,414 | 37,414 | 37,414 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y |

*Notes*: Table A2 presents the results from equation (1). The dependent variables in columns 1-8 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month and county fixed effects. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table A3: Impact of new sheriff taking office on higher-level crime rates**

| Incidents per 100k | Fraud | Drug | Gambling | Sexual Misconduct | Assault |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| NewSheriff x Post Jan | 1.10e-07 | -3.44e-06 | -6.48e-09 | -2.43e-07 | -2.42e-08 |
| | (9.98e-07) | (2.29e-06) | (2.77e-08) | (3.71e-07) | (1.96e-06) |
| Outcome Mean | 7.19e-05 | 0.000154 | 1.60e-07 | 1.75e-05 | 0.000274 |
| Observations | 20,577 | 20,577 | 20,577 | 20,577 | 20,577 |
| County and Time Fixed Effects | Y | Y | Y | Y | Y |
| Linear time Trend | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y |

*Notes*: Table A3 presents the results from equation (2). The dependent variables in columns 1-8 are continuous variables that represent population-weighted arrest rates per 100,000 people. All regressions include year-month and county fixed effects. Standard errors are clustered at the county level. Robust standard errors in parentheses. Asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.