

Democratic mayors have no effect on crime, but do reduce the Black share of arrests for petty crimes

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January 23, 2023

Abstract

We examine whether mayors' partisan affiliations lead to differences in crime rates, arrest rates, and the racial composition of arrests. We employ a regression discontinuity design centered around close mayoral elections to determine the causal effect of electing a Democratic rather than Republican mayor on policing and crime outcomes in medium and large US cities. Mayoral partisanship does not affect overall crime rates, arrests, or police employment and expenditures. However, it does influence the racial distribution of arrests. The election of a Democratic mayor decreases the Black share of arrests by a modest amount. This effect is driven by decreases in arrests of Black individuals for both “drug crimes” and “other crimes.” This may be tied to police staffing choices, as electing a Democratic mayor also affects police officer demographics: electing a Democratic mayor increases the Black share of police officers. These results reaffirm the importance of politics in policing.

Keywords: Local politics, policing, race, criminal justice, representation, elections

We appreciate excellent research assistance on this project from Camila Alvarez Bisbe, Caitlin Berg, Noam Brenner, Tom Cawley, Cole Dushin, Alexander Hupp, Josh Koppel, Jace Knie, Cory Maks-Solomon, Jeremy Marsh, Yusuf Mian, Daniel Perez, Rob Pressel, Annelies Quinton, John Ramsey, Annie Salyers, Anmol Sapru, Josiah Selagea, Mikaela Rose Tajo, Ariel Wexler, and Yiling Yao. We also appreciate feedback on earlier versions of this manuscript from Desmond Ang, Jennifer Doleac, Anna Gunderson, Mirya Holman, Josh Kalla, Jacob Kaplan, Dean Knox, Shiro Kuriwaki, Mark Moore, Ariel White, and Richard Zeckhauser, and seminar participants at Vanderbilt University, Tulane University, Louisiana State University, and Yale University. This work was supported by funding from the MIT Election Data and Science Lab and the Boston University Initiative on Cities.

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Political campaigns for mayor and other local offices often revolve around how the election will affect crime rates and arrest patterns. Republican mayors commonly take a “tough on crime” approach and promise that they will reduce local crimes rates, often via punitive policy (Beckett, 1997; Simon, 2007). At the national-level, former-President Trump blamed increases in crime rates on Democratic mayors, arguing that Democratic-run cities are “rampant with crime” (Giles, 2020). This suggests that the election of Republican mayor may decrease local crime rates. However, Democrats have also campaigned on promises to reduce crime, and have often implemented punitive policies (Beckett and Francis, 2020; Gunderson, 2022; Murakawa, 2014). At the same time, Democratic mayors and other local politicians often focus more than Republicans on racial inequities and especially on reducing inequities in policing (Einstein, Godinez Puig, and Piston, 2021; Yntiso, 2021). But, mayors and other elected officials only have narrow sets of tools to actually influence local crime rates, which are largely a function of larger societal forces (e.g. Agan, Doleac, and Harvey, 2021; Dynes and Holbein, 2020). So there may be limited or no effect of mayoral partisanship on crime and arrests.

To our knowledge, no previous study has systematically assessed whether mayoral partisanship affects local crime rates and arrest patterns. In this paper, we examine whether mayors’ partisan differences in reported views on policing translate into differences in policy and policing outcomes. We draw on nearly three decades worth of data on mayoral elections in medium and large American cities. We use a “quasi-experimental” method to identify the causal impact of mayoral partisanship. Specifically, we focus on narrowly won elections, where the winner is close-to-randomly selected from a set of one candidate from either party.

Using that approach, we assess the impacts of electing Democratic rather than Republican mayors on the overall levels of reported crime, arrests, and police employment and spending. On all of these outcomes, we find no difference in the impacts of electing a Democrat or a Republican. However, we find that Democratic mayors influence the demographic composition of police forces. Specifically, they increase the share of police officers that are

Black. Previous work documents that Black officers make fewer stops and arrests, especially of Black civilians, and that white officers use force far more in majority Black neighborhoods than Black officers (Ba et al., 2021; Hoekstra and Sloan, 2022). This suggests that changes in the racial composition of the police force from mayors could lead to changes in the racial composition of arrests. In line with this expectation, we find that the election of a Democratic mayor modestly reduces the Black share of arrestees, especially for drug crimes and crimes that do not fit in a clear category (e.g., vagrancy, loitering).

Background

A long line of research in political science demonstrates that parties shape the behavior of national and state level politicians. Republican politicians have more ideologically conservative policy positions and voting records than Democratic politicians in Congress and state legislatures (Lee, Moretti, and Butler, 2004; Shor and McCarty, 2011), and this polarization between parties has only increased over time (e.g. McCarty, Poole, and Rosenthal, 2016). Recent research has suggested that these partisan effects on policy outcomes extend to the local level (de Benedictis-Kessner and Warshaw, 2016, 2020). In particular, the election of a Democratic mayor (compared to a Republican mayor) leads to greater municipal expenditures (de Benedictis-Kessner and Warshaw, 2016).

Policing is an important area of local politics where mayoral partisanship may matter. Republican mayors often promise that they will reduce local crimes rates by increasing police spending and making criminal justice policies more punitive (Beckett, 1997; Simon, 2007). But mayors have important constraints on their ability to unilaterally influence policy (Gerber and Hopkins, 2011; Peterson, 1981). Mayors often face oversight both from below (by city councils) and above (by states), and potential policy changes are limited by budget limitations, civil service rules, and collective bargaining agreements. Moreover, pledges to increase spending on police often lie in tension with conservatives' larger policy goal of

shrinking the size of government. Thus, perhaps it is unsurprising that there is mixed evidence from past research on the effect of mayoral partisanship on police expenditures (de Benedictis-Kessner and Warshaw, 2016; Gerber and Hopkins, 2011). There has been little prior work on whether mayoral partisanship affects overall crime rates or arrest patterns, though some work has shown it has no impact on violent crime (Ferreira and Gyourko, 2009). In contrast, descriptive work finds that Democratically-led cities tend to have higher levels of crime – in large part because of underlying demographic patterns (Brownstein et al., 2021; Ferreira and Gyourko, 2009).

Mayoral partisanship could also affect the demographic composition of arrests. Previous academic work has shown that Black drivers are more likely to be stopped than white drivers; searches of Black drivers are less likely to produce “contraband,” indicating a lower threshold for pulling them over (Grogger and Ridgeway, 2006; Pierson et al., 2020; Roach et al., 2020). Contact with police is more likely to lead to arrest for Black Americans even controlling for contextual factors (Schleiden et al., 2020), with substantial evidence of this phenomenon in the context of drug arrests in particular (Mitchell and Caudy, 2015; Koch, Lee, and Lee, 2016). Democratic mayors and other local politicians often promise to reduce these racial inequities in policing (Einstein, Godinez Puig, and Piston, 2021).

Data and Research Design

In order to examine the policy effects of the partisan control of city governments, we collect data on city mayoral elections and criminal justice policy and outcomes in medium and large cities with a population of more than 75,000 people in 2020. We then leverage a regression discontinuity (RD) design to identify the causal effect of electing mayors of different parties on policing.

Data

The foundation of our analysis is administrative data on mayoral elections in medium and large cities. The elections data consists of 3,248 individual elections between 1990 and 2022 in 398 cities with at least 75,000 people in 2020. Our analysis requires information on each candidate’s partisanship even in officially nonpartisan elections. We augmented the raw election returns with information about individual candidates’ partisanship by matching the election returns with a wide range of auxiliary data. First, we sought to match each candidate to a record in L2 and TargetSmart’s national voter files by name and location. Second, we sought to match each candidate with campaign finance-based ideology scores (Bonica, 2014, 2019). Third, we matched candidates that served in Congress or state legislatures to determine their party and roll-call based ideal points (Shor and McCarty, 2011; Lewis et al., 2021). We also leveraged information from previous academic studies (Ferreira and Gyourko, 2009; Gerber and Hopkins, 2011)

We examine the impact of mayoral partisanship on a number of criminal justice outcomes. First, we use data on fiscal policy data from the Historical Database of Individual Government Finances to examine the effects of mayoral partisanship on policing-related government expenditures.¹ We also harness data from the Census Bureau’s Annual Survey of Public Employment and Payroll (ASPEP), which records both the number of employees of different types and the payroll expenditures on those employees for local governments. In tandem with these data, we also draw on data from Law Enforcement Management and Administrative Statistics (LEMAS), a survey of law enforcement agencies administered by the Bureau of Justice Statistics roughly every 4-5 years since 1987. The most recent available wave of the survey is from 2016. These surveys, for most of the survey waves, provide data on the demographics of officers, the overall number of sworn officers, and some administrative

¹These data are based on a Census of Governments conducted every five years and the Annual Survey of Governments collected in every non-census year. We adjusted all monetary figures into 2019 dollars based on the consumer price index. In our analyses of fiscal policy, we use logged per capita expenditures to account for population differences across cities.

features of the agencies – e.g., whether collective bargaining is allowed. We merge these data with our elections data to create outcomes based on changes in police demographics between the most recent LEMAS survey before the election and the next LEMAS survey after the election. These data are an imperfect source of over-time information on police forces, given that they are not conducted yearly, so we restrict our use of this outcome variable to surveys within a reasonable time range around the election by only using baseline pre-surveys that were 0-4 years before the election, and post-surveys that were 2-4 years after the election. Finally, as a corroborating source of data on police demographics, we use data from the FBI’s Law Enforcement Officers Killed and Assaulted (LEOKA) survey, which (along with information on violent police-civilian interactions) records the total number of police officers employed by a city and the gender of those officers.

Our data on crime and policing outcomes are drawn from the Federal Bureau of Investigation Uniform Crime Report (UCR) data (Kaplan, 2020, 2021). UCR data are compiled by the FBI based on reports from law enforcement agencies and provide annual agency-level counts of reported crime offenses, clearances, and arrests for a variety of offense types. As we study mayors, we restrict the law enforcement agencies we consider to city police departments. Throughout most of our analysis, we normalize variables that are in levels (rather than proportions) by the city’s population.

We report data on crimes overall and in several categories: total “index crimes,” which are the eight offenses used by the FBI to produce crime indices (murder, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and arson), violent index crimes, and property index crimes. The latter two are subsets of the eight index offense types. Likewise, we report results on arrests overall and by category, including property crime, violent crime, drug crime, and “other” crime. The “other” category of arrests includes offense types for which enforcement may be particularly subject to law enforcement officer discretion: e.g., vagrancy, loitering, or drunkenness, to name a few.

Finally, we leverage data on the racial composition of arrests in the UCR data. We

estimate the *Black share of arrests* based on the number of arrestees coded as Black in the data in a given city-year divided by the total number of arrests in that city-year. We construct this both for overall arrests and each of the categories noted above. We also construct the ratio of Black-to-white arrests as an alternative measure. Note that the arrests data are disaggregated by the age, race, and sex of the arrestee – but not by ethnicity (Hispanic vs. non-Hispanic).

Regression Discontinuity Design

We use a regression discontinuity (RD) design to identify the causal effect of electing mayors of different parties on policing, a strategy that has been widely employed to estimate the causal effects of elected official identity on political and policy outcomes.² We exploit the fact that a sharp electoral threshold, 50% of the two-party vote share, determines which party wins mayoral elections. Cities where the mayoral election was won by a very narrow margin of a Democrat over Republican (or vice versa) are *as-though* randomly assigned to one mayoral partisanship rather than the other. The RD method therefore focuses on differences in outcomes in very narrow elections. In practice, the effect of electing a Democratic mayor rather than a Republican mayor is identified by restricting the sample to elections within a bandwidth around the 50% threshold in the Democrats’ vote share³ and estimating the “jump” in outcome variables *at* the threshold – or the elections closest to a tie.⁴

²Previous studies in the urban politics literature have also used the regression discontinuity design to examine the local incumbency advantage (de Benedictis-Kessner, 2018; Ferreira and Gyourko, 2009; Trounstein, 2011), the effects of mayoral partisanship (Ferreira and Gyourko, 2009; Gerber and Hopkins, 2011; de Benedictis-Kessner and Warshaw, 2016) and race (Hopkins and McCabe, 2012) on fiscal policy, the effects of electing mayors or city councilmembers with business experience on city policies (Kirkland, 2021; Beach and Jones, 2016), the impact of racial diversity in city councils on spending patterns (Beach and Jones, 2017), and the impacts of partisan (Macartney and Singleton, 2018) and racial (Kogan, Lavertu, and Peskowitz, 2021) representation in school boards.

³Using the default optimal bandwidth options in the `rdrobust` package in R (Calonico, Cattaneo, and Titiunik, 2014a), which selects an optimal bandwidth to minimize mean-squared-error (MSE) in the estimate and adjusts confidence intervals to account for remaining bias from the bandwidth selection procedure (Calonico, Cattaneo, and Titiunik, 2014b; see also Imbens and Kalyanaraman, 2012).

⁴This design identifies a local average treatment effect at the threshold of 50% vote share, which might raise concerns about the applicability of the estimates from this design to cities where there are not close mayoral elections. This concern is at least partially assuaged by the fact that, of medium and large cities over 75,000

The validity of the RD design depends on the assumption that only the winning candidate — and not the distribution of units’ potential outcomes — changes discontinuously at the threshold (Hahn, Todd, and Klaauw, 2001; Lee and Lemieux, 2010). Results from tests in SI Appendix B document that these assumptions are likely satisfied in our setting. Consistent with a recent large-scale validation of electoral regression discontinuity (RD) design studies (Eggers et al., 2015), we also observe no significant discontinuities in lagged values of the running variable or outcome variables.⁵

In order to increase statistical efficiency, we estimate treatment effects on changes in outcomes rather than on levels (Lee and Lemieux, 2010). In order to account for the lag in time between a politician taking office and their ability to influence policy outcomes, our main analyses focus on the difference between policing outcomes in the election year and the average of outcomes measured two and three years after the election.⁶

Results

In this section, we discuss the impact of mayoral partisanship on the criminal justice system in cities. First, we examine the impact of mayors on overall police expenditures and staffing. Next, we examine whether mayoral partisanship affects aggregate crimes and arrests. Then, we examine how mayoral partisanship affects the demographic composition of police forces. Finally, we examine its effect on the racial composition of arrests.

in population in our data, our elections data cover 99% of the population in this target universe, and 89% of those cities in our elections data had a close election at some point and are therefore included in our RD analyses. The coverage of our data and the subsample of cities with close elections is further described in SI Appendix A.

⁵These placebo results are shown in SI Appendix C.

⁶This strategy enables us to increase statistical power over a strategy using changes in outcomes between the election year and two (or three) years after the election by reducing noise in outcomes from individual years in a similar approach to other RDD research (de Benedictis-Kessner and Warshaw, 2016, 2020; Gerber and Hopkins, 2011).

Police Expenditures and Staffing

Republican politicians’ tough on crime rhetoric implies they would raise police expenditures and staffing levels relative to Democrats. We evaluate this hypothesis by examining the impact of mayoral partisanship on police employment levels (using the Annual Survey of Public Employment and Payroll data) and related municipal expenditures (using the Historical Database of Individual Government Finances). Figure 1 displays these results. Each point represents the estimate of the “jump” in the noted outcome at the 50% threshold that determines which party wins – in other words, the causal effect of electing a Democratic mayor rather than a Republican. The bars emanating from each point are 90% and 95% robust bias-corrected confidence intervals.⁷

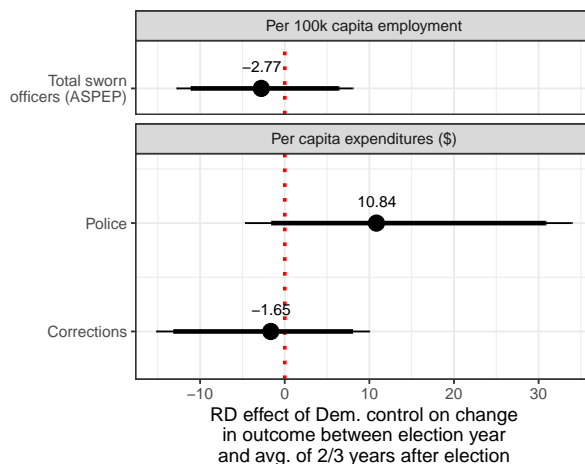


Figure 1: The effect of mayoral partisanship on municipal police employment and criminal justice spending. Points indicate estimates from the regression discontinuity design using the robust bandwidth selection procedure estimated with `rdrobust` and lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

The top panel of Figure 1 indicates that electing a Democratic mayor has little detectable impact on the changes in the per capita total number of police officers employed by a city.⁸

⁷We report tabular versions of these results and all others in this section showing the bandwidth selected by `rdrobust`, the effective n within that bandwidth, and the estimates and associated standard errors in SI Appendix D.

⁸We also replicate these analyses using two other datasets that also track the number of police officers employed by a city: the LEMAS and LEOKA datasets. Though we are most inclined to trust the estimates from the Census Bureau’s ASPEP rather than the other two datasets, which are based on voluntary opt-in surveys of police departments, we present all three results for the sake of transparency in SI Appendix E.

The bottom panel displays the estimates of mayoral partisanship on two categories of municipal spending: those directly on police protection as well as expenditures on corrections. In both cases, we find no discernible impact of electing a Democrat as mayor on per capita spending in these policy areas related to criminal justice.

Overall Crime, Arrests, and Policing

The lack of any partisan impacts on overall policing employment or expenditures suggests that despite Republicans' tough on crime platforms, there may not be substantial effects of mayoral partisanship on policy levers related to criminal justice. We next examine the empirical impact of mayoral partisanship on overall crime, clearance rates, and arrests in Figure 2. The horizontal axis reports our estimates of the causal impact of Democratic mayors (versus Republican ones) on the overall per capita levels of reported crime and clearance rates (left panel) and overall numbers of arrests (right panel).

Notably, none of the estimates are statistically different than zero. For example, the top point in the left panel of Figure 2 shows that electing a Democrat as mayor rather than a Republican has no detectable causal effect on overall levels of crime, though the point estimate is negative. The confidence interval around this estimate, while wide, allows us to rule out increases in overall crime of up to 0.35 crimes per 100,000 capita. Given concerns about potential underpowered analyses in regression discontinuity analyses (Stommes, Aronow, and Sävje, 2021), we also conduct post-hoc power analyses (Cattaneo, Idrobo, and Titiunik, 2022; Cattaneo, Titiunik, and Vazquez-Bare, 2019). These power calculations indicate that the probability of rejecting the null hypothesis were the true effect to be equivalent in size to 0.55 crimes per capita, or half a standard deviation, is relatively high, at 0.85. This suggests that the reason we are unable to reject the null hypothesis of no effect on crime is likely not a lack of statistical precision but instead the small size of these effects.

We also find no discernible effect of mayoral partisanship on crime when disaggregating to available categories of crimes (index, property, and violent), which we show in the next

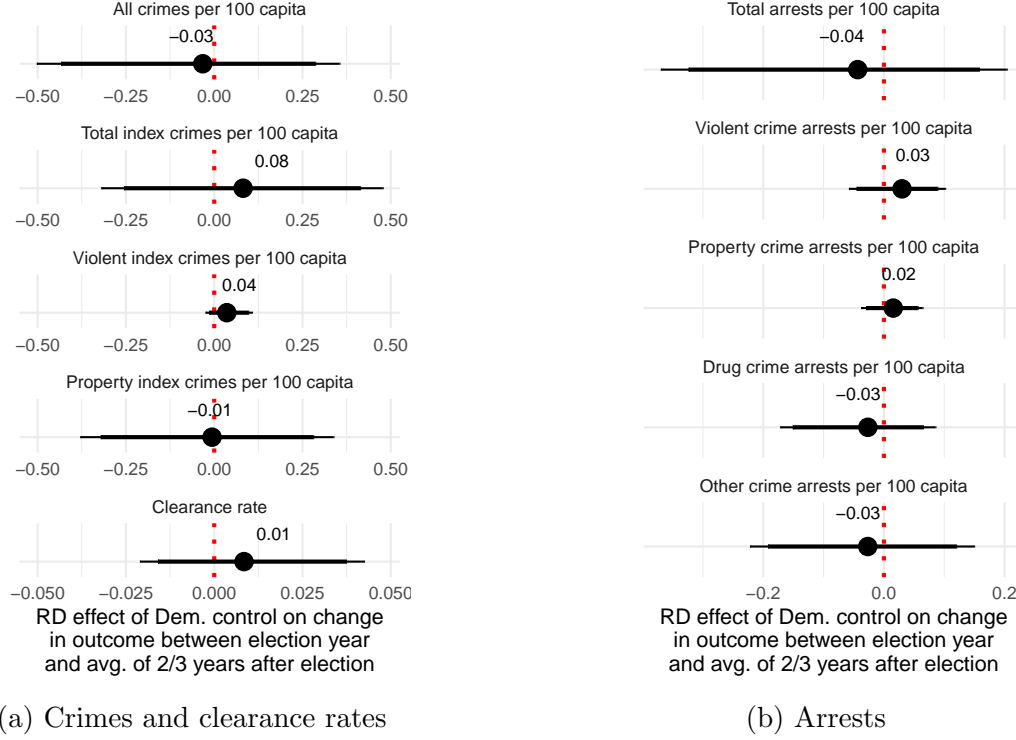


Figure 2: The null effect of mayoral partisanship on changes in per capita reported crimes and clearance rate (left) and per capita arrests (right) between the election year and the average of two and three years after the election. Points indicate estimates from the regression discontinuity design using the robust bandwidth selection procedure estimated with `rdrobust` and lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

set of points in the left panel of Figure 2. Likewise, we cannot reject the null hypothesis of no change in the clearance rate – the share of reported crimes that are resolved in some way (shown with the bottom point and lines in the left panel). In the righthand panel, we focus on arrests. The estimate of the impact of Democratic mayors on total arrests per capita is also not statistically distinguishable from zero.⁹ We also test for impacts on specific categories of arrests. We find that the estimated impacts of Democratic mayors on overall numbers of violent, property, and drug crime arrests are close to zero and are all statistically insignificant. Overall, we find that the election of a Democratic, rather than Republican,

⁹Post-hoc power calculations again indicate that these are relatively precisely estimated nulls, and that the probability of rejecting the null hypothesis were the true effect to be equivalent in size to half a standard deviation in the outcome, or 0.3 arrests per 100 capita, is 0.68.

mayor is not causally associated with differences in the levels of police employment, police spending, reported crimes, or arrests.

Racialized Policing

While mayoral partisanship has no effect on overall crime or arrests, it is possible that it leads to changes in the *way* that police forces act in the conduct of their jobs – and specifically the racial composition of their arrests.

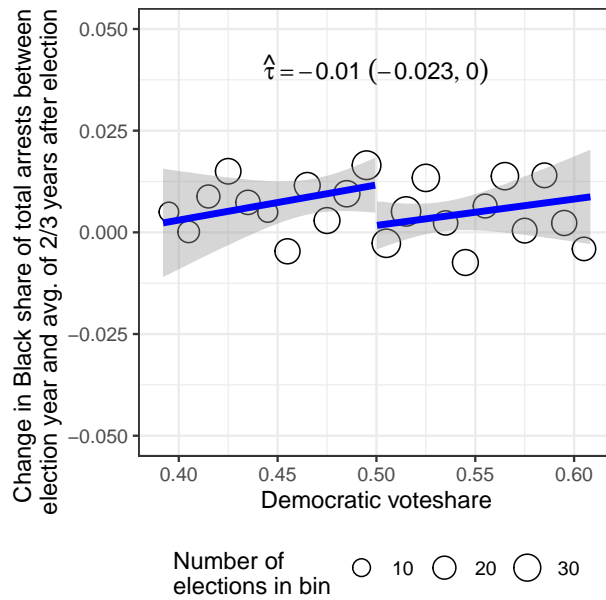


Figure 3: The effect of mayoral partisanship on the Black share of total arrests. Open circles indicate averages of the change in Black share of total arrests between the election year and the average of two and three years after the election, within bins of Democratic voteshare. Lines indicate regressions fit to the underlying data points with the triangular kernel to mimic our research design’s weighting of observations close to the threshold of 0.5.

Figure 3 shows the effect of mayoral partisanship on the Black share of total arrests. The vertical axis of the plot displays our outcome – the change in the Black share of total arrests between the election year and 2-3 years after the election. The horizontal axis displays the Democratic candidate’s voteshare, and each open circle represents the average outcome within a given bin of Democratic voteshare. As 50% is the threshold that determines whether the Democratic or Republican candidate wins, points to the right of 0.50 on the horizontal

axis represent elections where the Democrat won and points to the left represent elections where the Republican won. The lines represent regressions fit to the underlying data on either side of the threshold of 0.5. Our main focus, as outlined above, is on any “jump” or discontinuity in the lines at the threshold of 0.5, as that represents the causal effect of mayoral partisanship on changes in the outcome. We find that the narrow election of a Democrat rather than a Republican is associated with a one percentage point reduction in the Black share of total arrests; relative to a sample average of 30%, this represents a 3.3% drop. This effect also represents a large decrease of 52% relative to a more appropriate comparison of the typical within-city change in the Black share of total arrests over the course of 2-3 years, which is 1.9% (Mummolo and Peterson, 2018).

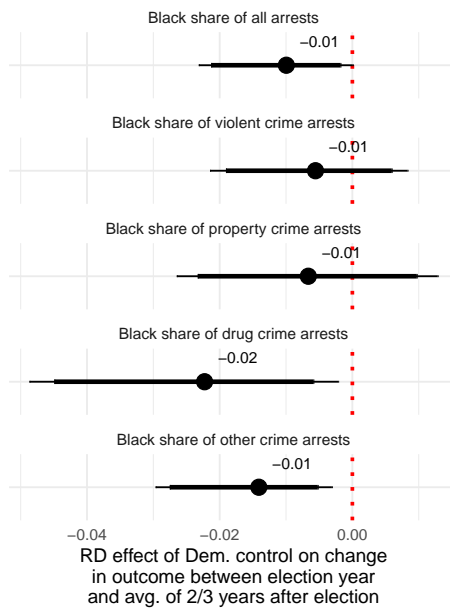


Figure 4: The effect of mayoral partisanship on the change in the Black share of arrests between the election year and the average of two and three years after the election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

Figure 4 depicts estimates from our regression discontinuity design, but now examining the Black share of arrests for each category of crimes separately. The top point again shows that the election of a Democratic mayor is associated with a statistically significant

one percentage point reduction in the Black share of all arrests, as previously reported in Figure 3. Looking among categories of arrests, displayed in the lower points, we detect no statistically significant impact on the Black share of violent crime or property crime arrests. However, there is a clearly statistically significant decline in the Black share of both “drug crimes” arrests and “other crimes” arrests. The sample average of Black share of drug crime arrests is 33.8% and other crime arrests is 24.1%, so these declines of 2.2 and 1.4 percentage points, respectively, represent 6.6% and 5.8% changes.¹⁰ In the supplementary materials, we show that these effects are no different in cities with strong mayors rather than council-manager systems of government (SI Appendix K), nor are they different in cities with officially partisan elections rather than those with officially nonpartisan elections (SI Appendix L). Despite the fact that our data cover a large time period that spans vastly different national narratives around race and policing, our effects also do not seem to be confined to a single time period, as we show in SI Appendix M.¹¹

One Potential Mechanism: Police Demographics

Why might Democratic mayors change the demographic patterns of arrests made by their city’s police forces? Recent research demonstrates how the demographics of police officers

¹⁰In SI Appendix F, we use the alternative outcome of the logged ratio of Black-to-white arrests rather than the Black share of arrests, as well as the outcome of the per capita number of Black arrests. Similarly, in SI Appendix G, we use logged per capita measures of crimes and arrests rather than just per capita measures displayed in the main body of the paper. These approaches yield similar results – albeit with some loss in statistical precision – and generally support the same basic conclusion. In SI Appendix H, we show that our results are largely similar when using either a 0-order polynomial (i.e. differences in means within a narrow bandwidth) or higher-order polynomials. In SI Appendix I, we also show that they are directionally consistent and largely similar in size when using alternative bandwidths to the MSE-optimal bandwidth selected by `rdrobust`. In SI Appendix J, we demonstrate the timeline of these effects, as well as the robustness of our analyses to the choice of time period over which we calculate our measures of change.

¹¹In addition, in SI Appendix N, we examine whether these effects are driven by the race of the mayor instead of their party by assessing the effect of mayoral partisanship using only White Democratic candidates running against Republicans, rather than Democrats of any racial background, and find that our results are substantively similar. Finally, in SI Appendix O, we present results using a different approach altogether. Namely, we estimate non-parametric difference-in-differences models using the PanelMatch method (Imai, Kim, and Wang, 2021), which compares units with similar treatment histories (i.e. party control) and similar pre-treatment outcomes (i.e. composition of arrests) that are “treated” with a Democrat taking control of the mayoral office vs. those that are not treated (i.e. a Republican takes control). These results are also consistent with our primary regression discontinuity-based approach.

can influence their use of force and arrest patterns. Indeed, research on the diversification of police forces indicates that Black officers engage in less enforcement than white officers, especially enforcement stops, arrests, and use of force against Black civilians (e.g. Ba et al., 2021; Edwards, Lee, and Esposito, 2019; Hoekstra and Sloan, 2022). Moreover, female officers are less likely to search drivers during traffic stops (Shoub, Stauffer, and Song, 2021). Thus, an increase in female police officers could reduce the Black share of arrests since traffic stops often disproportionately target Blacks (Roach et al., 2020).

To examine this potential moderator, we turned to data on *who* the police in cities are and examine how mayoral partisanship affects the demographic composition of police forces using the LEMAS data (for racial demographics) and both the LEMAS and LEOKA data (for gender). Though the LEMAS data on the racial composition of the police are limited in their precision due to the infrequency of the data collection, we take these results as tentative evidence of potential patterns. These results are reported in Figure 5.

We find that the share of officers who are Black significantly increases by 1.2 percentage points as a result of electing a Democrat (rather than a Republican) as mayor ($p = 0.06$); relative to the sample average of 9.6% Black share of police officers, the increase of 1.2 percentage points represents an increase of roughly 12.2%. We find mixed evidence that Democratic mayors increase or have no effect on the share of police officers that are women, depending on whether we use the LEMAS or the LEOKA data.

How might mayors be influencing the demographics of police forces without changing the overall numbers of police officers or their city’s spending on police? One crucial tool at the disposal of mayors is (in most places) the power to appoint a police chief who plays a more direct role in both police staffing and officers’ everyday practices when doing their job.

To examine the impact of mayors’ partisanship on police chiefs, we collect data on the names (and demographics) of police chiefs in the cities in our elections data for the period 2010-2022. Though this data collection process is still ongoing, we have some preliminary evidence that electing a Democratic mayor may increase the likelihood that the appointed

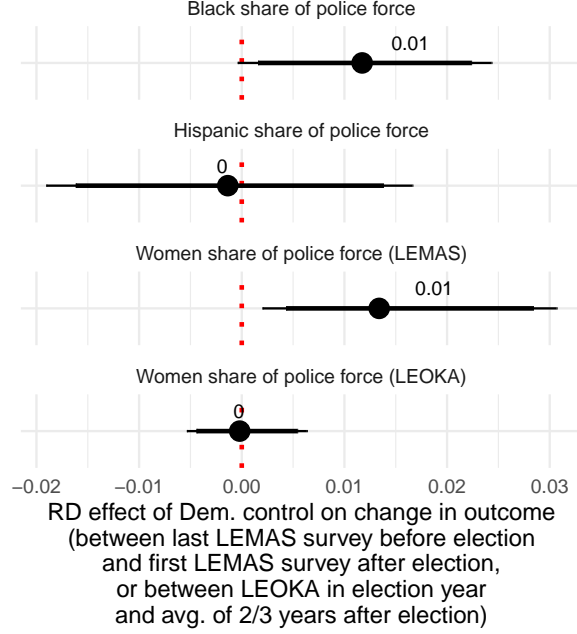


Figure 5: The effect of mayoral partisanship on changes in the demographics of police forces between the election year and the several years after the election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

police chief is not white. These results, from both a regression discontinuity design and a differences-in-differences analysis, are shown in SI Appendix P. The effects on these intermediate outcomes of both police chief and police force demographics are suggestive evidence of one plausible mechanism for the results we find in the previous section, though we caution that we cannot definitely conclude that these demographic shifts drive our main results.

Conclusion

In this paper, we examine whether political control of city governments in the US influences local policing, crime rates, and arrests. Using a large new dataset of local elections and a regression discontinuity design, we are able to disentangle the effect of the partisan control of the mayor's office from other city-level characteristics that might lead to these policing and crime outcomes.

We find no detectable effects of mayoral partisanship on police employment and expenditures, overall levels of crime, numbers of arrests, or the clearance rate of crimes. These results stand in stark contrast to national political rhetoric on crime rates and political partisanship. Candidates for political offices at the local, state, and federal level consistently raise crime as an important issue (e.g. de Benedictis-Kessner, 2022; Holman, 2016; Marion and Oliver, 2013). Voters may hold politicians accountable for these types of outcomes (e.g. Arnold and Carnes, 2012; Go, 2022; Rogers, 2013), at least partially as a result of increased news coverage (Kalmoe et al., 2019) – even if this coverage does not always match reality (Karakatsanis, 2020). Republican politicians in particular have claimed that increases in crime in large cities are a result of Democratic leaders in those places taking a “soft-on-crime” approach (McConnell, 2022). National news outlets have suggested that the outcomes of recent recall efforts and elections for prosecutors and mayors are a backlash to progressive policies on crime (Goldmacher, 2022; McCormick and Vielkind, 2022; Queally, Mason, and Nelson, 2022). Yet these popular claims ignore the reality that our results make clear: Democratic leadership of cities does not lead to any detectable increases in crime or arrests.

In contrast, we find significant effects of city leadership on the composition of arrests: electing a Democrat as mayor rather than a Republican leads to decreases in the Black share of overall arrests and the Black share of arrests for both drug and “other” crimes. In other words, Democratic mayors reduce racial disparities in arresting patterns.

This may be due to the fact that mayoral partisanship appears to influence the demographic composition of police forces. In particular, we find that electing a Democratic rather than a Republican mayor leads to increases in the Black share of police officers. Previous work on police use-of-force suggests that the racial composition of police officers can have a strong effect on racial disparities in policing activity and violence (Knox, Lowe, and Mummolo, 2020; Hoekstra and Sloan, 2022; Edwards, Lee, and Esposito, 2019). The effects we observe on police force demographics may therefore be a primary way in which local

politicians exert control to reduce racial disparities in citizen-police contact.

Overall, our results indicate that politics are an important influence on the police. Our analyses are inherently limited in their ability to uncover the exact mechanisms by which mayoral partisan influence on police officer behavior occurs due to a lack of broad intermediate data on mayoral influence or direct policymaking. For instance, Democratic mayors may appoint different types of police force leaders (including known “progressive” or “reform” chiefs) in their cities than Republican mayors, or they may require their police forces to undergo certain types of training to reduce racial biases in policing. Our analyses cannot assess whether these mechanisms are at play, and there are likely a bevy of mechanisms that operate together to result in these distributional changes in policing. Yet our results help build a more complete picture of crime and policing in US cities and reaffirm the importance of politics in the racialization of policing.

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Supplementary Appendix for
“Mayoral partisanship has no effect on crime, but
reduces the Black share of arrests for petty crimes”

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A Elections Data Sample

In this section, we provide further details on our mayoral elections data. Table A1 provides further details on the total elections data gathered as well as those elections used in our RDD analyses. The cities in our mayoral elections dataset encompass 99% of the population in our target universe of medium and large cities that elect mayors. Moreover, the elections that have a Democratic vote share between 40% and 60%, which roughly approximates the effective sample in many of our RDD analyses, covers 67% of the population in our target universe overall. It also covers a broad geographic range, as demonstrated by the comparison between Figure A1, which shows our full sample of cities in our elections data, and Figure A2, which shows those cities with close elections.

Table A1: Summary of Mayoral Elections Data Coverage

Subset	N Cities	N Elections	Min Pop.	Max Pop.	Avg. Pop.	Total Pop.	% of Target Uni. Pop.
All cities	19,481		0	8,804,190	10,526	205,058,014	
Medium and large cities	476		75,102	8,804,190	224,297	106,765,546	
Medium and large cities w/ mayoral elections (target universe)	419		75,102	8,804,190	240,204	100,645,272	100
Medium and large cities in elections dataset	396	3,238	75,102	8,804,190	252,594	100,027,292	99
Two-party contested elections in dataset	285	1,045	75,604	8,804,190	282,038	80,380,921	80
Two-party close elections in dataset	218	501	75,644	8,804,190	303,561	66,176,369	66

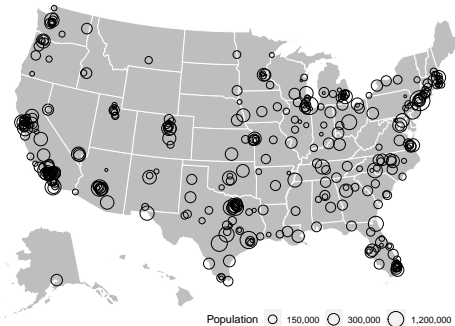


Figure A1: Cities in Elections Dataset

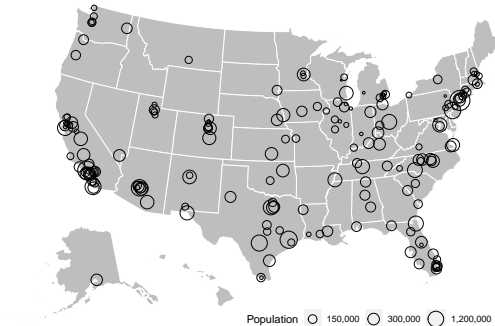


Figure A2: Cities in Elections Dataset with $40\% \leq \text{Democratic Voteshare} \leq 60\%$

B Continuity of Observations

In this appendix we present the results of the McCrary test for the continuity of the density of observations across the 50% vote threshold. These tests replicate the RDD framework but using the density of observations as the outcome. If the density of observations were to have a “jump” in numbers across the threshold, it would suggest a potential violation of the assumption that potential outcomes are continuous at the threshold.

In Table A2 below we present the results of the traditional McCrary test using the number of observations within half-percentage-point bins of voteshare. The coefficient in the second line, indicating the change in the number of observations at the threshold, represents the RDD effect on this outcome. We find a null effect, suggesting that the continuity assumption is likely to hold in this context.

Table A2: McCrary Tests

	<i>Dependent variable:</i>
	Number of observations in bin
Voteshare bin	51.383*** (16.780)
Voteshare ≥ 0.5	0.516 (1.507)
Voteshare bin \times Voteshare ≥ 0.5	-93.958*** (23.731)
Constant	10.872*** (1.065)
Observations	44
R ²	0.305
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	

We also present these results visually in Figure A3, which shows the binned number of observations both below and above the 50% vote threshold. Visual inspection corroborates the quantitative results shown in Table A2 that there is no statistically detectable effect on the density of observations at the threshold.

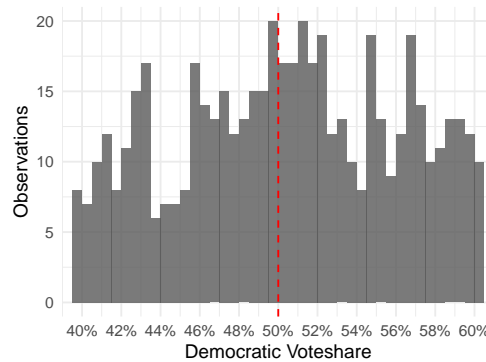


Figure A3: Histograms of observations within half percentage-point bins

A further check suggested by Cattaneo, Jansson, and Ma (2019) involves conducting

a nonparametric test for a discontinuity in the density of the running variable that does not require binning. We present the results from this nonparametric test, estimated using the R package `rddensity`, in Table A3 below. Similar to the test discussed earlier, this nonparametric test indicates no evidence of sorting across the threshold.

Table A3: Nonparametric Density Tests

t.statistic	p.value	Effective.N
0.72	0.47	552

In addition, Hartman suggests constructing an equivalence test based on the density of the forcing variable and calculating inverted p -values based on the null hypothesis of a difference in the density to the left and the right of the cutpoint (Hartman, 2021). We present results using this method in Table A4 below, which show the observed ratio between the density to the left and right of the threshold as well as the equivalence confidence interval and the p -value for the null hypothesis of a jump of greater than 50% in the density across the threshold. This test on our mayoral elections data indicates that the null hypothesis of a substantively important difference in densities can be rejected at the 90% confidence level. More importantly, the equivalence confidence interval suggests that the range in the substantive size of the difference in density across the threshold is fairly small as well.

Table A4: Density Equivalence Tests

Observed.Ratio	Equivalence.Confidence.Interval	p.value
0.85	(0.57, 1.76)	0.16

C Placebo Results

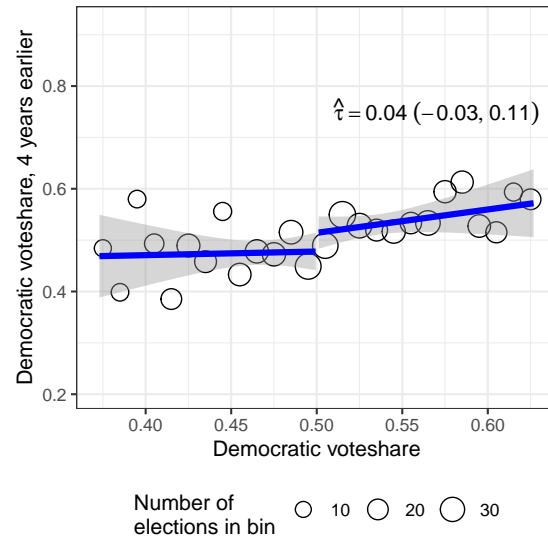


Figure A4: Placebo effect of partisanship on lagged democratic voteshare.

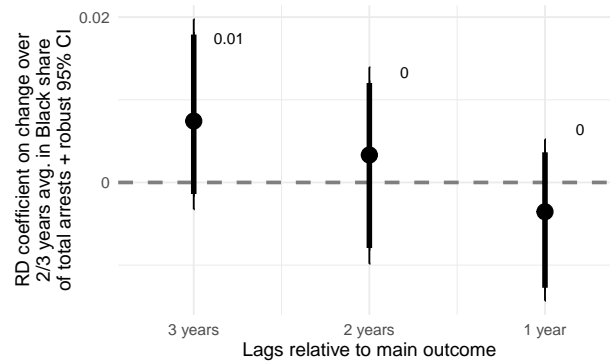


Figure A5: Placebo effect of partisanship on pre-treatment Black share of total arrests. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

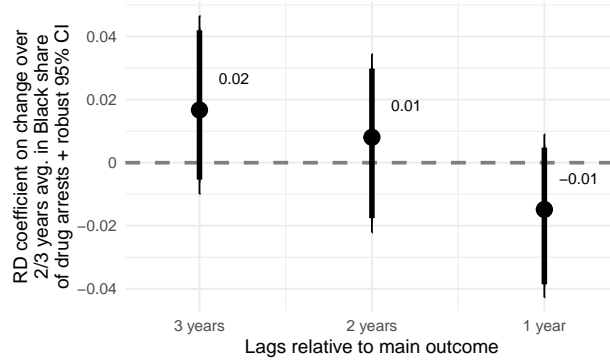


Figure A6: Placebo effect of partisanship on pre-treatment Black share of drug arrests. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

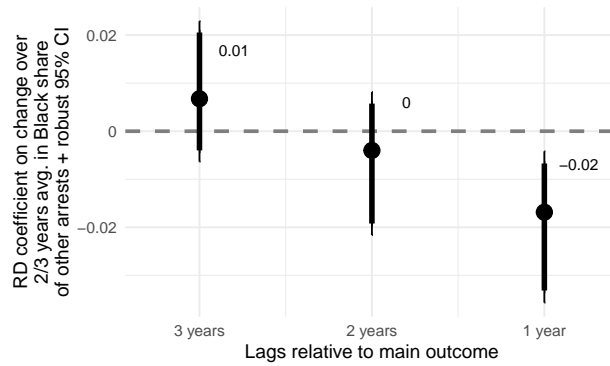


Figure A7: Placebo effect of partisanship on pre-treatment Black share of other arrests. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

D RDD Results in Tabular Format

In this appendix we present the results from the main RDD analyses of the effect of mayoral partisanship on a number of outcomes. First, in Table A7 we present the results from Figure 1 in the main manuscript, showing the effects of partisanship on overall police employment and expenditures. Then, in Table A9 we present the results showing the effects of partisanship on police force demographics from Figure 2 in the main manuscript. Tables A5 and A6 display the full RDD results analyzing the effect of mayoral partisanship on overall crime levels, clearance rates, and arrests from Figure 3 in the main manuscript. Finally, in Table A8 we present the results from Figure 4 and Figure 5 in the main manuscript on racialized arrest patterns.

Table A5: RDD Analyses: Crime

DV	Coef	p-value	BW	Obs
All crimes per 100 capita	-0.032 (-0.502, 0.355)	0.736	9.86	436
Total index crimes per 100 capita	0.082 (-0.32, 0.477)	0.698	10.7	462
Violent index crimes per 100 capita	0.036 (-0.024, 0.107)	0.218	8.03	370
Property index crimes per 100 capita	-0.006 (-0.379, 0.338)	0.911	10.9	470
Clearance rate	0.008 (-0.021, 0.042)	0.509	9.46	425

Table A6: RDD Analyses: Arrests

DV	Coef	p-value	BW	Obs
Total arrests per 100 capita	-0.043 (-0.37, 0.204)	0.57	8.35	299
Violent crime arrests per 100 capita	0.03 (-0.058, 0.102)	0.592	11.24	377
Property crime arrests per 100 capita	0.016 (-0.038, 0.064)	0.613	12.13	392
Drug crime arrests per 100 capita	-0.027 (-0.172, 0.085)	0.511	10.38	365
Other crime arrests per 100 capita	-0.027 (-0.222, 0.15)	0.703	9.71	345

Table A7: RDD Analyses: Employment and Municipal Expenditures

DV	Coef	p-value	BW	Obs
Total Sworn Officers per 100k capita (ASPEP)	-2.766 (-12.769, 8.024)	0.655	9.7	385
Police Exp. per capita	10.837 (-4.675, 33.916)	0.138	8.12	345
Corrections Exp. per capita	-1.647 (-15.155, 9.973)	0.686	9.7	398

Table A8: RDD Analyses: Racial Composition of Arrests (Shares)

DV	Coef	p-value	BW	Obs
Black share of all arrests	-0.01 (-0.023, 0)	0.051	10.93	374
Black share of violent crime arrests	-0.006 (-0.021, 0.008)	0.387	13.46	420
Black share of property crime arrests	-0.007 (-0.026, 0.013)	0.498	13.96	435
Black share of drug crime arrests	-0.022 (-0.049, -0.002)	0.032	11.08	376
Black share of other crime arrests	-0.014 (-0.03, -0.003)	0.016	10.74	369

Table A9: RDD Analyses: Police Officer Demographics

DV	Coef	p-value	BW	Obs
Black share of police force	0.012 (0, 0.024)	0.058	9.14	223
Hispanic share of police force	-0.001 (-0.019, 0.017)	0.895	10.77	243
Women share of police force	0.013 (0.002, 0.031)	0.025	7.31	181

E Alternative Employment Outcome Measurements

In the main manuscript (Figure 1) we present analyses of the effect of Democratic control on policing employment and finances using the Census Bureau’s Annual Survey of Public Employment and Payroll (ASPEP). However, both the LEMAS and LEOKA datasets also track the number of sworn police officers employed by a police force. We also analyze these independent measurements of employment, and present results including these alternative data sources in Figure A8 and Table A10 below.

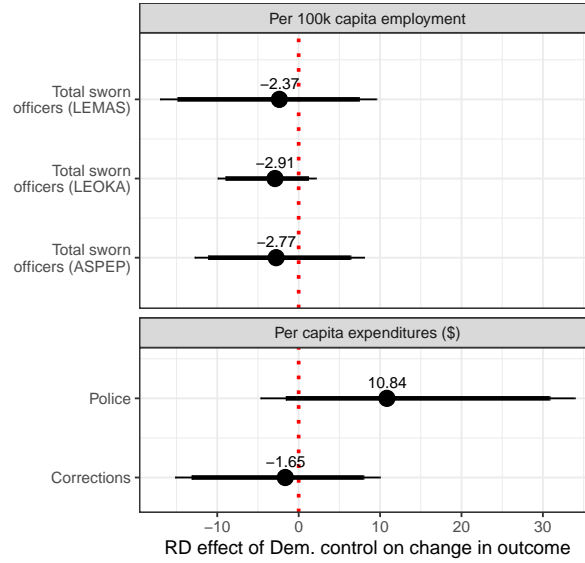


Figure A8: The effect of mayoral partisanship on municipal police employment and criminal justice spending including alternative employment outcome measurements. Points indicate estimates from the regression discontinuity design using the robust bandwidth selection procedure estimated with `rdrobust` and lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

Table A10: RDD Analyses: Employment and Municipal Expenditures

DV	Coef	p-value	BW	Obs
Total Sworn Officers per 100k capita (LEMAS)	-2.372 (-16.998, 9.533)	0.581	8.43	308
Total Sworn Officers per 100k capita (LEOKA)	-2.907 (-9.942, 2.111)	0.203	7.51	345
Total Sworn Officers per 100k capita (ASPEP)	-2.766 (-12.769, 8.024)	0.655	9.7	385
Police Exp. per capita	10.837 (-4.675, 33.916)	0.138	8.12	345
Corrections Exp. per capita	-1.647 (-15.155, 9.973)	0.686	9.7	398

F Robustness Checks: Alternative Outcomes of Black Arrest Ratios and Per Capita Numbers of Black Arrests

In the main manuscript (Figures 4 and 5), we present analyses of the effect of mayoral partisanship on the Black share of arrests. However, in this section we use an alternative outcome of the natural log of the Black *ratio* of arrests – i.e. the number of Black arrests over the number of White arrests.

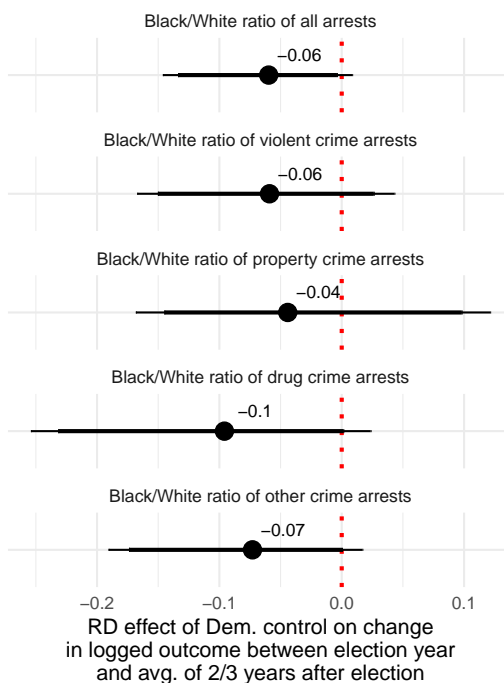


Figure A9: The effect of mayoral partisanship on the change in the natural log of the Black/White ratio of arrests two and three years after an election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

We also use an alternative outcome of the Black number of arrests (in per 100 capita terms) rather than the Black share of arrests in Figure A10 and Table A12.

Table A11: RDD Results: Racial Composition of Arrests (Ratios)

DV	Coef	p-value	BW	Obs
Black/White ratio of all arrests	-0.06 (-0.146, 0.009)	0.081	12.58	401
Black/White ratio of violent crime arrests	-0.059 (-0.167, 0.043)	0.247	11.34	379
Black/White ratio of property crime arrests	-0.044 (-0.168, 0.121)	0.751	10.85	374
Black/White ratio of drug crime arrests	-0.096 (-0.254, 0.024)	0.104	9.94	352
Black/White ratio of other crime arrests	-0.073 (-0.191, 0.017)	0.101	11.37	382

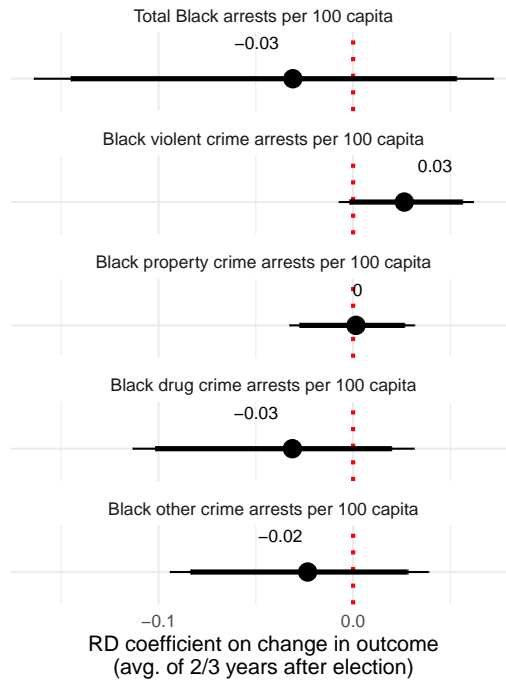


Figure A10: The effect of mayoral partisanship on the change in the per 100 capita number of Black arrests between the election year and the average of two and three years after the election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

Table A12: RDD Results: Racial Composition of Arrests (PC Number)

DV	Coef	p-value	BW	Obs
Total Black arrests per 100 capita	-0.031 (-0.164, 0.072)	0.445	11.22	377
Black violent crime arrests per 100 capita	0.026 (-0.007, 0.062)	0.123	13.92	435
Black property crime arrests per 100 capita	0.001 (-0.033, 0.031)	0.97	12.84	407
Black drug crime arrests per 100 capita	-0.031 (-0.113, 0.031)	0.265	9.94	353
Black other crime arrests per 100 capita	-0.023 (-0.094, 0.039)	0.413	15.49	463

G Robustness Checks: Alternative Logged Outcomes

In the main manuscript (Figure 3), we present analyses of the effect of mayoral partisanship on the per 100 capita number of crimes and arrests. However, in this section we use an alternative outcome of the logged per 100 capita numbers of crimes and arrests instead. The results from these analyses are similarly null, and provide no evidence of a causal effect of mayoral partisanship on logged levels of crime or arrests.

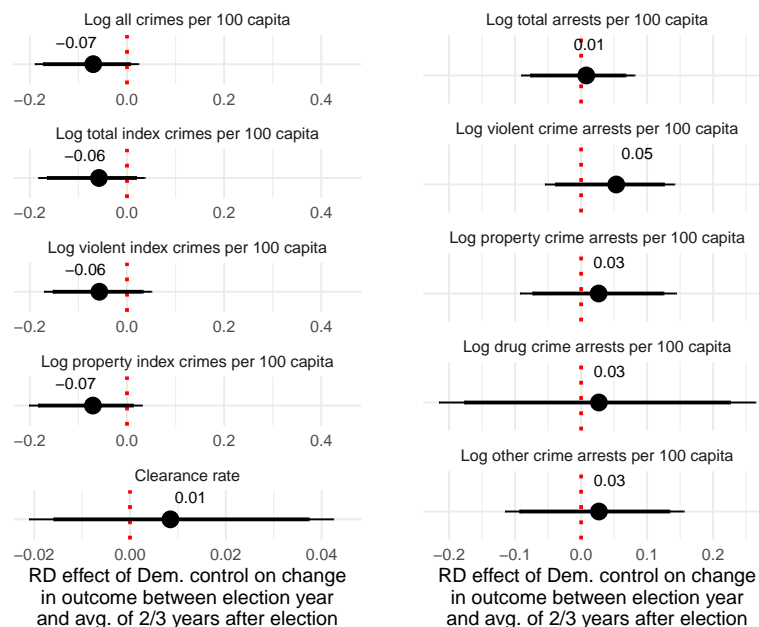


Figure A11: The effect of mayoral partisanship on changes in logged per capita reported crimes and clearance rate (left) and logged per capita arrests (right) between the election year and the average of two and three years after the election. Points indicate estimates from the regression discontinuity design using the robust bandwidth selection procedure estimated with `rdrobust` and lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

We also use an alternative outcome of the Black number of arrests (in logged per capita terms).

Table A13: RDD Analyses: Crime, Logged

DV	Coef	p-value	BW	Obs
Log all crimes per 100 capita	-0.07 (-0.19, 0.023)	0.126	12.36	500
Log total index crimes per 100 capita	-0.058 (-0.182, 0.036)	0.19	14.06	549
Log violent index crimes per 100 capita	-0.057 (-0.171, 0.05)	0.284	10.19	450
Log property index crimes per 100 capita	-0.07 (-0.201, 0.031)	0.149	13.1	524
Clearance rate	0.008 (-0.021, 0.042)	0.509	9.46	425

Table A14: RDD Analyses: Arrests, Logged

DV	Coef	p-value	BW	Obs
Log total arrests per 100 capita	0.008 (-0.091, 0.081)	0.912	9.46	335
Log violent crime arrests per 100 capita	0.053 (-0.055, 0.141)	0.388	11.56	386
Log property crime arrests per 100 capita	0.026 (-0.092, 0.144)	0.671	13.35	419
Log drug crime arrests per 100 capita	0.027 (-0.215, 0.264)	0.842	9.35	333
Log other crime arrests per 100 capita	0.027 (-0.115, 0.155)	0.769	11.9	389

Table A15: RDD Results: Racial Composition of Arrests (Logged PC Number)

DV	Coef	p-value	BW	Obs
Log total Black arrests per 100 capita	-0.046 (-0.192, 0.064)	0.325	9.47	339
Log Black violent crime arrests per 100 capita	-0.025 (-0.191, 0.096)	0.517	9.21	330
Log Black property crime arrests per 100 capita	-0.007 (-0.157, 0.157)	1	14.92	454
Log Black drug crime arrests per 100 capita	-0.076 (-0.386, 0.172)	0.454	8.33	297
Log Black other crime arrests per 100 capita	-0.031 (-0.24, 0.135)	0.583	10.3	362

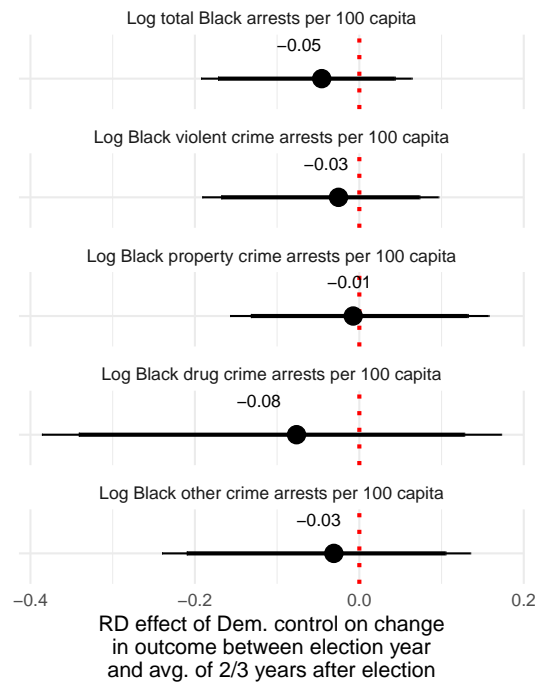


Figure A12: The effect of mayoral partisanship on the change in the natural log of the per 100 capita number of Black arrests two and three years after an election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

H Robustness Checks: Alternative Polynomials

Though our main results use a first-order polynomial, as a robustness check, in this section we present the results of RDD analyses using higher order polynomials as well as a simple difference in averages within the optimally-selected bandwidth (i.e., a 0-order polynomial) between cities that elected a Democrat versus those that did not. The results are similar, indicating that our main results are not simply an artifact of functional form.

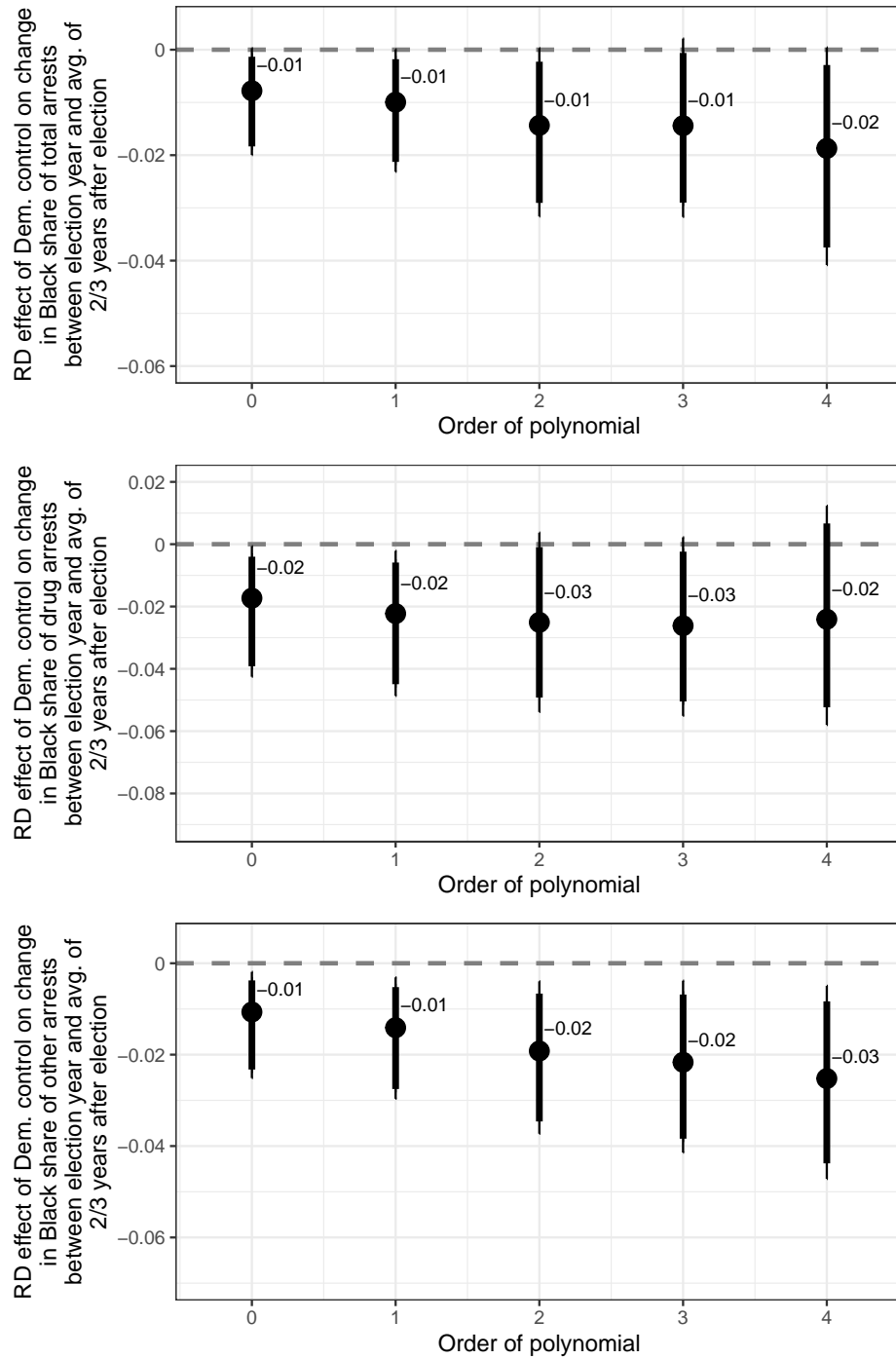
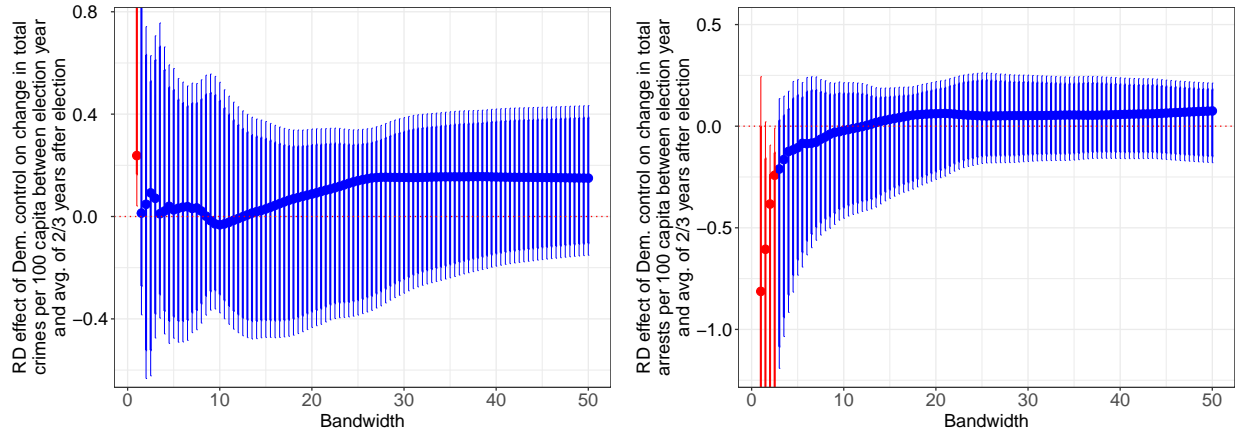


Figure A13: RDD effect on Black share of arrest types, with lower- and higher-order polynomials. Bars show 95% (thin lines) and 90% (thick lines) robust confidence intervals.

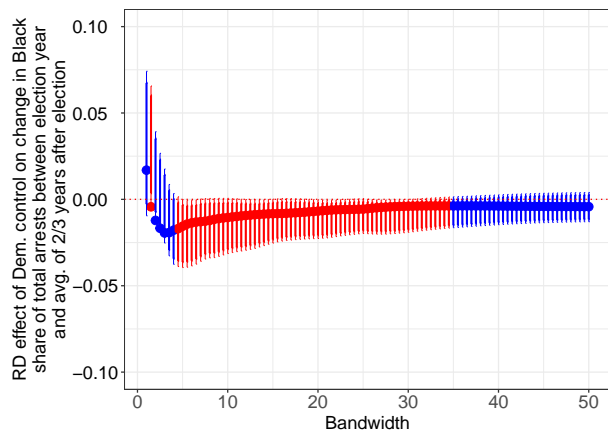
I Robustness Checks: Alternative Bandwidths



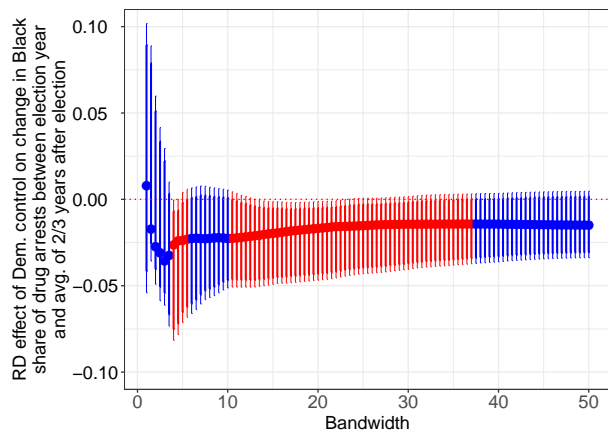
(a) Total crimes per 100 capita

(b) Total arrests per 100 capita

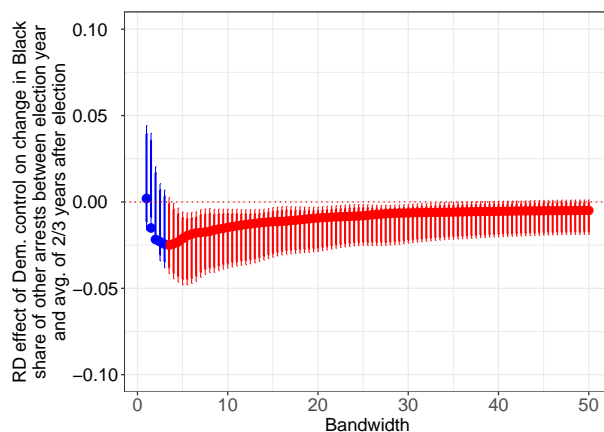
Figure A14: RDD effects on total crimes and arrests per 100 capita, with alternative bandwidths increasing by half a percentage point from 1 to 50 percentage points. Points indicate traditional point estimates and lines indicate bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals. Red points and lines indicate estimates that are significant at the 90% confidence level, while blue indicate those that are not.



(a) Black share of total arrests



(b) Black share of drug crime arrests



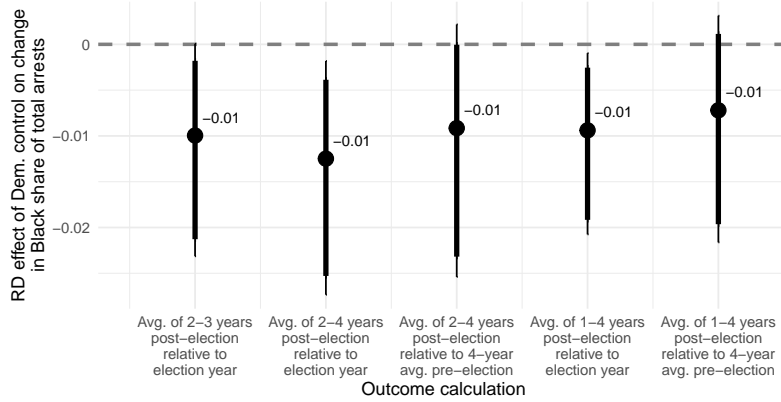
(c) Black share of other crime arrests

Figure A15: RDD effect on Black share of arrest types, with alternative bandwidths increasing by half a percentage point from 1 to 50 percentage points. Points indicate traditional point estimates and lines indicate bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals. Red points and lines indicate estimates that are significant at the 90% confidence level, while blue indicate those that are not.

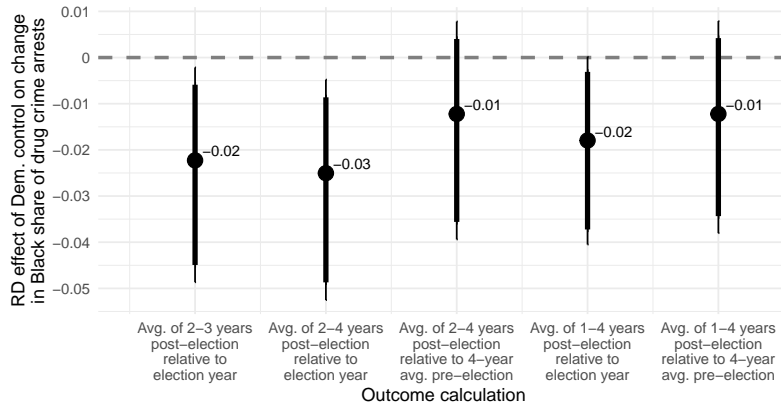
J Long-run Effects of Partisanship

In this section, we test for the effect of mayoral partisanship on the racial composition of arrests using alternative outcome measures, by calculating changes between different base years and averaging over different post-election years. We display these results in Figure A16, which indicate that the change outcome calculation method makes little difference for our overall conclusions.

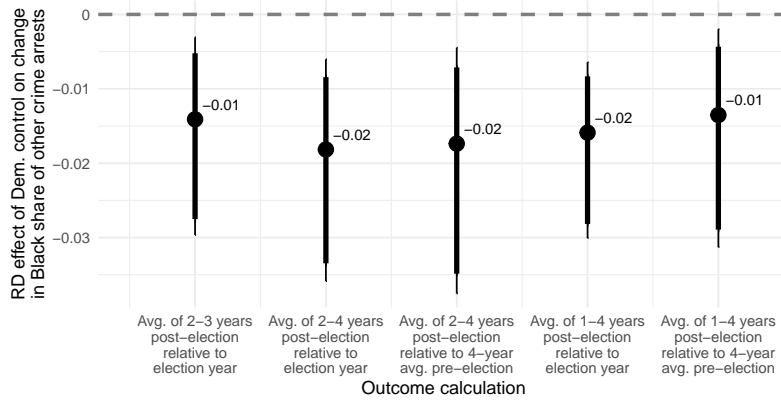
In addition, in Figure A17 we show the timeline in which these effects appear using outcomes that measure the change between the election year and a variety of different years after the election. These analyses indicate that our effects on the racial composition of arrests generally peak 4 years after the election, suggesting that the changes that we observe in this outcome may take longer to appear due to time needed for more proximate policy levers to change beforehand.



(a) Black share of total arrests

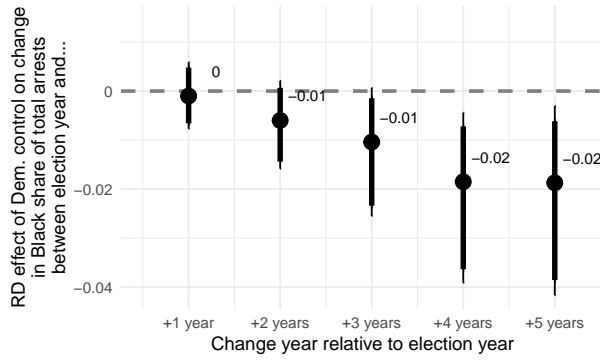


(b) Black share of drug crime arrests

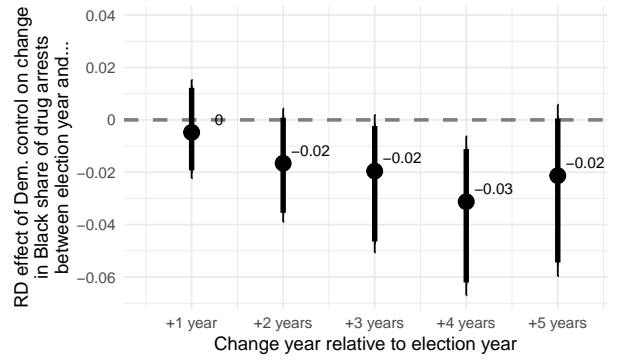


(c) Black share of other crime arrests

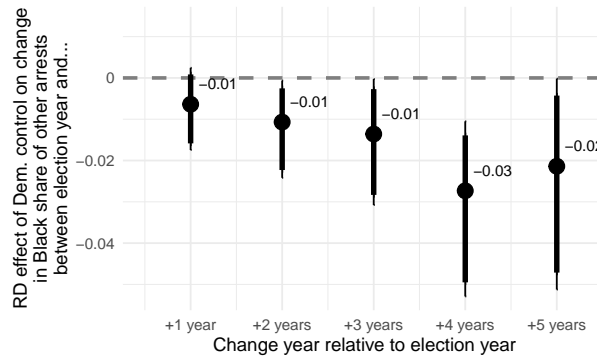
Figure A16: Effect of mayoral partisanship on the change in the Black share of types of arrests using alternative change measures. Thick bars show 90% robust confidence intervals and thin bars show 95% robust confidence intervals.



(a) Black share of total arrests



(b) Black share of drug arrests



(c) Black share of other arrests

Figure A17: Long-term effect of partisanship on the change in the Black share of types of arrests. Thick bars show 90% robust confidence intervals and thin bars show 95% robust confidence intervals.

K Heterogeneity: by Form of Government

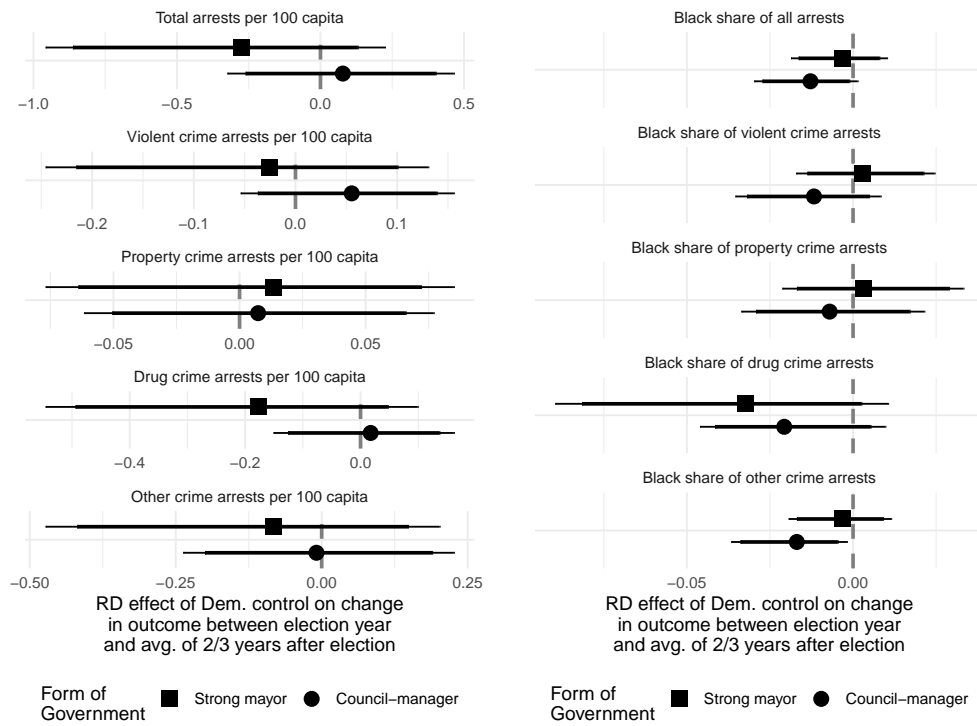


Figure A18: RDD effect on overall arrests and Black share of arrest types, by form of government. Points indicate traditional point estimates and lines indicate bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals, with filled squares indicating strong mayor cities and filled circles indicating council-manager cities.

L Heterogeneity: by Partisan Elections

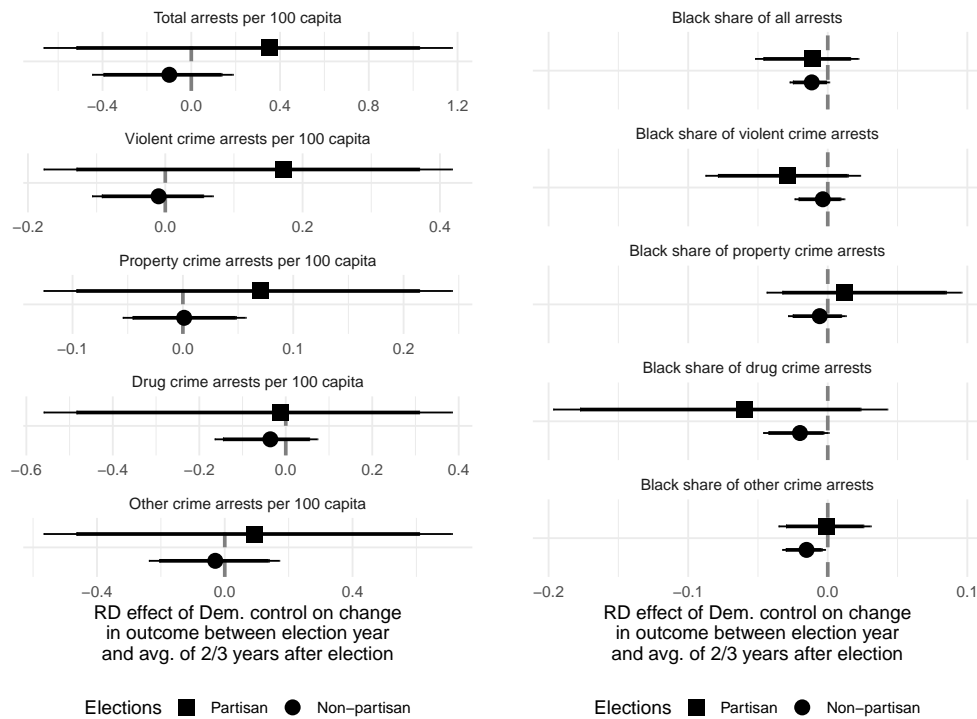


Figure A19: RDD effect on overall arrests and Black share of arrest types, by partisan ballots. Points indicate traditional point estimates and lines indicate bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals, with filled squares indicating cities with partisan elections and filled circles indicating cities with nonpartisan elections.

M Heterogeneity: by Decade

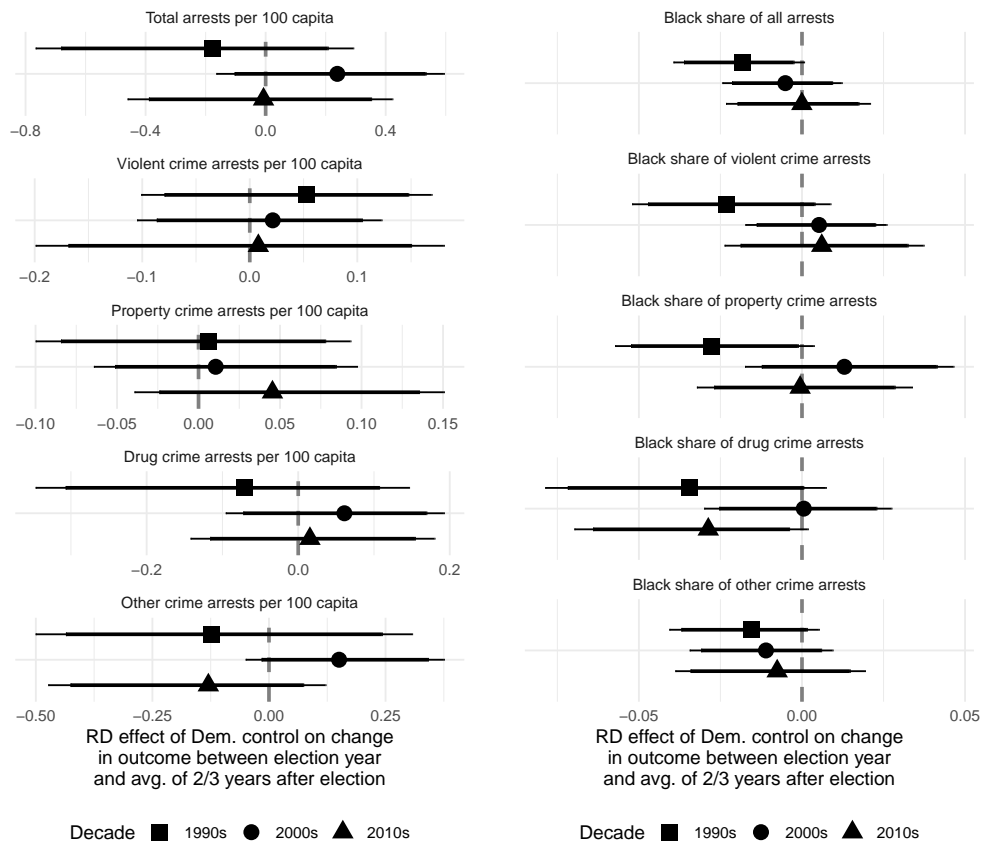


Figure A20: RDD effect on overall arrests and Black share of arrest types, by decade. Points indicate traditional point estimates and lines indicate bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals, with squares indicating elections in the 1990s, triangles indicating elections in the 2000s, and filled circles indicating elections in the 2010s.

N Effects of Race

In this section, we provide evidence that the effects of partisanship are unlikely to result from the candidates' racial backgrounds. To do so, we first examine the effects of electing a Democratic mayor rather than a Republican, using only white Democratic candidates. These results for our main outcomes of racialized arrest patterns are shown in Figure A21, and are quite similar to our main results.

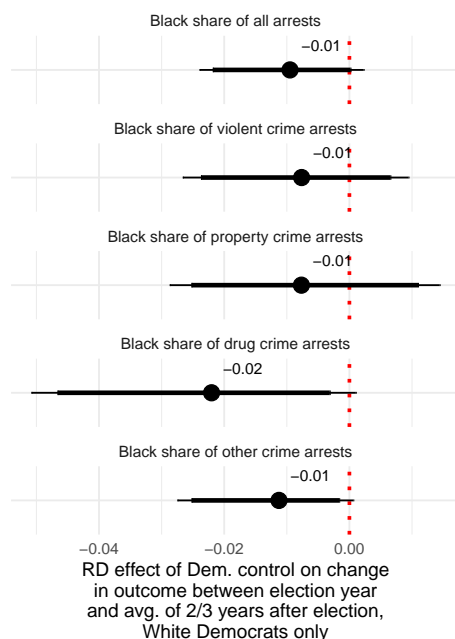


Figure A21: The effect of mayoral partisanship on the change in the Black share of arrests between the election year and the average of two and three years after the election, using White Democratic candidates only. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

Table A16: RDD Results: White Democratic Candidates Only

DV	Coef	p-value	BW	Obs
Black share of all arrests	-0.009 (-0.024, 0.002)	0.105	10.71	328
Black share of violent crime arrests	-0.008 (-0.027, 0.009)	0.351	11.05	336
Black share of property crime arrests	-0.008 (-0.029, 0.014)	0.516	13.74	387
Black share of drug crime arrests	-0.022 (-0.051, 0.001)	0.06	11.27	337
Black share of other crime arrests	-0.011 (-0.027, 0.001)	0.061	10.98	336

We also assess whether we can detect effects of a Black candidate (vs. a non-Black candidate), regardless of party. Though our power is limited for these analyses as there are very few mayoral elections with close victories or losses of a Black candidate vs. a non-Black candidate, we present these analyses for our main outcomes of racialized arrest patterns in Figure A22 and Table A17. We caution against interpreting these results as informative null effects given that our statistical power is limited with this minimal sample of elections. For instance, our power to detect an effect on the Black share of total arrests of half a standard deviation (or 0.01) is quite low: 0.31.

Table A17: RDD Results: Black Candidates vs. Non-Black Candidates

DV	Coef	p-value	BW	Obs
Black share of all arrests	-0.011 (-0.035, 0.01)	0.279	15.26	171
Black share of violent crime arrests	-0.013 (-0.047, 0.014)	0.286	15.6	173
Black share of property crime arrests	-0.022 (-0.058, 0.007)	0.127	16.58	179
Black share of drug crime arrests	-0.009 (-0.061, 0.039)	0.673	13.11	154
Black share of other crime arrests	-0.021 (-0.055, 0.008)	0.137	17.01	180

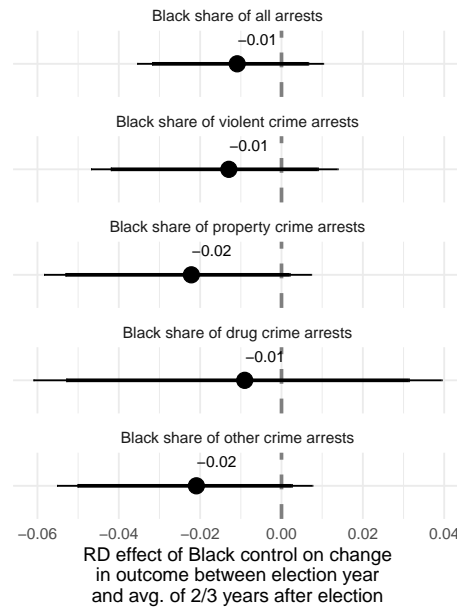


Figure A22: The effect of a Black mayor on the change in the Black share of arrests between the election year and the average of two and three years after the election. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

O Alternative Estimation Strategy: Difference-in-Differences

In this section, we present results from an entirely different estimation strategy than the RDD analyses presented in the main manuscript. Instead we use a difference-in-differences strategy that estimates the effect of changes in mayoral partisanship on the crime and arrests outcomes we examine in the main manuscript. Specifically, we estimate non-parametric difference-in-differences models using the PanelMatch method (Imai, Kim, and Wang, 2021), which compares units with similar treatment histories (i.e. party control) and similar pre-treatment outcomes (i.e. crimes or arrests or the Black share of arrests) that are “treated” with a Democrat taking control of the mayoral office vs. those that are not treated (i.e. a Republican takes control).¹² We prefer the regression discontinuity approach presented in the main text, as it better deals with the endogeneity in the likelihood of electing a Democrat. Despite that, we do ultimately find similar, albeit less precisely estimated, results in the difference-in-differences approach.

¹²Specifically, we match using Mahalanobis distance on lagged outcomes in the three years prior to treatment.

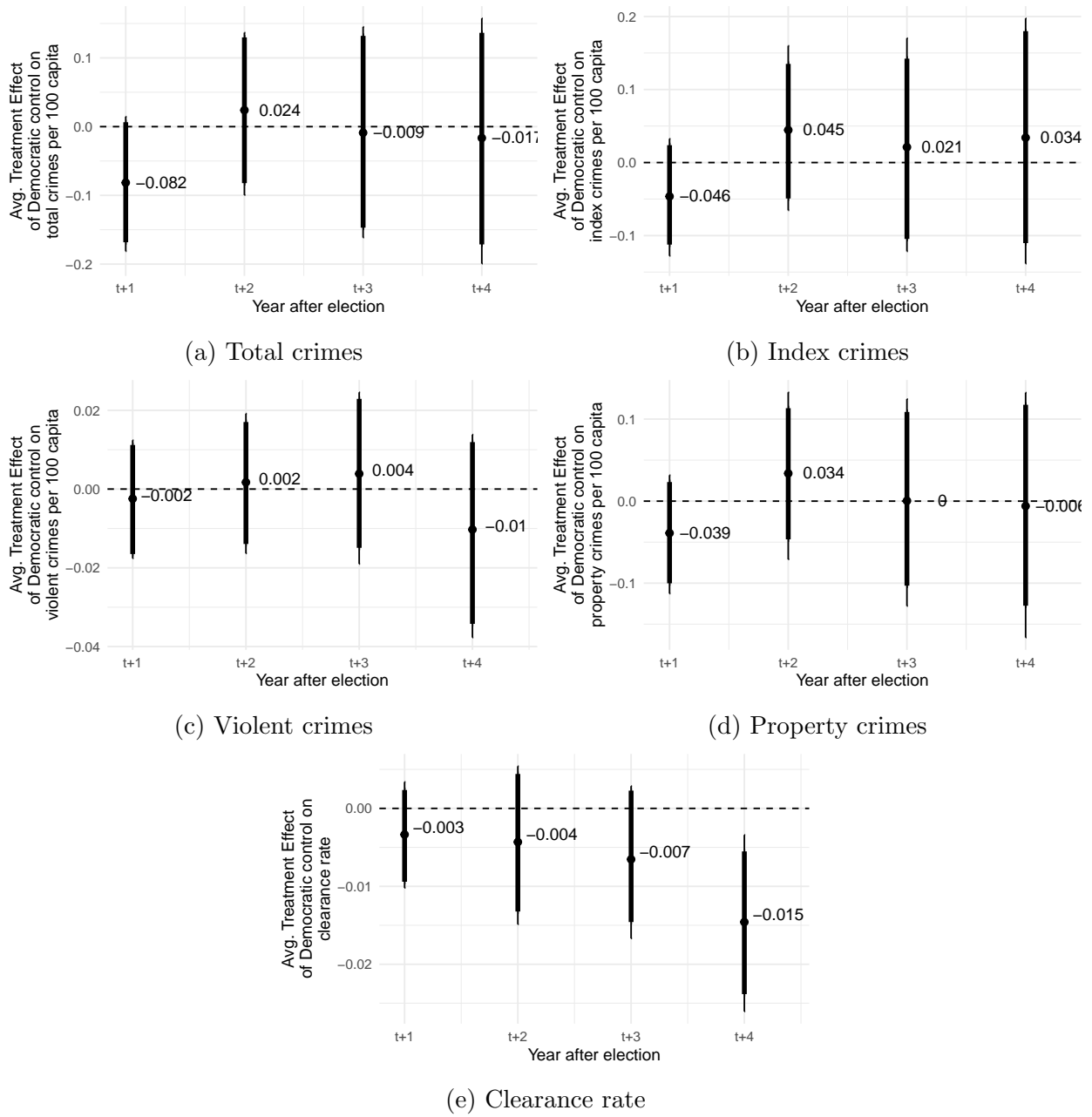


Figure A23: Difference-in-differences average treatment effect on the number of crimes per capita and the clearance rate. Bars show 95% (thin lines) and 90% (thick lines) confidence intervals.

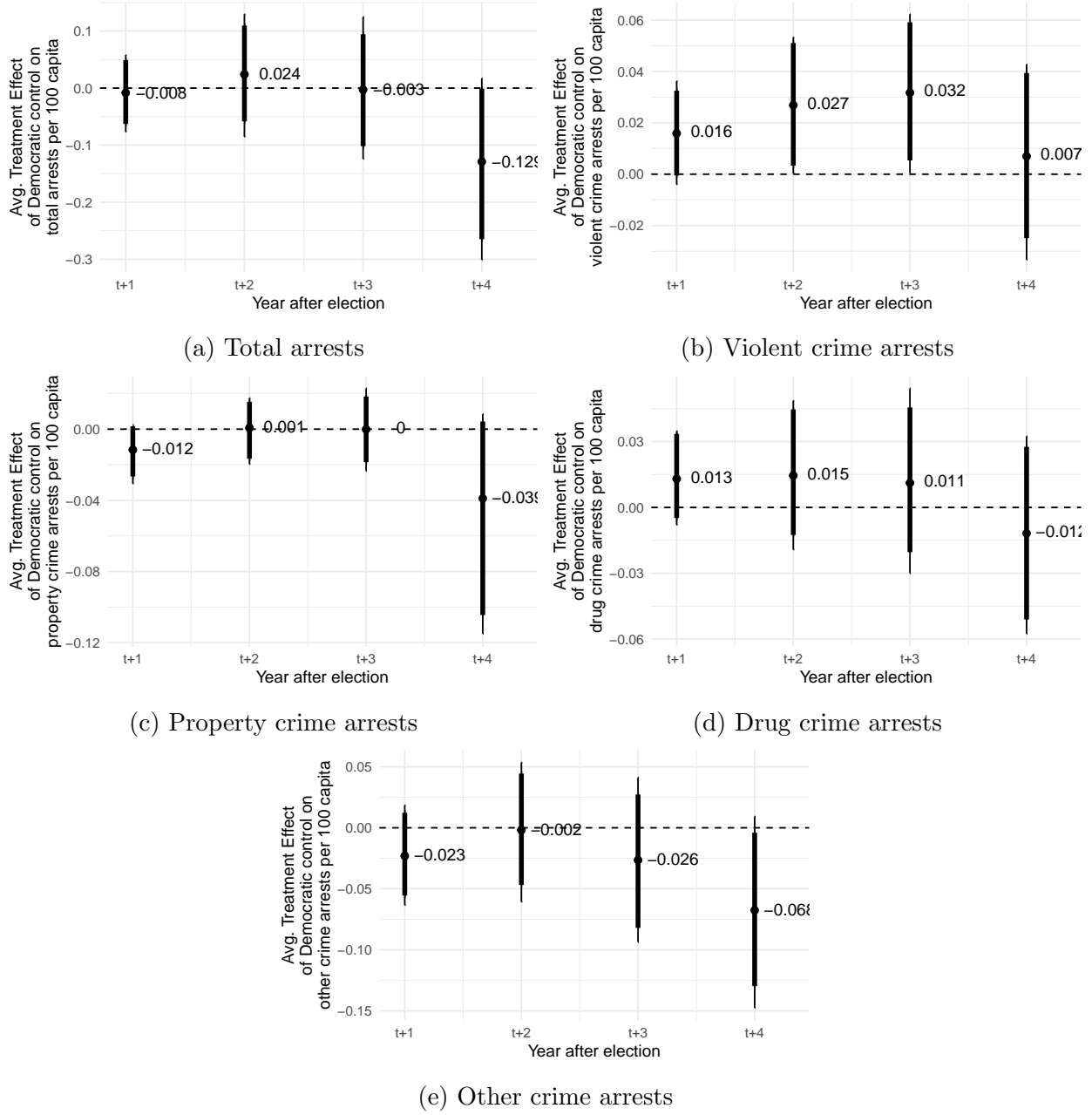
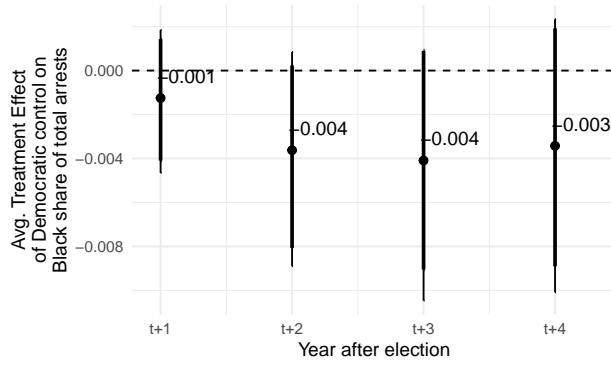
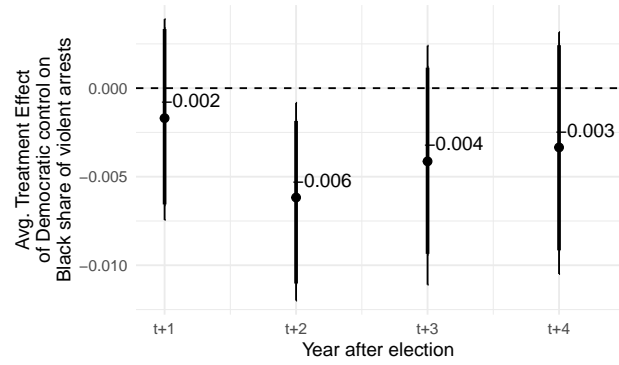


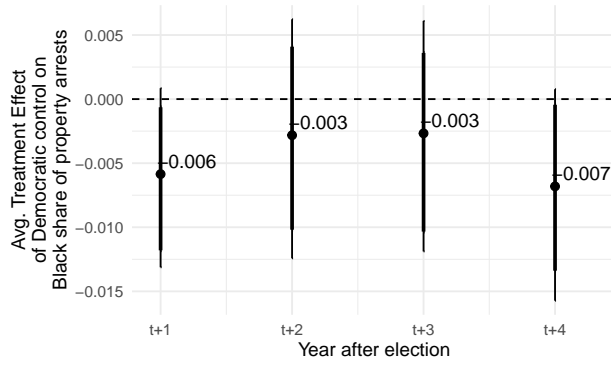
Figure A24: Difference-in-differences average treatment effect on the number of arrests per capita. Bars show 95% (thin lines) and 90% (thick lines) confidence intervals.



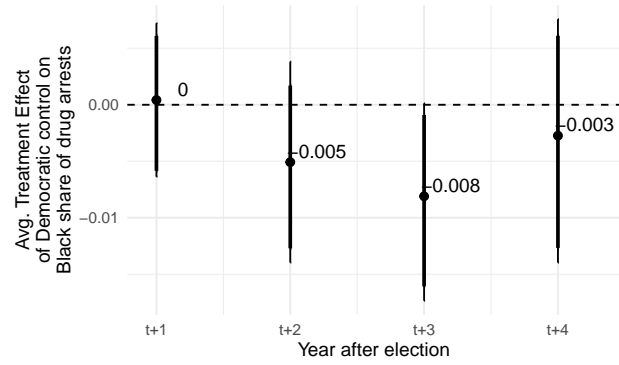
(a) Black share of total arrests



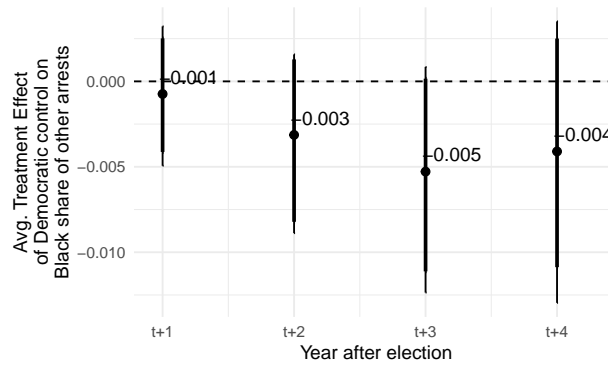
(b) Black share of violent crime arrests



(c) Black share of property crime arrests



(d) Black share of drug crime arrests



(e) Black share of other crime arrests

Figure A25: Difference-in-differences average treatment effect on Black share of arrest types, estimated using PanelMatch (Imai, Kim, and Wang, 2021). Bars show 95% (thin lines) and 90% (thick lines) confidence intervals.

P Effects of Democratic Control on Police Chief Demographics

In this section, we present results from both regression discontinuity and difference-in-differences estimation strategies to assess the effect of Democratic mayoral control on police chief demographics. A natural parallel to our primary results on policing in the main manuscript would involve a regression discontinuity approach with change outcomes, which would make use of observations with observed measurements of our outcomes both prior to and following close elections. However, our police chiefs data are imprecise and very limited in their time span to the 2010-2022 period. We therefore present results using three separate analytic methods.

First, to use the largest possible number of elections in our analyses while also recognizing the inability to rule out some sources of endogeneity using non-change outcomes, we present results from a regression discontinuity design using lead (level) outcomes. These results are presented in Figure A26, and provide evidence that the close election of a Democratic mayor leads to a higher likelihood of a Black police chief in the future.

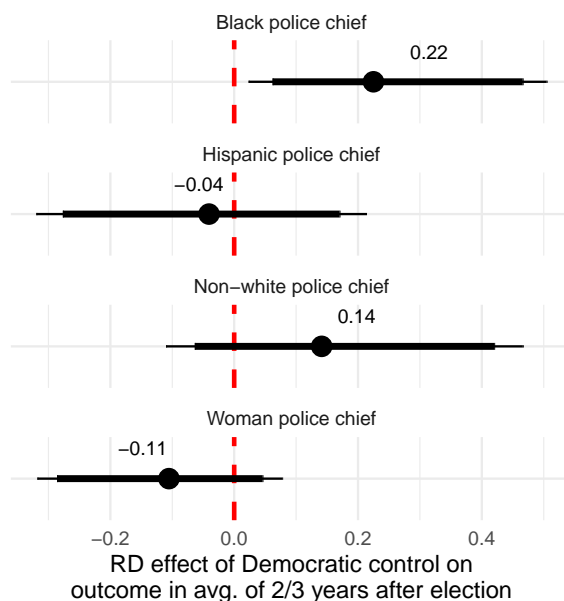


Figure A26: The effect of mayoral partisanship on the demographics of police chiefs. Points indicate estimates from the RDD using lead outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

Next, we present results from the RDD but using change (delta) outcomes in Figure A27. These analyses using change outcomes – relying on fewer observations – provide directionally consistent estimates but no statistically detectable evidence that electing a Democrat causes *changes* in police chief demographics.

Finally, we present our difference-in-differences analyses that estimate the effect of changes

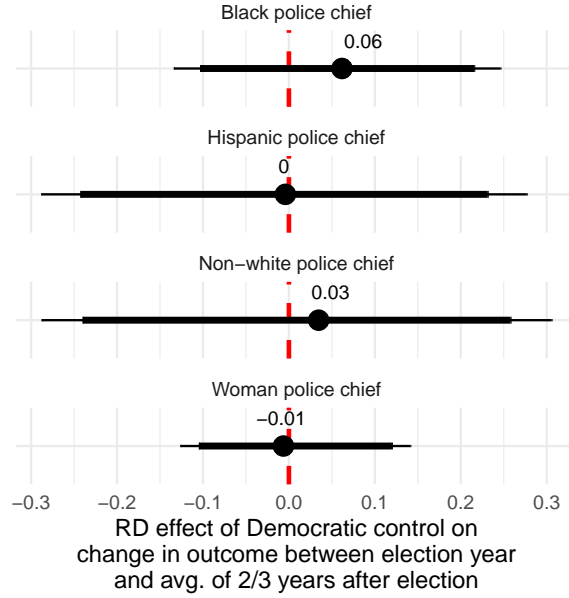


Figure A27: The effect of mayoral partisanship on changes in the demographics of police chiefs. Points indicate estimates from the RDD using change outcomes and using a robust bandwidth selection procedure estimated using `rdrobust`. Lines indicate robust bias-corrected 90% (thick lines) and 95% (thin lines) confidence intervals.

in mayoral partisanship on the demographics of city police chiefs in Figure A28.¹³ These analyses are directionally consistent with those from the RDD approach, and provide suggestive evidence that changing from a Republican mayor to a Democratic mayor may leads to the replacement of white police chiefs with non-white ones, though these results are not statistically significant.

¹³As in the previous section, we estimate non-parametric difference-in-differences models using PanelMatch (Imai, Kim, and Wang, 2021) to compare units with similar treatment histories (i.e. party control) and similar pre-treatment outcomes (i.e. chief demographics) that are “treated” with a Democrat taking control of the mayoral office vs. those that are not treated (i.e. a Republican takes control). Again, we match using Mahalanobis distance on lagged outcomes in the three years prior to treatment.

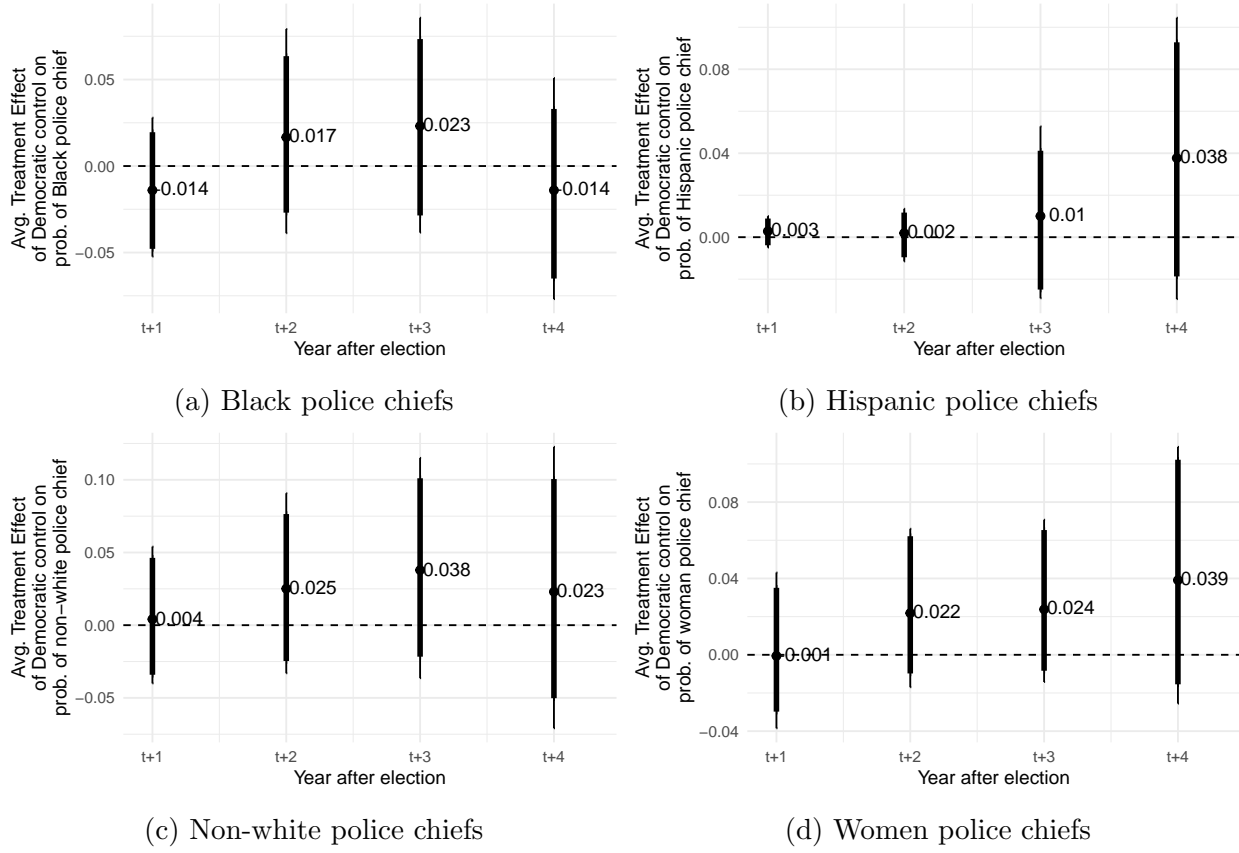


Figure A28: Difference-in-differences average treatment effect of Democratic control on the demographics of police chiefs. Bars show 95% (thin lines) and 90% (thick lines) confidence intervals.