Political Diversity in U.S. Police Agencies[*]

Bocar Ba, Haosen Ge, Jacob Kaplan, Dean Knox,
Mayya Komisarchik, Gregory Lanzalotto, Rei Mariman,
Jonathan Mummolo, Roman Rivera & Michelle Torres

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[*]Bocar Ba, Assistant Professor, Economics, Duke University, Social Sciences Building, Durham, NC 27708, USA, bocar.ba@duke.edu. Haosen Ge, Data Scientist, Analytics at Wharton, University of Pennsylvania, Philadelphia, PA 19104, USA, hge@wharton.upenn.edu. Jacob Kaplan, Professional Specialist, School of Public and International Affairs, Princeton University, Robertson Hall, Princeton, NJ 08540, USA, jk7785@princeton.edu. Dean Knox, Assistant Professor, Operations, Information and Decisions, University of Pennsylvania, Jon M. Huntsman Hall, Philadelphia, PA 19104, USA, dcknox@upenn.edu. Mayya Komisarchik, Assistant Professor, Political Science, University of Rochester, Harkness Hall, Rochester, NY 14611, USA, mayya.komisarchik@rochester.edu. Gregory Lanzalotto, Ph. D. Student, University of Pennsylvania, Jon M Hunstman Hall, Philadelphia, PA 19104, USA, glanza@wharton.upenn.edu. Rei Mariman, Director, Data Computing and Research Support, Analytics at Wharton, University of Pennsylvania, Philadelphia, PA 19104, USA, rmariman@wharton.upenn.edu. Jonathan Mummolo, Assistant Professor, Politics and Public Affairs, Princeton University, 001 Fisher Hall, Princeton, NJ 08544, USA, jmummolo@princeton.edu, corresponding author. Roman Rivera, Postdoctoral scholar, Institute for Research on Labor and Employment, University of California, Berkeley, 2521 Channing Way, Berkeley, CA 94720, USA, rgrivera@berkeley.edu. Michelle Torres, Assistant Professor, Political Science, University of California, Los Angeles, Bunche Hall, Los Angeles, California 90095, USA, smtorres@ucla.edu. Authors listed alphabetically. DK and JM designed the project with support from RM and JK. RM led data acquisition with additional contributions by BB, MK, RR, and MT. JK conducted data processing and statistical analysis with support from DK and JM, with additional contributions from RR, GL and HG. JM wrote the paper with support from JK, DK, and RM, with additional contributions from MT. This research was made possible in part by a grant from the Carnegie Corporation of New York. The statements made and views expressed are solely the responsibility of the authors.

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Abstract

Partisans are divided on policing policy, which may affect officer behavior. We merge rosters from 99 of the 100 largest local U.S. agencies—over one third of local law enforcement agents nationwide—with voter files to study police partisanship. Police skew more Republican than their jurisdictions, with notable exceptions. Using fine-grained data in Chicago and Houston, we compare behavior by Democratic and Republican officers facing common circumstances. We find minimal partisan differences after correcting for multiple comparisons. But consistent with prior work, we find Black and Hispanic officers make fewer stops and arrests in Chicago, and Black officers use force less often in both cities. Comparing same-race partisans, we find White Democrats make more violent-crime arrests than White Republicans in Chicago. Our results suggest that despite Republicans' preference for more punitive law enforcement policy and their overrepresentation in policing, partisan divisions often do not translate into detectable differences in on-the-ground enforcement.

Replication Materials: The data, code, and any additional materials required to replicate all analyses in this article are available on the *American Journal of Political Science Dataverse* within the Harvard Dataverse Network, at: http://dx.doi.org/10.7910/DVN/CZOPH3.

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Policing has become a locus of partisan strife in the United States (Eckhouse, 2019; Parker and Hurst, 2021; Grosjean, Masera and Yousaf, 2023). Republicans are far more likely than Democrats to trust police, more likely to believe police treat different groups equally, less likely to think police killings are a problem, and less likely to think Black Lives Matter protests are motivated by a genuine desire to hold police accountable (Pew, 2016). In fact, as we show below, party identification is among the most important individual-level predictors of policing-related attitudes, with roughly twice the importance of race or political ideology (see Figure 1 and accompanying discussion).

While partisans in the general public may disagree strongly about how police should function in society, few are empowered to translate their political views into action. Police officers experience no such constraint. Every day, armed agents of the state are deployed in American communities with extraordinary discretion over whether, when, and how to enforce the law (Wilson, 1968; Goldstein, 1977). It is no exaggeration to note that police officers often have the ability to make policing policy unilaterally, in real time (Lipsky, 1980). This power, combined with sharp partisan divisions over how police should do their jobs, raises several important questions that speak not only to the determinants of police behavior, but to the health of democratic representation (Kingsley, 1944; Meier, 1975). What share of police identify with the Republican and Democratic parties? To what extent do these identities reflect those of the local civilians whom police serve? And how do officers with differing partisan affiliations behave when interacting with those civilians?

Progress on these questions have been hampered by an incomplete and heterogeneous landscape of administrative data. Assembling basic facts about law enforcement agents remains remarkably difficult in many jurisdictions. Agencies rarely share information proactively and sometimes defy the near-universal requirement to disclose government employee rosters under freedom-of-information laws. In light of these obstacles, researchers typically turn to one of two alternatives. The first is to closely study single jurisdictions (Ba et al., 2021; Hoekstra and Sloan, 2020; Donahue, 2023), leaving open questions of generalizability. Alternatively, researchers have conducted national surveys of police officers (Morin et al., 2017), but because these studies sample small numbers of officers from numerous locations nationwide, they preclude examination of whether and how agencies represent their particular jurisdictions, especially in terms of political views and affiliations. In addition, survey-based methods are prone to severe selection bias, since many officers (and even entire police agencies) decline participation.[1]

In this paper, we analyze nearly a quarter million officers, covering 99 of the 100 largest local U.S. agencies and representing over one third of all local law enforcement agents nationwide, to study officers' partisan affiliations. Our data draw upon numerous open records requests, data-sharing agreements, and publicly available personnel rosters, merged with voter file and U.S. Census data. In addition to party identification, our data contain measures of officers' race/ethnicity, gender, age, income, voting history, and place of residence, allowing us to comprehensively characterize the degree to which police resemble their communities on a host of dimensions, as well as how this correspondence varies across jurisdictions. In addition, micro-level data on officers' day-to-day deployment and enforcement behaviors in two of the five largest local police forces in the U.S.—the Chicago Police Department (CPD) and the Houston Police Department (HPD)—allow us to carefully examine whether Democratic and Republican officers behave differently when facing common circumstances.

We use these data to address classic questions in the literature on "representative bureaucracy," (Kingsley, 1944; Dolan and Rosenbloom, 2003) which holds that bureaucrats sharing salient social identities with civilians will offer superior service, under some conditions. We first conduct the most comprehensive analysis to date of "passive representation" in policing: an assessment of whether bureaucrats resemble the civilians they serve on various dimensions (Meier, 2019). We demonstrate that relative to civilians in their jurisdictions, police officers are not only more likely to affiliate with the Republican Party: they also have higher household income, vote more often, and are more likely to be White. However, the degree of unrepresentativeness is heterogeneous, with some agencies closely mirroring their populations and others substantially diverging. We then broaden our analysis to examine the neighborhoods in which officers live, as residency programs are a prominent proposal for integrating officers into local civilian communities (President's Task Force on 21st Century Policing, 2015). We find the composition of officers' neighborhoods also differs systematically from that of the city at large. Areas where officers live are similarly higher on shares of Republicans, shares of White residents, voter turnout rates, and household income,

[1]A new working paper, (Adams et al., N.d.), interviewed police chiefs at large agencies and achieved roughly a 10% response rate.

compared to jurisdictions overall.

To probe the behavioral consequences of these patterns at a finer-grained level, we turn to our micro-level data in Chicago and Houston. Chicago represents a crucial case for the study of diversity in policing (McCrary, 2007): the agency has substantially diversified along racial, ethnic and gender lines in recent decades, the city remains a focal point for concerns over abusive policing practices, and public opinion polls there show sharp divergences between racial and ethnic groups of civilians on attitudes towards police (Harris, 2021). While HPD has also been criticized for racial disparities in policing outcomes (deGrood, 2023; Vasquez, 2023), it differs in an important respect: its ranks are roughly balanced between Democrats and Republicans, unlike CPD's heavily Democratic makeup. By analyzing the dynamics of police-civilian interactions across differing contexts, we can begin to move beyond the tendency in this literature to examine officer behavior in single jurisdictions, which is severely limiting in the U.S. federalist context.

Both our Chicago and Houston data include the precincts to which police officers are assigned, allowing us to evaluate a more specific form of passive representation: whether officers resemble civilians in the areas they patrol. We see striking gaps in political affiliation: every single district in Chicago and nearly every division in Houston is policed by officers who skew more Republican than local residents.

Having established these descriptive patterns, we then use data on CPD and HPD daily assignments and enforcement records to investigate how officers' partisan identities map to behavior on the job. In other words, we explore the extent to which police officers of various backgrounds practice "active representation" (AR), behaving in ways that accord with the preferences of civilians who are passively represented (Meier, 2019, 40). While this analysis is limited to two cities, we focus on them because it allows for the most credible test to date of behavioral differences between officers of differing political identities. As we explain in detail below, the incorporation of shift assignment data lets us address a key limitation in prior studies that link officer partisanship to behavior (e.g. Donahue, 2023) by allowing us to compare officers assigned to police comparable pools of civilians in comparable situations. This avoids the selection issues that prior work has shown can produce severe bias when analyzing enforcement data alone—e.g. selectively analyzing only the subset of situations where officers chose to make stops or issue citations (Knox, Lowe and Mummolo, 2020; Ba et al., 2021).

Specifically, we estimate differences in the overall numbers of stops, arrests and uses of force made by Democratic and Republican officers. We further examine the amount of enforcement directed toward various civilian racial groups and involving various types of arrests. Comparisons are made between Republican and Democratic officers in the aggregate, as well as between Republican and Democratic officers of the same race. Each test compares officers deployed to comparable places, times, and tasks, ensuring officer behavior is always evaluated against behavior by peers facing common circumstances.

In brief, we find few detectable differences across partisan groups after correcting for multiple comparisons. However, consistent with prior work (Ba et al., 2021), we find Black and Hispanic officers make fewer stops and arrests in Chicago, and Black officers use force less often in both cities. Among White officers in Chicago, Democrats make more arrests for violent crime than Republicans. Within other racial groups, Democratic and Republican behavior is statistically indistinguishable after multiple-testing corrections.

Taken together, our results provide new insight into how officers' social identities map to those of the civilians they serve, as well as officers' behavior during interactions with civilians. While police certainly skew Republican and White overall, there exist agencies where both the partisan and racial compositions of the force closely mirrors the population at large, such as the Birmingham, AL, Police Department. And though partisans disagree on how policing should be conducted (Pew, 2020), those divisions do not generally correspond to Democratic-Republican differences in officer behavior. Finally, where partisan differences can be found, Democrats are more active than Republicans in their enforcement—diverging from partisan preferences on policing policy in the general population.

Empirical Assessments of Diversity in Policing

A large interdisciplinary literature has investigated whether police officers demographically resemble the civilians they serve, as well as whether various officer attributes and identities are systematically related to behavior on the job. The vast majority of this work focuses on race and gender.

As previous reviews note, these studies have produced mixed results, especially with respect to police behavior (Sklansky, 2005). At least part of this apparent disagreement is due to the use of incomplete data sources and analytic approaches later shown to be vulnerable to selection bias.

Many earlier studies of diversity in law enforcement focused on cross-sectional comparisons, such as agency-level correlations showing whether diversity was associated with various aggregate outcomes. For example, Meier and Nicholson-Crotty (2006) finds that agencies with a higher percentage of female officers tend to see more sexual assault reports and arrests. Similarly, Wilkins and Williams (2008) finds that "the presence of black police officers [in an agency's division] is related to an increase in racial profiling in the division." The well-known concern with this class of studies is that police agencies—and divisions within single agencies—differ immensely in unobserved ways that correlate with both diversity and these outcomes, posing the strong risk of omitted variable bias.

A more recent set of studies has leveraged incident-level data to compare the post-stop enforcement actions of various officer groups, using data on civilians who were stopped. In an analysis of officers' decisions to search stopped motorists, Baumgartner et al. (2021) find that across officers of all racial groups, stops of Black male civilians lead to searches more often than any other civilian demographic. The study also found searches made by White male officers were less likely to lead to an arrest. In a related study, Shoub, Stauffer and Song (2021) studies traffic stops in two agencies and finds "female officers are less likely to search drivers than men," but "when female officers do conduct a search, they are more likely to find contraband and they confiscate the same net amount of contraband as male officers" (p. 1). Analyzing close election outcomes for sheriff, Thompson (2020) shows that Democrats and Republicans comply with federal requests relating to immigration enforcement at comparable rates. Most relevant to the current study is Donahue (2023), which merges data on Florida Highway Patrol traffic stops with voter records and finds "White Republican officers exhibit a larger racial disparity than White Democratic officers in their propensity to search motorists whom they have stopped" (p. 1).

These studies make important contributions, but they also each exhibit a common limitation: data is limited to police-civilian encounters in which officers chose to initiate a stop. As Donahue

(2023) itself acknowledges, this makes the conclusions vulnerable to selection bias (pp. 664–665).[2] Previous research has established that neglecting selection issues in police administrative records will generally lead to underestimates of discrimination (Knox, Lowe and Mummolo, 2020). Intuitively, this is because if police discriminate by stopping minorities in less severe circumstances, and those circumstances are not fully documented in police records (and therefore cannot be adjusted for), then minority stops will not be comparable to White stops despite being seemingly identical on officer-reported characteristics.

For studies that seek to estimate the frequency with which officers take actions against civilians (e.g. how often Black officers make arrests), it is thus crucial to account in some way for the denominator of all opportunities that were available for that action to be taken—not only the stops that were *actually* made, but also encounters in which civilians were allowed to pass freely (Knox and Mummolo, 2020). This detailed encounter-level data is rarely available for non-stops. To address this issue, a viable workaround is to use data on the places and times where officers are deployed, because researchers can infer that officers assigned to work in common circumstances will be faced with the same pool of encounters where action could be taken, even if those encounters cannot be directly observed themselves (Ba et al., 2021). But without this deployment data on the precise places and times where officers work—or research designs that can render time and place ignorable—a serious challenge arises. Constructing the correct denominator for enforcement rates becomes fraught, and behavioral differences between two groups of officers become difficult to disentangle from contextual differences in the types of assignments faced by the two groups.

Some recent studies have made progress in overcoming these challenges with deployment data. Using micro-level data in Chicago on officer shift assignments and behavior, and leveraging exogenous variation in rotating day-off schedules, Ba et al. (2021) finds deploying officers of color (relative to White officers) or female officers (relative to male officers) to otherwise similar circumstances leads to substantial reductions in stops, arrests and uses of force. Using data on

[2] The appendix of Donahue (2023) features a "veil of darkness" test comparing the demographics of stopped drivers before and after sunset (Grogger and Ridgeway, 2006), which is robust to selection bias. However, this test has low statistical power and, perhaps relatedly, Donahue (2023) finds no detectable difference in the rates at which Democratic and Republican officers stop Black civilians. In addition, Donahue (2023) matches 68% of officers to the voter file using name and date of birth. Our use of probabilistic record linkage allows us to match more than 85% of officers with at least 90% probability (Enamorado, Fifield and Imai, 2019).

dispatches to 911 calls within specific places and times, Hoekstra and Sloan (2020) finds that, "while white and black officers use gun force at similar rates in white and racially mixed neighborhoods, white officers are five times as likely to use gun force in predominantly black neighborhoods" (p. 1). And leveraging the quasi-random assignment of officers to the scene of traffic accidents, West (2018) finds "officers issue significantly more traffic citations to drivers whose race differs from their own" (p. 1). In this paper, we extend the approach in Ba et al. (2021) to the study of officer partisanship in the research design section.

Representative Bureaucracy and Partisan Identity

In this section, we draw on established literatures on representative bureaucracy and partisan polarization to theorize about the ways in which partisan identification might influence police behavior. Calls to diversify police forces represent perhaps the oldest proposed policing reform, and one argument for diversification springs from the literature on "representative bureaucracy" (RB). RB theories (Kingsley, 1944; Dolan and Rosenbloom, 2003) are premised on several assertions: bureaucratic oversight is often incapable of ensuring that bureaucrats will exercise discretion in desirable ways (Huber and Shipan, 2002); staffing agencies with workers who share values with the population at large will promote desirable outputs (Bendor and Meirowitz, 2004); and observable worker traits, often standard demographic indicators, are useful proxies for shared values (Meier, 1975).

A key precondition for RB is "passive representation" (PR), which describes the degree to which bureaucrats mirror their clients on a given attribute or identity. In this paper, we shed light on the extent of PR through a multi-dimensional assessment of the degree to which civilians share a host of traits with local officers across 99 of the largest 100 police agencies in the U.S. However, the mere existence of PR does not guarantee "active representation" (AR): "cases where the bureaucracy produces benefits for the clients passively represented" (Meier, 2019, 40). Over the years, RB scholars have posited various conditions under which bureaucrats are more likely to engage in AR. In this work, we assess AR in policing through a behavioral analysis that examines how partisanship and race simultaneously map to police behavior.

Prior work has theorized that AR is more likely to occur when the salience of a relevant identity increases (Meier, Pennington and Eller, 2005). The intensifying political polarization surrounding policing policy raises the possibility that partisan identity—which has taken on augmented prominence in society generally (Iyengar and Westwood, 2015)—-may be playing an increased role in how officers perform their day-to-day duties. Prior work on affective polarization offers several reasons why partisan affiliations might affect police behavior. For one, "partisanship has bled into the nonpolitical sphere, driving ordinary citizens to reward copartisans and penalize opposing partisans" (Iyengar et al., 2019, 133) in arenas as varied as hiring (Gift and Gift, 2015), dating (Huber and Malhotra, 2017), and online labor markets (McConnell et al., 2018). Recent evidence from public administration also shows that bureaucrats who run elections respond differently to voters' information requests when voters disclose their partisanship (Porter and Rogowski, 2018).

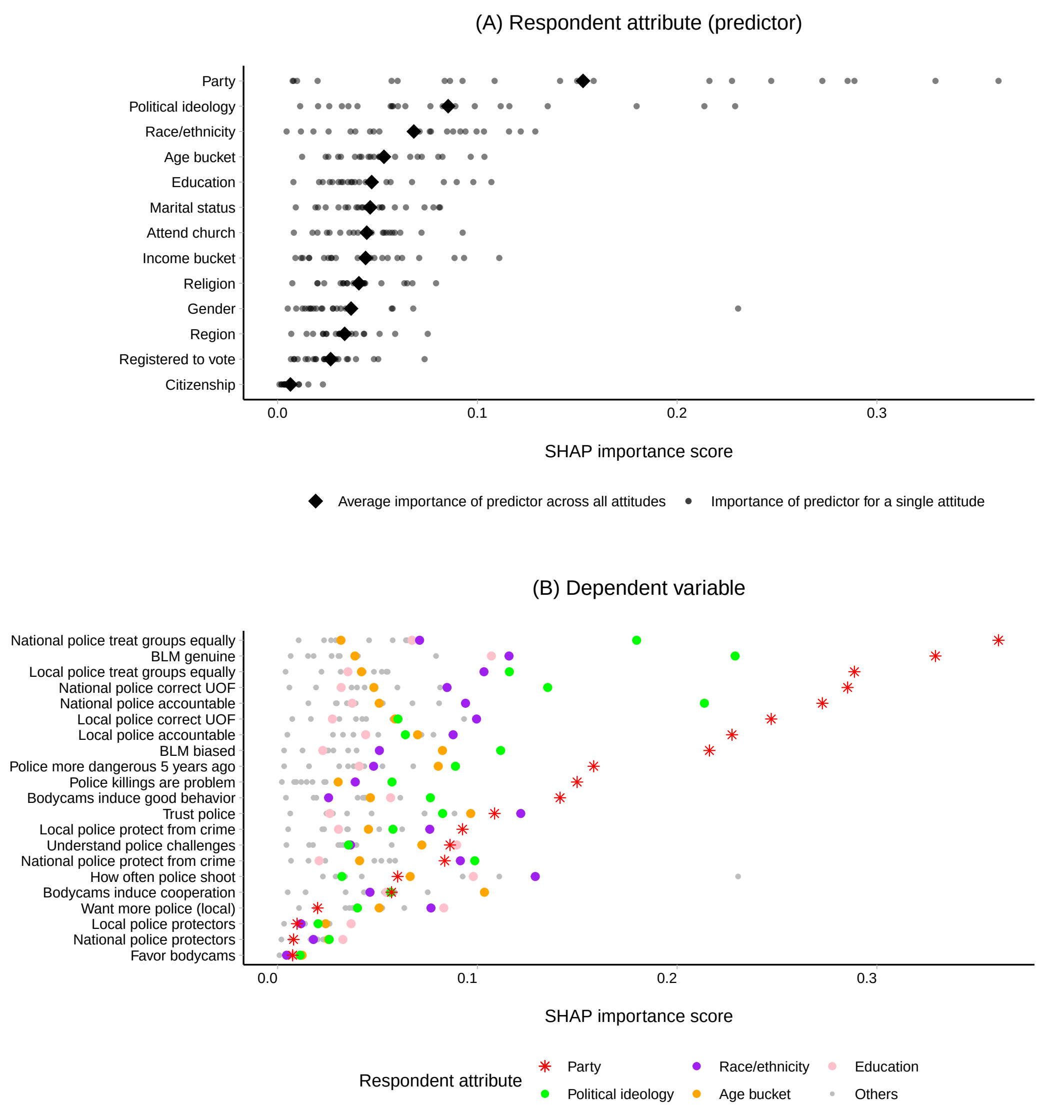
One potential obstacle to partisan AR in policing is that unlike other demographic characteristics, a civilian's partisanship is not readily observable by most officers, perhaps making it more difficult to actively provide preferential treatment. However, we theorize that there are at least two ways that partisan AR can still occur. First, recent experimental work has shown that racial stimuli can activate partisan animus, and vice versa (Westwood and Peterson, 2020). And because partisan divisions on policing policy are so strongly tied to matters of race, officers may actively represent copartisans indirectly through their treatment of various civilian racial groups. Consistent with this logic, Grosjean, Masera and Yousaf (2023) shows that police are more likely to stop Black drivers in the wake of Trump rallies—events where Trump has explicitly downplayed police brutality (Eversley, 2017). Second, in the realm of policing, civilians can accrue "benefits" from officers who share their social identity without directly interacting with those officers. For example, officers can suppress a certain type of crime that is of principal concern to in-group members. By behaving in ways consistent with copartisans' views on how policing should be done, officers can provide AR for their partisan group without identifying or knowingly interacting with individual copartisans.

The most obvious reason that officers of differing partisan identities might perform their jobs differently stems from public opinion data. National polls show clear evidence of partisan divides on a range of questions pertaining to how police should do their jobs. In Figure 1, we present the importance of partisan affiliation and other demographics in predicting policing attitudes in a national survey (Pew, 2016). The importance of each variable is quantified through its Shapley value, a standard machine-learning technique that assesses how much predictions change when the variable is omitted.[3] As the figure shows, partisan affiliation is among the most important predictors of policing attitudes, often eclipsing the predictive power of standard demographic variables including race/ethnicity and political ideology. If partisans in the general public mirror the preferences of partisans on police forces, it is plausible that these groups of officers behave in very different ways on the job. While we cannot directly measure officers' preferences, our analysis below examines the distribution and consequences of police partisanship to assess whether patterns are consistent with AR.

In what follows, we discuss our empirical strategies for assessing the distribution and consequences of police officers' partisan affiliations.

[3]Our analysis uses gradient-boosted decision trees (Chen and Guestrin, 2016) to assess the change in predicted attitudes when a demographic characteristic is included in the model (vs. a baseline model where it is excluded). For each specification of the baseline model (e.g. one that uses only an intercept), the inclusion of the variable (e.g. a model that uses partisan affiliation alongside the intercept) shifts the predicted values by some additive amount. The Shapley value represents the variable's overall contribution when averaging over all possible baseline model specifications (i.e. inclusion/exclusion decisions for the remaining variables). To estimate this Shapley value, we utilize a version of the computationally efficient SHapley Additive exPlanations (SHAP) method that is tailored for categorical predictors (Amoukou, Brunel and Salaün, 2022).

Figure 1: **Partisanship as a predictor of policing attitudes.** Notes: The upper panel depicts the Shapley importance score of various respondent attributes (horizontal axis) in predicting survey responses about policing in Pew (2016). Each small gray circle represents a policing attitude, with vertical position indicating the attribute's contribution to overall estimated responses (Amoukou, Brunel and Salaün, 2022) in a gradient-boosted decision tree model (Chen and Guestrin, 2016). Large black diamonds represent the overall importance of the respondent attribute, averaging over all attitudes. Partisanship has the highest overall importance, roughly double that of ideology and race/ethnicity. The lower panel shows disaggregated importance scores for each policing attitude (horizontal axis), with points for each respondent attribute. Partisanship is indicated with a red asterisk and other top-five predictors are indicated by colored dots; for clarity, less important attributes are shown only with gray dots. Partisanship is the most important predictor for a majority of policing attitudes.



Data and Measurement

We sought rosters of all sworn police officers in the largest 100 police agencies[4] in the United States. We define "largest" based on the number of officers whose primary duty is patrol, as these officers are the ones most likely to have contact with members of the public (Harrell and Davis, 2020). We assembled data on 50 agencies by scouring public sources such as open-data portals managed by local governments, news agencies and nonprofits, as well as data previously released through public-records requests on muckrock.com. We obtained the remainder from a combination of open-records requests and data-sharing agreements. Roughly three quarters of rosters come from 2019–2021; about one fifth originate from 2015–2018; and the remainder do not specify a year.

Ultimately, we received data covering roughly 220,000 officers from 99 police agencies.[5] In 91 agencies, we also obtained employee titles, which we use to distinguish sworn police officers and unsworn civilian roles (such as lab technicians and analysts). This information allows us to subset to sworn officers for much of our analysis.

Figure 2 shows the location of each agency included in this study. Our data cover agencies in 32 states and the District of Columbia. In all, the roughly 220,000 officers in our agency rosters represent over one third of the roughly 642,000 local police officers and sheriffs' deputies nationwide (Hyland and Davis, 2019), making this the largest examination of descriptive representation in policing to date.[6]

Measuring Officer Attributes

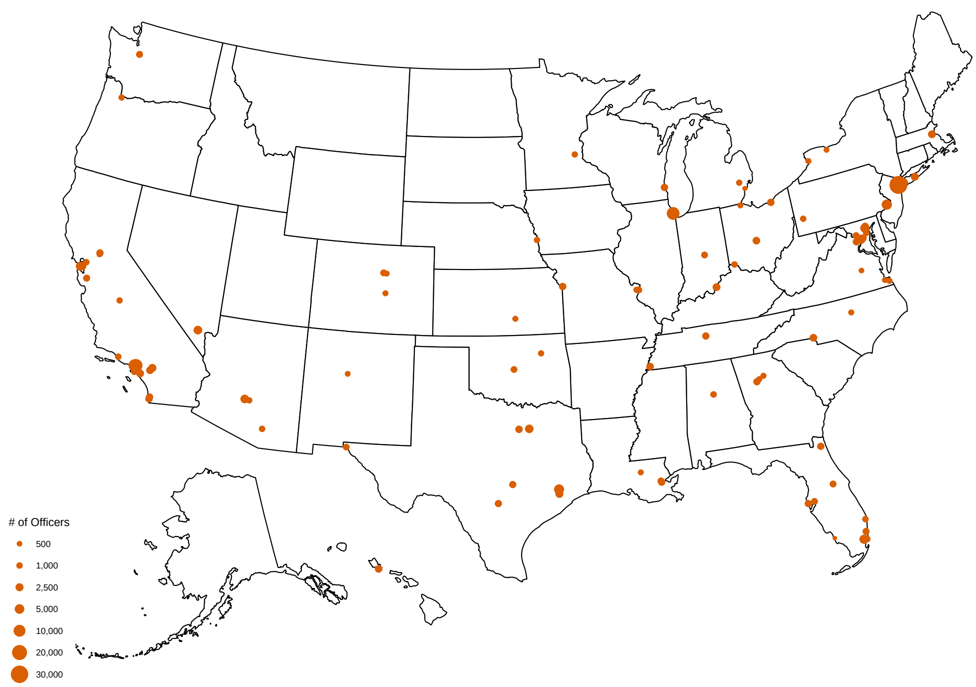
Employee rosters contain full officer names, with the exception of a limited number of undercover agents in certain jurisdictions who are excluded from analysis. For our analysis comparing agencies to civilians in their jurisdictions (see the following section), we measure officer attributes with a combination of sources. We use voter-file estimates to quantify party identification, turnout,

[4]We began with agencies contained in DOJ (2016), then limited our sample to sheriff's departments and local or county police. We also excluded state police and sheriff's departments that do not engage in law enforcement services. Remaining agencies were then ranked by number of full-time sworn officers according to the Census of State and Local Law Enforcement Agencies (CSLLEA), the most complete record of agency size available.

[5]We were unable to secure data from the Detroit, MI, Police Department.

[6]See Appendix Table E.1 (Appendix p. 3) for comparisons of officers in our data to (1) officers nationwide and (2) the U.S. population (Hyland and Davis, 2019).

Figure 2: **Agency locations.** Notes: Included agencies cover roughly 220,000 officers across 32 states and Washington, D.C., representing 34% of the nation's roughly 642,000 sworn local police officers and sheriffs' deputies (Hyland and Davis, 2019). Together, jurisdictions covered in our data serve about 23% of the U.S. population. Each dot is scaled by the number of sworn officers.



age, and household income for individual officers, which we then aggregate to the agency level. For officer race and gender, we rely on agency responses to federal surveys, avoiding the estimated voter-file proxies. In our behavioral analysis of Chicago and Houston (pp. 20), we use voter-file measures of party identification but rely on individual-level racial data obtained through open-records requests.

We merge officer rosters with a commercial voter file from L2 (l2-data.com) via a two-step process. We restricted candidate matches to only individuals residing in or adjacent to the counties containing their agency, including adjacent out-of-state counties. We then attempted to find a match for each officer in our roster based on the officer's first name, their middle initial (if available), and their last name. Rather than using exact matching, we employ the probabilistic technique of Enamorado, Fifield and Imai (2017, 2019) via the *fastlink* `R` package.[7] See Appendix Sections B (Appendix pp. 1-2) and I (Appendix pp. 14-23) for details on our matching procedure

[7]After matching officers to voters in the L2 database, we retain all officers with a 0.9 or greater posterior probability of a match. Alternative core results using a cutoff of 0.95 appear in Appendix Table I.2. (Appendix p. 18)

and extensive validation tests, respectively.

Data in the L2 voter file includes party identification, age, household income, and voter turnout history for both officers and civilians in their jurisdictions. We use these covariates, along with 2015–2019 five-year American Community Survey data, to evaluate passive representation.[8] We divide officers and civilians into three partisan categories based on L2's labels: Democrat, Republican, and an "other/unknown party" category that represents all other party affiliations in L2 along with all individuals not appearing in the L2 data. These categories rely on proprietary L2 algorithms to characterize the party affiliation of officers and civilians, which introduces potential bias due to error in machine-learning based proxies (Knox, Lucas and Cho, 2022). While error in these imputations may bias estimated levels of party affiliation, at least some of this bias would likely wash out when computing *differences* between officers and civilians (our primary quantities of interest) because the same imputation method is applied to both groups. In addition, several studies have sought to validate L2's imputed partisanship measures and found they correlate strongly to both official election returns (Fraga, Holbein and Skovron, 2018) and self-reports in surveys.[9] Studies of another potential source of error in voter files, so-called "insincere" party registration by partisans seeking to sabotage their opponents, has found virtually no evidence of the phenomenon (Stephenson, 2011).

Nevertheless, to address these concerns, we take extensive steps in Appendix I (Appendix pp. 14-23) to deal with potential measurement error in party identification: we compute bounds using extreme assumptions about covariates of unobserved individuals; we re-compute core results using an alternate measure of party identification; and we report results using only states in which voters can identify their preferred political party when registering to vote, where party identification data may be most accurate. Our core conclusions—e.g. about the overrepresentation of Republican and White identities in policing—remain supported across nearly all of these robustness checks.[10]

To measure race, ethnicity and gender, we primarily rely on 2021 Law Enforcement Officers

[8] See Appendix B (Appendix pp. 1-2) for details on jurisdiction geography and Census merges.

[9] For example, Hersh and Goldenberg (2016) used a similar merging approach to obtain physicians' partisan registration, and compared results to a survey of a stratified sample of the matched physicians, which included a question about political ideology. Only 2% reported opposite ideologies to the imputed partisan affiliation.

[10] Extreme assumptions about the nature of measurement error—e.g. assuming that an officer is Democratic if even one of their multiple L2 matches fits this description—do affect some conclusions. See extended discussion in Appendix I (Appendix pp. 14-23).

Killed and Assaulted (Kaplan, 2023, LEOKA, which reports gender breakdowns for officers in each reporting agency;) and 2020 Law Enforcement Management and Administrative Statistics data (LEMAS, 2020, agency surveys reporting racial composition). These datasets contain demographic information on 100% and 86% of the agencies in our study, respectively. For missing agencies, we rely on L2's estimated race and ethnicity. We similarly rely on L2 for measures of officers' household income and age. See Appendix C (Appendix p. 2) for additional details.[11]

Officers' Political Affiliations in Local Context

We now compare the partisan affiliations of officers to those of civilians within their jurisdictions. We also characterize descriptive representation of civilians on additional dimensions including race, ethnicity, gender, household income, age, and political participation as measured by general election turnout. Civilian attributes are obtained by aggregating over all Census tracts where the agency has jurisdiction.[12]

Table 1 first displays aggregate results. The leftmost values represent average officer attributes, aggregating across our 99 jurisdictions.[13] Because each officer is given equal weight, larger agencies account for a larger share of these aggregate statistics; results disaggregated by agency are given in Appendix Table F.1 (Appendix pp. 6-8). The next column corresponds to the expected attribute value if, hypothetically, police agencies were perfectly representative—for example, the expected proportion of Republican officers across the 99 agencies, if each current officer was instead replaced with a random draw from their respective jurisdiction while holding agency sizes fixed.[14] Subsequent columns display officer-civilian differences and 95% confidence intervals.[15]

Results show police officers diverge from their jurisdictions on every attribute we measure.

[11]See Tables H.1 and H.2 for robustness checks related to potential mismeasurement of race/ethnicity.

[12]See Appendix B (Appendix pp. 1-2) for details on matching tracts to jurisdictions.

[13]Note for aggregate results, the total number of observations across racial/ethnic groups differs slightly from the total for other variables. This is the result of rounding after multiplying agency-level proportions from LEMAS (2020) by agency-level officer counts to recover the number of officers in each race/ethnicity category.

[14]Specifically, this hypothetical value is computed as $\frac{\sum_i \overline{X}_i N_i}{\sum_i N_i}$, where i indexes agencies, $\overline{X}_i$ refers to the average civilian attribute in the agency's jurisdiction, and N_i is the number of officers employed by the agency.

[15]We note that civilian age is computed using data on all civilians, including those too young to serve on police forces, in keeping with our goal of comparing officers to all civilians in their jurisdictions, not just those eligible to serve. However, for reference, the median age among adult civilians is 44. Civilian party identification, computed using voter file records, is restricted to adults. In addition, turnout analyses exclude voter turnout for agencies in Kentucky, which account for about 1% of officers, due to missing data in L2.

We find officers are far more likely to be Republican than civilians in their jurisdictions: as a share of the voting-age population, we estimate 32% of officers are Republican (vs. 14% of civilians). Officers are also less likely to identify with the Democratic party (31% vs. 44%). Officers are much more politically active than a representative group of civilians would be: 69% of officers voted in the 2020 general election (vs. 55%).

In terms of race, 51% of officers in our data are White. If officers were representative of civilians in their jurisdictions, that share would fall to 38%; correspondingly, the Black and Hispanic proportion would rise by about 5 and 4 percentage points (p.p.), respectively. By far the largest representation gap is in gender: 83% of officers in our data are male, likely due in part to the difficulty of recruiting female candidates into law enforcement (Kringen, 2014). This gap is especially noteworthy given recent research showing that, when faced with common circumstances, female officers are less likely to use force than their male counterparts (Ba et al., 2021). Officers also have higher household incomes: on average, officers' households in our data make over $114,000 a year, whereas a representative group of civilian households would earn roughly $22,000 less.

Our pooled results mask heterogeneity across agencies. To explore this variation, Figure 3 plots each jurisdiction in terms of officer and civilian Republican share; the pooled means from Table 1 are plotted as vertical lines for reference. Agency-level comparisons to civilians on race, voter turnout, gender, age, and household income for all 99 agencies appear in Appendix Table F.1 (Appendix pp. 6-8). These results show agencies ranging from unrepresentative and partially representative to highly representative in terms of party identification and race/ethnicity. Representativeness along racial lines does not always correspond to representativeness along partisan lines.

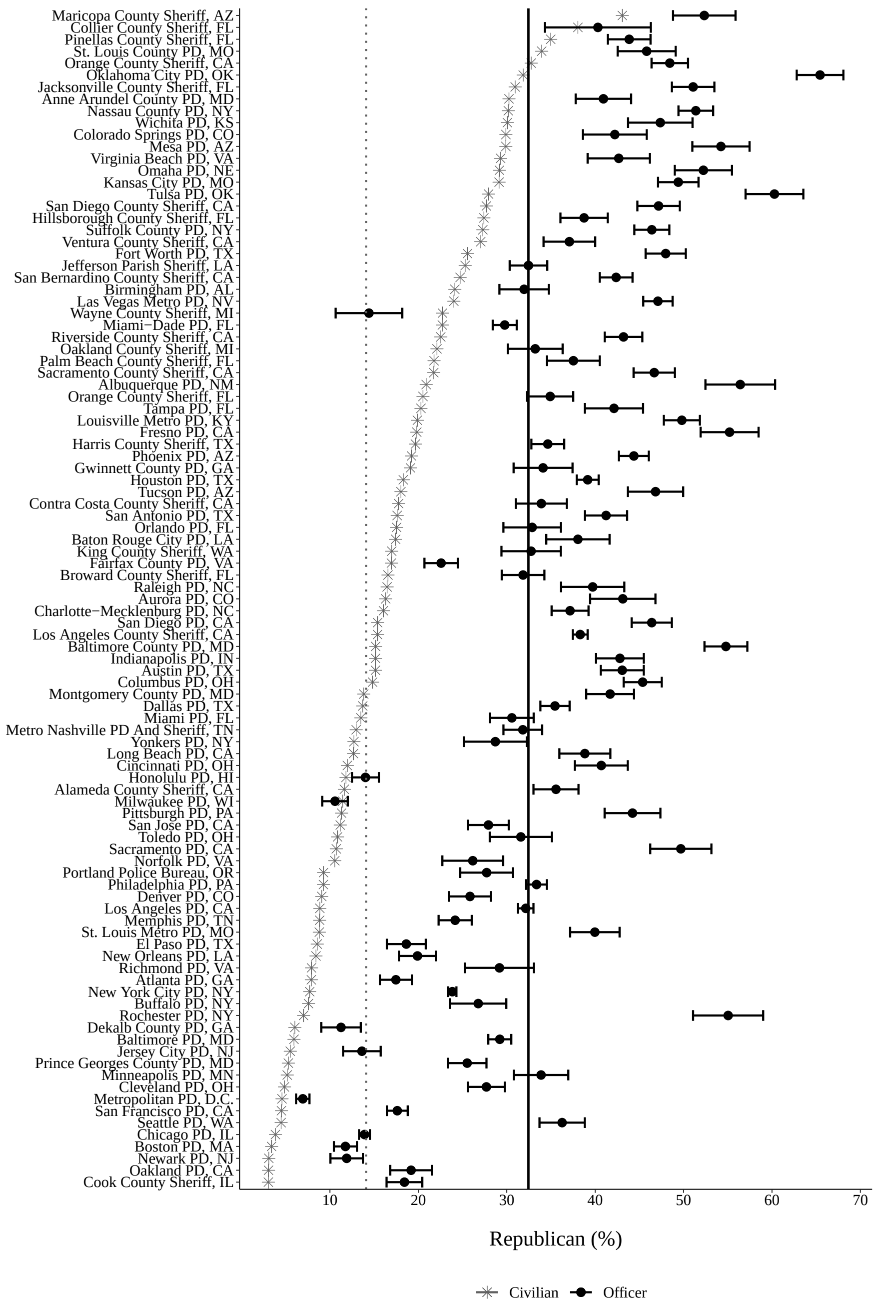
Consider the Rochester, NY, Police Department: a highly unrepresentative jurisdiction in which at least 55% of its police officers are Republican, compared to only 10% of residents. In addition, we find that 75% of Rochester officers are White, compared to 38% of civilians. On the other hand, we observe agencies like the L.A. County, CA, Sheriff's Department, which is highly representative in some racial categories (e.g. 7% Black officers vs. 8% Black residents), but highly unrepresentative politically (38% Republican officers vs. 21% Republican residents). Finally, we also see agencies that are roughly representative on both dimensions, such as the Birmingham, AL, Police Department, comprised of 32% Republican officers (vs. 27% civilians), 37% White officers

Table 1: **Comparison of average officer and civilian traits.** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. The Difference column is made by taking the difference between the officer and civilian trait. For median age, the difference column shows the mean difference between each officer's age and the median civilian age in their jurisdiction. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer	Hypothetical representative officer	Difference	N
Race	White	51.26%	37.95%	13.31** [13.11, 13.51]	112,446
	Hispanic	23.75	27.98	−4.23** [−4.40, −4.06]	52,089
	Black	16.05	21.26	−5.21** [−5.36, −5.06]	35,207
	Other/unknown race	3.65	3.42	0.23** [0.15, 0.30]	8,000
	Asian	5.30	9.40	−4.10** [−4.19, −4.01]	11,625
Party (Voting age population)	Republican	32.45%	14.11%	18.34** [18.15, 18.53]	71,177
	Democratic	31.32	43.50	−12.18** [−12.37, −11.99]	68,705
	Other/unknown party	36.23	42.64	−6.41** [−6.61, −6.20]	79,483
General turnout, 2020	Voting age population	69.39%	54.62%	14.76** [14.57, 14.96]	150,609
Gender	Male	82.75%	48.69%	34.07** [33.91, 34.22]	181,532
	Female	17.25	51.31	−34.07** [−34.22, −33.91]	37,833
Median age (years)	–	44.00	36.84	8.07** [8.00, 8.13]	187,382
Mean household income ($)	–	114,199.67	92,220.54	21,979.13** [21,704.20, 22,254.06]	186,778

(vs. 35% civilians), and 61% Black officers (vs. 57% civilians). In response to a reviewer comment, we also tested whether disparities differed between police and sheriff's agencies. As Appendix Table G.2 (Appendix p. 11) shows, both types of agencies show overrepresentation of white officers, but the degree of overrepresentation is 5 percentage points larger among police agencies. Likewise, Democrats are underrepresented in both types of agencies, but the underrepresentation is 7 percentage points larger for police agencies. These patterns are consistent with, but not dispositive of, elections promoting descriptive representation in policing.

Figure 3: **Average shares of Republicans among officers and civilians in the same jurisdictions.** Notes: Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions.



Micro-Level Case Studies in Chicago and Houston

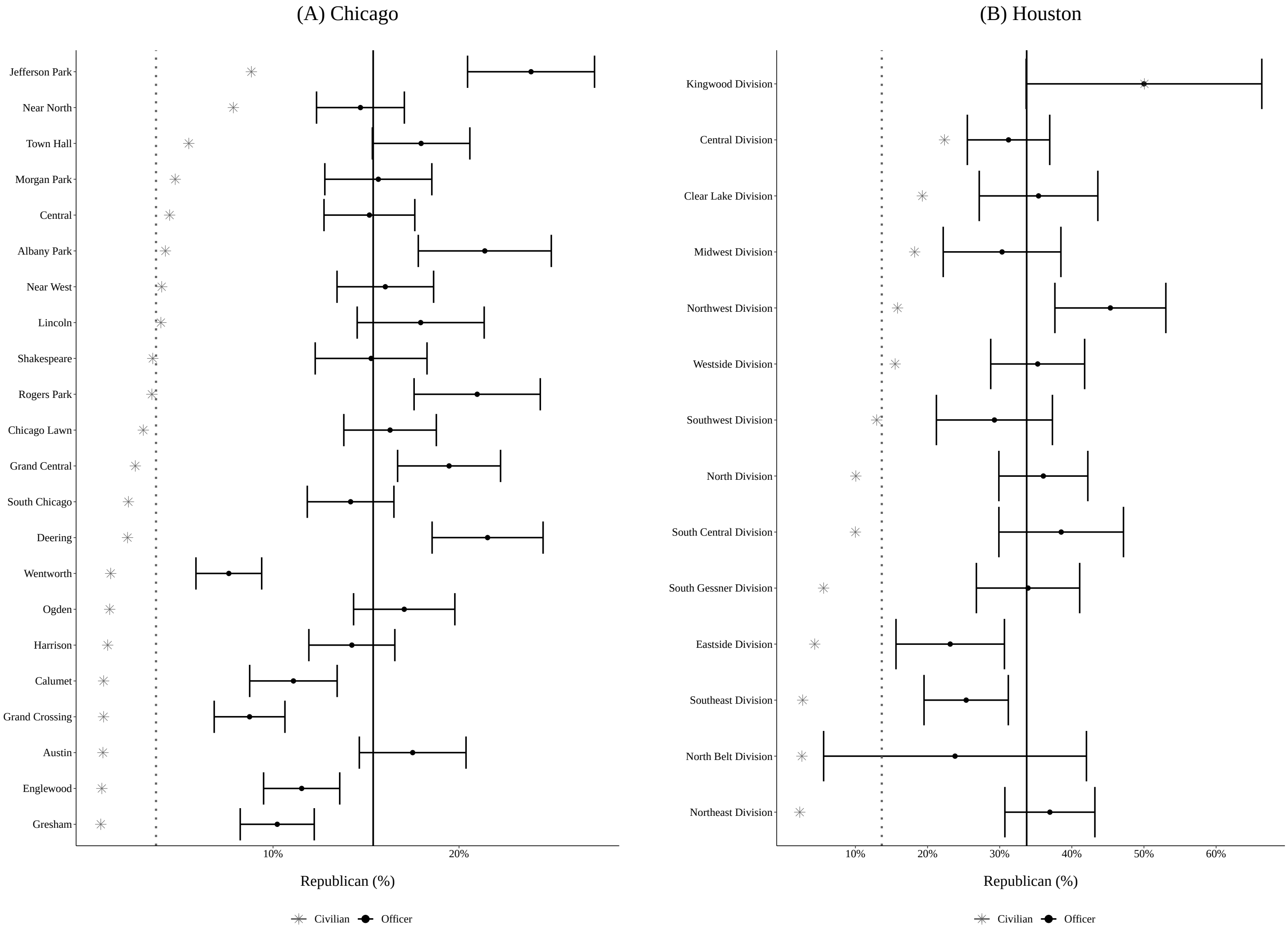
We now turn to detailed case studies of two large agencies, the Chicago Police Department (CPD) and Houston Police Department (HPD), where we obtained rich data on officer deployment and enforcement behavior. We use these data to conduct several analyses. First, we assess passive representation at a more fine-grained level, using deployment data to test whether officers are representative of the civilians with whom they likely interact. Second, we investigate whether officers of different social identities—in particular, political affiliations—treat civilians differently in ways consistent with actively representing partisan preferences for how policing should be conducted. While this analysis would ideally study behavior in even more jurisdictions, we have found that data on day-to-day officer deployment—which is crucial for the credibility of the analysis—is extremely difficult to procure, with many agencies denying open records requests or failing to maintain historical data in usable form. When obtainable, however, deployment records offer a rare opportunity to compare officers while holding working conditions fixed.

Political Representation in Police-Civilian Interactions

To investigate whether officers are politically representative of the civilians with whom they most likely interact, we associated Chicago and Houston officers with the districts or divisions in which they most frequently worked. We then compared officers to residents of their assigned unit. Figure 4 shows a striking mismatch for both agencies. In our behavioral data, 15% of CPD officers are Republican. However, even in the district with the highest share of Republican residents, civilians are roughly 9% Republican. And as Figure 4 shows, Republicans are overrepresented among police officers in every Chicago district. We see a similar portrait in Houston. Overall, 36% of HPD officers are Republican. Parity is reached in the most right-leaning division—where approximately half of officers and civilians are Republican—but in every other division, Republican officers are overrepresented. In the division with the lowest share of Republican residents, only 2% of civilians are Republican, compared to 37% of officers.[16]

[16] Tables G.3 and G.4 also display district-level comparisons between officer and civilian race/ethnicity for Chicago and Houston, respectively. Throughout this section, we use officer-level race/ethnicity data provided by CPD and HPD; note that this diverges from the approach in Table 1, which relied on more widely available data sources for consistency. Summary statistics in this section are computed using CPD and HPD data prior to additional filtering described in the next section.

Figure 4: **Average shares of Republican officers and civilians in officers' assigned districts, in Chicago (panel A) and Houston (panel B).** Notes: Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census data. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district.



A Research Design to Compare Officer Behavior Across Partisan Groups

We employ a research design developed in Ba et al. (2021) to identify the effect of deploying an officer with one social identity (vs. another officer of a differing identity) to otherwise similar circumstances. From a theoretical perspective, this analysis probes a key observable implication of active representation—if officers from different social identities do not treat civilians differently, there is little reason to suspect active representation is occurring. We examine the overall volume of stops, arrests, and uses of force made by Democratic (vs. Republican) officers, as well as the volume of arrests made for specific types of crimes. We further assess partisan differences in treatment of racial/ethnic minorities. Each behavioral outcome represents one potential channel through which partisan officers might actively represent copartisans' preferences on how policing should be performed.

To conduct this analysis, we analyze 2012–2019 CPD shift-assignment and enforcement records, collecting new data to double the 2012–2015 coverage of Ba et al. (2021). Our Houston data covers 2017–2020. Tables 2 and 3 summarize these datasets. As the tables show, our data include observations on the behavior of almost 12,000 officers across 6.7 million shifts in Chicago, as well as roughly 2,400 officers across 1.2 million shifts in Houston.[17]

We note that the data provided by HPD suffers numerous quality issues, often making judgement calls necessary during preprocessing. For example: (1) officers were not identified by badge or employee numbers in HPD-provided enforcement data, and names were often abbreviated inconsistently even within a single dataset; (2) all instances of the number "8" appear to have been manually deleted from dates and times in the use-of-force data, requiring imputation to remedy; and (3) civilian ethnicity was excluded from stop data despite evidence that HPD tracks this information for its annual reports.

Table 2: **Summary of Chicago data on officer behavior (counts), 2012-2019**

	White	Black	Hispanic	Male	Female	Republican	Democratic	Other/unknown party
Stops	1,037,792	355,786	538,171	1,563,521	368,228	353,242	1,132,438	446,069
Arrests	236,208	84,498	137,462	376,634	81,534	79,299	255,252	123,617
Force	10,512	3,605	5,357	16,777	2,697	3,421	11,004	5,049
Shifts	3,273,026	1,603,495	1,779,986	5,212,874	1,443,633	1,100,840	4,043,087	1,512,580
Officers	5,763	2,682	3,219	8,808	2,856	1,791	6,888	2,985

[17]We estimate that party affiliations for CPD officers included in this analysis are approximately as follows: White officers: 53% Democrat, 23% Republican; Black officers: 84% Democrat, 5% Republican; Hispanic officers: 49% Democrat, 12% Republican. In Houston, the party affiliations for officers included in the analysis are: White officers: 18% Democrat, 63% Republican; Black officers: 66% Democrat, 17% Republican; Hispanic officers: 70% Democrat, 19% Republican.

Table 3: **Summary of Houston data on officer behavior (counts), 2017–2020**

	White	Black	Hispanic	Male	Female	Republican	Democratic	Other/unknown party
Stops	255,280	183,268	206,769	618,884	26,433	316,808	273,192	55,317
Arrests	58,871	27,035	53,591	126,206	13,291	51,296	64,132	24,069
Force	20,773	6,637	15,552	39,278	3,684	16,731	18,618	7,613
Shifts	499,398	297,672	431,422	1,085,435	143,057	462,866	577,503	188,123
Officers	986	553	867	2,088	318	876	1,143	387

Our analyses compare officers working standard patrol assignments in the same month-year (e.g. January 2012), day of week, 8-hour shift, and beat (a specific task or assignment, often small patrol areas about one square mile in Chicago). We refer to these units as "MDSBs." The target quantity in this analysis is the average treatment effect of taking all shifts worked by one group in the MDSB and, counterfactually, reassigning them officers of another group who were eligible to work in the same MDSB (and vice versa). This quantity is equivalent to the average within-MDSB difference in expected enforcement activity between the two groups of officers. However, these differences cannot be feasibly estimated in MDSBs that have no variation in treatment assignment, e.g. when all working officers are Republican; for this reason, we focus on the average treatment effect among MDSBs where comparisons can feasibly be made. We stress that the treatment of interest—the deployment of an officer of one group, vs. another—is inherently bundled. Officers of a particular partisan identity, for example, differ in many ways besides political orientation. In practice, however, commanders can only deploy whole officers; they cannot modify an officer's identity while holding its correlates fixed, meaning that the bundled treatment effect is in fact the quantity of greatest substantive relevance. Put differently, we seek to estimate the effect of *deploying* an officer of one identity relative to another, with all their associated traits (Sen and Wasow, 2016); we do not seek to estimate the effect of modifying the identity itself.[18]

We use weighted fixed-effects regressions to compare the enforcement decisions of officer groups within each MDSB and aggregate these into an overall estimate of the deployment disparity. Weights based on the within-MDSB prevalence of each group are used to obtain unbiased estimates of the average treatment effect (see Appendix D (Appendix pp. 2-3) for additional details on estimation). Standard errors are clustered by officer. The key assumption underlying this analysis is that,

[18]See Hall (2015) for a related discussion on interpreting bundled treatments.

prior to post-deployment decisions about how to spend their shifts, officers from different groups are equally likely to encounter the same types of civilians, scenarios and conditions within MDSBs. As outlined in Ba et al. (2021), a rotating day-off scheduling system in the CPD greatly limits the ability of officers to select into working environments with systematically different conditions. In line with the assumption of as-if random assignment of officers to shifts within small slices of time and space, balance tests using incident-level crime data show that crime conditions are statistically indistinguishable across officer groups within MDSBs in Chicago (see Appendix J, Appendix p. 24).

Our behavioral analyses are organized as follows. At a high level, six comparisons are made. These include unconditional comparisons between (1) Democratic and Republican officers, (2) Black and White officers, and (3) Hispanic and White officers, as well as conditional Democratic-Republican comparisons within (4) Black, (5) Hispanic, and (6) White subsets of officers. These comparisons correspond to six "families" of null hypotheses, each stating that the two officer groups make the same average decisions, across all types of enforcement, when deployed to common circumstances. We note that the effective sample we are analyzing changes across analyses depending on the comparison being made (Aronow and Samii, 2016). Because the MDSBs where comparisons are feasible differ across subsets, it is not possible to compare results across these groups of analyses (e.g. comparing Democratic-Republican differences to Black-White differences) while holding circumstances constant. However, within each of these groups of tests, the logic of the within-MDSB comparisons hold. To account for the large number of analyses performed, we use the hierarchical multiple-testing procedure of Peterson et al. (2016). See Appendix D (Appendix pp. 2-3) for details. Note that in Figures 5–8, we depict unadjusted 95% confidence intervals with robust standard errors; results that remain significant after multiple-testing corrections are indicated in red.

Results of Behavioral Analysis

We first report our aggregate test of whether Democrats and Republicans behave differently when facing common circumstances (see left panels in Figure 5), which includes all MDSBs where cross-party comparisons can be made. As the figure shows, our unadjusted results suggest that Democrats in Chicago made significantly fewer arrests for drug crimes (0.1 fewer per 100 shifts; $p_{\text{unadj.}} = 0.022$, $p_{\text{adj.}} = 0.344$) and traffic crimes (0.1 fewer per 100 shifts; $p_{\text{unadj.}} = 0.004$, $p_{\text{adj.}} = 0.126$), but made more arrests for property crimes (0.04 more per 100 shifts; $p_{\text{unadj.}} = 0.030$, $p_{\text{adj.}} = 0.344$). However, these differences lose statistical significance after multiple-testing corrections, as the larger $p_{\text{adj.}}$ values indicate. Similarly, in Houston, Figure 6 shows Democrats used less force against Black civilians than Republicans (0.3 fewer force uses per 100 shifts; $p_{\text{unadj.}} = 0.028$, $p_{\text{adj.}} = 1$). Across both cities, after correcting for multiple comparisons, we find no significant differences between Democratic and Republican officers facing common circumstances in terms of total policing activity, activity toward various civilian groups, and arrests for different crime types.

One possible explanation for the lack of detectable differences between Democratic and Republican officers in the aggregate is that these groups are not monolithic. For example, partisan groups contain different proportions of officers with Black, Hispanic, White or other racial/ethnic identities, and prior work has shown that these other attributes are strongly predictive of officers' enforcement behavior. In principle, it is possible that this other source of variation could make it statistically difficult to detect partisan differences. To examine this possibility, we next extend our analysis in two ways: (1) by comparing minority to White officers, and (2) by comparing Democratic officers to Republican officers *of the same race/ethnicity*.[19]

The central panels in Figure 5 show that across all variants of outcomes, and after correcting for multiple testing, Black officers in Chicago make fewer stops and arrests and use force less often than White officers facing common circumstances. Specifically, Black officers make 8.9 fewer stops, 1.4 fewer arrests, and have 0.1 fewer uses of force per 100 shifts (all $p_{\text{unadj.}} \leq 0.001$, $p_{\text{adj.}} \leq 0.001$). These reductions are equivalent to 28.1%, 19.4%, and 31.3% of the average output of White officers citywide. Black officers also make 7.3 fewer stops, 1.0 arrests, and 0.06 uses of force involving Black civilians specifically (per 100 shifts; all $p_{\text{unadj.}} \leq 0.001$, $p_{\text{adj.}} \leq 0.001$). Some of these patterns are shared by Hispanic officers, who make 0.4 fewer arrests overall, 0.3 fewer arrests of Black civilians, 1.7 fewer stops overall, 1.8 fewer stops of Black civilians, and 0.03 fewer uses of force overall and against Black civilians specifically (per 100 shifts; all $p_{\text{unadj.}} \leq 0.001$, $p_{\text{adj.}} \leq 0.001$). Racial/ethnic enforcement differences are less pronounced in Houston, where the HPD's smaller size, differing deployment

[19]We reiterate that even using these refined comparisons, differences in behavior cannot be interpreted as the causal effect of changing an officer's partisanship: despite holding race/ethnicity fixed, there are numerous other differences between Democratic and Republican officers, such as socioeconomic status. As in our primary analyses, results are best interpreted as the effect on enforcement outcomes that a commander can expect if deploying a randomly drawn officer from one group, vs. another group, among those available to work in a particular place and time.

patterns, and a number of data issues mean that effects are estimated with substantially more noise.

As Figure 6 shows, Black HPD officers engage in 0.8 fewer uses of force ($p_{\text{unadj.}} = \leq 0.001$, $p_{\text{adj.}} = 0.001$) and Hispanic officers engage in 4.7 additional stops per 100 shifts than White officers in comparable circumstances ($p_{\text{unadj.}} = \leq 0.001$, $p_{\text{adj.}} = 0.026$), but we do not detect other behavioral differences across racial/ethnic lines. As these two jurisdictions and agencies differ on many dimensions—including racial composition, political history, and local culture—it is difficult to discern why race-based differences are so pronounced in Chicago but less prevalent in Houston. This may be in part due to the aforementioned differences in data quality, but other factors, such as Chicago's requirement that all officers reside within the city, may also play a role. Future work is necessary to investigate these contextual differences. However, part of the present study's contribution is to underscore that such variation exists. In a nation of 18,000 law enforcement agencies, discussions of "policing" writ large may often mask important heterogeneity.

Finally, Figure 7 tests whether Democrats in Chicago behave differently, compared to Republican peers of the same race/ethnicity. Prior to multiple-testing corrections, results are mixed: Hispanic Democratic officers appear to use more force than co-ethnic Republicans, whereas Black Democratic officers appear to use less force than co-racial Republicans. As the figure shows, however, only one comparison survives a multiple testing correction, with White Democrats making more violent crime arrests than White Republicans (an increase of 0.04 arrests per 100 shifts; $p_{\text{unadj.}} = 0.001$, $p_{\text{adj.}} = 0.036$). In Houston, we find no detectable differences across partisan groups within officer racial/ethnic groups.

Figure 5: **Deployment effects in Chicago.** Notes: The plot displays the effect of deploying a Democrat vs. a Republican officer in similar circumstances on various outcomes. Estimates in grey are nonsignificant. Estimates in black were statistically significant prior to multiple testing correction. Estimates in red remain significant after multiple testing correction.

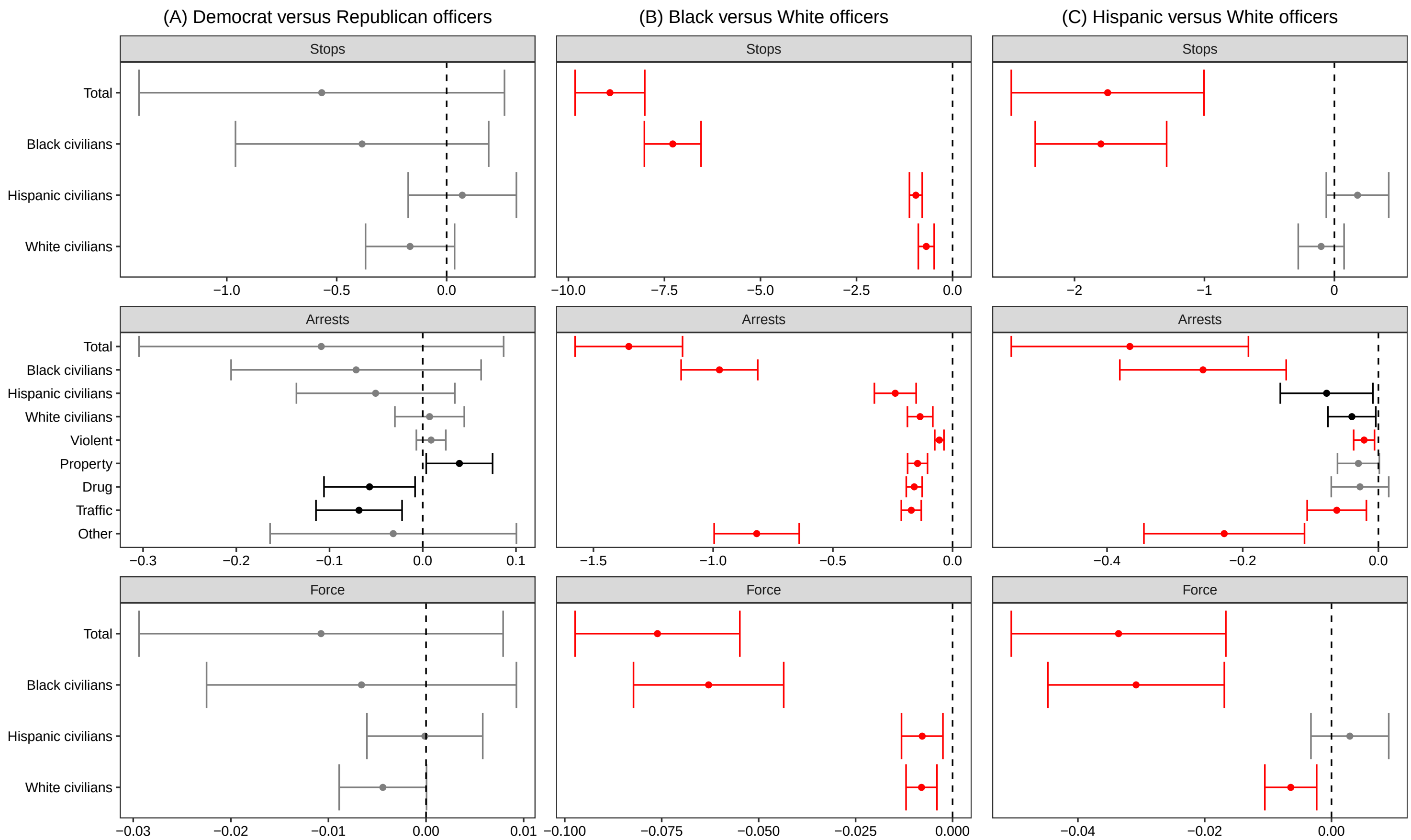


Figure 6: **Deployment effects in Houston.** Notes: The plot displays the effect of deploying a Democrat vs. a Republican officer in similar circumstances on various outcomes. Conventional 95% confidence intervals with officer-clustered standard errors displayed. Estimates in grey are nonsignificant. Estimates in black were statistically significant prior to multiple testing correction. Estimates in red remain significant after multiple testing correction.

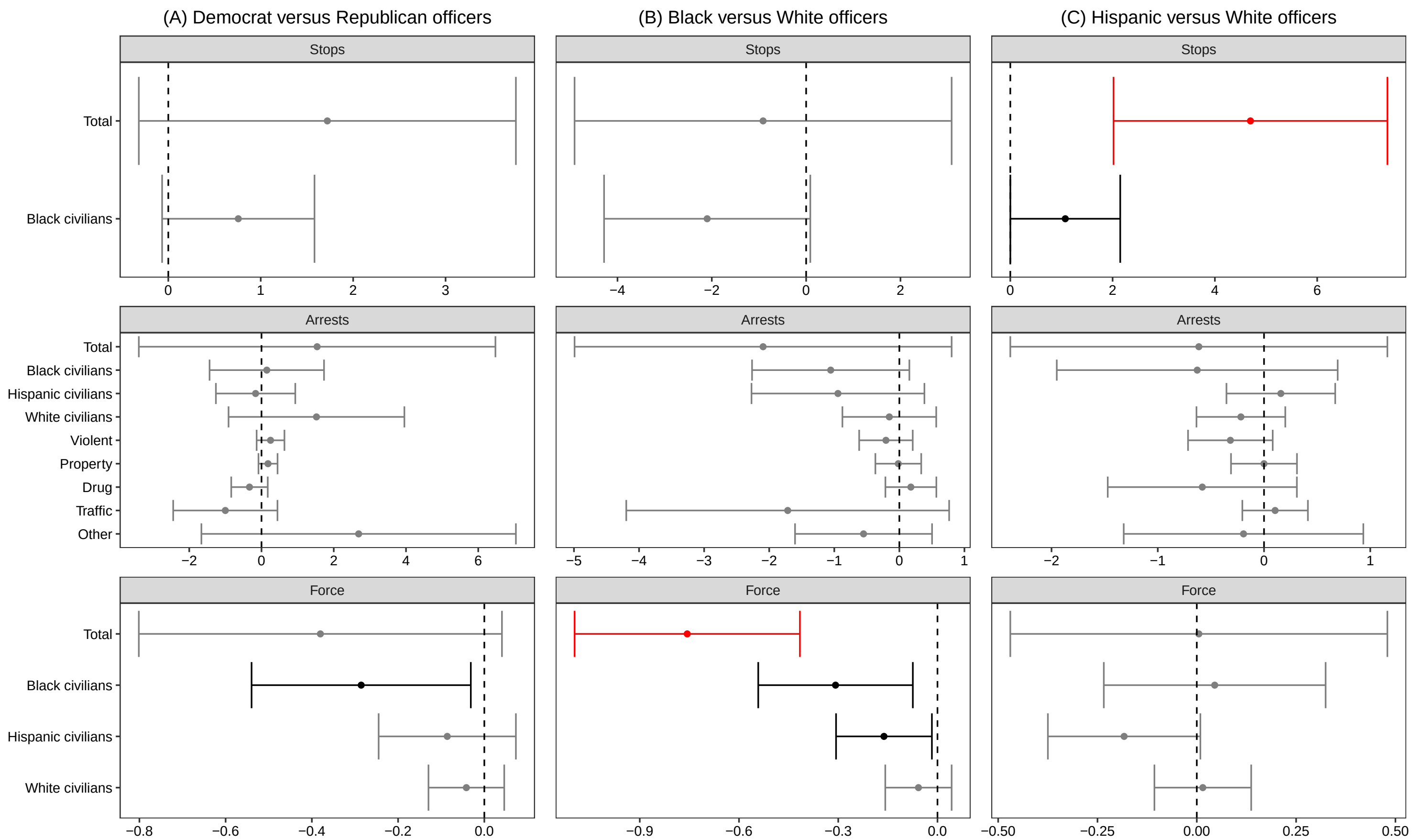


Figure 7: **Deployment effects in Chicago within racial groups.** Notes: The plot displays the effect of deploying a Democrat vs. a Republican officer in similar circumstances on various outcomes. Conventional 95% confidence intervals with officer-clustered standard errors displayed. Estimates in grey are nonsignificant. Estimates in black were statistically significant prior to multiple testing correction. Estimates in red remain significant after multiple testing correction.

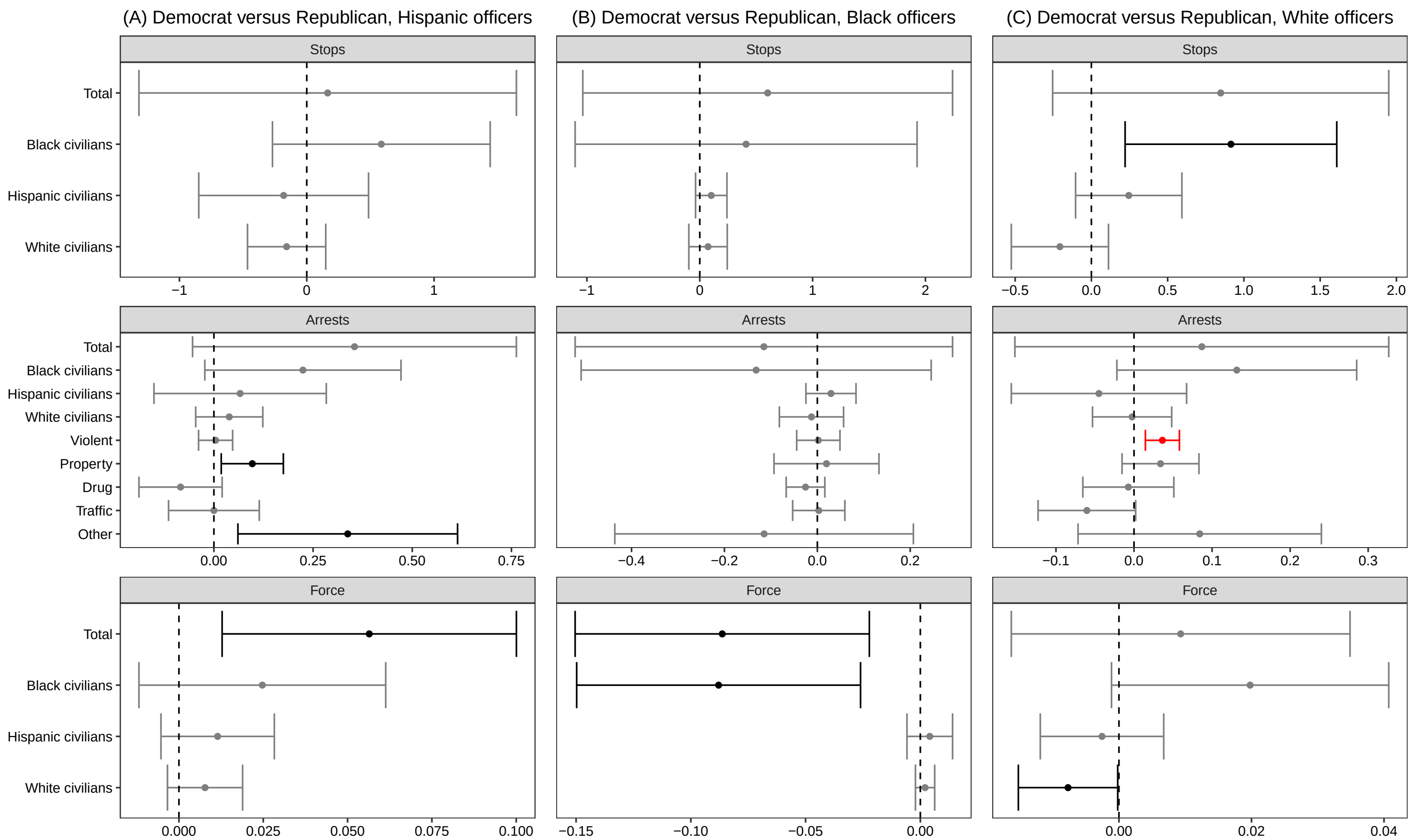
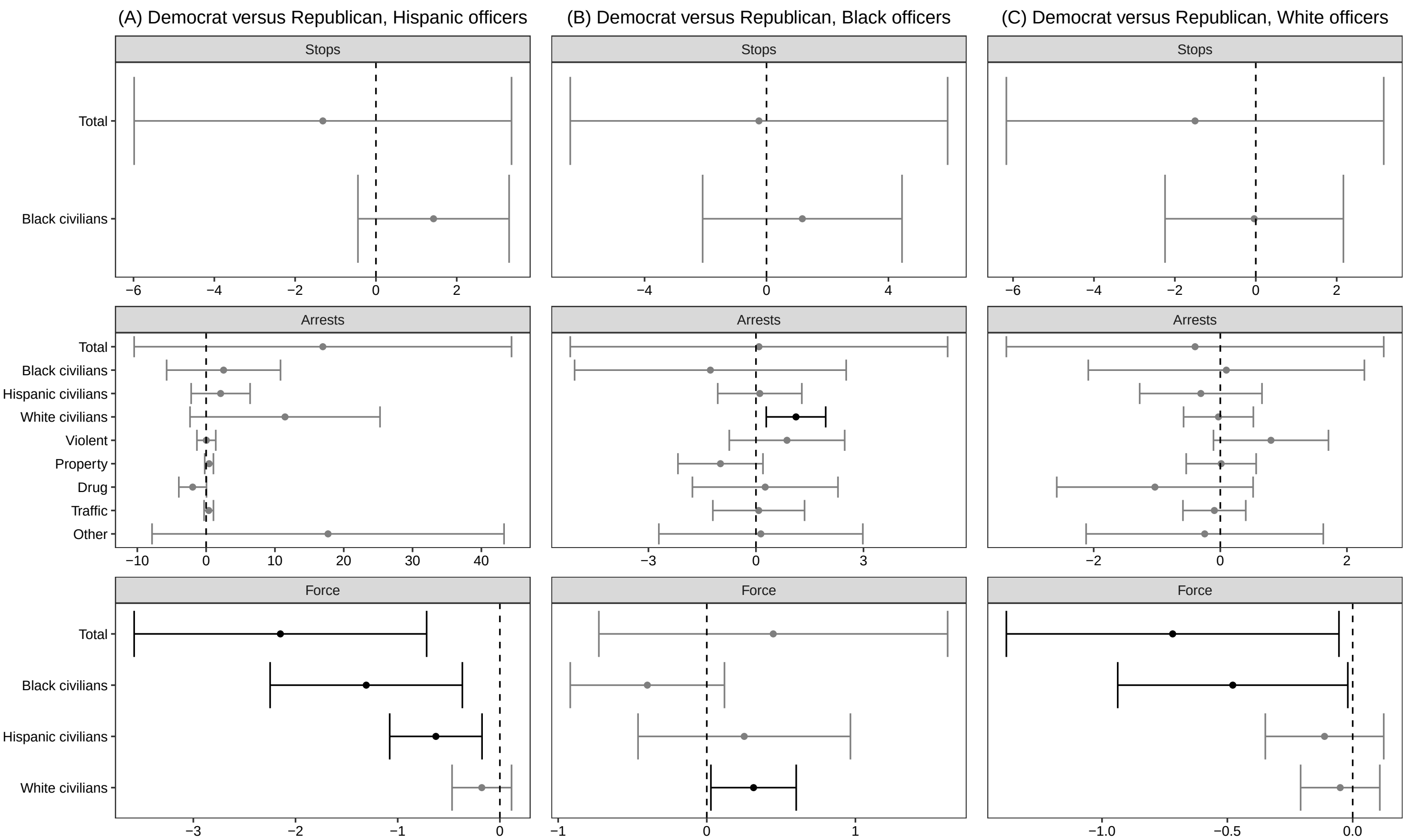


Figure 8: **Deployment effects in Houston within racial groups.** Notes: The plot displays the effect of deploying a Democrat vs. a Republican officer in similar circumstances on various outcomes. Conventional 95% confidence intervals with officer-clustered standard errors displayed. Estimates in grey are nonsignificant. Estimates in black were statistically significant prior to multiple testing correction. Estimates in red remain significant after multiple testing correction.



Discussion and Conclusion

Democrats and Republicans strongly disagree on how policing should be conducted in the U.S. These sharp divisions motivate a close examination of the partisan affiliations and behavior of a particular group of Americans that is well-situated to translate these preferences into policy: police officers themselves. If officers of different political persuasions hold dramatically different views of how policing should be done, these attitudes may manifest in on-the-job behavior, with potentially severe consequences for civilians.

In this paper, we draw on original data characterizing police officers from 99 of the 100 largest local law enforcement agencies in the U.S., as well as micro-level behavioral data in Chicago and Houston, to assess the prevalence and consequences of political diversity in policing. Our results confirm that police differ systematically from the communities they serve in every way we can measure—that is, in the parlance of representative bureaucracy theories, they exhibit deficiencies in passive representation. The majority of police agencies we study are out of step with the communities they serve, with officers skewing more Republican and being far more politically active. But just as importantly, we find heterogeneity: our broad agency-level data collection allows us to identify some highly representative agencies that could not be discerned in prior, coarser analyses. In addition, we show that representativeness along racial lines does not always correspond to representativeness along partisan lines.

Despite shortfalls of partisan representation in policing, our micro-level analyses using fine-grained Chicago and Houston data also show that officer behavior does not tend to diverge across partisan lines in ways that are statistically detectable. After correcting for multiple comparisons, we find little evidence that Democrats behave differently than Republicans, both in the aggregate and within racial groups. White officers in Chicago represent a notable exception, with White Democrats making more arrests for violent crimes than White Republicans in Chicago.

This stands in stark contrast to the sharp racial/ethnic divides in policing. Consistent with (Ba et al., 2021), we find, for example, that Black and Hispanic officers in Chicago make fewer stops and arrests, and they use force less often than White officers facing common circumstances, especially during encounters with Black civilians. In Houston, we find that when facing common circumstances, Black officers use force less often than their White peers, while Hispanic officers make more stops than their White officers peers. These results paint a complex portrait of how officer identity maps to police-civilian interactions that previous analyses of single jurisdictions and social identities have failed to uncover.

Our paper also offers a template for future data collection efforts for the study of bureaucrats. Unlike other professions such as law and medicine, which provide public-facing lists of accredited members, law enforcement agencies are sometimes reluctant to disclose the identities of public employees. Despite this obstacle, we obtained detailed data on officers from nearly all of the top 100 largest agencies by combining information from open-data portals managed by local governments and data repositories maintained by news agencies and nonprofits, and via open records requests—some of which required months of followup communications with municipalities and appeals after initial denials.

Of course, our analysis also has limitations. For one, our data do not allow us to assess whether the deployment of various officer groups has second-order effects on social outcomes such as community trust in police, crime rates or public safety. However, we view this analysis as a crucial first step in the empirical evaluation of longstanding theories of descriptive representation in the policing context. It also remains exceedingly difficult to obtain the detailed shift assignment records necessary to make principled behavioral comparisons across officer groups. As a result, our behavioral analysis is limited to two major cities. Even when such records can be obtained, months of cleaning and standardization are required before a multi-jurisdiction analysis is possible. In some cases, such as Houston, consistent officer identifiers are not always available, and extensive manual work is necessary to produce analysis-ready data. The degree to which progress will be made in this literature not only depends on scholars seeking similar administrative data, but on the willingness of agencies to generate, maintain and distribute high-quality records.

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Online Appendix

Table of Contents

A Civilian comparison data

We compare officers to civilians who live in their agency's jurisdiction. For individual-level data on officers and civilians registered to vote, data come from L2. These data contains the same variables as those used for officers: political party, race/ethnicity, gender, age, and household income. For data on all residents of the jurisdiction we use the American Community Survey (ACS) 2015–2019 data.[20]

B Voter File Record Linkage

To obtain officer-level data, we matched each officer to L2 records for individuals living in the agency's county and any neighboring counties, since officers may commute from outside the jurisdiction. For civilian data, however, we only include people who live within the jurisdiction of each agency. We define a jurisdiction as the area for which each agency claims primary responsibility. More specifically, the area is the county or Census Place (typically a city) where the agency claims authority. In the case of city police departments, this is the city itself. The jurisdiction for the Philadelphia Police Department, for example, is the census place called the City of Philadelphia. For sheriffs' offices, we use self-described jurisdictions per official websites. For example, Wayne County Sheriff's Office in Michigan defines their jurisdiction as "unincorporated villages and townships within Wayne County," [21] meaning that incorporated places in the county—such as Detroit, the seat of Wayne County—are not included. Sheriffs' offices variously cover only unincorporated places in a county, specific parts of the county including both incorporated and unincorporated places, or all of a county.

For both L2- and Census-based comparison groups, we used all people who reside in a Census tract within the agency's jurisdiction. A Census tract is a small geographic unit that covers an average of 4,000 people and in urban areas is the Census' rough approximation of a neighborhood.[22] Census tracts are fully contained within counties, but can extend to cover multiple Census Places (e.g. cities, towns) meaning that different parts of a single tract may lie inside and outside of an agency's jurisdiction. This is rare and occurs primarily in extremely rural areas with low population density.

Each individual in L2 data is associated with an address (including tract, county and state). For computational efficiency, we operate at the tract level when processing L2 data. Tracts with fewer than 100 entries in L2 were excluded. We spatially join the remaining L2 tracts with Census Place shapefiles from the US Census. Tracts that were not in any Place were considered to be in an unincorporated part of that county. We then used the jurisdiction for each agency, as defined above, to identify all tracts for which an agency has at least partial jurisdiction. For example, an agency whose jurisdiction is only a single Census Place (e.g. City of Philadelphia) was assigned every tract in that Place. An agency whose jurisdiction is an entire county, excluding certain Places, was assigned all tracts in that county other than those in the excluded Places. We used the same tract-based operationalization of jurisdiction when analyzing both L2 and Census data.

In the case of officers matching to multiple L2 records, the record with the highest match probability is retained. If there are multiple records that are tied for highest match probability, one is randomly selected.

[20]While the 2020 decennial Census is complete, currently available data does not contain all of the variables that we use.

[21]https://waynecountysheriff.com/about/

[22]https://www2.census.gov/geo/pdfs/reference/GARM/Ch1GARM.pdf

We note that approximately 38% of officers had more than one match after retaining only matches with the highest match probability. The median number of matches was one. Of officers with more than one match, 30% had two matches, 14% had three matches, 8% had four matches, 6% had five matches, 4% had six matches, 3% had seven matches, 3% had eight matches, 2% had nine matches, and the remaining 29% had 10 or more matches.

See Appendix sections H (Appendix p. 14) and I (Appendix pp. 14-23) for a series of robustness checks gauging the impact of potential mismatches.

C Data on Officer Race/Ethnicity and Gender

As explained in the main text, we rely on 2021 LEOKA data (Kaplan, 2023) for gender data on agencies, due to its near-complete coverage. When agencies do not report officer gender in 2021 we use their submissions from either 2020 or 2019. Seven agencies did not report in 2021, but did report in 2020; two agencies did not report in either 2021 or 2020, but did report in 2019. The seven agencies that use 2020 data are: Chicago Police Department, Cincinnati Police Department, Columbus Police Department, Indianapolis Police, Jacksonville City County Police Department, Nassau County Police Department, and Philadelphia Police Department. We use data from 2019 for Wichita Police Department and for New Orleans Police Department. In addition, because LEOKA data does not contain racial/ethnic measures, we obtain those from the 2020 LEMAS data for 86% of agencies, and use L2 estimates of officers' racial and ethnic identities for the remaining agencies.

D Estimation of Behavioral Differences

Our estimation strategy is based on an extension of Ba et al. (2021), which computes average differences in counts of police behaviors using OLS regressions on MDSB-demeaned data, a computationally efficient procedure that is equivalent to fixed-effects regression when combined with our degrees-of-freedom correction to account the demeaning step. We report 95% confidence intervals that cluster on officers, ensuring that inferences are robust to arbitrary within-officer dependence, including overwork in one shift causing less effort in the following shift, life events causing fluctuation in officer behavior on a timescale of a few months, or discontinuous life events e.g. birth of a child causing long-term changes in behavior. We weight each observation inversely by the variance of officer group membership in the MDSB to which it belongs, ensuring that regressions return unbiased estimates of the average treatment effect. Note: in Chicago, beat codes do not always denote geographic locations. However, additional qualitative information on these codes indicates that officers assigned to the same beat code are working in common circumstances, even though their precise location is sometimes unknown. See Section S1.6 of the Supplementary Information in Ba et al. (2021) for an extended discussion of this issue.

At a high level, six comparisons are made. These include unconditional comparisons between (1) Democratic and Republican officers, (2) Black and White officers, and (3) Hispanic and White officers, as well as conditional Democratic-Republican comparisons within (4) Black, (5) Hispanic, and (6) White subsets of officers. These comparisons correspond to six "families" of null hypotheses, each stating that the two officer groups make the same average decisions, across all types of enforcement, when deployed to common circumstances.

Table E.1: **Descriptive Statistics on Police Officers.** Demographics of police officers in our sample relative to police nationwide and the U.S. as a whole. In-sample estimates for police offices from various sources (see Data and Measurement section). National police estimates from Hyland and Davis (2019). National party identification estimates from 2020 American National Election Studies; partisan leaners counted as independents. Other national estimates from U.S. Census. These statistics show our officers skew heavily male (83%) and have much higher household income than the average American household ($114,200 vs. $62,843, respectively). Officers in our data are more racially and ethnically diverse than both officers nationwide and the U.S. population, likely due to our focus on large population centers, which tend to be themselves diverse. Still, the jurisdictions we study—covering 26.7% of the U.S. population and responsible for investigating 41.6% of all murders and conducting 17.4% of all arrests reported to the FBI in 2019 (Kaplan, 2020, 2022)—are important to study in their own right. To generate these numbers we take the sum of murders and arrests, respectively, for the studied agencies, divided by the number of murders and arrests reported by all agencies in 2019.

Variable	Values	Officers in sample	Police in U.S.	U.S.
Race	White	51.26	71.5	60.70
	Hispanic	23.75	12.5	18.00
	Black	16.05	11.4	12.30
	Other/unknown	3.65	4.7	3.60
	Asian	5.30	–	5.50
Party	Republican	32.45	–	31.54
	Democratic	31.32	–	34.72
	Other/unknown party	36.23	–	33.74
Gender	Male	82.75	87.7	49.20
	Female	17.25	12.3	50.80
Median age (years)	–	44.00	–	38.10
Mean household income ($)	–	114,199.70	–	62,843.00
N		219,365.00	701,000.0	330 mm

Within each family of hypothesis tests, we test an average of 16 hypotheses about specific forms of enforcement—relating to the numbers of stops, arrests, and uses of force involving various civilian demographic groups and crime types.[23]

To correct for multiple comparisons, we use the hierarchical multiple-testing procedure of Peterson et al. (2016). High-level p-values are obtained with a two-step method: (1) Simes' method (Simes, 1986) is used to test whether all specific tests within a family are jointly null; and (2) a Benjamini-Hochberg (BH) correction (Benjamini and Hochberg, 1995) is used to correct for the fact that there are six family-level tests. Low-level p-values are calculated with a complementary two-step method: (1) BH corrections are applied to the raw p-values, and (2) these values are further inflated based on the proportion of families that are insignificant.

E Descriptive Statistics

[23] In Chicago, we examine 17 outcomes. Of these, 12 represent the number of stops, arrests, and uses of force involving all civilians as well as Black, Hispanic, and White civilians specifically. Additional outcomes capture arrests for drug, property, traffic, violent, and other crimes. In Houston, we examine 15 outcomes due to the absence of ethnicity information, which makes it impossible to distinguish Hispanic and White civilians in stops.

Table E.2: **Chicago stops, arrests, and uses of force per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	19.43	17.53	18.31	19.23	16.56	18.45	18.47	19.28
White civ.	4.65	3.60	1.80	3.74	3.49	4.91	3.50	3.29
Hispanic civ.	6.23	7.86	1.39	5.83	4.30	7.04	4.96	5.83
Total civ.	31.71	30.23	22.19	29.99	25.51	32.09	28.01	29.49

(a) **Stops per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	4.65	4.96	4.54	4.92	3.92	4.46	4.44	5.58
White civ.	0.88	0.79	0.30	0.74	0.63	0.88	0.64	0.82
Hispanic civ.	1.61	1.90	0.39	1.49	1.04	1.78	1.17	1.71
Total civ.	7.22	7.72	5.27	7.23	5.65	7.20	6.31	8.17

(b) **Arrests per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	0.23	0.21	0.19	0.24	0.13	0.21	0.20	0.25
White civ.	0.03	0.02	0.01	0.03	0.02	0.03	0.02	0.03
Hispanic civ.	0.05	0.05	0.01	0.04	0.02	0.05	0.03	0.05
Total civ.	0.32	0.30	0.22	0.32	0.19	0.31	0.27	0.33

(c) **Uses of force per 100 shifts, by officer and civilian group.**

Table E.3: **Houston stops, arrests, and uses of force per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	13.32	18.63	13.28	15.71	6.11	17.98	13.70	9.01
Total civ.	51.12	61.57	47.93	57.02	18.48	68.44	47.31	29.40

(a) **Stops per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	6.16	5.32	6.08	6.08	4.78	5.73	5.81	6.77
White civ.	1.58	1.19	1.72	1.57	1.28	1.54	1.47	1.70
Hispanic civ.	2.79	1.73	3.34	2.79	2.22	2.62	2.72	3.02
Total civ.	11.79	9.08	12.42	11.63	9.29	11.08	11.11	12.79

(b) **Arrests per 100 shifts, by officer and civilian group.**

Officer group	White	Hispanic	Black	Male	Female	Rep.	Dem.	Other party
Black civ.	1.88	1.15	1.62	1.66	1.26	1.63	1.50	1.90
White civ.	0.46	0.28	0.38	0.40	0.32	0.41	0.34	0.46
Hispanic civ.	1.15	0.48	1.06	0.99	0.66	0.96	0.89	1.14
Total civ.	4.16	2.23	3.60	3.62	2.58	3.61	3.22	4.05

(c) **Uses of force per 100 shifts, by officer and civilian group.**

F Within-Jurisdiction Comparisons

Agency		White (%)	Hispanic (%)	Black (%)	Other/ unknown race (%)	Asian (%)	Democratic (%)	Republican (%)	Other/ unknown party (%)	General turnout, 2020 (%)	Male (%)	Female (%)	Median age	Mean household income ($)
Alameda County Sheriff, CA	Officers	59.06*	15.61*	10.16*	4.20*	10.97*	27.91*	35.57*	36.52*	72.90*	87.33*	12.67*	45.00*	148,576.62*
	Civilians	31.50	24.40	7.90	5.70	30.50	52.80	15.70	31.60	82.60	49.40	50.60	39.53	142,168.74
Albuquerque PD, NM	Officers	52.39*	39.47*	0.00*	7.61	0.53*	19.90*	56.41*	23.68	81.91	86.02*	13.98*	42.00*	101,322.84*
	Civilians	38.80	49.50	2.60	6.40	2.70	48.40	28.10	23.50	79.90	48.90	51.10	37.93	74,444.38
Anne Aroundel County PD, MD	Officers	80.38*	3.08*	14.21	0.53*	1.80*	21.74*	40.93*	37.33*	62.25*	85.68*	14.32*	39.00	133,895.69*
	Civilians	68.70	7.80	15.80	3.90	3.80	43.00	33.10	23.90	76.30	49.10	50.90	39.62	125,186.26
Atlanta PD, GA	Officers	29.33*	5.11	63.24*	0.77*	1.54*	52.43*	17.46*	30.11*	63.36	81.95*	18.05*	43.00*	101,074.31
	Civilians	37.60	4.20	51.50	2.40	4.30	73.30	8.20	18.50	62.20	48.20	51.80	34.78	102,188.66
Aurora PD, CO	Officers	79.16*	10.42*	3.76*	4.49	2.17*	8.54*	43.13*	48.34*	78.00*	88.71*	11.29*	42.00*	128,488.70*
	Civilians	46.70	26.90	14.90	4.60	6.80	36.10	20.90	43.00	83.00	49.70	50.30	35.37	89,350.88
Austin PD, TX	Officers	66.60*	21.78*	7.60	1.51*	2.51*	31.14*	43.06*	25.80*	72.82*	89.01*	10.99*	45.00*	118,422.88*
	Civilians	49.10	33.40	7.40	2.80	7.30	61.30	19.60	19.10	76.50	50.50	49.50	34.89	106,135.19
Baltimore County PD, MD	Officers	79.56*	2.35*	15.26*	0.68*	2.16*	21.87*	54.79*	23.35*	76.90*	82.77*	17.23*	41.50*	121,241.00*
	Civilians	44.70	5.40	42.60	2.90	4.50	64.60	17.90	17.50	67.60	47.20	52.80	38.69	90,048.91
Baltimore PD, MD	Officers	44.40*	12.53*	40.53*	0.28*	2.26	36.04*	29.21*	34.74*	60.77	84.19*	15.81*	46.00*	112,276.43*
	Civilians	27.60	5.40	61.60	2.90	2.50	77.90	7.40	14.70	60.70	47.00	53.00	36.48	73,579.96
Baton Rouge City PD, LA	Officers	60.62*	1.84*	36.40*	0.00*	1.13*	34.65*	38.05*	27.30	81.90*	90.10*	9.90*	43.00*	99,406.15*
	Civilians	38.70	4.40	51.50	1.90	3.40	51.80	22.40	25.80	69.00	47.80	52.20	33.61	71,381.90
Birmingham PD, AL	Officers	37.03	0.19*	60.54*	1.87	0.37*	62.15*	31.96*	5.89*	74.86*	86.07*	13.93*	44.00*	82,515.96*
	Civilians	35.40	4.00	57.30	1.70	1.60	69.40	27.30	3.30	65.90	47.10	52.90	37.53	72,188.57
Boston PD, MA	Officers	69.89*	11.08*	10.48*	6.39*	2.16*	26.72*	11.75*	61.54*	76.54*	85.76*	14.24*	49.00*	136,974.91*
	Civilians	44.50	19.80	22.70	3.40	9.60	49.20	5.00	45.80	72.60	48.00	52.00	33.54	100,987.60
Broward County Sheriff, FL	Officers	48.88*	26.61	21.16*	1.40*	1.96*	28.42*	31.84*	39.73*	69.41*	86.80*	13.20*	43.00*	108,136.03*
	Civilians	36.60	27.30	30.10	2.70	3.30	51.00	20.40	28.60	74.50	49.00	51.00	40.86	85,697.49
Buffalo PD, NY	Officers	67.47*	8.97*	21.29*	1.74*	0.54*	44.44*	26.77*	28.78*	76.97*	80.19*	19.81*	47.00*	96,956.41*
	Civilians	43.10	12.30	35.60	3.30	5.80	67.60	9.20	23.20	61.40	47.70	52.30	34.13	54,432.29
Charlotte-Mecklenburg PD, NC	Officers	68.63*	6.06*	16.42*	7.24*	1.65*	16.44*	37.16*	46.40*	71.89*	85.17*	14.83*	40.00*	106,445.15*
	Civilians	42.30	14.10	34.00	3.20	6.30	46.40	18.90	34.70	77.00	48.00	52.00	35.28	93,640.73
Chicago PD, IL	Officers	47.01*	28.08	20.23*	1.25*	3.44*	55.22*	13.91*	30.87*	76.68*	76.77*	23.23*	44.00*	106,716.58*
	Civilians	33.50	28.70	29.10	2.20	6.50	67.20	4.80	28.00	65.60	48.60	51.40	35.52	86,285.44
Cincinnati PD, OH	Officers	68.27*	0.19*	28.27*	3.17	0.10*	22.85*	40.69*	36.45*	73.67*	76.95*	23.05*	48.00*	109,367.49*
	Civilians	51.00	3.80	39.40	3.70	2.10	55.90	14.00	30.10	70.20	48.40	51.60	34.01	65,613.80
Cleveland PD, OH	Officers	66.89*	9.21*	22.43*	1.41*	0.06*	32.11*	27.70*	40.19*	73.32*	82.65*	17.35*	48.00*	85,443.25*
	Civilians	33.70	11.90	48.30	3.60	2.50	63.50	6.20	30.30	58.40	48.10	51.90	37.17	45,996.85
Collier County Sheriff, FL	Officers	80.23*	14.34*	3.10*	1.94	0.39*	9.69*	40.31*	50.00*	51.94*	85.66*	14.34*	40.50*	102,648.70
	Civilians	62.80	27.90	6.70	1.30	1.30	24.60	49.30	26.10	83.90	49.30	50.70	50.30	105,857.78
Colorado Springs PD, CO	Officers	82.36*	10.28*	4.17*	0.42*	2.78	8.89*	42.22*	48.89*	75.00*	83.33*	16.67*	42.00*	115,307.85*
	Civilians	69.90	16.90	5.70	4.80	2.80	21.40	35.20	43.40	84.80	50.10	49.90	36.37	88,822.61
Columbus PD, OH	Officers	86.71*	1.61*	9.64*	0.97*	1.07*	17.04*	45.37*	37.59	81.89*	88.80*	11.20*	49.00*	117,215.03*
	Civilians	59.20	5.80	25.10	4.10	5.70	42.30	18.30	39.40	74.20	48.90	51.10	34.32	76,750.07
Contra Costa County Sheriff, CA	Officers	63.10*	18.56	6.38	8.20*	3.76*	28.31*	33.91*	37.78*	74.20*	85.02*	14.98*	44.00*	140,269.15*
	Civilians	53.50	20.10	5.00	5.30	16.00	50.40	21.30	28.30	86.30	49.10	50.90	42.14	168,748.68
Cook County Sheriff, IL	Officers	38.20*	24.81*	35.36*	0.35	1.28*	52.02*	18.43*	29.55*	71.30*	73.21*	26.79*	50.00*	103,477.31*
	Civilians	15.80	83.60	0.00	0.60	0.00	25.60	6.90	67.50	46.90	47.80	52.20	24.50	46,678.44
Dallas PD, TX	Officers	44.95*	25.52*	25.77*	0.90*	2.86*	33.31*	35.45*	31.23*	63.83*	80.97*	19.03*	46.00*	114,976.13*
	Civilians	29.30	41.00	23.70	2.00	4.00	66.10	21.30	12.60	68.50	49.50	50.50	33.41	81,583.54
Dekalb County PD, GA	Officers	29.24*	4.79	63.78*	0.65*	1.55*	55.76*	11.25*	32.99*	56.92*	79.43*	20.57*	41.00*	89,409.53*
	Civilians	20.70	5.10	67.50	2.60	4.10	81.80	6.30	11.90	65.80	46.30	53.70	37.17	79,784.37
Denver PD, CO	Officers	64.34*	21.86*	8.90	2.15*	2.76	21.47*	25.84*	52.68*	70.48*	85.20*	14.80*	48.00*	119,848.55*
	Civilians	54.20	29.90	8.90	3.40	3.60	47.00	11.40	41.60	86.40	50.10	49.90	35.09	98,085.25
El Paso PD, TX	Officers	14.98*	81.45	2.25*	0.17*	1.16	70.80*	18.64*	10.57*	64.23*	86.02*	13.98*	42.00*	74,383.85*
	Civilians	12.50	81.80	3.10	1.30	1.20	82.90	11.50	5.60	58.60	49.00	51.00	33.88	64,323.75
Fairfax County PD, VA	Officers	79.60*	7.84*	1.06*	6.20*	5.30*	31.53*	22.58*	45.89*	60.20*	82.94*	17.06*	41.00*	155,032.44*
	Civilians	50.80	16.00	9.60	4.30	19.30	64.40	20.30	15.30	80.00	49.50	50.50	39.17	159,196.16
Fort Worth PD, TX	Officers	68.25*	18.11*	6.33*	6.15*	1.16*	31.05*	47.98*	20.97*	73.15*	86.79*	13.21*	46.00*	110,367.84*
	Civilians	41.80	33.70	17.40	2.70	4.30	47.60	34.70	17.70	69.60	48.90	51.10	33.21	84,488.63
Fresno PD, CA	Officers	48.30*	38.80*	5.88	0.34*	6.67*	18.55*	55.20*	26.24*	77.15*	88.46*	11.54*	42.00*	113,003.66*
	Civilians	28.00	49.20	6.60	2.90	13.30	42.60	28.10	29.40	71.60	49.20	50.80	32.41	70,003.28
Gwinnett County PD, GA	Officers	75.03*	7.46*	14.67*	0.77*	2.06*	21.49*	34.11*	44.40*	69.88	89.96*	10.04*	37.00*	97,447.43
	Civilians	39.50	21.60	25.00	2.80	11.10	41.50	22.40	36.00	71.40	48.90	51.10	35.72	94,655.81
Harris County Sheriff, TX	Officers	31.63*	32.58*	32.18*	0.32*	3.29*	43.02*	34.64*	22.34*	68.61	82.70*	17.30*	47.00*	103,529.01*
	Civilians	29.60	42.90	18.60	2.00	6.90	56.10	28.90	15.00	68.80	49.70	50.30	34.02	89,357.77
Hillsborough County Sheriff, FL	Officers	70.43*	16.00*	8.86*	3.61	1.10*	11.84*	38.75*	49.41*	60.00*	82.90*	17.10*	38.00	98,909.08*
	Civilians	49.60	29.60	13.80	3.00	3.90	37.30	32.10	30.60	76.40	48.90	51.10	38.66	82,399.32
Honolulu PD, HI	Officers	11.39*	1.49*	1.34*	32.00*	53.79	22.44*	14.02*	63.55*	68.60*	86.83*	13.17*	52.00*	123,780.11*
	Civilians	15.40	7.30	2.00	23.00	52.30	38.90	19.00	42.10	72.80	49.80	50.20	42.36	102,709.63
Houston PD, TX	Officers	41.07*	30.19*	20.52	0.39*	7.84	41.25*	39.15*	19.59*	71.14*	82.76*	17.24*	47.00*	111,168.35*
	Civilians	27.80	41.00	21.10	1.90	8.20	58.10	27.00	14.80	69.30	49.60	50.40	33.85	88,784.95
Indianapolis PD, IN	Officers	82.32*	2.44*	6.93*	8.01*	0.29*	15.71*	42.80*	41.49	67.18*	85.68*	14.32*	50.00*	105,491.72*
	Civilians	54.90	10.30	28.10	3.40	3.40	43.20	17.70	39.10	62.60	48.20	51.80	34.94	69,007.27

Agency		White (%)	Hispanic (%)	Black (%)	Other/ unknown race (%)	Asian (%)	Democratic (%)	Republican (%)	Other/ unknown party (%)	General turnout, 2020 (%)	Male (%)	Female (%)	Median age	Mean household income ($)
Jacksonville County Sheriff, FL	Officers	73.02*	6.97*	15.87*	1.02*	3.12*	15.32*	51.08*	33.59*	70.37*	83.95*	16.05*	39.00*	98,909.54*
	Civilians	51.70	9.90	30.10	3.70	4.70	42.30	34.60	23.20	73.60	48.40	51.60	36.62	75,331.11
Jefferson Parish Sheriff, LA	Officers	52.21	5.68*	32.13*	9.11*	0.87*	30.74*	32.46	36.81*	65.02*	74.37*	25.63*	46.00*	86,885.06*
	Civilians	53.60	12.60	27.00	2.40	4.40	39.30	31.20	29.40	71.10	48.30	51.70	40.38	75,496.01
Jersey City PD, NJ	Officers	42.25*	38.37*	12.92*	0.20*	6.26*	40.56*	13.62*	45.83*	56.56*	83.60*	16.40*	39.00*	106,534.42*
	Civilians	21.90	28.50	21.10	3.60	24.90	56.20	7.80	36.00	64.90	49.60	50.40	34.76	99,941.83
Kansas City PD, MO	Officers	76.93*	5.44*	11.59*	5.33*	0.71*	23.07*	49.40*	27.53*	78.56*	85.64*	14.36*	44.00*	109,277.94*
	Civilians	57.30	10.10	26.30	3.70	2.60	46.80	33.80	19.40	71.20	48.60	51.40	36.14	79,082.43
King County Sheriff, WA	Officers	74.57*	6.26*	5.99	7.46	5.73*	35.69*	32.76*	31.56*	83.09	88.15*	11.85*	44.00*	133,286.34
	Civilians	61.80	8.70	5.70	6.60	17.20	58.00	19.50	22.40	85.20	49.70	50.30	39.91	133,919.76
Las Vegas Metro PD, NV	Officers	59.14*	20.98*	6.61*	8.13*	5.14*	14.97*	47.10*	37.93*	73.30*	85.43*	14.57*	37.00*	114,793.54*
	Civilians	44.20	32.10	11.50	5.30	6.90	40.30	28.20	31.50	69.70	50.00	50.00	38.57	82,764.96
Long Beach PD, CA	Officers	46.03*	38.65*	5.56*	0.27*	9.48*	27.26*	38.83*	33.91*	75.48	87.97*	12.03*	42.00*	123,735.21*
	Civilians	28.20	42.60	12.20	4.20	12.80	52.90	16.90	30.10	73.90	49.40	50.60	35.61	83,535.95
Los Angeles County Sheriff, CA	Officers	28.82*	55.27*	7.06*	3.15*	5.70*	27.29*	38.31*	34.40*	73.77*	81.53*	18.47*	47.00*	121,402.38*
	Civilians	21.20	52.40	8.20	2.70	15.50	49.40	20.70	29.90	75.50	49.40	50.60	37.18	94,900.95
Los Angeles PD, CA	Officers	29.50*	49.93*	9.43*	0.70*	10.44*	34.34*	32.15*	33.50*	75.26*	81.39*	18.61*	45.00*	113,559.23*
	Civilians	28.60	48.30	8.60	3.00	11.50	57.10	12.90	30.00	73.40	49.50	50.50	36.16	91,558.33
Louisville Metro PD, KY	Officers	82.42*	2.51*	12.99*	0.48*	1.60*	30.06*	49.81*	20.14*	8.27*	86.01*	13.99*	44.00*	101,029.21*
	Civilians	59.00	4.70	30.30	3.10	2.90	68.10	22.20	9.70	NaN	48.30	51.70	37.07	63,315.77
Maricopa County Sheriff, AZ	Officers	72.79*	21.22*	3.65	0.52*	1.82	15.62*	52.34*	32.03	79.69*	94.92*	5.08*	49.00*	105,564.36*
	Civilians	77.60	12.60	2.50	4.90	2.40	22.30	47.90	29.90	86.00	47.70	52.30	51.25	98,345.95
Memphis PD, TN	Officers	40.96*	2.40*	55.84*	0.00*	0.80*	32.35*	24.16*	43.48*	71.54*	82.28*	17.72*	48.00*	95,219.09*
	Civilians	27.10	7.00	62.40	1.70	1.90	37.00	11.90	51.00	63.10	47.10	52.90	34.91	63,789.12
Mesa PD, AZ	Officers	77.17*	15.37*	3.29	1.43*	2.74	9.33*	54.23*	36.44	70.47*	87.38*	12.62*	45.00*	113,803.71*
	Civilians	62.40	27.00	3.80	4.70	2.10	26.60	39.50	33.90	78.50	49.40	50.60	38.57	79,346.04
Metro Nashville PD And Sheriff, TN	Officers	81.84*	2.07*	11.01*	3.86	1.21*	14.12*	31.82*	54.06*	69.45*	89.05*	10.95*	42.00*	108,840.14*
	Civilians	56.10	10.30	26.90	3.00	3.60	35.40	17.20	47.40	73.70	48.10	51.90	35.33	85,892.17
Miami PD, FL	Officers	7.37*	66.67*	24.93*	0.45	0.60	28.79*	30.58*	40.62*	68.53*	78.72*	21.28*	39.00*	94,036.36*
	Civilians	10.80	70.70	16.90	0.70	0.90	45.50	22.60	31.90	71.20	49.40	50.60	40.24	62,758.97
Miami-Dade PD, FL	Officers	15.28*	60.40*	22.92*	0.00*	1.40*	24.11*	29.77	46.12*	60.57*	75.00*	25.00*	47.00*	99,395.11*
	Civilians	11.60	70.50	15.20	1.00	1.80	38.00	29.80	32.20	75.70	48.40	51.60	39.89	79,002.34
Milwaukee PD, WI	Officers	65.61*	13.81*	17.28*	1.25*	2.05*	14.84*	10.57*	74.59*	21.15*	83.91*	16.09*	50.00*	88,312.78*
	Civilians	35.80	18.80	37.80	3.40	4.20	63.40	8.80	27.80	42.50	48.10	51.90	32.43	56,810.28
Minneapolis PD, MN	Officers	73.05*	6.16*	9.13*	4.73	6.93	20.68*	33.88*	45.43*	79.43*	84.27*	15.73*	43.00*	123,532.79*
	Civilians	60.00	9.60	18.90	5.60	5.90	83.30	6.70	10.00	88.80	50.60	49.40	33.15	86,513.22
Montgomery County PD, MD	Officers	74.06*	8.62*	12.38*	0.16*	4.78*	24.61*	41.69*	33.70*	73.35*	80.64*	19.36*	42.00*	151,632.88*
	Civilians	44.30	19.20	18.40	3.90	14.20	60.70	15.80	23.40	76.60	48.30	51.70	40.57	155,878.84
Nassau County PD, NY	Officers	75.69*	7.71*	4.99*	10.65*	0.96*	17.66*	51.38*	30.95	83.34*	89.28*	10.72*	44.00*	149,027.32*
	Civilians	62.10	14.80	9.90	2.30	11.00	38.70	31.10	30.20	71.50	48.90	51.10	42.21	155,602.15
New Orleans PD, LA	Officers	37.04*	3.12*	52.20*	6.23*	1.42*	40.58*	19.90*	39.52*	65.01*	76.70*	23.30*	43.00*	82,648.64*
	Civilians	30.80	5.50	58.70	2.10	2.90	64.40	10.10	25.50	70.20	47.20	52.80	37.46	71,994.31
New York City PD, NY	Officers	46.26*	29.31	15.26*	0.78*	8.39*	34.73*	23.84*	41.43*	58.44	80.70*	19.30*	39.00*	116,001.53*
	Civilians	32.10	29.10	21.80	3.00	14.00	67.40	10.10	22.50	58.60	47.60	52.40	37.35	97,203.36
Newark PD, NJ	Officers	13.48*	36.60	27.64*	21.78*	0.50*	39.36*	11.89*	48.74*	55.36*	76.05*	23.95*	42.00*	97,160.86*
	Civilians	10.90	36.50	48.10	2.70	1.80	55.90	4.20	39.90	49.70	48.30	51.70	34.47	52,205.17
Norfolk PD, VA	Officers	69.22*	7.18	18.82*	0.64*	4.15	31.42*	26.16*	42.42*	63.96*	88.68*	11.32*	40.00*	100,074.30*
	Civilians	42.40	7.20	42.30	4.50	3.50	64.40	15.00	20.60	69.30	50.30	49.70	33.85	70,929.58
Oakland County Sheriff, MI	Officers	86.04*	4.17*	8.90*	0.23*	0.68*	38.85*	33.22*	27.93*	76.69*	85.47*	14.53*	44.00*	105,111.82*
	Civilians	57.40	10.00	22.20	3.30	7.10	65.40	23.00	11.60	69.80	48.20	51.80	38.55	92,462.99
Oakland PD, CA	Officers	33.99*	28.21	16.67*	3.07*	18.06*	30.45*	19.18*	50.37*	58.94*	84.92*	15.08*	40.00*	142,625.87*
	Civilians	28.30	27.00	23.20	6.10	15.30	70.20	4.10	25.80	79.70	48.30	51.70	36.78	104,486.40
Oklahoma City PD, OK	Officers	81.48*	6.82*	6.50*	4.17*	1.04*	13.39*	65.44*	21.17	71.77	88.61*	11.39*	43.00*	107,762.39*
	Civilians	56.40	18.20	12.90	8.40	4.20	35.40	45.40	19.20	72.30	49.20	50.80	35.20	80,933.52
Omaha PD, NE	Officers	80.13*	6.33*	2.41*	10.38*	0.76*	12.90*	52.24*	34.86*	76.61	84.59*	15.41*	42.00*	116,319.84*
	Civilians	68.60	12.80	11.30	3.40	3.90	39.20	35.20	25.60	78.30	49.40	50.60	35.08	89,033.82
Orange County Sheriff, CA	Officers	55.70*	29.12*	3.29*	2.98*	8.90*	20.21*	48.44*	31.34*	79.07*	86.73*	13.27*	43.00	129,489.68*
	Civilians	58.00	20.80	1.30	4.20	15.70	31.50	40.00	28.50	89.30	48.70	51.30	42.92	146,606.01
Orange County Sheriff, FL	Officers	60.34*	21.85*	13.61*	2.41*	1.79*	15.09*	34.91*	50.00*	57.85*	84.45*	15.55*	36.00	93,363.26*
	Civilians	38.50	32.00	20.00	3.70	5.80	42.40	25.00	32.60	73.50	49.20	50.80	35.45	84,691.67
Orlando PD, FL	Officers	58.38*	23.62*	14.75*	0.75*	2.50*	17.50*	32.88*	49.62*	58.75*	84.75*	15.25*	39.00*	97,103.17*
	Civilians	36.40	33.20	23.40	3.00	4.00	47.40	21.20	31.40	71.60	48.50	51.50	35.26	73,921.74
Palm Beach County Sheriff, FL	Officers	67.39*	18.23*	12.61*	0.49*	1.28*	18.33*	37.54*	44.14*	67.09*	86.40*	13.60*	42.00*	111,594.87*
	Civilians	51.40	24.10	19.40	2.30	2.80	43.70	26.40	29.90	77.50	48.40	51.60	44.59	91,846.96
Philadelphia PD, PA	Officers	56.97*	9.86*	30.70*	0.48*	2.00*	47.54*	33.37*	19.09*	78.52*	78.42*	21.58*	46.00*	101,931.92*
	Civilians	34.50	14.70	40.80	2.80	7.20	76.40	11.50	12.10	72.80	47.30	52.70	35.39	65,363.44
Phoenix PD, AZ	Officers	71.11*	19.69*	3.94*	2.68*	2.59*	17.38*	44.38*	38.24*	74.17*	85.87*	14.13*	48.00*	107,438.95*
	Civilians	42.80	42.50	6.60	4.60	3.60	38.00	27.50	34.40	75.70	49.80	50.20	34.30	78,537.91
Pinellas County Sheriff, FL	Officers	77.74*	6.89	13.84*	0.25*	1.29*	15.93*	43.85*	40.22*	70.05*	84.69*	15.31*	44.00*	92,627.00*
	Civilians	81.40	7.70	4.30	3.10	3.50	30.50	39.90	29.60	81.40	48.00	52.00	49.91	84,030.27
Pittsburgh PD, PA	Officers	84.98*	1.26*	11.87*	1.16*	0.74*	40.55*	44.22*	15.23	86.13*	85.82*	14.18*	39.00*	98,137.54*
	Civilians	64.70	3.20	22.70	3.60	5.80	71.60	13.50	14.90	72.70	48.70	51.30	34.73	72,381.50
Portland Police Bureau, OR	Officers	82.02*	5.22*	3.83*	2.90*	6.03*	24.13*	27.73*	48.14*	70.65*	82.71*	17.29*	43.00*	120,769.68*
	Civilians	70.50	10.10	5.40	5.90	8.10	53.40	9.60	37.10	73.80	49.50	50.50	37.93	97,193.34
Prince Georges County PD, MD	Officers	41.97*	10.57*	43.34*	0.20*	3.92	44.13*	25.52*	30.35*	66.25*	85.38*	14.62*	40.00*	138,893.52*

Agency		White (%)	Hispanic (%)	Black (%)	Other/ unknown race (%)	Asian (%)	Democratic (%)	Republican (%)	Other/ unknown party (%)	General turnout, 2020 (%)	Male (%)	Female (%)	Median age	Mean household income ($)
	Civilians	12.70	18.40	61.70	3.10	4.10	78.50	6.40	15.10	71.00	48.10	51.90	38.14	102,998.63
Raleigh PD, NC	Officers	81.67*	5.56*	9.86*	1.25*	1.67*	15.83*	39.72*	44.44*	85.14	89.17*	10.83*	40.00*	107,125.53*
	Civilians	55.20	11.00	26.40	2.90	4.50	42.50	19.80	37.70	84.00	48.40	51.60	35.80	96,560.05
Richmond PD, VA	Officers	59.09*	5.00*	27.05*	7.05*	1.82	43.76*	29.17*	27.06*	72.17	82.53*	17.47*	48.00*	109,578.36*
	Civilians	40.90	7.00	46.50	3.60	2.00	74.60	9.60	15.80	70.70	47.70	52.30	35.70	73,864.18
Riverside County Sheriff, CA	Officers	50.65*	34.57*	3.89*	6.96*	3.94*	22.85*	43.21*	33.94*	77.39*	89.49*	10.51*	43.00*	114,417.27*
	Civilians	35.40	48.80	6.10	3.30	6.30	39.70	32.20	28.00	79.60	49.70	50.30	36.60	89,235.25
Rochester PD, NY	Officers	74.55*	11.74*	10.91*	0.66*	2.15	14.71*	55.04*	30.25*	77.69*	85.45*	14.55*	40.00*	102,547.01*
	Civilians	37.90	18.90	36.90	3.40	2.90	64.20	9.90	26.00	46.60	48.50	51.50	33.24	51,660.92
Sacramento County Sheriff, CA	Officers	66.13*	16.59*	4.75*	2.63*	9.90*	21.80*	46.68*	31.52*	82.04*	83.70*	16.30*	45.00*	124,007.91*
	Civilians	50.60	21.30	8.40	7.30	12.50	41.30	29.90	28.80	84.00	48.50	51.50	37.14	84,117.66
Sacramento PD, CA	Officers	69.12*	13.08*	5.35*	3.11*	9.34*	16.31*	49.69*	34.00*	81.20	83.19*	16.81*	43.00*	136,215.84*
	Civilians	31.80	29.30	12.80	7.50	18.60	55.40	15.50	29.20	82.60	48.90	51.10	35.41	80,100.12
St. Louis Metro PD, MO	Officers	65.96*	2.03*	30.48*	0.59*	0.93*	40.05*	39.97*	19.98*	75.53*	83.49*	16.51*	44.00*	101,782.60*
	Civilians	43.60	4.00	46.20	2.80	3.30	85.20	11.30	3.50	67.50	48.40	51.60	36.74	62,162.18
San Antonio PD, TX	Officers	37.69*	54.98*	4.70*	1.53	1.10*	40.81*	41.23*	17.96*	73.85*	88.52*	11.48*	48.00*	101,306.88*
	Civilians	26.70	61.70	6.70	2.10	2.70	62.90	24.20	12.90	67.80	49.40	50.60	34.32	75,298.32
San Bernardino County Sheriff, CA	Officers	53.26*	34.12*	5.06*	4.66*	2.90*	27.37*	42.37*	30.26	74.87*	85.25*	14.75*	43.00*	107,251.53*
	Civilians	37.70	42.90	7.30	3.70	8.40	36.30	34.30	29.40	77.20	49.80	50.20	35.31	83,483.57
San Diego County Sheriff, CA	Officers	53.25	32.49	5.48*	0.66*	8.12*	19.68*	47.17*	33.15*	79.54*	81.23*	18.77*	41.00*	127,554.58*
	Civilians	55.00	30.40	3.70	4.40	6.40	33.80	35.60	30.60	84.70	50.60	49.40	38.48	109,814.86
San Diego PD, CA	Officers	59.39*	25.45*	5.74	4.87	4.55*	20.90*	46.40*	32.70	84.08	83.70*	16.30*	44.00*	130,034.69*
	Civilians	42.80	29.90	6.10	4.50	16.80	45.40	21.30	33.30	82.90	50.40	49.60	36.27	108,601.61
San Francisco PD, CA	Officers	47.55*	17.72*	9.58*	1.92*	23.24*	27.82*	17.62*	54.57*	59.22*	85.49*	14.51*	43.00*	156,316.63
	Civilians	40.50	15.20	5.00	5.20	34.10	62.50	6.80	30.80	86.50	51.00	49.00	39.29	157,990.14
San Jose PD, CA	Officers	46.33*	28.47*	1.95*	10.53*	12.71*	32.63*	27.93*	39.44*	74.25*	86.92*	13.08*	43.00*	156,770.67*
	Civilians	27.10	31.20	2.80	4.20	34.80	50.00	17.10	32.90	83.40	50.50	49.50	37.59	142,187.18
Seattle PD, WA	Officers	67.80*	5.47*	7.98	10.78*	7.98*	29.76*	36.26*	33.97*	78.58*	84.79*	15.21*	50.00*	142,190.79*
	Civilians	63.70	6.80	7.20	7.00	15.30	75.20	5.50	19.30	86.20	50.60	49.40	36.47	128,545.84
St Louis County PD, MO	Officers	86.00*	1.92	10.38*	0.11*	1.58*	31.49*	45.82*	22.69*	77.77	83.97*	16.03*	41.00*	105,515.56*
	Civilians	70.70	2.00	22.30	2.40	2.70	56.40	38.00	5.60	75.80	47.70	52.30	42.09	92,985.21
Suffolk County PD, NY	Officers	84.94*	10.18*	2.67*	1.15*	1.07*	15.76*	46.41*	37.83*	85.68*	88.80*	11.20*	47.00*	150,138.86*
	Civilians	67.60	19.30	7.20	2.00	3.90	34.50	30.80	34.70	74.20	49.20	50.80	41.76	129,328.37
Tampa PD, FL	Officers	68.52*	16.90*	12.50*	0.23*	1.85*	13.66*	42.13*	44.21*	67.01*	82.52*	17.48*	42.00*	106,850.47*
	Civilians	43.70	27.20	22.10	2.90	4.20	46.10	25.30	28.70	74.00	48.80	51.20	36.34	84,284.38
Toledo PD, OH	Officers	76.96*	5.54*	4.29*	12.68*	0.54*	23.55*	31.59*	44.86*	69.45*	83.31*	16.69*	46.00*	90,639.24*
	Civilians	60.10	8.50	25.80	4.30	1.30	46.20	13.80	40.00	65.70	48.20	51.80	36.23	53,321.56
Tucson PD, AZ	Officers	62.07*	31.60*	2.35*	1.43*	2.56	14.11*	46.83*	39.06*	71.68*	84.87*	15.13*	44.00*	99,503.07*
	Civilians	45.40	42.90	4.30	4.40	3.00	44.00	23.50	32.50	74.80	49.20	50.80	35.86	61,498.06
Tulsa PD, OK	Officers	86.75*	3.56*	3.13*	5.56*	1.00*	11.27*	60.28*	28.46*	68.18*	85.48*	14.52*	43.00*	106,118.80*
	Civilians	54.90	16.00	14.50	11.30	3.40	38.80	42.40	18.80	73.60	48.60	51.40	36.17	74,644.31
Ventura County Sheriff, CA	Officers	64.16*	27.93	2.19*	0.38*	5.34*	31.94*	37.08*	30.98	79.50*	85.80*	14.20*	44.00*	121,719.11*
	Civilians	59.90	26.90	1.30	3.60	8.30	39.00	32.60	28.40	88.10	48.80	51.20	42.84	134,713.45
Virginia Beach PD, VA	Officers	82.43*	4.89*	7.27*	2.91*	2.51*	22.32*	42.67*	35.01*	75.17	82.83*	17.17*	40.00*	112,010.98*
	Civilians	61.70	8.10	18.40	5.10	6.60	45.50	33.70	20.80	73.30	49.00	51.00	37.74	97,309.03
Washington DC PD, DC	Officers	34.77*	10.14	50.75*	0.07*	4.27	49.25*	6.93*	43.81*	52.40*	77.00*	23.00*	47.00*	124,423.49
	Civilians	36.60	11.00	45.40	3.10	3.90	77.10	5.50	17.40	69.80	47.40	52.60	34.53	125,850.25
Wayne County Sheriff, MI	Officers	53.85*	4.17	31.41*	9.62*	0.96*	65.17*	14.41*	20.42	66.37*	76.58*	23.42*	42.00	78,755.56*
	Civilians	69.60	3.40	14.80	3.00	9.30	54.50	22.10	23.30	78.20	49.10	50.90	41.98	106,198.82
Wichita PD, KS	Officers	52.77*	5.26*	4.43*	35.87*	1.66*	9.14*	47.37*	43.49*	61.08*	88.50*	11.50*	44.00*	94,709.58*
	Civilians	64.20	16.50	10.20	4.40	4.80	28.40	38.50	33.10	72.30	49.30	50.70	35.88	74,713.90
Yonkers PD, NY	Officers	77.54*	15.02*	6.79*	0.00*	0.65*	20.32*	28.71*	50.97*	60.97*	84.84*	15.16*	43.00*	132,011.10*
	Civilians	36.70	38.30	16.10	2.60	6.30	54.80	17.30	27.90	66.20	47.90	52.10	38.96	90,688.29

Table F.1: **Comparison of Officer and Civilian Traits for all Included Agencies**. The table displays the share of officers and civilians in each jurisdiction with a given attribute. Stars denote a statistically significant difference between officers and civilians.

G Officers' Place of Residence

Even if police do not themselves reflect the communities they serve, they may live in representative neighborhoods, which could facilitate awareness of and empathy for the issues experienced by civilians they encounter on the job (Pettigrew, 1998). In addition, recent work theorizes that the groups with whom officers socialize with off the clock can distort beliefs about other groups' behavior, leading to discriminatory policing (Little and & Hübert, 2022). Often invoking similar logic, 26 of the 100 largest agencies have adopted policies that encourage or require officers to reside inside their jurisdictions, according to our close examination of police union contracts, hiring webpages, and personnel policies for each jurisdiction. It is clear that numerous top agencies regard officer residency as an important consideration.[24]

To characterize officers' home neighborhoods, we matched officer home addresses from L2—redacted from our replication data for security and privacy reasons—to U.S. Census tracts. We compared the traits of these tracts to the overall jurisdiction. The results are displayed in Table G.1.[25] Officers' home tracts tend to have higher shares of Republicans (+9 p.p.) and White residents (+13 p.p.). They also tend to have a higher median household annual income (+$12,558) and participate in elections at greater rates (+10 p.p. among voting-age population). In the same vein, officers tend to live in areas with lower shares of Black (−7 p.p.) and Hispanic (−5 p.p.) residents than the jurisdiction-wide average.

Table G.2 displays the share of police officers/sheriff's deputies with various attributes, relative to the hypothetical compositions their agencies would have if randomly drawn from their jurisdictions. The table also displays difference in differences testing whether sheriff's deputies are closer on each attribute to their local populations than are police officers. The table indicates that on various key attributes, sheriff's agencies are more similar to their local populations than are police agencies. For example, both types of agencies show overrepresentation of white officers, but the degree of overrepresentation is 5 percentage points larger among police agencies. Likewise, Democrats are underrepresented in both types of agencies, but the underrepresentation is 6 percentage points larger for police agencies. These patterns are consistent with the idea that elections promote descriptive representation in policing, though as police and sheriff's agencies and jurisdictions differ in multiple unobserved ways, a more thorough examination of this causal account would be necessary before drawing that conclusion.

[24] Our complete data for residency rules for each agency can be found here: https://dl.dropboxusercontent.com/s/2se7l3be55bnank/residency_data_table.pdf?dl=0.

[25] This analysis is restricted to the 86% of officers matched to the L2 database, which contains officer addresses.

Table G.1: **Average Attributes of Officers' Home Census Tracts Relative to their Jurisdictions.** The table displays the average characteristics of the U.S. Census Tracts in which police officers reside, the average characteristics of their jurisdictions, and the difference between the two. The Difference column is made by taking the difference between the officer and civilian trait. For median age, the difference column shows the mean difference between each officer's age and the median civilian age in their jurisdiction. **denotes $p < .01$; * denotes $p < .05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Race	White	50.66	38.03	12.62** [12.50, 12.74]	187,952
	Hispanic	23.23	28.11	−4.88** [−4.97, −4.80]	187,952
	Black	14.27	21.16	−6.89** [−6.99, −6.80]	187,952
	Other/unknown race	3.40	3.40	0.01 [−0.00, 0.02]	187,952
	Asian	8.44	9.30	−0.86** [−0.90, −0.81]	187,952
Party (Voting age pop.)	Republican	23.54	14.17	9.36** [9.29, ,9.43]	187,943
	Democratic	39.04	43.27	−4.23** [−4.30, −4.16]	187,943
	Other/unknown party	39.51	42.65	−3.14** [−3.20, −3.08]	187,943
General turnout, 2020	Voting age pop.	64.25	54.61	9.63** [9.56, 9.71]	185,757
Gender	Male	48.82	48.69	0.12** [0.11, 0.14]	187,952
	Female	51.18	51.31	−0.12** [−0.14, −0.11]	187,952
Median age (years)	–	38.80	36.85	2.32** [2.29, 2.35]	187,949
Mean household income ($)	–	104783.35	92225.06	12558.29** [12363.44, 12753.13]	187,924

Table G.2: **Comparison of Average Officer and Civilian Traits for municipal police agencies ('Officer') and for Sheriff's Offices ('Sheriff').** The table displays, from left to right, the actual share of municipal officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; the actual share of Sheriff officers with a given attribute; the share of Sheriff officers who would have the attribute if taken as a random draw from their jurisdictions. For median age, the difference column shows the mean difference between each officer's age and the median civilian age in their jurisdiction. The 'Difference in Difference' column shows the difference between the Officer-Civilian difference and the Sheriff-Civilian difference. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Actual Sheriff %	Hypothetical representative sheriff (%)	Difference in difference
Race	White	51.83	37.47	49.00	39.85	5.20** [4.70, 5.70]
	Hispanic	21.83	26.05	31.38	35.68	0.08 [−0.38, 0.53]
	Black	17.28	23.89	11.13	10.76	−6.98** [−7.32, −6.64]
	Other/unknown race	3.56	3.43	3.99	3.36	−0.50** [−0.70, −0.29]
	Asian	5.50	9.16	4.50	10.35	2.18** [1.96, 2.41]
Party (Voting age pop.)	Republican	30.83	12.32	38.92	21.24	0.82** [0.32, 1.33]
	Democratic	32.47	45.95	26.72	33.71	−6.49** [−6.96, −6.02]
	Other/unknown party	36.70	42.03	34.36	45.08	5.39** [4.88, 5.90]
General turnout, 2020	Voting age pop.	68.49	53.36	72.91	59.62	1.84** [1.37, 2.32]
Gender	Male	82.60	48.58	83.37	49.11	−0.24 [−0.63, 0.15]
	Female	17.40	51.42	16.63	50.89	0.24 [−0.15, 0.63]
Median age (years)	–	43.00	36.46	45.00	38.35	0.97** [0.80, 1.14]
Mean household income ($)	–	114097.10	90990.40	114602.25	97048.46	5552.92** [4867.16, 6238.68]

Table G.3: **Comparison of Chicago Police Officer and Civilian Traits by district.** The table displays the share of officers and civilians in each police district with a given attribute. Stars denote a statistically significant difference between officers and civilians.

District		White (%)	Hispanic (%)	Black (%)	Other/ unknown race (%)	Democratic (%)	Republican (%)	Other party (%)
Albany Park	Officers	0.68*	0.22*	0.04	0.06*	0.43	0.21*	0.22
Albany Park	Civilians	0.40	0.40	0.03	0.16	0.40	0.04	0.25
Austin	Officers	0.56*	0.22*	0.19*	0.04*	0.48*	0.18*	0.27*
Austin	Civilians	0.03	0.09	0.87	0.01	0.89	0.01	0.07
Calumet	Officers	0.34*	0.10*	0.55*	0.01	0.63*	0.11*	0.14*
Calumet	Civilians	0.02	0.04	0.93	0.02	0.96	0.01	0.06
Central	Officers	0.57*	0.13*	0.28*	0.02*	0.56*	0.15*	0.17*
Central	Civilians	0.53	0.07	0.17	0.23	0.38	0.04	0.27
Chicago Lawn	Officers	0.66*	0.25*	0.07*	0.02	0.50	0.16*	0.23
Chicago Lawn	Civilians	0.17	0.62	0.19	0.02	0.48	0.03	0.21
Deering	Officers	0.65*	0.25*	0.08*	0.03*	0.54*	0.22*	0.17*
Deering	Civilians	0.15	0.54	0.10	0.20	0.36	0.02	0.22
Englewood	Officers	0.42*	0.23*	0.32*	0.03*	0.59*	0.12*	0.22*
Englewood	Civilians	0.01	0.06	0.91	0.01	0.97	0.01	0.07
Grand Central	Officers	0.66*	0.24*	0.05*	0.04	0.46*	0.19*	0.25
Grand Central	Civilians	0.15	0.69	0.13	0.03	0.42	0.03	0.27
Grand Crossing	Officers	0.27*	0.18*	0.53*	0.02	0.63*	0.09*	0.19*
Grand Crossing	Civilians	0.04	0.03	0.90	0.03	0.84	0.01	0.05
Gresham	Officers	0.30*	0.19*	0.49*	0.02	0.61*	0.10*	0.21*
Gresham	Civilians	0.01	0.02	0.95	0.02	0.94	0.01	0.04
Harrison	Officers	0.53*	0.25*	0.18*	0.04*	0.49*	0.14*	0.29*
Harrison	Civilians	0.04	0.16	0.77	0.02	0.84	0.01	0.13
Jefferson Park	Officers	0.81*	0.14*	0.03*	0.03*	0.44	0.24*	0.17*
Jefferson Park	Civilians	0.63	0.27	0.01	0.09	0.41	0.09	0.29
Lincoln	Officers	0.70*	0.15	0.06*	0.09*	0.47	0.18*	0.21
Lincoln	Civilians	0.55	0.18	0.09	0.18	0.48	0.04	0.24
Morgan Park	Officers	0.60*	0.11*	0.28*	0.01*	0.59*	0.16*	0.15*
Morgan Park	Civilians	0.34	0.05	0.58	0.03	0.86	0.05	0.10
Near North	Officers	0.61*	0.15*	0.19*	0.04*	0.52*	0.15*	0.22*
Near North	Civilians	0.73	0.06	0.07	0.15	0.35	0.08	0.34
Near West	Officers	0.53*	0.33*	0.11*	0.02*	0.53*	0.16*	0.24*
Near West	Civilians	0.46	0.26	0.17	0.12	0.47	0.04	0.32
Ogden	Officers	0.41*	0.51*	0.07*	0.02	0.48	0.17*	0.27*
Ogden	Civilians	0.05	0.64	0.30	0.01	0.47	0.01	0.18
Rogers Park	Officers	0.73*	0.15*	0.05*	0.07*	0.48*	0.21*	0.19*
Rogers Park	Civilians	0.44	0.19	0.18	0.19	0.42	0.03	0.25
Shakespeare	Officers	0.51	0.37	0.06	0.06	0.44	0.15*	0.28*
Shakespeare	Civilians	0.53	0.35	0.05	0.07	0.46	0.04	0.33
South Chicago	Officers	0.48*	0.22*	0.29*	0.02	0.55*	0.14*	0.21*
South Chicago	Civilians	0.07	0.30	0.62	0.01	0.73	0.02	0.14
Town Hall	Officers	0.62*	0.23*	0.09*	0.06*	0.47	0.18*	0.23*
Town Hall	Civilians	0.74	0.10	0.06	0.10	0.45	0.05	0.31
Wentworth	Officers	0.22	0.14*	0.62*	0.02*	0.68*	0.08*	0.16*
Wentworth	Civilians	0.19	0.04	0.66	0.11	0.73	0.01	0.11

Table G.4: **Comparison of Houston Police Officer and Civilian Traits by division.** The table displays the share of officers and civilians in each police district with a given attribute. Stars denote a statistically significant difference between officers and civilians. Two police districts where the jurisdiction was an airport ('Airport-Hobby Division' and 'Airport-IAH Division') were excluded due to a lack of a civilian comparison.

Division		White (%)	Hispanic (%)	Black (%)	Other/ unknown race (%)	Democratic (%)	Republican (%)	Other party (%)
Central Division	Officers	0.34*	0.38*	0.09	0.14	0.46	0.31*	0.15
Central Division	Civilians	0.57	0.27	0.06	0.10	0.41	0.22	0.17
Clear Lake Division	Officers	0.43*	0.34*	0.04*	0.16	0.38	0.35*	0.19*
Clear Lake Division	Civilians	0.28	0.49	0.12	0.12	0.33	0.19	0.11
Eastside Division	Officers	0.27*	0.49*	0.07*	0.10*	0.49	0.23*	0.22*
Eastside Division	Civilians	0.06	0.90	0.03	0.02	0.42	0.04	0.06
Kingwood Division	Officers	0.42*	0.36*	0.11	0.11	0.33	0.50	0.14
Kingwood Division	Civilians	0.68	0.19	0.07	0.06	0.30	0.50	0.12
Midwest Division	Officers	0.35	0.24*	0.07*	0.12	0.43*	0.30*	0.22*
Midwest Division	Civilians	0.37	0.36	0.12	0.15	0.25	0.18	0.12
North Belt Division	Officers	0.48*	0.24*	0.05*	0.24*	0.38	0.24*	0.19
North Belt Division	Civilians	0.08	0.57	0.30	0.05	0.33	0.03	0.04
North Division	Officers	0.50*	0.30*	0.06*	0.12*	0.42	0.36*	0.16*
North Division	Civilians	0.16	0.62	0.20	0.03	0.48	0.10	0.06
Northeast Division	Officers	0.49*	0.26*	0.08*	0.14*	0.39*	0.37*	0.17*
Northeast Division	Civilians	0.05	0.56	0.38	0.01	0.59	0.02	0.04
Northwest Division	Officers	0.39*	0.30*	0.05*	0.13*	0.39*	0.45*	0.09
Northwest Division	Civilians	0.28	0.56	0.09	0.07	0.26	0.16	0.09
South Central Division	Officers	0.55*	0.19*	0.12*	0.11	0.40*	0.39*	0.16
South Central Division	Civilians	0.33	0.28	0.28	0.11	0.49	0.10	0.12
South Gessner Division	Officers	0.38*	0.27*	0.14*	0.16*	0.47*	0.34*	0.12*
South Gessner Division	Civilians	0.12	0.55	0.26	0.08	0.32	0.06	0.05
Southeast Division	Officers	0.41*	0.34*	0.13*	0.10*	0.49*	0.25*	0.18*
Southeast Division	Civilians	0.04	0.47	0.45	0.03	0.61	0.03	0.04
Southwest Division	Officers	0.34	0.29	0.16*	0.09	0.50	0.29*	0.14
Southwest Division	Civilians	0.26	0.34	0.28	0.11	0.59	0.13	0.09
Westside Division	Officers	0.31	0.27*	0.06*	0.14	0.35*	0.35*	0.21*
Westside Division	Civilians	0.28	0.35	0.21	0.16	0.28	0.16	0.10

H Measurement Error in Race/Ethnicity

Imputed L2 race and ethnicity variables are used for 14 percent of agencies, which contain approximately 8% of our officers. To get a sense of the scale of the potential for mismeasurement in the L2 race data, we compare the shares of each racial/ethnic group as measured in LEMAS vs. L2 for the agencies found in both data sets.

The table below, Table H.1, displays the proportion of officers in each racial/ethnic category as measured by L2 vs. LEMAS. As the table shows, among these agencies, L2 underrepresents the share of officers who are white by 13 percentage points, on average. L2 also under-represents racial and ethnic minorities relative to LEMAS. The main discrepancy stems from the "other/unknown" category, which is 22% in L2 but only 2% in LEMAS (2020).

The following table, Table H.2 shows the comparison between officers and civilians after adjusting for the measurement error shown in Table H.1 for agencies that are not covered by the LEMAS data. Because 92% of our officers being in agencies covered by LEMAS, results are nearly identical to Table 1.

I Measurement Error in Party ID

At a high level, there are two potential sources of measurement error in our method for ascertaining officers' party identification: (i) officers who have partisan identities are erroneously not matched to the voter file, and (ii) officers are matched to the voter file but their party identification is mismeasured, which could occur due to matching to the wrong individual, erroneous imputation, or "stale" registrations. To address these issues, we engage in a series of bounding exercises assuming conservative assumptions about the nature of measurement error, employ an alternate measure of party identification based on recent primary participation, and subset to states where voters can identify which party they are affiliated with on their voter registration forms.

To address measurement error due to a failure to match officers to L2, we include an extensive best- and worst-case bounding exercise which evaluate the hypothetical impact of all unmatched officers being Democrats or Republicans (see Table I.1 below). Even using the most conservative worst case scenario for the officers who are not matched to the voter file, officers overall are still far more likely to be Republican than civilians in their jurisdictions. This exercise also shows that under this worst-case measurement error scenario, we cannot reject the possibility that Democrats are slightly overrepresented on police forces by 2 percentage points. We note this test is extremely conservative, as it assumes all unmatched officers identify

Table H.1: Comparison of Average Officer Race when using LEMAS Compared to using L2 for the 86% of Agencies (Covering 92% of Officers) with LEMAS data.

Race (%)	Data from L2	Data from LEMAS	Change (%)
White	44.72	50.57	13.08
Hispanic	19.95	25.02	25.41
Black	10.52	16.69	58.69
Other/unknown	21.71	2.12	−90.26
Asian	3.10	5.61	80.75

Table H.2: **Comparison of Average Officer and Civilian Race Variables after Approximate Debiasing of L2 Race Data.** L2 race estimates are used for 8% of officers (14% of agencies). However, as Table H.1 shows, L2 race estimates are in general not well-calibrated. In this analysis, we adjust L2 estimates by taking the proportion of officers of each race, only among agencies with only L2 race data, and shifting it based on estimated misclassification rates in agencies where LEMAS-based ground truth is available. For example, Table H.1 shows that when LEMAS ground-truth race data is available, L2 undercounts the share of White officers by 13%. Here, for agencies where only L2 is available, we therefore inflate the share of White officers by a corresponding factor. Agencies in which LEMAS race data is available are unchanged. The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. The Difference column is made by taking the difference between the officer and civilian trait. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Race	White	52.07	37.95	14.12^{**}	114,216
				[13.92, 14.32]	
	Hispanic	23.82	27.98	-4.16^{**}	52,247
				[−4.33, −3.99]	
	Black	16.52	21.26	-4.75^{**}	36,229
				[−4.90, −4.60]	
	Other/unknown race	2.20	3.42	-1.22^{**}	4,821
				[−1.28, −1.16]	
	Asian	5.40	9.40	-3.99^{**}	11,856
				[−4.08, −3.90]	

with one of the two major parties, when in reality at least some share identify as pure independents or with a minor party. Because of this, we view it as extremely unlikely that the worst-case estimate is correct.

To address measurement error due to mismatching, we first re-compute our core results using an alternate threshold for the posterior probability of a correct match of 0.95 (see Table I.2 below). As the table shows, our core conclusions remain virtually unaffected. Second, we employ an alternate measure of party ID: the most recent party primary a voter participated in, according to L2 (see Table I.3 below). This approach has the simultaneous benefit of using a recent measure of party identification, which partially addresses concerns over "stale" registrations, while avoiding reliance on imputed measures. If officers and civilians did not participate in any primaries on record, we code them as "other/unknown" party for this test. Table I.3 shows our core results using L2's imputed party identification measure, while the bottom table shows results using the most recent primary alternative measure. As the table shows, while this alternate measure changes the base rates of party ID, our overall conclusion that Republicans are substantially overrepresented holds.

As a further check, we also re-compute core results after subsetting to states where voters are allowed to indicate which political party they are affiliated with when registering to vote and where L2 is presumably less reliant on imputation. These results, shown in Table I.4 below, are consistent with our core conclusions in terms of the disparities between officers and civilians.

Next, we consider the potential for mismeasurement in party identification due to erroneous matches in the voter file in the case of multiple high probability matches. To evaluate the potential scale of this problem for our study, we conducted a bounding exercise assuming best/worst case scenarios for officers with multiple matches. Specifically, we re-compute core results assuming that every officer with a multiple match was erroneously paired with an individual of a different party identification. As Table I.5 below shows, these extremely conservative assumptions lead to very wide bounds. For example, under these best/worst case scenarios, the difference in the share Republican among officers and civilians ranges between 9 and 34 percentage points. For Democrats, it ranges from -25 to 2 percentage points. In other words, even under the most extreme scenarios possible, we can definitively conclude that officers are more heavily Republican compared to representative civilians, but we cannot draw firm conclusions about the share of Democratic officers.

However, using an anonymous reviewer's helpful suggestion to incorporate additional information such as age in the merge procedure, we are able to gain a more realistic portrait of the potential severity of measurement error here. In addition to name-only matching, we conduct a validation exercise with 20 agencies where officer age is also available (Table I.6). In addition, we conduct the same exercise using the three agencies which include the officer's exact date of birth (Table I.7). We find that results are nearly identical when using name-only as when using name+age or name+date-of-birth.

Taken together, we believe that i) the substantial reduction in duplicate matches we see when incorporating additional merge information combined with ii) the near-identical results we obtain when doing so, demonstrates that our central conclusions are not being driven by erroneous record linkages.[26]

[26]Incorporating age when matching reduces the number of officers with more than one potential match from 38% of officers to 16%; using date of birth rate than age reduces the multiple-match officers even further to only 2% of officers.

Table I.1: **Average Officer Traits Relative to Jurisdictions (Estimated Bounds Based on Extreme Values for Unmatched Officers).** The table displays, from left to right, the lowest possible share of officers with a given attribute; the largest share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the differences between this hypothetical share and the lower and upper bounds. Lower and upper bounds are computed by assigning maximally extreme values to officers not observable in any of our data sources (e.g. that no unmatched officers are Democrats, or that all are Democrats). "Difference" columns report the gap between the hypothetical representative value and these upper/lower bounds. **denotes $p < .01$; * denotes $p < .05$

Variable	Value	Officer lower bound (%)	Officer upper bound (%)	Hypothetical representative officer (%)	Difference lower bound	Difference upper bound
Race	White	51.26	52.24	37.95	13.31**	14.29**
	Hispanic	23.75	24.73	27.98	−4.23**	−3.25**
	Black	16.05	17.03	21.26	−5.21**	−4.23**
	Other/unknown race	2.66	3.65	3.42	−0.76**	0.23**
	Asian	5.30	6.28	9.40	−4.10**	−3.11**
Party (Voting age pop.)	Republican	32.45	46.14	14.11	18.34**	32.03**
	Democratic	31.32	45.01	43.50	−12.18**	1.52**
	Other/unknown party	22.54	36.23	42.64	−20.10**	−6.41**
General turnout, 2020	Voting age pop.	69.39	83.15	54.62	14.76**	28.52**

Table I.2: **Comparison of Average Officer and Civilian Traits (0.95 Match Probability Threshold).** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. The Difference column is made by taking the difference between the officer and civilian trait. For median age, the difference column shows the mean difference between each officer's age and the median civilian age in their jurisdiction. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Race	White	50.78	37.95	12.83** [12.63, 13.03]	111,391
	Hispanic	23.53	27.98	−4.44** [−4.61, −4.28]	51,623
	Black	15.99	21.26	−5.27** [−5.42, −5.13]	35,072
	Other/unknown race	4.49	3.42	1.07** [0.98, 1.15]	9,843
	Asian	5.21	9.40	−4.18** [−4.27, −4.09]	11,438
Party (Voting age pop.)	Republican	25.50	14.11	11.39** [11.21, 11.57]	55,928
	Democratic	22.86	43.50	−20.64** [−20.82, −20.47]	50,136
	Other/unknown party	51.65	42.64	9.01** [8.81, 9.21]	113,301
General turnout, 2020	Voting age pop.	52.04	54.62	−2.58** [−2.79, −2.38]	112,953
Gender	Male	82.75	48.69	34.07** [33.91, 34.22]	181,532
	Female	17.25	51.31	−34.07** [−34.22, −33.91]	37,833
Median age (years)	–	44.00	36.94	7.87** [7.80, 7.94]	139,135
Mean kousehold income ($)	–	115131.11	92002.72	23 128.39** [22812.62, 23444.15]	138,631

Table I.3: **Comparison of Officer and Civilian Party Identification.** Top panel reports L2-estimated party identification; bottom panel reports party based on the most recent primary in which an individual voted. The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. The Difference column is made by taking the difference between the officer and civilian trait. **denotes $p < .01$; * denotes $p < .05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Party (Voting age pop.)	Republican	32.45	14.11	18.34** [18.15, 18.53]	71,177
	Democratic	31.32	43.50	−12.18** [−12.37, −11.99]	68,705
	Other/unknown party	36.23	42.64	−6.41** [−6.61, −6.20]	79,483

(a) **Party ID as identified by L2**

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Party (Voting age pop.)	Republican	20.49	8.10	12.39** [12.22, 12.55]	44,940
	Democratic	22.26	25.21	−2.96** [−3.13, −2.79]	48,825
	Other/unknown party	57.26	66.93	−9.68** [−9.88, −9.47]	125,600

(b) **Party ID based on the most recent party primary election**

Table I.4: **Comparison of Average Officer and Civilian Traits for States with Partisan Affiliations Recorded for Registered Voters.** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. The "Difference" column is made by taking the difference between the officer and civilian trait. For median age, the difference column shows the mean difference between each officer's age and the median civilian age in their jurisdiction. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. denotes. N indicates number of officers.

Variable	Value	Actual officer (%)	Hypothetical representative officer (%)	Difference	N
Race	White	48.64	37.65	11.00** [10.75, 11.24]	69,620
	Hispanic	28.46	29.89	−1.43** [−1.64, −1.21]	40,739
	Black	15.09	18.75	−3.66** [−3.84, −3.48]	21,599
	Other/unknown race	1.71	3.41	−1.69** [−1.76, −1.63]	2,452
	Asian	6.09	10.31	−4.23** [−4.35, −4.10]	8,711
Party (Voting age pop.)	Republican	36.91	14.88	22.04** [21.79, 22.28]	52,831
	Democratic	30.62	41.66	−11.04** [−11.27, −10.80]	43,821
	Other/unknown party	32.47	43.47	−11.00** [−11.24, −10.76]	46,469
General turnout, 2020	Voting age pop.	74.59	55.14	19.46** [19.23, 19.68]	105,337
Gender	Male	89.36	48.65	40.71** [40.55, 40.87]	127,895
	Female	10.64	51.35	−40.71** [−40.87, −40.55]	15,226
Median age (years)	–	43.00	37.51	7.04** [6.96, 7.12]	131,864
Mean household income ($)	–	116738.99	94942.25	21 796.75** [21461.31, 22132.18]	130,898

Table I.5: **Officer Traits Relative to Jurisdictions (Estimated Bounds for Officers with Multiple Matches).** The table displays, from left to right, the lowest possible share of officers with a given attribute; the largest share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the differences between this hypothetical share and the lower and upper bounds. Lower and upper bounds are computed by, e.g., assuming that an officer is Democratic if even one of their multiple L2 matches fits this description. **denotes $p<.01$; * denotes $p<.05$

Variable	Value	Officer lower bound (%)	Officer upper bound (%)	Hypothetical representative officer (%)	Difference lower bound	Difference upper bound
Race	White	50.66	51.60	37.95	12.71^{**}	13.65^{**}
	Hispanic	23.66	23.84	27.98	-4.31^{**}	-4.13^{**}
	Black	15.80	16.58	21.26	-5.46^{**}	-4.68^{**}
	Other/unknown race	3.59	3.79	3.42	0.17^{**}	0.37^{**}
	Asian	5.28	5.35	9.40	-4.11^{**}	-4.04^{**}
Party (Voting age pop.)	Republican	23.52	48.55	14.11	9.42^{**}	34.44^{**}
	Democratic	18.52	45.44	43.50	-24.98^{**}	1.94^{**}
	Other/unknown party	27.26	52.45	42.64	-15.38^{**}	9.81^{**}
General turnout, 2020	Voting age pop.	53.38	77.98	54.62	-1.25^{**}	23.35^{**}
Median age (years)	–	36.00	50.00	36.84	1.17^{**}	15.66^{**}
Mean household income ($)	–	90855.54	146160.98	92220.54	-1365.00^{**}	53940.44^{**}

Table I.6: **Name-only and Name/Age Matching in Officer-Civilian Trait Comparisons.** Comparisons based on full name only (top panel) and based on both full name and age (bottom panel) are shown for the 20 agencies with officer age available. The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. N indicates number of officers.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	54.71	38.69	16.02** [15.53, 16.52]	20,216
	Hispanic	19.63	24.72	-5.09** [-5.48, -4.69]	7,255
	Black	21.85	28.12	-6.27** [-6.68, -5.85]	8,073
	Other/Unknown Race	1.40	2.58	-1.18** [-1.30, -1.06]	517
	Asian	2.41	5.90	-3.49** [-3.65, -3.33]	890
Party (Voting Age Pop.)	Republican	27.23	10.95	16.28** [15.84, 16.72]	10,062
	Democratic	41.62	49.38	-7.75** [-8.25, -7.26]	15,380
	Other/Unknown Party	31.15	39.67	-8.52** [-9.00, -8.04]	11,509
General Turnout, 2020	Voting Age Pop.	73.07	55.47	17.60** [17.13, 18.06]	27,000
Gender	Male	80.42	48.31	32.10** [31.70, 32.51]	29,715
	Female	19.58	51.69	-32.10** [-32.51, -31.70]	7,236
Median Age (Years)	-	43.00	35.94	8.36** [8.20, 8.51]	33,337
Mean Household Income ($)	-	103639.23	80704.08	22935.15** [22319.33, 23550.96]	33,030

(a) **Using name only**

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	54.68	38.69	15.99** [15.50, 16.48]	20,204
	Hispanic	19.63	24.72	-5.09** [-5.48, -4.69]	7,255
	Black	21.85	28.12	-6.27** [-6.68, -5.85]	8,074
	Other/Unknown Race	1.43	2.58	-1.15** [-1.27, -1.03]	528
	Asian	2.41	5.90	-3.49** [-3.65, -3.33]	890
Party (Voting Age Pop.)	Republican	28.56	10.95	17.61** [17.16, 18.06]	10,555
	Democratic	41.48	49.38	-7.90** [-8.39, -7.41]	15,326
	Other/Unknown Party	29.96	39.67	-9.71** [-10.18, -9.24]	11,070
General Turnout, 2020	Voting Age Pop.	74.91	55.47	19.44** [18.98, 19.89]	27,680
Gender	Male	80.42	48.31	32.10** [31.70, 32.51]	29,715
	Female	19.58	51.69	-32.10** [-32.51, -31.70]	7,236
Median Age (Years)	-	43.00	36.01	7.01** [6.89, 7.13]	34,095
Mean Household Income ($)	-	105576.41	80699.28	24877.12** [24273.29, 25480.95]	32,897

(b) **Using name and age**

Table I.7: **Name-only and Name/Date-of-Birth Matching in Officer-Civilian Trait Comparisons.** Comparisons based on full name only (top panel) and based on both full name and date-of-birth (bottom panel) are shown for the three agencies with officer age available. The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. **denotes $p<.01$; * denotes $p<.05$; brackets contain 95% confidence intervals. N indicates number of officers.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	45.76	33.97	11.79** [11.00, 12.58]	6,693
	Hispanic	31.05	32.07	-1.02** [-1.73, -0.32]	4,541
	Black	17.62	25.85	-8.23** [-8.84, -7.62]	2,577
	Other/Unknown Race	2.50	2.20	0.29* [0.04, 0.55]	365
	Asian	3.08	5.90	-2.83** [-3.10, -2.55]	450
Party (Voting Age Pop.)	Republican	16.70	5.81	10.89** [10.30, 11.48]	2,442
	Democratic	53.85	52.99	0.86* [0.07, 1.66]	7,876
	Other/Unknown Party	29.45	41.21	-11.75** [-12.49, -11.02]	4,308
General Turnout, 2020	Voting Age Pop.	75.65	52.43	23.22** [22.52, 23.91]	11,065
Gender	Male	78.02	48.68	29.34** [28.66, 30.01]	11,411
	Female	21.98	51.32	-29.34** [-30.01, -28.66]	3,215
Median Age (Years)	-	44.00	35.36	9.06** [8.85, 9.28]	13,870
Mean Household Income ($)	-	104670.96	84678.77	19992.20** [19053.12, 20931.28]	13,676

(a) **Using name only**

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	45.58	33.97	11.61** [10.81, 12.40]	6,666
	Hispanic	30.99	32.07	-1.08** [-1.78, -0.37]	4,533
	Black	17.65	25.85	-8.20** [-8.81, -7.59]	2,582
	Other/Unknown Race	2.70	2.20	0.50** [0.24, 0.76]	395
	Asian	3.08	5.90	-2.83** [-3.10, -2.55]	450
Party (Voting Age Pop.)	Republican	16.01	5.81	10.20** [9.62, 10.78]	2,341
	Democratic	49.56	52.99	-3.42** [-4.22, -2.63]	7,249
	Other/Unknown Party	34.43	41.21	-6.78** [-7.54, -6.01]	5,036
General Turnout, 2020	Voting Age Pop.	69.00	52.43	16.57** [15.82, 17.32]	10,092
Gender	Male	78.02	48.68	29.34** [28.66, 30.01]	11,411
	Female	21.98	51.32	-29.34** [-30.01, -28.66]	3,215
Median Age (Years)	-	44.00	35.34	8.07** [7.89, 8.24]	11,827
Mean Household Income ($)	-	108107.45	84525.80	23581.65** [22594.68, 24568.62]	11,729

(b) **Using name and date of birth**

J Balance Tests for Behavioral Analysis in Chicago

We conduct a series of balance tests to validate that we are comparing officers working in common circumstances in the Chicago behavioral analysis. We merged our Chicago behavioral data with incident-level data on crimes reported from the city's open-data portal for beats where geographic location was available. Specifically, we paired each officer shift with the number of reported incidents of each category in the time and location of each officer shift. We then code these incidents based on whether they were likely non-discretionary (i.e., initiated by civilians, as opposed to officers) based on Table 4 of Abdul-Razzak and Hallberg (2022). The logic of this test is that imbalance in the number of discretionary incidents may be an effect of an officer's deployment (and are thus not used in this test) but imbalance in non-discretionary incidents would indicate that our research design failed to hold circumstances fixed. We estimate separate OLS models predicting the propensity of a Democratic officer to be assigned as a function of the number of non-discretionary crimes of a given category, with MDSB fixed effects. Standard errors are clustered by officers. Coefficients indicate change in the propensity score given a one-unit increase in a crime. Raw p values and BH-corrected p-values are displayed for each test. Table J.1 shows that no crime variables predict deployment of a Democrat after a multiple testing correction.

Table J.1: **Balance Tests Predicting Deployment of Democrat.** The table displays the coefficients on crime counts from individual OLS regressions with MDSB fixed effects predicting the deployment of a Democratic officer. No crimes are predictive of deployment of a Democrat after a multiple testing correction, consistent with as-if random assignment of officers within MDSBs.

Crime	Coef.	Raw p value	BH-corrected p value
Forgery counterfeiting	0.014	0.048	0.334
Vandalism	0.002	0.266	0.884
Sexual assault	−0.003	0.660	0.884
Sexual abuse	0.002	0.789	0.884
Murder	−0.002	0.884	0.884
Manslaughter	−0.063	0.569	0.884
Burglary	0.001	0.570	0.884