Political Diversity in U.S. Police Agencies*

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Abstract

Partisans are increasingly divided on policing policy, a cleavage that may affect police officers' conduct. National surveys of officers' politics preclude examinations of how local civilians compare to police and whether partisanship maps to officers' behavior. We merge personnel data on roughly 220,000 officers from 98 of the 100 largest local U.S. agencies—over one third of local police nationwide—with voter-file data to study officer partisanship and its implications for police-civilian interactions. While officers skew Republican relative to their jurisdictions on average, and diverge on many other attributes, there is considerable heterogeneity at the local level, where policing decisions are made. We find that when facing common circumstances, Democrats in Chicago make fewer stops and arrests, and use force less often, than Republicans. The partisan difference in force rivals the Black-White officer gap. Depending on the partisan identity of officers encountered, civilians can expect large, systematic differences in treatment.

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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, 2022). 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 attitudes on issues relating to policing, comparable to the predictiveness of race and political ideology combined (see Figure 1 and accompanying discussion).

While partisans in the mass public may disagree strongly as to how police should function in society, few individuals are empowered to translate their political views on these issues into action. But police officers themselves experience no such constraint. Every day, armed agents of the state are deployed in American communities with extraordinary discretion over when and how they 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 immense power, combined with the 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 correspond to civilians in their jurisdictions? And how do officers' partisan affiliations map to their interactions with civilians?

Progress on these questions have been hampered by a scattered, 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 they sample small numbers of officers from numerous locations nationwide, they preclude close 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 to participate in interviews.[1]

In this paper, we analyze nearly a quarter million officers,[2] covering 98 of America's 100 largest local agencies, and representing over one third of all local law enforcement nationwide, to examine the distribution and consequences of 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. The resulting data set allows us to comprehensively characterize the degree to which police resemble their communities on a host of dimensions, and how this correspondence varies across jurisdictions. In addition, micro-level data from Chicago on the precise times and places of officers' deployments and behaviors allow us to examine for the first time whether Democratic and Republican officers behave differently when facing otherwise common circumstances.

Using our newly assembled data, we first 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 nonrepresentativeness is highly heterogeneous—a fact heretofore masked by national surveys—with some agencies closely mirroring their populations and others substantially diverging. We also broaden our analysis to account for the neighborhoods in which

[1]For example, a new working paper (Adams et al., N.d.) attempts to interview police chiefs at large agencies, obtaining a 9.98% response rate.

[2]Throughout, we use "officers" to refer to sworn employees of law enforcement agencies, including both police officers and sheriffs' deputies.

officers live, and find find the composition of officers' neighborhoods also differs systematically from that of the city at large. Areas where officers live have higher: shares of Republicans; shares of White residents; voter turnout rates; and household income than the jurisdiction overall.

To probe these patterns at a finer-grained level, we then turn to our micro-level data in Chicago, acquired through a series of public records requests filed over a 5-year period. 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 show sharp divergences between racial and ethnic groups of civilians on attitudes towards police (Harris, 2021). Among numerous other features and activities, our Chicago data describe the specific areas in which police officers work. This allows us to evaluate whether officers resemble civilians in the areas they patrol—that is, civilians with whom they are most likely to interact. We see striking gaps in political affiliation: every single district in Chicago is policed by officers who skew more Republican than local residents. We also find that in the vast majority of Chicago police districts, officers diverge from the civilians they serve in terms of race and ethnicity.

Having established these descriptive patterns, we then use data on CPD shift assignments and enforcement records covering an eight-year period to investigate how officers' partisan affiliation maps to behavior on the job. Specifically, we estimate differences in the number of stops, arrests and uses of force by officers of various partisan identities when facing common circumstances. We find striking differences in the way police officers of different partisan affiliations do their jobs. Relative to Republican officers, Democratic officers make fewer stops, arrests, and use force less often, with the average reduction in the use of force rivaling the effect of deploying a Black (v. White) officer. These effects are substantial in magnitude, representing reductions equal to 14%, 12% and 24% of the citywide average volume of stops, arrests and uses of force among Republican officers per 100 shifts citywide, respectively. We also find these reductions primarily stem from reduced engagement with Black civilians, who are much less likely to be stopped, arrested or subjected to force when Democrats (v. Republican officers) are deployed.

Our results show that the widespread partisan divisions over how police should operate in society map closely to divergences in behavior among officers themselves. Depending on the partisan identity of an officer a civilian encounters, they can expect large and systematic differences in how they are treated. Our results challenge purely institutional narratives of policing—consistent with recent studies of officer race, ethnicity and gender (Ba et al., 2021; Hoekstra and Sloan, 2020), officers of different political persuasions do not converge behaviorally, despite facing common recruiting experiences and training, and even when confronting similar conditions in the field. As debates over how to improve policing remain a central fixture of national political debate, our study reinforces the fact that in addition to structural factors, officer discretion meaningfully affects police-civilian interactions. In addition, our results add needed complexity to classic notions of descriptive representation in the bureaucracy (Kingsley, 1944; Meier, 1975) and diversity in policing in particular (Sklansky, 2005). While scholars and activists have long debated the importance of officer race and gender in police civilian interactions, our analysis underscores the value of a multi-dimensional conception of diversity in policing.

Incorporating Political Orientation into the Study of Diversity in Policing

Calls to diversify police forces—which for much of American history were nearly all White and male (Forman Jr., 2017)—represent perhaps the oldest proposed policing reform, and one logic for diversification springs from the literature on "representative bureaucracy." In general, theories of representative bureaucracy (Kingsley, 1944; Dolan and Rosenbloom, 2003) are premised on several key assertions: bureaucratic oversight is often incapable of ensuring 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).

Empirical studies of representative bureaucracy that focus on political ideology have mostly focused on the executive branch of the national government (Clinton and Lewis, 2008), and to a lesser extent, state-level actors (Smith, 1980; but see Kropf, Vercellotti and Kimball, 2013). However, because such a large share of individuals' face-to-face interactions with government occur at the local level, it is critical to examine the dynamics of representation in these settings.

In the policing context, a vast related literature has investigated whether police forces which better reflect the demographics of the populations they serve has sought to empirically evaluate whether officers of different social identities treat civilians differently. However, this literature has tended to be fairly narrow in scope: longstanding concerns over racial bias and abusive policing practices (Lerman and Weaver, 2014) have understandably led scholars to focus overwhelmingly on race and to a lesser extent, gender when studying diversity in policing, with mixed results. While decades of correlational research relying on coarse data reached mixed conclusions (Sklansky, 2005), newly available granular data on police demographics and behavior, combined with improved research designs, have provided strong evidence that diversity affects policing outcomes. 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 dispatches to 911 calls, 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." 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."

While an empirical consensus may be developing with respect to officer race, assessments of the distribution and consequences of officers' political leanings remain extremely rare due to data constraints. Using data from the General Social Survey, Roscigno and Preito-Hodge (2021) write that "police uniquely believe that they should receive more funding and have the right to use physical force against citizens; they are also more racist, a pattern especially apparent among white male officers." However, Peyton (2021) argues that the strategy of pooling attitudinal data on a relatively small number of police officers across waves of the GSS limits the reliability of the inferences in Roscigno and Preito-Hodge (2021). Other assessments of the political orientations of police come from national polls. For example, using a nationwide survey of police officers, Morin et al. (2017) finds that police are far more likely than the general public to think that police killings of Black Americans are isolated incidents rather than signs of a broader problem. Officers are also far less likely than the general public to believe additional changes are necessary to allow Black Americans to enjoy equal rights.

The limitations of survey approaches to the study of officers' politics are numerous. Selection bias in which officers choose to respond to pollsters is likely severe—a recent attempt to interview police chiefs at large agencies obtained only a 9.98% response rate (Adams et al., N.d.). Polls that sample only small numbers of officers from many jurisdictions also offer no way to determine whether officers' politics overlap with the specific civilians they serve.

Finally, anonymous surveys offer no way to link officer attitudes with behaviors, but the need to do so is evident. Figure 1 displays an analysis of the relative importance of standard demographics in predicting attitudes on issues relating to policing using a national Pew Research Center survey (Pew, 2016). The figure presents Shapley values, a concept derived from machine learning that assesses the relative significance of variables for prediction tasks.[3] As the figure

[3]Central to these values is the property of additivity, meaning that each value represents an additive contribution to the overall prediction of the model. A widely adopted method for practically computing these values is SHAP (SHapley Additive exPlanations). We utilize a version of SHAP tailored for categorical predictors, allowing us to evaluate the combined impact of a single categorical variable (Amoukou, Brunel and Salaün, 2022).

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.

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

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. The majority (77%) of rosters come from 2019-2021; 19% originate from 2015-2018 and 4% do not specify a precise year.

Ultimately, we received data covering roughly 220,000 officers from 98 police agencies. Descriptive statistics on these individuals are given in Table 1. In 90 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 37 states, plus 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 nation-

[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.

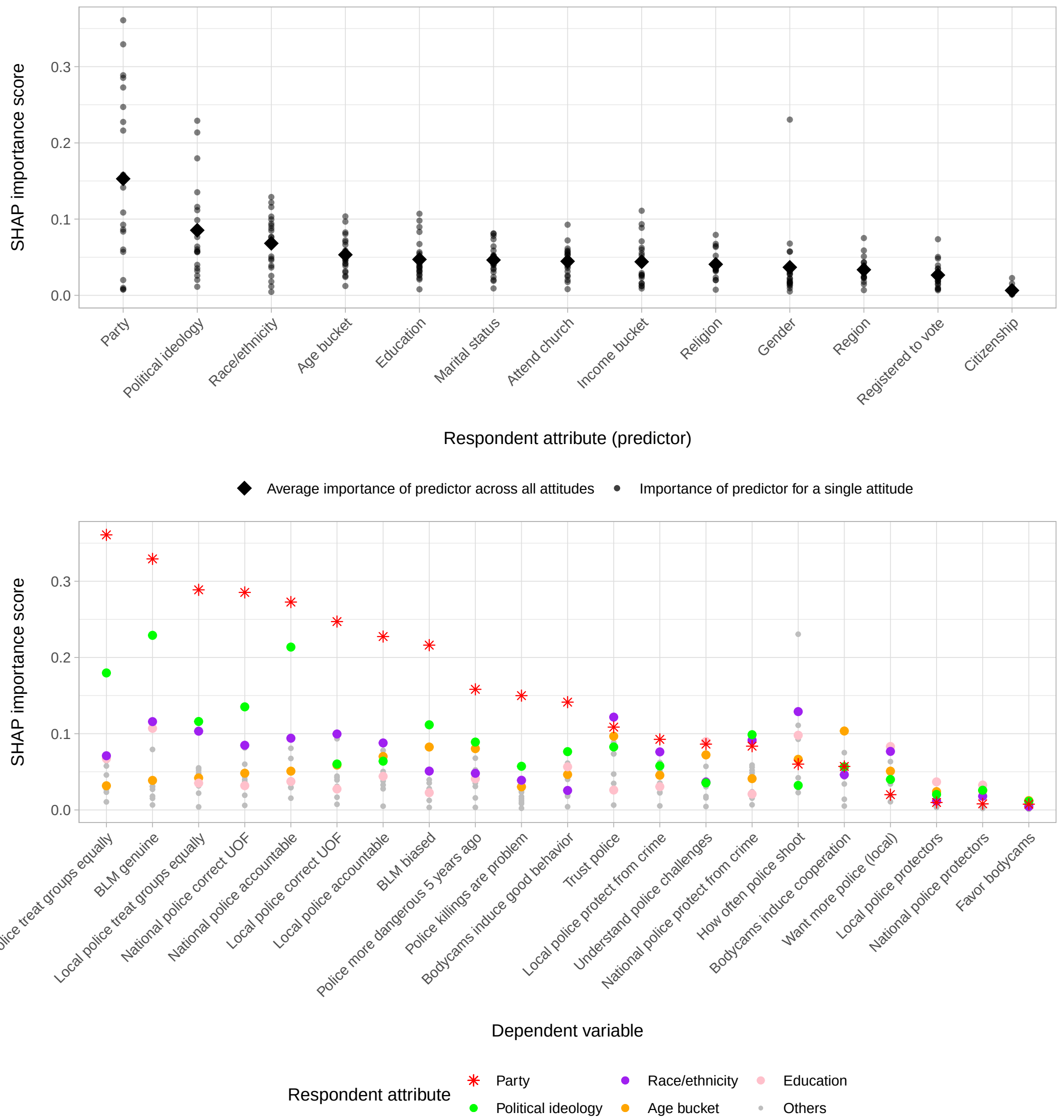

Figure 1: **Partisanship is the most important predictor of policing attitudes.** The upper panel depicts the "importance score" of various respondent attributes (horizontal axis) in predicting survey responses about policing in Pew (2016). Each small circle represents a policing attitude, with vertical 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 diamonds represent the overall importance of the respondent attribute, averaged over all attitudes. Partisanship is shown to have an overall importance that is on par with combined predictiveness of ideology and race/ethnicity. The lower panel shows disaggregated importance scores for each policing attitude (x-axis), with each point representing a 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 12 out of 21 policing attitudes.

wide (Hyland and Davis, 2019), making this the largest examination of descriptive representation in policing to date.[5]

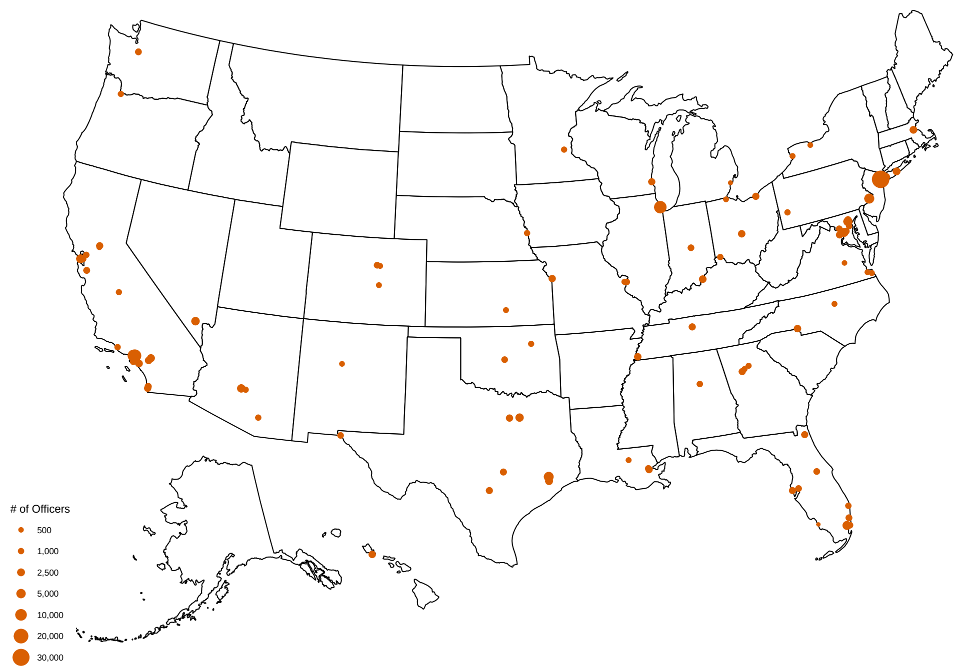

Figure 2: **Agency Locations.** Included agencies cover roughly 220,000 officers across 38 states (including Washington, D.C.), representing 34% of the nation's roughly 641,000 sworn local police officers and sheriffs' deputies (Hyland and Davis, 2019). Together, jurisdictions covered in our data serve about 23% of the U.S. population. Each dot is scaled by the number of sworn officers.

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. We merge these with a commercial voter file from L2 (`l2-data.com`) via a two-step process. We restrict candidate matches to only individuals residing in or adjacent to the county containing their agency, including adjacent out-of-state counties. (In cases where an agency covers multiple counties, the

[5]See Appendix Table A1 for comparisons of officers in our data to (1) officers nationwide and (2) the U.S. population (Hyland and Davis, 2019).

Variable	Description	N	Percent
Political Party	Republican	70,882	32.44
	Democratic	68,360	31.29
	Other	49,248	22.54
Gender	Male	149,423	68.39
	Female	38,555	17.65
Race	White	100,200	45.86
	Other_Unknown_Race	46,996	21.51
	Hispanic	41,929	19.19
	Black	22,762	10.42
	Asian	6,590	3.02
Most Common Primary Party	Democratic	44,400	47.42
	Republican	49,236	52.58
Most Recent Primary Party	Democratic	48,653	52.1
	Republican	44,724	47.9
Median Age (Years)		44.00	-
Mean Household Income ($)		114,240	-

Table 1: **Officer Descriptive Statistics** Note: All parties other than Republican or Democratic are grouped together as 'Other' party. Most Common Primary Party percent is out of all officers who participated in at least two primary election. Most Recent Primary Party percent is out of all officers who participated in at least one primary election. For both Median Age and Mean Household Income the value presented is the median and mean, rather the the N.

set of candidate matches covers all of the agency's counties and all their adjacent counties.) We then attempt 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 in Enamorado, Fifield and Imai (2019), using the *fastlink* `R` package (Enamorado, Fifield and Imai, 2017)[6]. See Appendix Sections A.2 and A.10 for additional details on matching procedure and the results of extensive validation, respectively.

Data in the L2 voter file includes party identification, age, household income, and voter turnout history. We use these covariates to compare officers to civilians in their jurisdictions using both L2 and 2015–2019 five-year American Community Survey data.[7] We divide officers

[6]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 A11.

[7]See Appendix A.2 for details on jurisdiction geography and Census merges.

and civilians into three partisan categories based on L2's labels: Democrat, Republican, and an aggregate of numerous other party affiliations and individuals not appearing in the L2 data, which we label "other/unknown party." 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.[8] 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 (Frank Stephenson, 2011).

Nevertheless, we take extensive steps in Appendix A.10 to address 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 both major parties held closed presidential/congressional 2020 primary elections, where party identification data may be most accurate. Our core conclusions, e.g. that officers are more likely to be Republican and White, remain supported across nearly all of these robustness checks.[9]

To measure race, ethnicity and gender, we primarily rely on the 2019 Law Enforcement Officers Killed and Assaulted data (LEOKA) (Kaplan, 2021), which contains the gender breakdown for

[8]For example, Hersh and Goldenberg (2016) used a similar merging approach to obtain the partisan registration of physicians throughout the country. They 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.

[9]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 A.10.

officers in each reporting agency, and the 2016 Law Enforcement Management and Administrative Statistics (LEMAS, 2016), a survey of law enforcement agencies which contains racial composition data for a select number of agencies. These datasets contain demographic information on 100% and roughly 86% of the agencies in our study, respectively. For missing agencies, we rely on imputed values of race and ethnicity from the L2 data set. We similarly rely on L2 for measures of officers' household income and age. See Appendix A.3 for additional details on these measures.[10]

Officers' Political Affiliations in Local Context

We now compare the average rates of partisan affiliation of officers and civilians within their jurisdictions. We also characterize how well officers descriptively represent civilians on multiple additional dimensions, including race, ethnicity, gender, household income, age, and political participation as measured by general election turnout. Civilian attributes are measured using data from L2 and 2015–2019 5-year American Community Survey data, aggregating all tracts for which the agency has jurisdiction.[11]

Table 2 first displays aggregate results. The left estimates correspond to officers in our data, aggregating across our 98 jurisdictions. 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 A5. The next column corresponds to the hypothetical value for perfectly representative police agencies—for example, the proportion of Republican officers that could be expected if each officer was replaced with a representative draw from their respective jurisdiction, holding the size of each agency fixed.[12] Subsequent columns display officer-civilian

[10]See Tables A8 and A9 for robustness checks related to potential mismeasurement of race/ethnicity.

[11]See Appendix A.2 for details on matching tracts to jurisdictions.

[12]Specifically, this hypothetical value is computed as $\frac{1}{\sum_i \#\{\text{agency}_i\}} \sum_i \bar{x}_i \cdot \#\{\text{agency}_i\}$, where i indexes agencies, $\bar{x}_i$ refers to the average civilian in the agency's jurisdiction, and $\#\{\text{agency}_i\}$ is the number of officers employed by the agency.

differences and 95% confidence intervals.[13]

Results show police officers diverge from their jurisdictions on every attribute we measure. Turning first to partisan affiliation, we find officers are 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 than civilians (31% vs. 43%). Officers are also much more politically active than a representative group of civilians: 69% of officers voted in the 2020 general election (vs. 55% of civilians).

In terms of race and ethnicity, roughly 56% of officers in our data are White. To put this in context, note that if officers were representative of civilians in their jurisdictions, that share would fall to roughly 38%; correspondingly, the Black and Hispanic proportion would rise by about 5 and 7 percentage points (p.p.), respectively. By far the largest representation gap pertains to gender: roughly 83% of officers in our data are male, likely due 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 considerable heterogeneity across agencies. To explore this variation, Figures 4 and 3 plot average officer and civilian shares of Republican and White individuals, respectively, separately for each jurisdiction; the cross-jurisdiction means from Table 2 are plotted as vertical lines for reference. These results show agencies ranging from unrepresentative and partially representative to highly representative in terms of party identification and race/ethnicity. In other words, representativeness along racial lines does not always correspond

[13]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 also 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.

to representativeness along partisan lines.

Consider Rochester, NY: about 7% of its roughly 210,000 residents are Republican, in contrast to at least 55% of its police officers. Moreover, we find that 73% of Rochester Police Department officers are White, compared to 38% of civilians. On the other hand, we observe agencies like the L.A. County Sheriff's Department, which is highly representative in some racial categories (e.g. 9% Black officers vs. 8% Black residents), but highly unrepresentative politically (38% Republican officers vs. 15% 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. 24% civilians), 40% White officers (vs. 35% civilians), and 58% Black officers (vs. 57% civilians.)

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	56.02	37.82	18.15*** [17.95, 18.35]	215,740
	Hispanic	20.90	28.10	-7.16*** [-7.32, -7.00]	215,740
	Black	16.35	21.21	-4.86*** [-5.01, -4.71]	215,740
	Other/Unknown Race	1.84	3.42	-1.57*** [-1.63, -1.52]	215,740
	Asian	4.89	9.45	-4.55*** [-4.64, -4.46]	215,740
Party (Voting Age Pop.)	Republican	32.44	14.09	18.38*** [18.18, 18.57]	217,850
	Democratic	31.29	43.41	-12.13*** [-12.32, -11.93]	217,850
	Other/Unknown Party	36.27	42.75	-6.50*** [-6.70, -6.30]	217,850
General Turnout, 2020	Voting Age Pop.	69.36	54.59	14.78*** [14.59, 14.98]	215,541
Gender	Male	83.22	48.69	34.52*** [34.36, 34.67]	217,850
	Female	16.78	51.31	-34.52*** [-34.67, -34.36]	217,850
Median Age (Years)	-	44.00	36.85	8.07*** [8.01, 8.14]	186,048
Mean Household Income ($)	-	114239.99	92266.90	22001.55*** [21725.37, 22277.73]	185,459

Table 2: **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. Stars denote $p < .001$; brackets contain 95% confidence intervals.

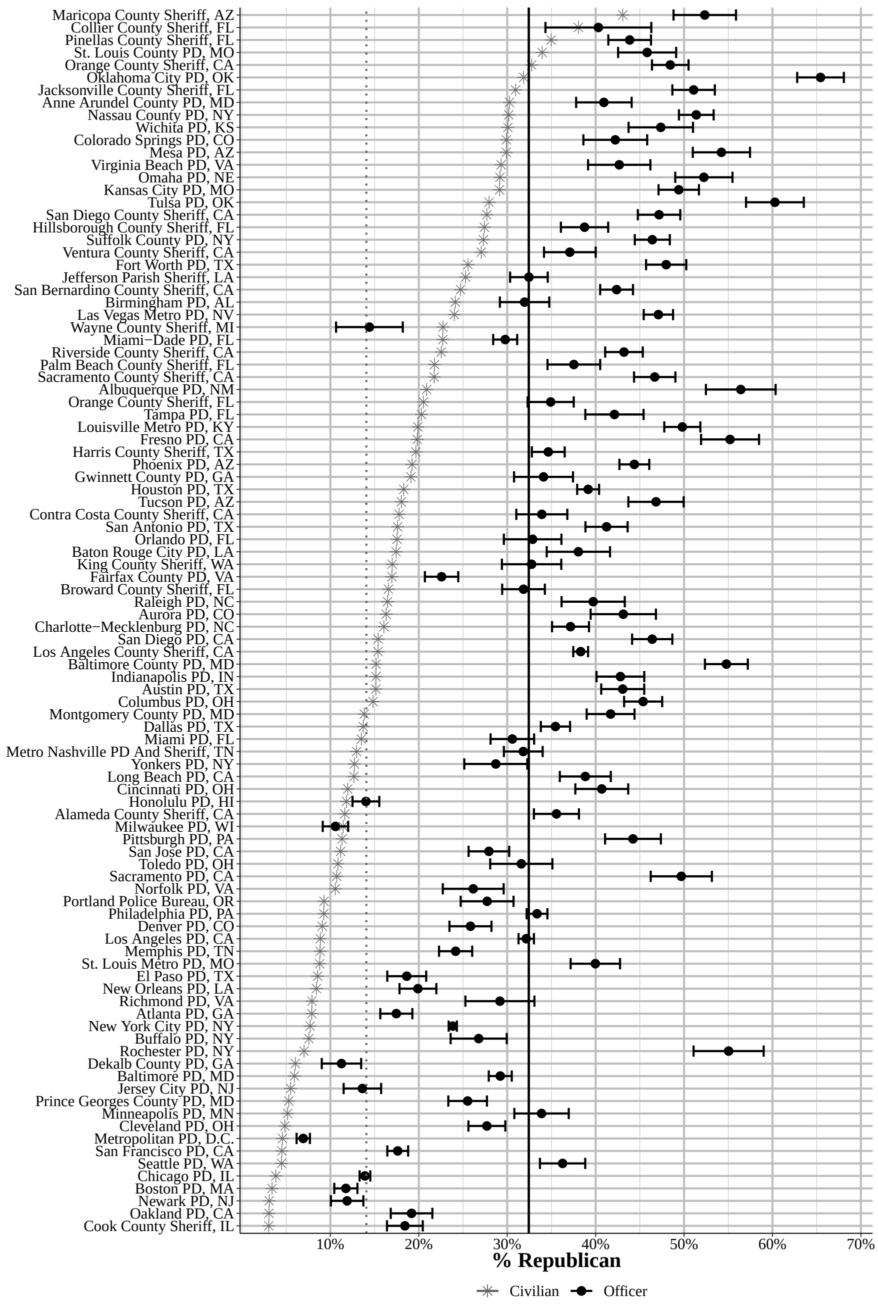

Figure 3: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled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

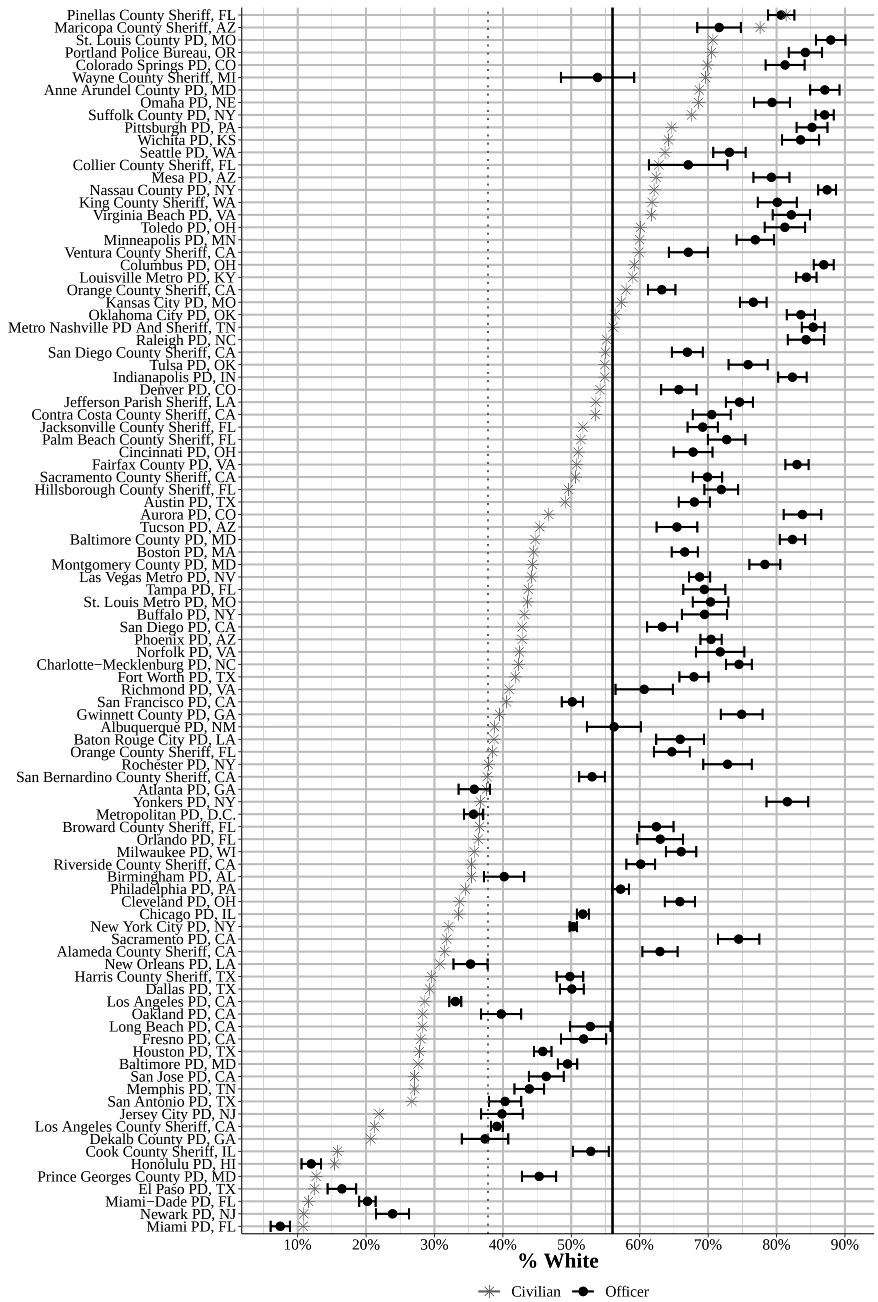

Figure 4: **Average Shares of White Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEMAS (2016) and L2 with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions.

Officers' Places 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, 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.[14]

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 Appendix Table A6.[15] 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 (+\$12,927) 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.

The Chicago Police Department: A Micro-Level Case Study

In this section, we use micro-level data on officer shift assignments and enforcement actions to incorporate officer behavior into our analysis. First, we conduct a disaggregated analysis of representation across districts of the Chicago Police Department (CPD), to see whether officers

[14] 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.

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

are representative of the civilians with whom they likely interact. Second, we directly assess whether officers of different racial, ethnic and political backgrounds behave differently when facing common circumstances.

Representation in Police-Civilian Interactions

We associated Chicago officers with the district in which they most frequently worked, as indicated by monthly unit rosters. We then used our CPD data, along with the Census and L2 data, to characterize officers and civilians in those districts. Figure 5 shows a striking mismatch. Overall, 15% of CPD officers are Republican. However, even in the most right-leaning district, civilians are no more than 9% Republican. If each officer was replaced with a representative draw from their local district population, this group would be 4% Republican. And as Figure 5 shows, Republican partisans are overrepresented among police officers in every district in Chicago. In Appendix Table A7, we present additional results showing Democrats are underrepresented in almost every district, indicating these results are not simply driven by increased political engagement or lower rates of nonpartisanship among officers.[16]

Figure 6 shows the share of officers assigned to each district who are White according to CPD personnel records, as well as the share of civilians who are White in those same districts based on Census data. The solid vertical line shows that, aggregating over all CPD districts, 52% of officers are White according to CPD personnel records. If officers perfectly represented civilians in their districts, however, that figure would be 34% (dashed vertical line). Similar to our analysis of partisan affiliation, we find the vast majority of CPD districts are policed by officers who skew more White than the local population, often by a substantial margin. Residents of Chicago's "Austin" District, located on the west side of the city, are 87% Black and 9% Hispanic. Yet about 56% of officers assigned to this area are White. In contrast, the "Shakespeare" district—

[16]Note that for comparability with other agency-level estimates, we rely on measures of race and ethnicity for Chicago from LEMAS (2016) in Table 2. In Chicago-specific analyses, we use individual-level race/ethnicity data on officers from personnel files.

located only slightly to the northeast—is a mixed-race area in which the estimated share of officers identifying as White diverges from local residents by only a few percentage points.

Deploying Officers of Differing Political Orientations

In this section, we employ a research design developed by Ba et al. (2021), which identifies the effect of deploying an officer of one social identity versus another, to otherwise similar circumstances. From a theoretical perspective, this analysis probes a key assumption underlying the claimed benefits of representative bureaucracy—i.e., whether officers from different social identities treat civilians differently when facing common situations.

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). Table 3 describes our sample for this analysis. As the table shows, our data include observations on the behavior of almost 12,000 officers across more than 6 million shifts.[17]

	White Officers	Black Officers	Hispanic Officers	Male Officers	Female Officers	Republican Officers	Democrat Officers	Other Party Officers
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	5,762	2,681	3,218	8,807	2,856	1,791	6,888	2,985

Table 3: **Overview of CPD Data.** Counts, 2012–2019

Our analyses compare officers working in the same month-year (e.g. January 2012), day of week, 8-hour shift, and beat (a specific task or assignment, often a small patrol area about one square mile in area)—units dubbed "MDSBs" for short. The target quantity in this analysis is the average within-MDSB difference in enforcement activity between groups of officers. We stress

[17]We estimate that party affiliations for CPD officers are approximately as follows. White officers: 53% Democrat, 23% Republican, 25% Other Party; Black officers: 84% Democrat, 5% Republican, 11% Other Party; Hispanic officers: 50% Democrat, 12% Republican, 39% Other Party.

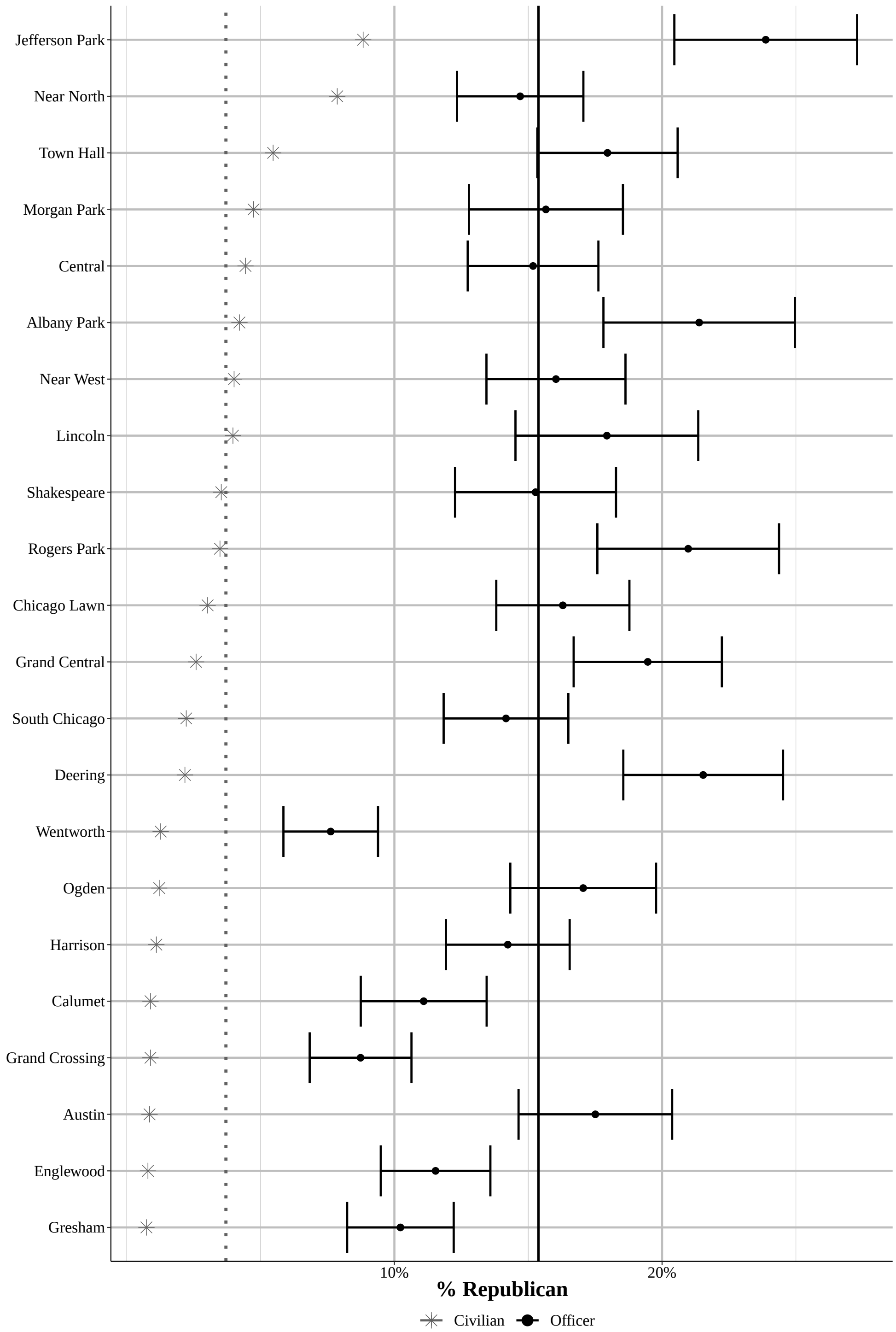

Figure 5: **Average Shares of Republican Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

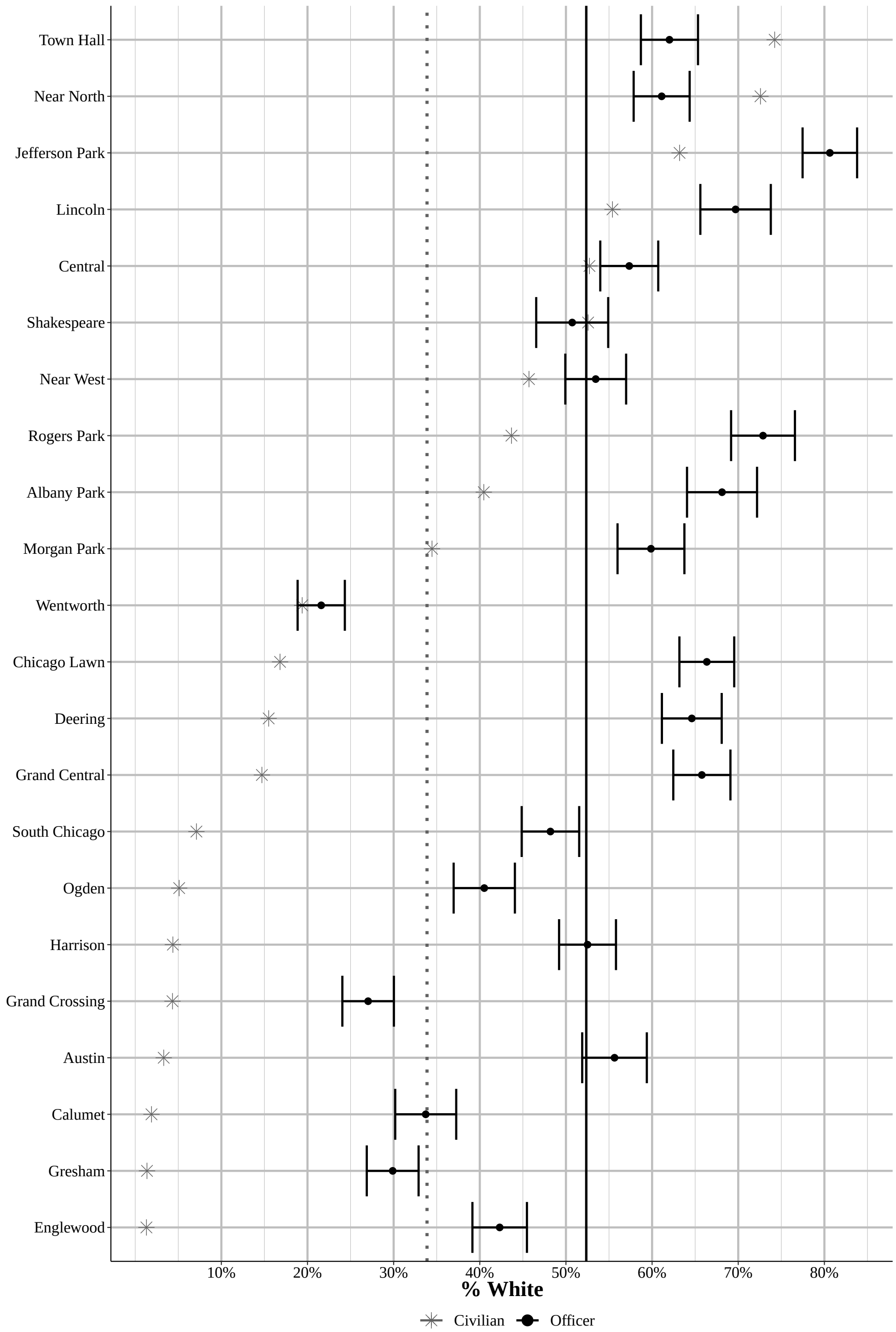

Figure 6: **Average Shares of White Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

that the treatment—the deployment of an officer of one group, versus another—is inherently bundled. Officers of a particular partisan identity, for example, differ in many ways besides their 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 is precisely the policy-relevant quantity of interest here. 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.

Within each MDSB, we compute differences in discretionary enforcement between officer groups, then aggregate these to an overall deployment disparity estimate by taking the weighted average according to the number of patrol slots within each MDSB (see Appendix A.4 for additional details on estimation). The key assumption underlying this analysis is that, prior to initial 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 (see Appendix A.11).

Though our central focus is on political affiliation, we simultaneously examine the deployment effects of race/ethnicity to put the magnitude of any partisan effects in context. We focus on two scenarios in which comparisons of officers of different racial/ethnic and political affiliations can be made. First, we present results based on the subset of MDSBs in which Democratic, Republican, Black, and White, Democratic officers appear at least once.[18] This ensures that cross-party and cross-race comparisons are based on the same sets of times and

[18]This can occur with as few as two officers in an MDSB, e.g. if one is a Black Democrat and another is a White Republican.

places. A second set of analyses subsets to MDSBs with Democratic, Republican, Hispanic, and White officers. We caution these two sets of times and places differ, meaning that results should not be directly compared across sets of analyses. See Appendix A.8 for additoinal information on these feasibility constraints.

Figures 7–8 display the results of these behavioral analyses (all p-values adjusted for multiple testing Benjamini and Hochberg, 1995). Turning first to Figure 7, we find Democratic officers detain 4.5 fewer civilians, make 0.89 fewer arrests and engage in 0.07 fewer uses of force per 100 shifts, compared to Republican officers faced with similar circumstances (all $p_{\text{adj}} \leq 0.007$). To put their magnitude in perspective, these effects represent reductions equal to 14%, 12% and 24% of the citywide average volume of stops, arrests and uses of force among Republican officers per 100 shifts citywide, respectively (see Appendix Tables A2–A4). While substantial, the Democrat-Republican officer gap in discretionary policing is smaller than the corresponding Black-White officer gap for stops (by a factor of roughly 1.8x; $p_{\text{diff}} < 0.001$).[19] However, race- and party-based deployment effects are indistinguishable in size for arrests and uses of force. When examining all combinations of race and party, we see a similar dynamic: Black Democratic, Black Republican, and White Democratic officers all make fewer stops than White Republican officers facing similar circumstances.

We next turn to scenarios where Democratic-Republican officer differences in enforcement can be contrasted with Hispanic-White differences, estimated in MDSBs where at least one individual from each group was present. In these circumstances—which we emphasize can differ from those above—Democratic officers are not significantly different from their Republican counterparts in terms of stops, arrests and uses of force. However, as Figure 8 shows, deploying a Hispanic officer instead of a White officer yields reductions of 1.8 stops of, 0.44 arrests of and 0.05 uses of force against civilians per 100 shifts, respectively (all $p_{\text{adj}} < 0.046$).

[19]However, we caution that this difference in disparities may be due in part to differential measurement error, as we obtain direct measures of race/ethnicity from Chicago personnel records, but rely on estimated party identification from the L2 voter file.

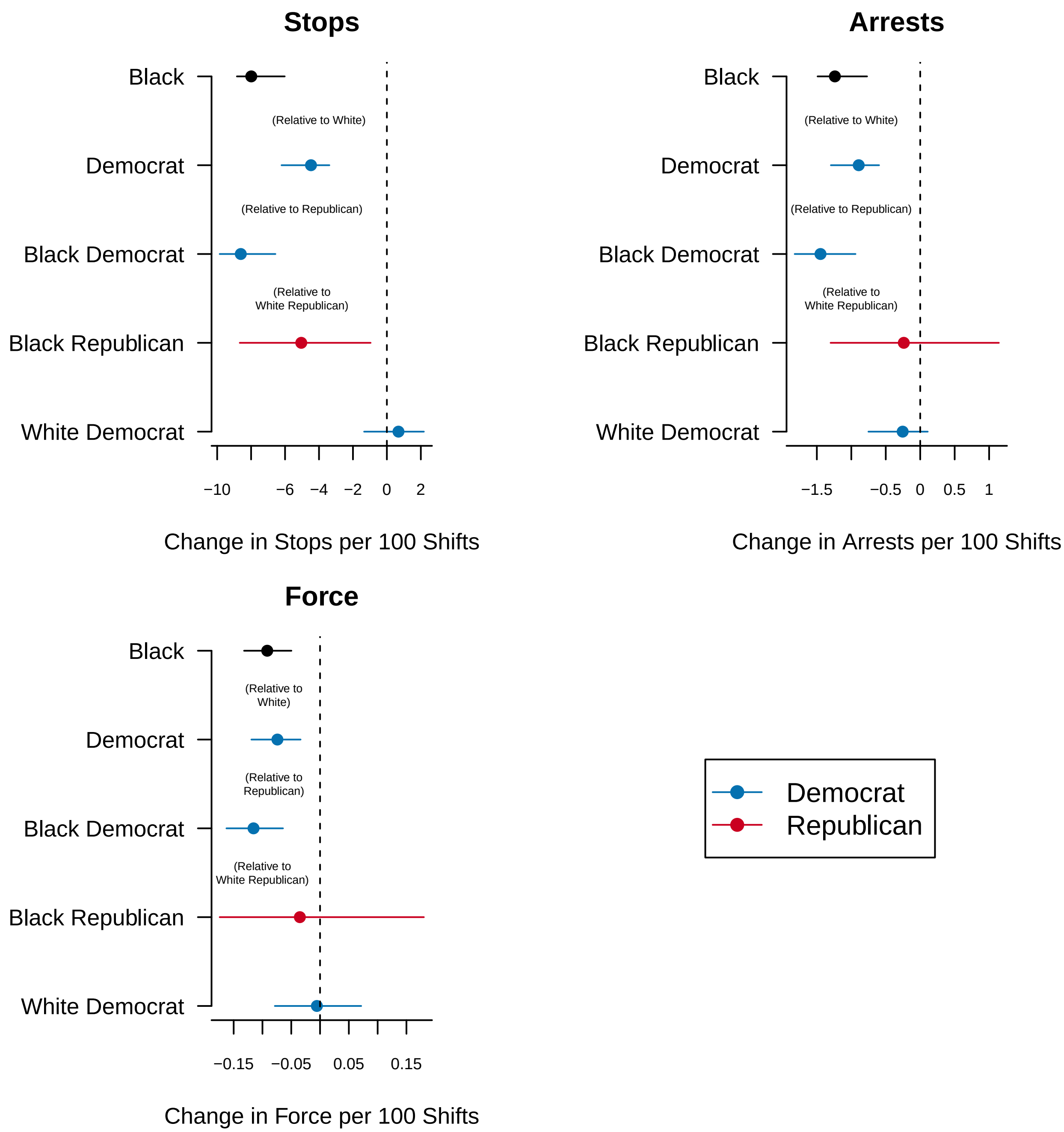

Figure 7: **Race and Party Deployment Effects, Black vs. White Officers**. The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to otherwise common circumstances. Estimates computed using only places and times where at least one Black, White, Republican and Democratic officer was deployed.

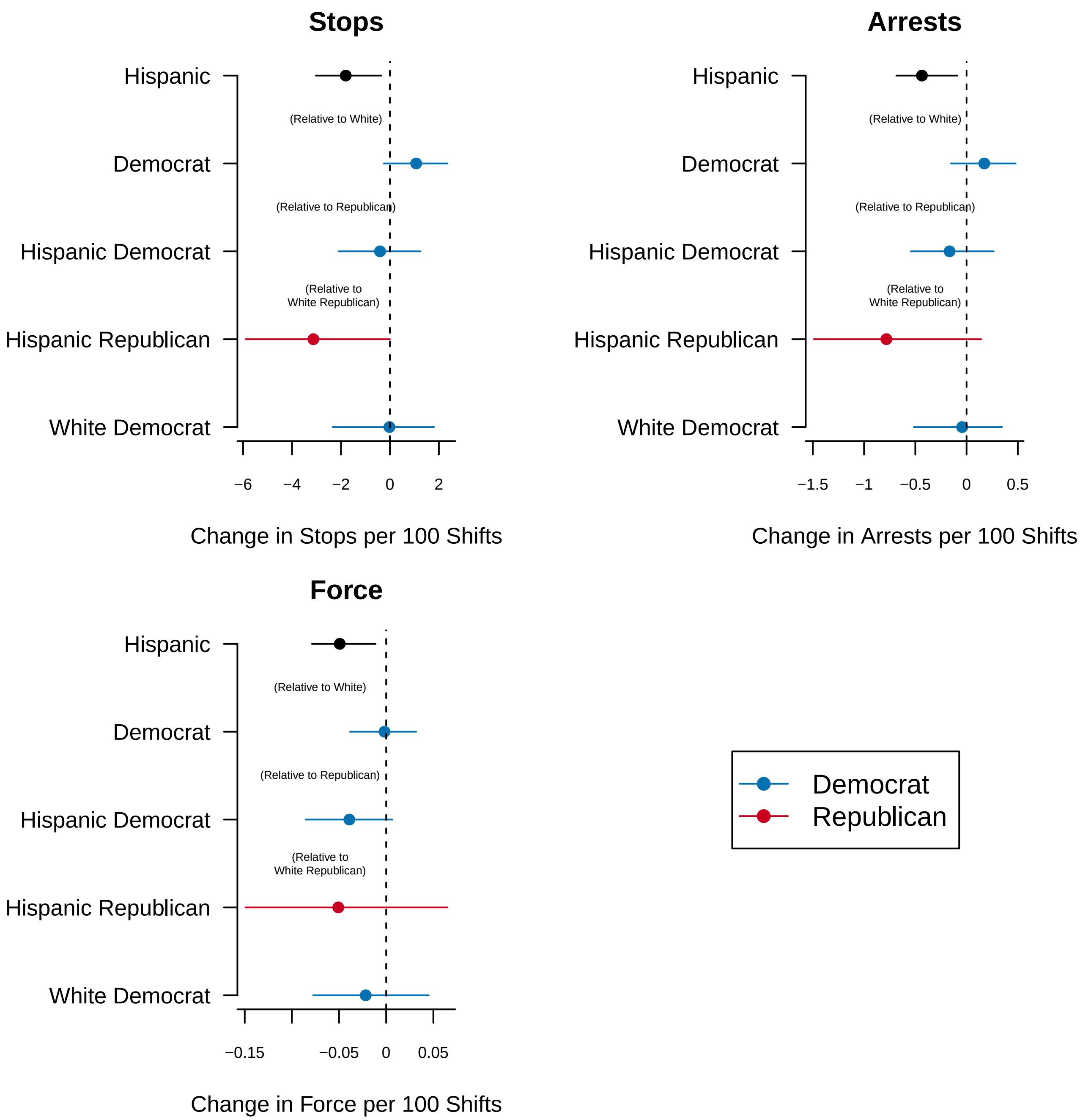

Figure 8: **Race and Party Deployment Effects, Hispanic vs. White Officers**. Average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to common circumstances. Estimates computed using only places and times where at least one Hispanic, White, Republican and Democratic officer was deployed.

To investigate how different groups of civilians are impacted by these deployments, Figures A1–A2 present results by civilian race/ethnicity. In MDSBs where Democratic, Republica, Black and White officers all worked at least one shift, both party- and race-based deployments yield significant reductions, which are concentrated in encounters with Black civilians. Specifically, deploying a Democratic officer vs. a Republican officer yields reductions of 3.32 stops of, 0.59 arrests of and 0.05 uses of force against Black civilians per 100 shifts, respectively (all $p_{\text{adj}} < 0.02$; $p_{\text{diff}} < 0.001$ for stops). Deploying a Black officer vs. a White officer yields reductions of 6.26 stops of, 0.86 arrests of and 0.07 uses of force against Black civilians per 100 shifts. As in the previous analysis, party- and race-based deployment effects are indistinguishable for arrests and use of force, though again, both effects are most pronounced in interactions with Black civilians. Deploying a Democrat rather than a Republican reduces Hispanic-civilian stops by 0.44 and arrests by 0.22 per 100 shifts; we also see 0.49 fewer stops of White civilians (all $p_{\text{adj}} \leq 0.008$). When deploying Black instead of White officers, we also see significant reductions in stops and arrests of Hispanic and White civilians (1.13 and 0.27 fewer stops and arrests of Hispanic civilians per 100 shifts when deploying Black officers; 0.65 and 0.11 fewer stops and arrests of White civilians per 100 shifts; all $p_{\text{adj}} < 0.001$ except White arrests, which is $p_{\text{adj}} = 0.046$).

Consistent with the above results, we see that the effect of deploying Hispanic officers is similarly concentrated among Black civilians, with reductions of 1.86 stops, 0.34 arrests and 0.04 uses of force in this group per 100 shifts, respectively (all $p_{\text{adj}} \leq 0.022$). We also see a reduction in use of force against White civilians (0.01 per 100 shifts; $p_{\text{adj}} = 0.039$). For all other outcomes involving Hispanic officers, we see no detectable differences in enforcement, including toward Hispanic civilians.

Discussion and Conclusion

Policing in the United States is now a consistent focal point of national political debate, with Democrats and Republicans strongly disagreeing on how to improve the treatment of police by civilians, and on whether any systemic problems with police behavior exist at all. These sharp divisions necessitate a close examination of the partisan affiliations of a particular group of Americans: police officers themselves. If officers of different political persuasions hold dramatically different views of how policing should be done—a strong possibility given national political trends—then it is possible officers display systematically different behaviors on the job in ways that translate to severe consequences in the lives of civilians. However, assessing the distribution and consequences of officer partisanship has previously been precluded by severe data limitations.

In this paper, we draw on original data characterizing police officers from 98 of the 100 largest local law enforcement agencies in the U.S., as well as micro-level behavioral data in Chicago, to assess the prevalence and consequences of political diversity in policing. Improving on prior work in this area, which tends to focus on just one or two officer traits, we present a multidimensional analysis that allows us to characterize the degree to which officers share common political, demographic, and experiential attributes with the civilians in their jurisdictions.

Our results confirm civilians differ systematically from police in their communities in every way we can measure. Officers are much more likely to be Republican than their civilian counterparts. Police are also far more politically active than civilians, turning out to vote at extremely high rates. We also find that nationwide patterns showing the overrepresentation of White police officers are also present within jurisdictions. But just as importantly, we find wide heterogeneity in these results: while many jurisdictions are out of step with local civilians on numerous attributes, some are highly representative, a pattern which prior coarse analyses has masked and which may offer a clue as to where abusive policing practices are most likely to manifest. In addition, representativeness along racial lines does not always correspond to representativeness along partisan lines.

Our micro-level analysis in also Chicago shows the importance of these traits for police behavior, using detailed data on officer shift assignments and enforcement activities to compare officers facing common circumstances. We first show deploying Democratic (vs. Republican) officers to otherwise similar circumstances corresponds to large reductions in enforcement activity, with effects on arrests and uses of force statistically indistinguishable from the deployment effects we observe when examining officer race (Black v. White). When deploying Hispanic officers (relative to White), we similarly see reduced enforcement—both overall and toward Black civilians—but find no differences in how Hispanic officers treat Hispanic civilians. These results complicate conventional narratives surrounding diversity initiatives, illustrating how officer race and ethnicity alone paint an incomplete portrait of enforcement behavior toward marginalized groups.

In addition to adding valuable empirical evidence to the study of representative bureaucracy, our paper also illustrates the feasibility of large-scale data collection efforts on the personal attributes of bureaucrats via open records requests. Unlike other professions such as law and medicine, which provide public-facing lists of accredited members, law enforcement agencies are often more guarded and occasionally even refuse to comply with their legal obligation to disclose the identities of public employees. Our efforts demonstrate the feasibility of obtaining such information in the vast majority of cases, at least for large agencies.

Using these records, our study offers the most comprehensive assessment of officers' political affiliations to date, and provides a template for studying diversity in policing in a multidimensional framework. But important issues remain. For one, due to the difficulty of obtaining shift assignment data, our analysis of officer behavior is limited to a single city. Much more research is needed before we can generalize broadly about how officers from different groups enforce the law. In addition, more work is needed on the root causes of representational gaps between civilian populations and the police who patrol them. Disentangling the complex processes of recruitment strategy and self-selection which dictate the staffing of public agencies remains an important frontier in the study of representative bureaucracy.

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Online Appendix

Table of Contents

A Supplementary Information and Additional Results

A.1 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 comes from L2. This 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]

A.2 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, sinceofficers 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

[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

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) will be assigned every tract in that Place. An agency whose jurisdiction is an entire county, excluding certain Places, will be 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. We note that approximately 37.6% 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, 30.5% had two matches, 13.7% had three matches, 8.4% had four matches, 5.7% had five matches, 4.3% had six matches, 3.4% had seven matches, 2.7% had eight matches, 2.3% had nine matches, and the remaining 29% had 10 or more matches.

See Appendix sections A.9 and A.10for a series of robustness checks gauging the impact of potential mismatches.

A.3 Data on Officer Race/Ethnicity and Gender

As explained in the main text, we rely on 2019 LEOKA data (Kaplan, 2021) for gender data on agencies, due to its near-complete coverage. Two exceptions are the Columbus Police Department, in Ohio, and the Jefferson Parish Sheriff's Office, in Louisiana, which do not report officer gender in 2019; here we use 2018 LEOKA data which did include officer gender. In addition, because LEOKA data does not contain racial/ethnic measures, we obtain those from the 2016 LEMAS data for 86% of agencies, and use L2 estimates of officers' racial and ethnic identities for the remaining agencies.

A.4 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 with MDSB fixed effects. We report 95% confidence intervals based on officer-block bootstrapping, ensuring 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. In each block bootstrap draw, we recompute the feasible set of MDSBs (i.e. the set of MDSBs in which officers of each group being compared are present), ensuring estimates are always based on within-MDSB comparisons.

A.5 Descriptive Statistics

Variable	Values	Officers in Sample	Police in U.S.	U.S.
Race	White	56.02	71.5	60.7
	Hispanic	20.9	12.5	18.0
	Black	16.35	11.4	12.3
	Other/Unknown	1.84	4.7	3.6
	Asian	4.89	–	5.5
Party (Registered Voters)	Republican	37.61	–	31.54
	Democratic	36.27	–	34.72
	Other Party	26.13	–	33.74
Gender	Male	83.22	87.7	49.2
	Female	16.78	12.3	50.8
Median Age (Years)	–	44	–	38.1
Mean Household Income ($)	–	114,239.99	–	62,843
N		218,477	701,000	330mm

Table A1: **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 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 ($114,240 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.

Officer Group:	All	White	Black	Hisp.	Male	Female	Rep.	Dem.	Other Party
Black Civ.	18.65	19.43	18.31	17.53	19.23	16.56	18.45	18.47	19.30
White Civ.	3.68	4.65	1.80	3.60	3.74	3.49	4.91	3.50	3.29
Hispanic Civ.	5.50	6.23	1.39	7.86	5.83	4.30	7.04	4.96	5.82
Total Civ.	29.02	31.71	22.19	30.23	29.99	25.51	32.09	28.01	29.49

Table A2: **Stops per 100 shifts, by officer and civilian group.**

Officer Group:	All	White	Black	Hisp.	Male	Female	Rep.	Dem.	Other Party
Black Civ.	4.70	4.65	4.54	4.96	4.92	3.92	4.46	4.44	5.58
White Civ.	0.72	0.88	0.30	0.79	0.74	0.63	0.88	0.64	0.81
Hispanic Civ.	1.39	1.61	0.39	1.90	1.49	1.04	1.78	1.17	1.71
Total Civ.	6.88	7.22	5.27	7.72	7.23	5.65	7.20	6.31	8.17

Table A3: **Arrests per 100 shifts, by officer and civilian group.**

Officer Group:	All	White	Black	Hisp.	Male	Female	Rep.	Dem.	Other Party
Black Civ.	0.22	0.23	0.19	0.21	0.24	0.13	0.21	0.20	0.25
White Civ.	0.02	0.03	0.01	0.02	0.03	0.02	0.03	0.02	0.02
Hispanic Civ.	0.04	0.05	0.01	0.05	0.04	0.02	0.05	0.03	0.05
Total Civ.	0.29	0.32	0.22	0.30	0.32	0.19	0.31	0.27	0.33

Table A4: **Uses of force per 100 shifts, by officer and civilian group.**

A.6 Within-Jurisdiction Comparisons

Agency		White %	Hispanic %	Black %	Other/Unknown Race %	Asian %	Democratic %	Republican %	Other Party %	General Turnout, 2020 %	Male %	Female %	Median Age	Mean Household Income ($)
Alameda County Sheriff, CA	Officers	62.96*	13.62*	10.38*	2.65*	10.38*	27.91*	35.57*	25.69*	72.90*	86.82*	13.18*	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	56.25*	38.98*	1.97	1.81*	0.99*	19.90*	56.41*	17.88*	81.91	84.70*	15.30*	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	87.06*	2.23*	9.44*	0.42*	0.85*	21.74*	40.93*	19.48*	62.25*	86.96*	13.04*	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	35.81	4.45	58.73*	0.24*	0.77*	52.43*	17.46*	16.35*	63.36	82.78*	17.22*	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	83.79*	7.81*	4.20*	2.75*	1.45*	8.54*	43.13*	39.80	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	67.98*	19.77*	9.79*	0.25*	2.20*	31.14*	43.06*	15.69*	72.82*	89.70*	10.30*	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	82.33*	1.79*	13.47*	0.49*	1.91*	21.87*	54.79*	18.73	76.90*	83.26*	16.74*	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	49.45*	8.64*	40.02*	0.19*	1.70*	36.04*	29.21*	20.56*	60.77	84.11*	15.89*	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	65.91*	0.99*	32.11*	0.00*	0.99*	34.65*	38.05*	22.71*	81.90*	90.81*	9.19*	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	40.19*	1.68*	58.04	0.00*	0.09*	62.15*	31.96*	1.95*	74.86*	85.89*	14.11*	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	66.58*	8.84*	22.39	0.00*	2.19*	26.72*	11.75*	58.76*	76.54*	87.01*	12.99*	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	62.43*	21.44*	14.25*	0.49*	1.40*	28.42*	31.84*	30.74	69.41*	87.43*	12.57*	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	69.48*	7.63*	22.22*	0.40*	0.27*	44.44*	26.77*	23.56	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	74.51*	4.52*	17.56*	1.12*	2.29*	16.44*	37.16*	35.14	71.89*	85.26*	14.74*	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	51.67*	22.62*	22.32*	0.33*	3.06*	55.22*	13.91*	27.69	76.68*	76.91*	23.09*	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	67.79*	0.77*	29.22*	1.45*	0.77*	22.85*	40.69*	29.06	73.67*	77.34*	22.66*	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	65.88*	9.44*	23.33*	1.30*	0.06*	32.11*	27.70*	34.97*	73.32*	84.28*	15.72*	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	67.09	17.09*	9.49	6.33*	0.00*	9.69*	40.31*	18.35*	51.94*	86.82*	13.18*	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

Agency		White %	Hispanic %	Black %	Other/Unknown Race %	Asian %	Democratic %	Republican %	Other Party %	General Turnout, 2020 %	Male %	Female %	Median Age	Mean House-hold Income ($)
Colorado Springs PD, CO	Officers	81.25*	10.42*	5.00	0.42*	2.92	8.89*	42.22*	37.52*	75.00*	83.06*	16.94*	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	86.90*	1.07*	10.37*	0.15*	1.51*	17.04*	45.37*	31.41*	81.89*	89.09*	10.91*	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	70.53*	14.69*	7.34*	0.48*	6.96*	28.31*	33.91*	26.65	74.20*	85.12*	14.88*	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	52.86*	18.20*	18.05*	9.85*	1.05*	52.02*	18.43*	25.26*	71.30*	73.14*	26.86*	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	50.08*	20.71*	25.99*	0.96*	2.27*	33.31*	35.45*	12.35	63.83*	81.19*	18.81*	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	37.39*	3.36*	57.05*	0.78*	1.42*	55.76*	11.25*	18.55*	56.92*	83.83*	16.17*	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	65.72*	20.94*	9.74	1.00*	2.61*	21.47*	25.84*	39.21	70.48*	86.04*	13.96*	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	16.47*	79.45*	2.41	0.58*	1.08	70.80*	18.64*	4.44	64.23*	86.11*	13.89*	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	82.99*	5.09*	7.53*	0.00*	4.40*	31.53*	22.58*	22.59*	60.20*	84.21*	15.79*	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	67.92*	18.22*	10.78*	1.29*	1.78*	31.05*	47.98*	14.92*	73.15*	87.12*	12.88*	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	51.81*	35.18*	5.66	0.68*	6.67*	18.55*	55.20*	20.20*	77.15*	88.57*	11.43*	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	74.90*	3.73*	19.31*	0.00*	2.06*	21.49*	34.11*	40.33*	69.88	92.02*	7.98*	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	49.80*	20.95*	26.63*	0.08*	2.54*	43.02*	34.64*	12.87*	68.61	83.21*	16.79*	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	71.92*	14.51*	9.33*	3.06	1.18*	11.84*	38.75*	27.36*	60.00*	83.53*	16.47*	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	11.99*	1.19*	1.34*	33.23*	52.25	22.44*	14.02*	56.58*	68.60*	87.96*	12.04*	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	45.84*	26.24*	21.34	0.15*	6.43*	41.25*	39.15*	14.44	71.14*	82.99*	17.01*	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*	26.17*	67.18*	86.07*	13.93*	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
Jacksonville County Sheriff, FL	Officers	69.21*	7.77*	15.98*	6.16*	0.88*	15.32*	51.08*	18.99*	70.37*	84.13*	15.87*	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	74.58*	3.01*	20.04*	1.18*	1.18*	30.74*	32.46	26.64*	65.02*	71.14*	28.86*	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	39.86*	31.41*	11.13*	13.22*	4.37*	40.56*	13.62*	35.88	56.56*	82.31*	17.69*	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	76.61*	4.79*	11.70*	5.98*	0.92*	23.07*	49.40*	21.51*	78.56*	85.09*	14.91*	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	80.11*	5.82*	0.85*	10.09*	3.12*	35.69*	32.76*	26.99*	83.09	93.48*	6.52*	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	68.76*	13.02*	9.80*	2.99*	5.43*	14.97*	47.10*	28.52*	73.30*	89.83*	10.17*	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	52.78*	32.18*	5.10*	0.55*	9.39*	27.26*	38.83*	26.62*	75.48	89.70*	10.30*	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	39.13*	44.61*	8.99*	0.26*	7.02*	27.29*	38.31*	25.21*	73.77*	82.01*	17.99*	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	33.05*	46.01*	10.45*	0.61*	9.88*	34.34*	32.15*	28.45*	75.26*	81.64*	18.36*	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	84.37*	1.91*	11.56*	0.30*	1.86*	30.06*	49.81*	13.47*	8.27*	85.58*	14.42*	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	71.61*	17.17*	1.11*	9.28*	0.83*	15.62*	52.34*	27.70	79.69*	94.79*	5.21*	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	43.86*	1.50*	53.79*	0.80*	0.05*	32.35*	24.16*	37.77*	71.54*	83.08*	16.92*	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	79.25*	13.72*	3.84	0.77*	2.41	9.33*	54.23*	23.82*	70.47*	87.71*	12.29*	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	85.36*	1.61*	11.24*	1.50*	0.29*	14.12*	31.82*	43.48*	69.45*	90.14*	9.86*	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	7.45*	66.38*	23.96*	1.86*	0.34*	28.79*	30.58*	32.43	68.53*	78.50*	21.50*	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	20.20*	57.97*	20.52*	1.28	0.02*	24.11*	29.77	27.16*	60.57*	75.57*	24.43*	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

Agency		White %	Hispanic %	Black %	Other/Unknown Race %	Asian %	Democratic %	Republican %	Other Party %	General Turnout, 2020 %	Male %	Female %	Median Age	Mean Household Income ($)
Milwaukee PD, WI	Officers	66.06*	12.73*	17.34*	1.99*	1.88*	14.84*	10.57*	20.88*	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	76.90*	4.40*	8.58*	4.51	5.61	20.68*	33.88*	35.92*	79.43*	85.92*	14.08*	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	78.29*	6.82*	11.29*	0.08*	3.53*	24.61*	41.69*	22.24	73.35*	81.74*	18.26*	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	87.39*	6.74*	4.58*	0.32*	0.96*	17.66*	51.38*	27.91*	83.34*	89.56*	10.44*	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	35.27*	5.23	52.37*	6.14*	1.00*	40.58*	19.90*	29.13*	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	50.29*	26.86*	15.15*	0.82*	6.88*	34.73*	23.84*	28.74*	58.44	81.60*	18.40*	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	23.87*	41.54*	34.34*	0.00*	0.25*	39.36*	11.89*	38.31	55.36*	77.89*	22.11*	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	71.77*	6.06	18.18*	0.16*	3.83	31.42*	26.16*	27.80*	63.96*	89.00*	11.00*	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 PD, CA	Officers	39.76*	23.46*	18.34*	3.54*	14.90	30.45*	19.18*	29.96*	58.94*	85.94*	14.06*	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	83.56*	5.77*	6.17*	3.53*	0.96*	13.39*	65.44*	13.01*	71.77	88.93*	11.07*	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	79.34*	9.62*	8.52*	0.77*	1.75*	12.90*	52.24*	24.56	76.61	83.28*	16.72*	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	63.22*	23.29*	3.38*	2.63*	7.48*	20.21*	48.44*	25.47*	79.07*	87.27*	12.73*	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	64.70*	18.43*	13.69*	1.56*	1.63*	15.09*	34.91*	30.26	57.85*	84.91*	15.09*	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	63.00*	17.75*	16.50*	0.38*	2.38*	17.50*	32.88*	32.27	58.75*	84.00*	16.00*	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	72.71*	14.58*	11.13*	0.30*	1.28*	18.33*	37.54*	27.49	67.09*	87.00*	13.00*	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	57.21*	8.37*	32.52*	0.10*	1.80*	47.54*	33.37*	14.66*	78.52*	78.45*	21.55*	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	70.42*	18.10*	0.85*	9.29*	1.33*	17.38*	44.38*	29.85*	74.17*	85.69*	14.31*	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	80.69	5.47*	12.73*	0.18*	0.92*	15.93*	43.85*	27.30*	70.05*	85.85*	14.15*	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	85.19*	1.16*	12.92*	0.11*	0.63*	40.55*	44.22*	11.32*	86.13*	85.19*	14.81*	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	84.22*	3.83*	3.83*	1.86*	6.26*	24.13*	27.73*	37.66	70.65*	83.76*	16.24*	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	45.30*	8.81*	42.43*	0.20*	3.26	44.13*	25.52*	19.83*	66.25*	85.57*	14.43*	40.00*	138,893.52*
	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	84.31*	3.61*	10.42*	0.83*	0.83*	15.83*	39.72*	41.35*	85.14	84.86*	15.14*	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	60.65*	4.22*	33.01*	0.19*	1.92	43.76*	29.17*	13.64	72.17	82.34*	17.66*	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	60.15*	31.73*	3.60*	1.97*	2.54*	22.85*	43.21*	29.11	77.39*	89.53*	10.47*	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	72.84*	9.69*	3.81*	12.63*	1.04*	14.71*	55.04*	26.99	77.69*	86.78*	13.22*	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	69.91*	14.07*	4.98*	1.43*	9.61*	21.80*	46.68*	24.72*	82.04*	83.75*	16.25*	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	74.47*	10.83*	4.23*	1.62*	8.84*	16.31*	49.69*	27.20	81.20	83.94*	16.06*	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	70.35*	2.54*	16.32*	9.88*	0.91*	40.05*	39.97*	14.32*	75.53*	83.57*	16.43*	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	40.32*	52.90*	4.52*	1.22*	1.04*	40.81*	41.23*	11.64	73.85*	89.55*	10.45*	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	53.03*	33.10*	3.78*	8.16*	1.93*	27.37*	42.37*	25.10*	74.87*	85.51*	14.49*	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	66.97*	21.12*	4.45	0.78*	6.68	19.68*	47.17*	26.52*	79.54*	81.53*	18.47*	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	63.29*	21.28*	6.28	0.65*	8.50*	20.90*	46.40*	28.85*	84.08	83.32*	16.68*	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	50.14*	16.25	9.43*	1.89*	22.29*	27.82*	17.62*	33.67*	59.22*	85.12*	14.88*	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

Agency		White %	Hispanic %	Black %	Other/Unknown Race %	Asian %	Democratic %	Republican %	Other Party %	General Turnout, 2020 %	Male %	Female %	Median Age	Mean Household Income ($)
San Jose PD, CA	Officers	46.33*	28.47*	1.95*	10.53*	12.71*	32.63*	27.93*	30.66	74.25*	88.69*	11.31*	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	73.12*	4.87*	8.57	5.91	7.53*	29.76*	36.26*	22.40*	78.58*	84.56*	15.44*	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	87.92*	1.47	9.48*	0.79*	0.34*	31.49*	45.82*	18.84*	77.77	85.67*	14.33*	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	87.03*	8.78*	2.54*	0.49*	1.15*	15.76*	46.41*	36.56	85.68*	88.31*	11.69*	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	69.44*	15.28*	13.31*	0.35*	1.62*	13.66*	42.13*	26.52	67.01*	82.99*	17.01*	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	81.22*	5.81*	11.92*	0.00*	1.04	23.55*	31.59*	33.93*	69.45*	83.16*	16.84*	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	65.44*	28.43*	2.04*	1.12*	2.97	14.11*	46.83*	28.28*	71.68*	85.69*	14.31*	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	75.84*	3.14*	8.83*	10.69	1.51*	11.27*	60.28*	12.25*	68.18*	87.11*	12.89*	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	67.11*	24.79	2.29*	0.29*	5.53*	31.94*	37.08*	26.87	79.50*	86.56*	13.44*	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	82.17*	3.57*	8.98*	2.91*	2.38*	22.32*	42.67*	28.38*	75.17	84.28*	15.72*	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	35.71	8.03*	52.83*	0.07*	3.35*	49.25*	6.93*	21.16*	52.40*	77.51*	22.49*	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*	15.06*	66.37*	75.68*	24.32*	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	83.52*	6.93*	6.23*	0.28*	3.05*	9.14*	47.37*	26.09*	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	81.58*	11.79*	6.14*	0.00*	0.48*	20.32*	28.71*	35.59*	60.97*	86.13*	13.87*	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 A5: **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.

A.7 Officers' Place of Residence

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	50.52	37.84	12.79*** [12.68, 12.91]	200,954
	Hispanic	23.30	28.04	-5.05*** [-5.13, -4.96]	200,954
	Black	14.27	21.27	-6.92*** [-7.01, -6.82]	200,954
	Other/Unknown Race	3.41	3.42	0.02*** [0.01, 0.03]	200,954
	Asian	8.50	9.43	-0.85*** [-0.90, -0.81]	200,954
Party (Voting Age Pop.)	Republican	23.48	14.07	9.38*** [9.31, 9.45]	201,676
	Democratic	38.97	43.42	-4.38*** [-4.45, -4.31]	201,676
	Other/Unknown Party	39.68	42.75	-3.13*** [-3.18, -3.07]	201,676
General Turnout, 2020	Voting Age Pop.	64.13	54.57	9.62*** [9.55, 9.70]	199,445
Gender	Male	48.81	48.69	0.12*** [0.10, 0.13]	201,687
	Female	51.19	51.31	-0.12*** [-0.13, -0.10]	201,687
Median Age (Years)	-	38.80	36.86	2.35*** [2.32, 2.38]	201,683
Mean Household Income ($)	-	105149.07	92549.81	12926.67*** [12734.57, 13118.77]	201,655

Table A6: **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. In the case of median age this difference does not equal the median officer age minus the median civilian age as the difference was made at the officer-level, before finding the median age. Stars denote $p < .001$; brackets contain 95% confidence intervals.

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 A7: **Comparison of Chicago Police Officer and Civilian Traits for districts in the city.** 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.

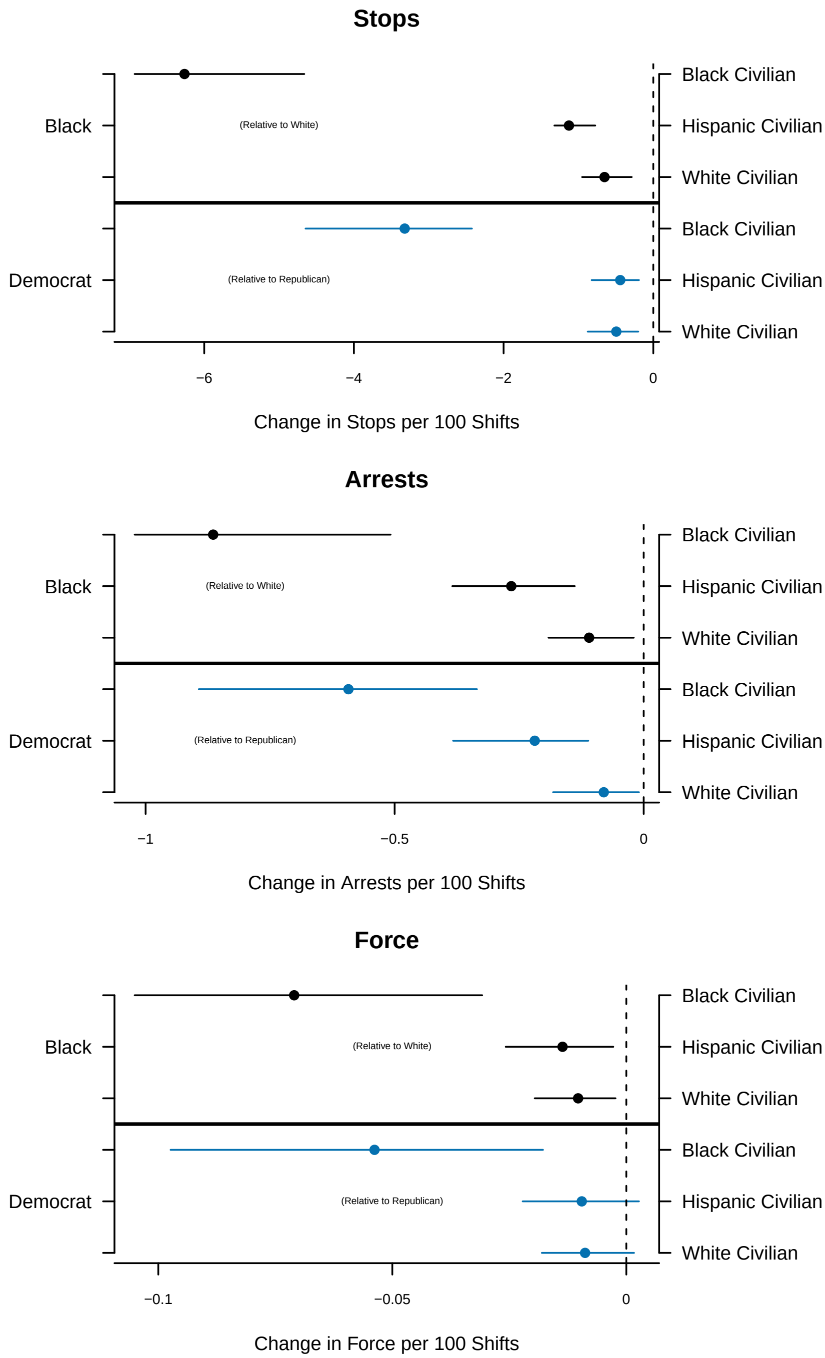

Figure A1: **Race and Party Deployment Effects, Black vs. White Officers by Civilian Race.** The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian characteristics. These estimates are computed using only places and times where at least one Black, White, Republican and Democratic officer was deployed.

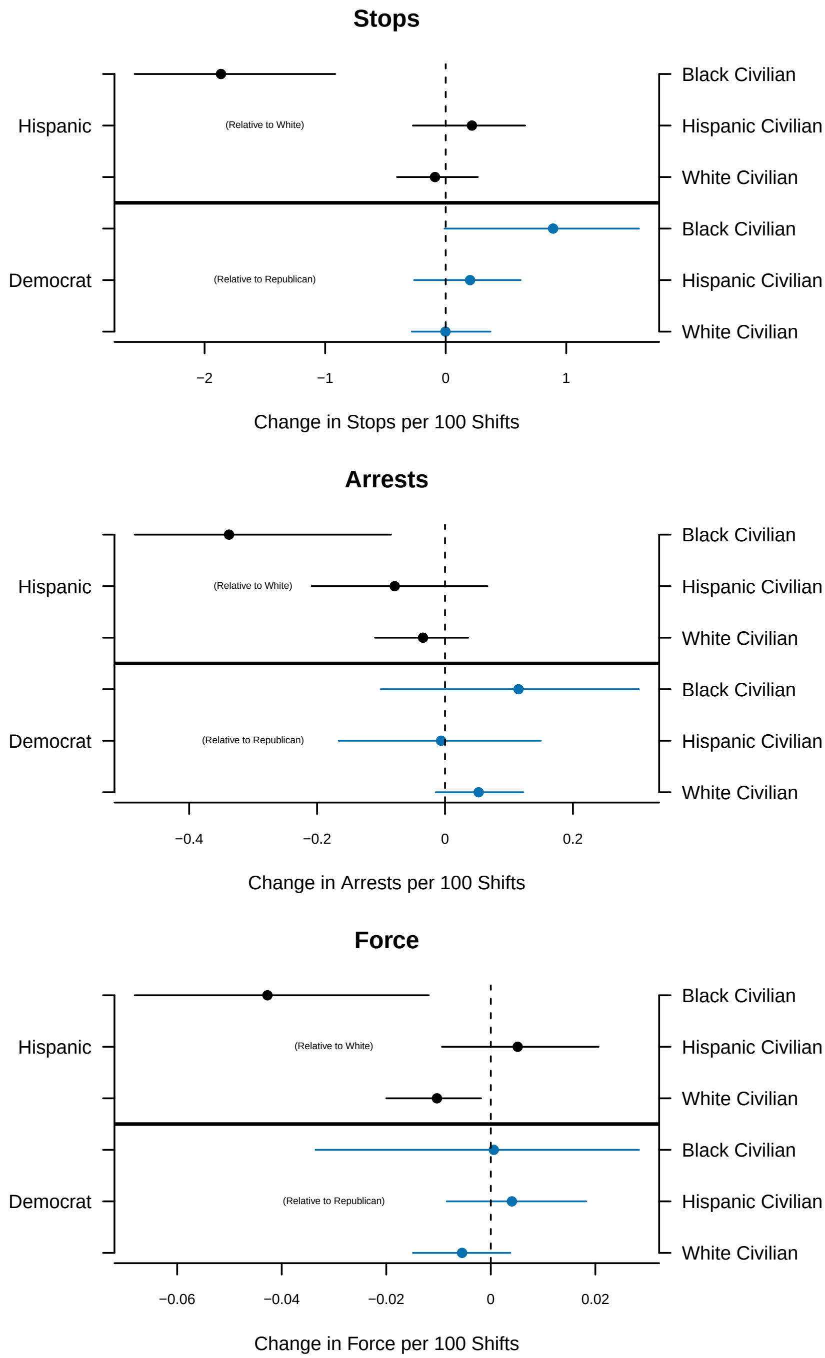

Figure A2: **Race and Party Deployment Effects, Hispanic vs. White Officers by Civilian Race.** The figure displays the average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian characteristics. These estimates are computed using only places and times where at least one Hispanic, White, Republican and Democratic officer was deployed.

A.8 Feasibility of Comparisons

Overall, 8.7% of MDSBs (containing 15.3% of shift assignments) have Black, White, Democrat, and Republican officers assigned to them and are therefore feasible for the "BWDR" analysis presented in Figure 7. For the analysis presented in Figure 7, 15.8% of MDSBs (containing 26.0% of shift assignments) have Hispanic, White, Democrat, and Republican officers assigned to them and are therefore feasible.

A.9 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 A8, 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 10.5 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 21.77% in L2 but only 1.31% in LEMAS (2016).

The following table, Table A9 shows the comparison between officers and civilians after adjusting for the measurement error shown in Table A8 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 2.

Race (%)	Data from L2	Data from LEMAS	% Change
White	45.34	55.84	23.17
Hispanic	19.35	20.99	8.50
Black	10.43	16.74	60.59
Other/Unknown	21.77	1.31	-94.00
Asian	3.12	5.12	63.84

Table A8: **Comparison of LEMAS and L2 Measures of Officer Race.** Comparison is based on the 86% of agencies (covering 92% of officers analyzed) for which LEMAS data is available.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	56.15	37.87	18.27*** [18.08, 18.47]	218,477
	Hispanic	20.82	28.05	-7.23*** [-7.39, -7.07]	218,477
	Black	16.73	21.26	-4.53*** [-4.68, -4.38]	218,477
	Other/Unknown Race	1.36	3.42	-2.06*** [-2.11, -2.02]	218,477
	Asian	4.95	9.41	-4.46*** [-4.55, -4.37]	218,477

Table A9: **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 A8 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 A8 shows that when LEMAS ground-truth race data is available, L2 undercounts the share of White officers by 23%. 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. Stars denote $p < .001$; brackets contain 95% confidence intervals.

A.10 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 party identification is directly reported by states.

To address measurement error due to a failure to match officers to L2, we include an extensive best- and worst-case bounding exercise which evaluates the hypothetical impact of all unmatched officers being Democrats or Republicans (see Table A10 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 1.59 p.p.. We note this test is extremely conservative, as it assumes all unmatched officers identify 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 A11 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 A12 below). This approach has the simultaneous benefit of using a recent measure of party identification, which partially addresses concerns over "stale" registration, 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 A12 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 with closed primaries, where citizens must register with a political party to participate and where L2 is less reliant on imputation. These results, shown in Table A13 and Table A14 below, are consistent with our core conclusions in terms of the disparities between officers and civilians. We note that Illinois requires party registration for primary election participation, making us more confident that our measures of party ID are accurate in our behavioral analysis.

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 A15 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 A16). In addition, we conduct the same exercise now using the three agencies which include the officer's exact date of birth (Table A17). 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.

Variable	Value	Officer Lower Bound %	Officer Upper Bound %	Hypothetical Representative Officer %	Difference Lower Bound	Difference Upper Bound
Race	White	56.01	56.01	37.84	18.18***	18.18***
	Hispanic	20.90	20.90	28.04	-7.14***	-7.14***
	Black	16.35	16.35	21.27	-4.92***	-4.92***
	Other/Unknown Race	1.84	1.84	3.42	-1.58***	-1.58***
	Asian	4.89	4.89	9.43	-4.54***	-4.54***
Party (Voting Age Pop.)	Republican	32.44	46.17	14.07	18.37***	32.09***
	Democratic	31.29	45.01	43.42	-12.13***	1.59***
	Other/Unknown Party	22.54	36.27	42.75	-20.21***	-6.48***
General Turnout, 2020	Voting Age Pop.	69.36	83.15	54.57	14.79***	28.58***
Median Age (Years)	-	42.00	45.00	36.86	7.01***	8.91***
Mean Household Income ($)	-	111,151.03	119,713.86	92,549.81	18,601.22***	27,164.06***

Table A10: **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. Note that age results are based on the median of differences, which can differ from the difference of medians. Stars denote $p < .001$

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	56.04	38.03	18.01*** [17.81, 18.21]	208,394
	Hispanic	20.68	27.25	-6.57*** [-6.73, -6.41]	208,394
	Black	16.74	21.84	-5.10*** [-5.25, -4.94]	208,394
	Other/Unknown Race	1.58	3.42	-1.85*** [-1.90, -1.79]	208,394
	Asian	4.96	9.45	-4.50*** [-4.59, -4.40]	208,394
Party (Voting Age Pop.)	Republican	25.46	14.07	11.39*** [11.21, 11.57]	218,477
	Democratic	22.79	43.42	-20.63*** [-20.80, -20.46]	218,477
	Other/Unknown Party	51.75	42.75	8.99*** [8.79, 9.20]	218,477
General Turnout, 2020	Voting Age Pop.	51.94	54.57	-2.63*** [-2.84, -2.43]	216,168
Gender	Male	83.22	48.69	34.53*** [34.37, 34.69]	218,477
	Female	16.78	51.31	-34.53*** [-34.69, -34.37]	218,477
Median Age (Years)	-	44.00	36.92	7.88*** [7.81, 7.95]	138,301
Mean Household Income ($)	-	115,191.09	91,998.15	23191.12*** [22,874.21, 23,508.04]	137,806

Table A11: **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. In the case of median age this difference does not equal the median officer age minus the median civilian age as the difference was made at the officer-level, before finding the median age. Stars denote $p < .001$; brackets contain 95% confidence intervals.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Party (Voting Age Pop.)	Republican	32.44	14.07	18.37*** [18.18, 18.56]	218,477
	Democratic	31.29	43.42	-12.13*** [-12.32, -11.94]	218,477
	Other/Unknown Party	36.27	42.75	-6.48*** [-6.69, -6.28]	218,477

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

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Party (Voting Age Pop.)	Republican	20.47	8.07	12.40*** [12.24, 12.57]	218,477
	Democratic	22.27	25.21	-2.94*** [-3.11, -2.77]	218,477
	Other/Unknown Party	57.26	66.97	-9.71*** [-9.91, -9.50]	218,477

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

Table A12: **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. Stars denote $p < .001$; brackets contain 95% confidence intervals.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	54.25	37.80	16.45*** [16.11, 16.79]	71,815
	Hispanic	21.41	25.29	-3.88*** [-4.16, -3.60]	71,815
	Black	20.18	25.59	-5.40*** [-5.69, -5.12]	71,815
	Other/Unknown Race	0.30	2.97	-2.68*** [-2.72, -2.64]	71,815
	Asian	3.86	8.36	-4.50*** [-4.64, -4.36]	71,815
Party (Voting Age Pop.)	Republican	35.59	13.71	21.88*** [21.54, 22.23]	72,059
	Democratic	34.25	48.11	-13.85*** [-14.19, -13.51]	72,059
	Other/Unknown Party	30.16	38.18	-8.03*** [-8.36, -7.70]	72,059
General Turnout, 2020	Voting Age Pop.	72.06	53.63	18.43*** [18.10, 18.76]	70,153
Gender	Male	90.46	48.05	42.41*** [42.20, 42.63]	72,059
	Female	9.54	51.95	-42.41*** [-42.63, -42.20]	72,059
Median Age (Years)	-	41.00	37.97	5.56*** [5.45, 5.67]	65,672
Mean Household Income ($)	-	114098.19	92886.67	21214.22*** [20740.93, 21687.51]	65,998

Table A13: **Comparison of Average Officer and Civilian Traits for States with Closed Congressional Primaries.** 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. In the case of median age this difference does not equal the median officer age minus the median civilian age as the difference was made at the officer-level, before finding the median age. Stars denote $p < .001$; brackets contain 95% confidence intervals.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	54.98	38.60	16.38*** [16.04, 16.72]	70,503
	Hispanic	21.29	24.48	-3.19*** [-3.47, -2.91]	70,503
	Black	19.40	25.25	-5.85*** [-6.13, -5.57]	70,503
	Other/Unknown Race	0.37	3.02	-2.64*** [-2.69, -2.60]	70,503
	Asian	3.96	8.67	-4.71*** [-4.86, -4.57]	70,503
Party (Voting Age Pop.)	Republican	35.48	13.17	22.32*** [21.97, 22.66]	70,738
	Democratic	34.41	48.92	-14.51*** [-14.85, -14.16]	70,738
	Other/Unknown Party	30.11	37.91	-7.81*** [-8.14, -7.47]	70,738
General Turnout, 2020	Voting Age Pop.	72.59	54.03	18.56*** [18.23, 18.89]	68,832
Gender	Male	90.44	48.07	42.38*** [42.16, 42.59]	70,738
	Female	9.56	51.93	-42.38*** [-42.59, -42.16]	70,738
Median Age (Years)	-	42.00	37.94	5.90*** [5.79, 6.01]	64,937
Mean Household Income ($)	-	114941.40	93798.66	21140.14*** [20664.79, 21615.49]	64,906

Table A14: **Comparison of Average Officer and Civilian Traits for States with Closed Presidential Primaries.** 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. In the case of median age this difference does not equal the median officer age minus the median civilian age as the difference was made at the officer-level, before finding the median age. Stars denote $p < .001$; brackets contain 95% confidence intervals.

Variable	Value	Officer Lower Bound %	Officer Upper Bound %	Hypothetical Representative Officer %	Difference Lower Bound	Difference Upper Bound
Race	White	55.31	56.46	37.84	17.47***	18.62***
	Hispanic	20.66	21.07	28.04	-7.38***	-6.97***
	Black	16.12	16.91	21.27	-5.15***	-4.36***
	Other/Unknown Race	1.77	2.12	3.42	-1.66***	-1.30***
	Asian	4.87	5.00	9.43	-4.56***	-4.43***
Party (Voting Age Pop.)	Republican	23.54	48.50	14.07	9.46***	34.43***
	Democratic	18.52	45.38	43.42	-24.90***	1.96***
	Other/Unknown Party	27.30	52.46	42.75	-15.45***	9.71***
General Turnout, 2020	Voting Age Pop.	53.37	77.93	54.57	-1.20***	23.36***
Median Age (Years)	-	36.00	50.00	36.86	1.19***	15.69***
Mean Household Income ($)	-	90,710.59	146,361.91	92,549.81	-1,508.16***	54,143.17***

Table A15: **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. Stars denote $p < .001$

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	58.15	38.67	19.48*** [18.99, 19.97]	36,743
	Hispanic	16.47	24.59	-8.12*** [-8.49, -7.74]	36,743
	Black	22.00	28.23	-6.23*** [-6.65, -5.82]	36,743
	Other/Unknown Race	1.27	2.59	-1.31*** [-1.43, -1.20]	36,743
	Asian	2.11	5.93	-3.82*** [-3.97, -3.67]	36,743
Party (Voting Age Pop.)	Republican	27.23	10.95	16.28*** [15.84, 16.72]	36,951
	Democratic	41.62	49.38	-7.75*** [-8.25, -7.26]	36,951
	Other/Unknown Party	31.15	39.67	-8.52*** [-9.00, -8.04]	36,951
General Turnout, 2020	Voting Age Pop.	73.07	55.47	17.60*** [17.13, 18.06]	36,951
Gender	Male	80.60	48.31	32.29*** [31.89, 32.69]	36,951
	Female	19.40	51.69	-32.29*** [-32.69, -31.89]	36,951
Median Age (Years)	-	43.00	35.95	8.36*** [8.20, 8.51]	33,337
Mean Household Income ($)	-	103639.23	80705.94	22935.15*** [22319.33, 23550.96]	33,030

(a) **Using name only**

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	58.18	38.71	19.47*** [18.98, 19.96]	36,734
	Hispanic	16.50	24.53	-8.04*** [-8.41, -7.67]	36,734
	Black	21.95	28.24	-6.29*** [-6.70, -5.88]	36,734
	Other/Unknown Race	1.26	2.59	-1.33*** [-1.44, -1.21]	36,734
	Asian	2.11	5.93	-3.82*** [-3.97, -3.67]	36,734
Party (Voting Age Pop.)	Republican	28.56	10.95	17.61*** [17.16, 18.06]	36,951
	Democratic	41.48	49.38	-7.90*** [-8.39, -7.41]	36,951
	Other/Unknown Party	29.96	39.67	-9.71*** [-10.18, -9.24]	36,951
General Turnout, 2020	Voting Age Pop.	74.91	55.47	19.44*** [18.98, 19.89]	36,951
Gender	Male	80.60	48.31	32.29*** [31.89, 32.69]	36,951
	Female	19.40	51.69	-32.29*** [-32.69, -31.89]	36,951
Median Age (Years)	-	43.00	35.95	7.09*** [6.97, 7.22]	32,912
Mean Household Income ($)	-	105576.41	80719.73	24877.12*** [24273.29, 25480.95]	32,897

(b) **Using name and age**

Table A16: **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. Stars denote $p < .001$; brackets contain 95% confidence intervals.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	50.51	33.97	16.54*** [15.75, 17.33]	14,626
	Hispanic	26.47	32.07	-5.60*** [-6.26, -4.93]	14,626
	Black	19.82	25.85	-6.03*** [-6.67, -5.39]	14,626
	Other/Unknown Race	0.38	2.20	-1.83*** [-1.92, -1.73]	14,626
	Asian	2.82	5.90	-3.08*** [-3.35, -2.82]	14,626
Party (Voting Age Pop.)	Republican	16.70	5.81	10.89*** [10.30, 11.48]	14,626
	Democratic	53.85	52.99	0.86* [0.07, 1.66]	14,626
	Other/Unknown Party	29.45	41.21	-11.75*** [-12.49, -11.02]	14,626
General Turnout, 2020	Voting Age Pop.	75.65	52.43	23.22*** [22.52, 23.91]	14,626
Gender	Male	78.07	48.68	29.38*** [28.71, 30.05]	14,626
	Female	21.93	51.32	-29.38*** [-30.05, -28.71]	14,626
Median Age (Years)	-	44.00	35.36	9.06*** [8.85, 9.28]	13,870
Mean Household Income ($)	-	104670.96	84661.13	19992.20*** [19053.12, 20931.28]	13,676

(a) **Using name only**

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	50.51	33.97	16.54*** [15.75, 17.33]	14,626
	Hispanic	26.47	32.07	-5.60*** [-6.26, -4.93]	14,626
	Black	19.82	25.85	-6.03*** [-6.67, -5.39]	14,626
	Other/Unknown Race	0.38	2.20	-1.83*** [-1.92, -1.73]	14,626
	Asian	2.82	5.90	-3.08*** [-3.35, -2.82]	14,626
Party (Voting Age Pop.)	Republican	16.01	5.81	10.20*** [9.62, 10.78]	14,626
	Democratic	49.56	52.99	-3.42*** [-4.22, -2.63]	14,626
	Other/Unknown Party	34.43	41.21	-6.78*** [-7.54, -6.01]	14,626
General Turnout, 2020	Voting Age Pop.	69.00	52.43	16.57*** [15.82, 17.32]	14,626
Gender	Male	78.07	48.68	29.38*** [28.71, 30.05]	14,626
	Female	21.93	51.32	-29.38*** [-30.05, -28.71]	14,626
Median Age (Years)	-	44.00	35.35	8.12*** [7.94, 8.29]	11,632
Mean Household Income ($)	-	108107.45	84521.94	23581.65*** [22594.68, 24568.62]	11,729

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

Table A17: **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. Stars denote $p < .001$; brackets contain 95% confidence intervals.

A.11 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. 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.

If officers from different groups face the same conditions within their MDSBs, then we should not be able to predict the propensity for an officer of a given group to be assigned to work using crime incident data (for non-discretionary incidents) after conditioning on their MDSB. To test this, we estimate separate OLS models predicting the propensity of an officer of a given group to be assigned as a function of the number of non-discretionary crimes of a given category in that time and place, given MDSB fixed effects (per our research design). Standard errors are clustered by officers. Counts of crimes enter linearly in tests below; we also conducted tests with binarized versions of crime counts (above/below median) which are omitted here for space but are available in our replication materials. The results of these tests are reported in Tables A18–A21. Coefficients indicate change in the propensity score given a one-unit increase in a crime. Raw p values are also displayed for each test. Using the Simes method (Sarkar and Chang, 1997), we compute p-values for the joint null hypothesis that all estimates in a given table are zero, adjusting for multiple testing. Tests computed in feasible MDSBs only, where at least one member of each comparison group is present.

Across seven different kinds of non-discretionary incidents (ranging from vandalism to murder), four different tests of imbalance, and two different model specifications (measures of crime incidents that are binarized above/below median and continuous linear), we consistently find no evidence that—after conditioning on the specific patrol task to which a group of officers is assigned—that Black, Hispanic, White, Democrat, or Republican officers systematically select into different weeks within the MDSB (e.g., the first Monday vs. the last Monday of a month) that involve more or less criminal activity. The sole exception is that forgery incidents appear to predict the appearance of a Black officer in an MDSB; this can be seen in the second row of Table A18 (continuous measure), p=0.03. We find a similar result when binarizing the count variable. We view these as likely false positives given that 56 separate tests were conducted, and indeed, when using Simes tests that are specifically designed to fuse separate p-values to test the joint null hypothesis under multiple testing, we find that not a single analysis shows significant imbalance. All joint balance tests return $p > 0.05$, consistent with balance within MDSBs.

Crime	Coef	p
Burglary	0.00	0.78
Forgery/Counterfeiting	0.02	0.03
Manslaughter	0.18	0.39
Murder	0.01	0.46
Sexual Abuse	0.00	0.88
Sexual Assault	-0.00	0.69
Vandalism	0.00	0.39
Simes: 0.187		

Table A18: **Propensity to Assign Black Officer to MDSB.**

Crime	Coef	p
Burglary	0.00	0.96
Forgery/Counterfeiting	0.01	0.58
Manslaughter	-0.20	0.29
Murder	0.00	0.92
Sexual Abuse	-0.01	0.62
Sexual Assault	-0.01	0.43
Vandalism	0.00	0.70
Simes: 0.964		

Table A19: **Propensity to Assign Democrat Officer to MDSB.**

Crime	Coef	p
Burglary	0.00	0.98
Forgery/Counterfeiting	-0.00	0.73
Manslaughter	-0.02	0.86
Murder	-0.02	0.06
Sexual Abuse	-0.00	0.91
Sexual Assault	0.00	0.85
Vandalism	-0.00	0.28
Simes: 0.397		

Table A20: **Propensity to Assign Hispanic Officer to MDSB.**

Crime	Coef	p
Burglary	0.00	0.33
Forgery/Counterfeiting	0.01	0.16
Manslaughter	-0.05	0.68
Murder	-0.01	0.61
Sexual Abuse	0.00	0.85
Sexual Assault	-0.00	0.72
Vandalism	0.00	0.34
Simes: 0.789		

Table A21: **Propensity to Assign Democrat Officer to MDSB.**