Who are the Police? Descriptive Representation in the Coercive Arm of Government*

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October 28, 2022

Abstract

Policies to make police forces more representative of communities have centered on race. But race may crudely proxy views and lived experiences, undermining classic theories of representative bureaucracy. To conduct a multi-dimensional analysis, we merge personnel records, voter files and census data to examine roughly 220,000 officers from 98 of the 100 largest local U.S. agencies—over one third of local law enforcement agents nationwide. We show that officers diverge from the communities they serve on every dimension measured: they are more likely to be White, Republican, politically active, male, and high-income than their jurisdictions; moreover, officers tend to live near similarly unrepresentative neighbors. In a behavioral analysis in Chicago, we find Democratic, Black, and Hispanic officers initiate fewer stops, arrests, and uses of force than Republican and White counterparts facing common circumstances. Our results complicate conventional understandings of descriptive representation, highlighting the importance of multi-dimensional perspectives of diversity.

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Authors listed alphabetically. DK and JM designed the project with support from RM and JK. RM led data acquisition with additional contributions by BB, MK, RR, and MT. JK conducted data processing and statistical analysis with support from DK and JM, with additional contributions from RR. JM wrote the paper with support from JK, DK, and RM, with additional contributions from MT.

A "representative bureaucracy" (Kingsley, 1944; Meier, 1975) that shares salient attributes and social identities with the population it serves has long been theorized to enhance the quality of government service, especially for marginalized groups (Dolan, 2001; Potter and Volden, 2021). The need for descriptive representation in unelected sectors of government is thought to be especially pronounced in settings where effective oversight of bureaucrats' sometimes considerable discretion is challenging and "external controls fail" to promote desirable and fair agency outputs (Meier, 1975, 528). In the realm of policing—where agents routinely exercise discretion to protect, punish, or even kill, and where oversight and accountability are notoriously difficult (Brehm and Gates, 1999; Goldstein, 1977)—scholars have spent decades trying to assess both the prevalence and impact of descriptive representation. Due to longstanding concerns over racial discrimination in policing (Alexander, 2010; Lerman and Weaver, 2014; Glaser, 2014), the overwhelming focus of this literature has been officer race and ethnicity (Ba et al., 2021; Harvey and Mattia, 2019; McCrary, 2007; Miller and Segal, 2012, 2018; Sklansky, 2005). But as Ba et al. (2021) notes, "Officers are multidimensional, and crafting effective personnel reforms will likely require thinking beyond the coarse demographic categories typically used in diversity initiatives and consideration of how multiple attributes relate police to the civilians they serve" (701).

In this paper, we analyze nearly a quarter million officers,[1] covering 98 of America's 100 largest local agencies and representing over one third of all local law enforcement nationwide, to provide a comprehensive, multi-dimensional account of descriptive representation in policing. Our data contain measures of officers' race, ethnicity, gender, age, income, political affiliation, voting history, and place of residence. They draw upon numerous open records requests, data-sharing agreements, and publicly available personnel rosters, merged with voter file and U.S. Census data. The resulting data set allows us to comprehensively characterize the degree to which police resemble their communities on a host of dimensions.

Our analysis is motivated by the fact that race and ethnicity alone may be crude indicators of how officers relate to civilians or behave on the job. In the words of Dolan and Rosenbloom (2003), "a bureaucracy that looks like the population it serves may not effectively translate the policy wishes of the population into public policy" if bureaucrats do not share the public's "values, opinions, and attitudes" (77). This is a particular concern

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

given the politicization of policing in the United States, with Democrats and Republicans strongly disagreeing on policing policy (Eckhouse, 2019; Pew, 2017; Parker and Hurst, 2021; Grosjean, Masera and Yousaf, 2022). Simply put, people who identify with a particular racial or ethnic group are not monolithic, and recent evidence shows support for conservative policy is more pronounced among racial minorities than previously thought (White, Laird and Allen, 2014). Such findings underscore the need to study the prevalence and consequences of not only demographic, but *political* diversity in the coercive arm of government. While political orientation may not be as salient an identity as race or gender, there is reason to suspect it may still play a role in street-level bureaucrats' decision-making, especially given the ways in which the politics of policing have so dramatically split along partisan lines and, relatedly, how the gap between Democrats' and Republicans' views on racial inequality has widened (Tesler, 2020).

Progress on this question has been stymied by a scattered, incomplete and heterogeneous landscape of administrative data (Knox and Mummolo, 2020). Assembling basic facts about law enforcement agents remains remarkably difficult in many jurisdictions. Agencies rarely share information proactively and, in our experience, 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), 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.[2] Our approach—gathering administrative data covering the vast majority of officers in the largest jurisdictions—alleviates these concerns.

Using our newly assembled data, we first demonstrate that relative to civilians in their jurisdictions, police officers are more likely to be White, affiliate with the Republican Party, have higher household income, and vote. However, the degree of nonrepresentativeness is highly heterogeneous, with some agencies closely mirroring their populations and others substantially diverging. Next, we broaden our analysis to account for

[2]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.

the neighborhoods in which officers live. Some scholars and political elites have claimed policing outcomes will be more equitable if officers are required to live amongst and have ties to the communities they serve, a policy which may also benefit the local economy (though evidence remains mixed; Eisinger, 1983; Smith, 1980*a*; Murphy and Worrall, 1999; Hauck and Nichols, 2020).[3] However, even within jurisdictions, we find the composition of officers' neighborhoods also differs systematically from that of the city at large. Areas where officers live have higher shares of White residents, shares of Republicans, voter turnout rates and household income than the jurisdiction overall.

To probe these patterns at a finer-grained level, we then turn to a micro-level dataset, acquired from the Chicago Police Department (CPD) through roughly 5 years of public records requests. As previous scholars have noted, 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 find that in the vast majority of Chicago police districts, officers diverge from the civilians they serve in terms of race and ethnicity. We also see striking gaps in political affiliation: every single district in Chicago is policed by officers who skew more Republican than local residents.

Having established these patterns, we then investigate longstanding theoretical claims about the potential benefits of descriptive representation, especially for marginalized groups. Using data on CPD shift assignments and enforcement records covering an eight-year period—doubling the coverage of data previously analyzed in Ba et al. (2021)—we estimate differences in the number of stops, arrests and uses of force by officers of various racial, ethnic, and partisan identities when facing common circumstances. While these metrics cannot capture the full consequences of enforcement decisions, including potential downstream effects on public safety (discussed below, Manski and Nagin, 2017), they are crucial to studying the impact of representation among armed agents of the state. And while we are not equipped to evaluate the full slate of implications of officer diversity in

[3] In an examination of personnel policies for the nation's 100 largest agencies, we find that over a quarter mandate or encourage local residency; see Appendix Table B4.

this setting, our data allow a unique opportunity to evaluate a key assumption embedded in theories of representative bureaucracy: differential behavior across groups of bureaucrats.

Our results paint a complex portrait of the role of race, ethnicity and partisanship across officer groups. First, we find that in scenarios where both comparisons can be made, the Black-White gap in officer enforcement decisions has the same sign as the Democratic-Republican gap: When deploying either Black or Democratic officers, the result is fewer stops, arrests, and uses of force (compared to White or Republican officers, respectively). We observe similar but smaller gaps between Hispanic and White officers (though we note that the scenarios in which Hispanic-White comparisons differ from those used in Black-White comparisons). 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 than when White or Republican officers are deployed. Our analysis underscores the multi-dimensional nature of descriptive representation in the bureaucracy. Police officers are as multifaceted as the civilians they serve, and adequately assessing the status and implications of diversity in law enforcement requires more than an analysis of race alone.

1 Conceptualizing Representative Bureaucracy in the Policing Context

In general, theories of representative bureaucracy (Kingsley, 1944; Dolan and Rosenbloom, 2003) are premised on several key assertions: bureaucratic oversight is 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; Meier, Wrinkle and Polinard, 1999).

But do demographic indicators really convey "shared values" in the bureaucracy? There are at least two reasons for skepticism. First, bureaucratic staffing processes, which rely on self-selection and screening based on adherence to shared missions, could easily lead to the selection of particular group members who hold atypical policy preferences relative to group members at large (Linos, 2017). Second, recent work underscores that conservative segments of minority communities, African Americans in particular, may be more prevalent than previously thought (White, Jonathon A. Cooper and Raganella, 2010). Indeed, recent work suggests policing agencies may select unusually conservative members of minority communities who tend to support status-quo policing practices more than their liberal counterparts (Forman Jr., 2017; Pew, 2017; Parker and Hurst, 2021), upending the logic of representative bureaucrats "colored by their political outlook and by the climate of opinion in their social group" (Lipset, 1975, 80).

Even stipulating to the broad assumptions that underlie theories of representative bureaucracy, several key concepts require more careful thought in the context of policing. First, we must determine how to craft meaningful comparisons between police and civilians. The existence of specific eligibility requirements for police officers mechanically limits the degree to which agencies will mirror civilians on particular dimensions. In addition to age requirements, many jurisdictions prohibit recruits with criminal records and mandate minimum levels of education (Decker and Huckabee, 2002; LEMAS, 2016). Obviously, currently incarcerated individuals are also excluded from police service. These limitations must be kept in mind when interpreting disparities between the demographic makeup of police agencies and jurisdictions overall, as some are ensured by institutional design. But such disparities, however they came to be, remain important to measure and examine. Unlike many other bureaucrats, who primarily serve particular age or income groups, police can encounter anyone and everyone. Because of this, we conceptualize descriptive representation in policing as the degree to which officers mirror their entire jurisdictions.

Having defined descriptive representation, we must also grapple with competing normative perspectives on desirable law enforcement behavior. On the one hand, persistent concerns over racial discrimination, harassment and excessive force in policing suggest reductions in some enforcement—especially toward marginalized civilians—represent a desirable output. Several jurisdictions have adhered to this logic when crafting recent reforms, e.g. eliminating the enforcement of low-level traffic violations in an effort to reduce disparities (Raguso, 2021). Indeed, allegations of excessive force and an overzealous crackdown on minor offenses have long been at the heart of calls to diversify police agencies (Forman Jr., 2017). On the other hand, policymakers and scholars (Manski and Nagin, 2017) have long asserted that reductions in police activity can lead to increases in crime and threaten public safety.

We offer several comments on this concern. For one, while there is considerable evidence that the overall *presence* of police officers reduces certain types of crimes (Chalfin and McCrary, 2017), there remain serious doubts as to whether the same can be said of aggressive police *tactics* (Mummolo, 2018*b*; Lowande, 2021; Gunderson et al., 2021).[4] And even if stops and arrests conceivably deter crime, we are aware of no study showing a compelling causal effect on crime rates, based on the frequency with which officers use force during police-civilian encounters. So while it is difficult to definitively evaluate whether a representative bureaucracy produces net benefits overall, it is plausible that certain measurable reductions—reduced use of force, in particular—contribute positively.[5] More generally, however, we emphasize that our main contribution is to provide a credible test of a key mechanism through which the benefits of descriptive representation are said to manifest: divergent behavior across groups of bureaucrats.

Setting aside the impact of officer diversity on jurisdictions writ large, prior research seeking to measure differences in officer behavior has reach mixed conclusions. For one, most empirical studies of descriptive representation tend to focus on race and gender, which may only crudely proxy for relevant social views; as Sklansky (2005) notes, results in this literature have been ambiguous. Some provide agency-level correlations showing that more diversity is associated with certain interaction types; for example, Meier and Nicholson-Crotty (2006) finds having more female officers is associated with more sexual assault reports and arrests. Further, Wright II and Headley (2020) presents descriptive evidence that force is more common in encounters between White officers and Black civilians. However, others argue "occupational ethos and organizational culture" produce homogeneous behavior, regardless of officers' backgrounds and identities (Sklansky, 2005, 1225), and some correlational evidence is consistent with this claim (Fyfe, 1981; Walker, Spohn and DeLone, 2016).

In recent years, newly available granular data on police demographics and behavior, combined with more credible research designs, have provided strong evidence that diversity affects policing outcomes, at least in the times and places where adequate data is available. Using micro-level data in Chicago on officer shift assignments and behavior, 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 large-scale data on dispatches to 911

[4]For example, Rosenfeld and Fornango (2014) found that the controversial "Stop Question and Frisk" (SQF) tactic in New York City yielded "few effects of SQF on robbery and burglary" (1). Mummolo (2018*a*) found no effect of SWAT team formation on violent crime in the jurisdiction.

[5]However, it may be difficult to reduce force usage while holding stops and arrests fixed.

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 a tentative empirical consensus may be forming with respect to race and gender, the political affiliations and ideologies of bureaucrats complicate these narratives. However, data limitations have stymied empirical inquiry. Studies of representative bureaucracy and 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*b*; but see Kropf, Vercellotti and Kimball, 2013). 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.

2 Data

To move beyond single-jurisdiction analyses of descriptive representation, we sought rosters of all sworn police officers employed in the largest 100 police agencies[6] 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). As police departments are public institutions, police roster data, including the names of current employees, are—with the exception of certain protected units such as undercover officers—nominally a matter of public record. For 50 agencies, we acquired these data from public sources such as open data portals managed by local governments, news agencies and nonprofits, or from 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. Rosters from two agencies—the Detroit Police Department and the Oakland County Sheriff's Office, both in Michigan—were not provided at the time of this writing.

[6] 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. The remaining agencies were then ranked by their 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.

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 1 shows the location of each agency included in this study. Our dataset covers 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 nationwide (Hyland and Davis, 2019), making this the largest examination of descriptive representation in policing to date.

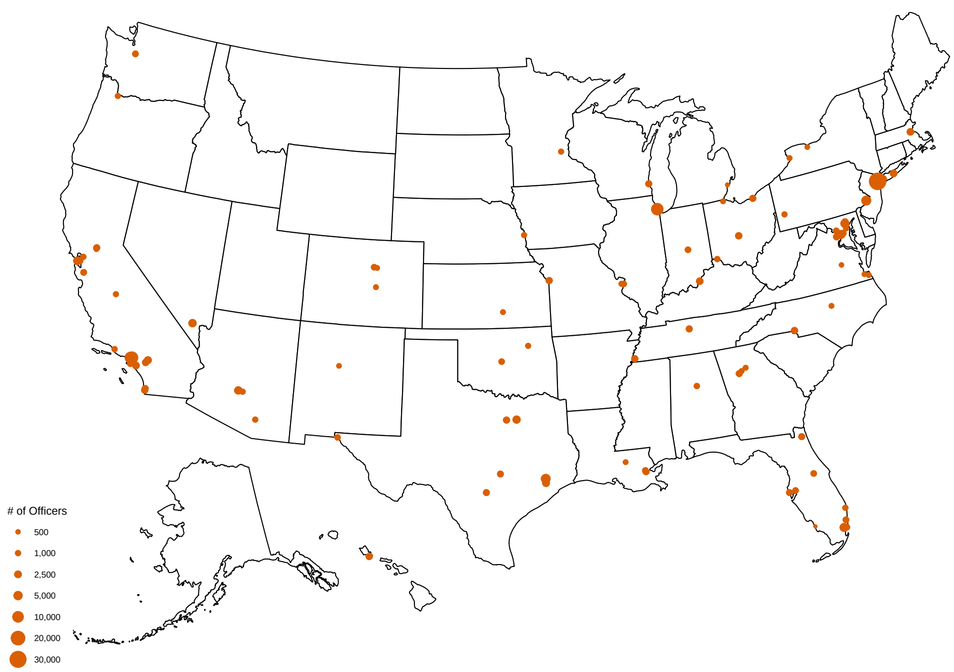

Figure 1: **Agency Locations.** Our agency rosters cover roughly 220,000 officers across 38 states (including Washington, D.C.), representing 34% of the nation's roughly 641,000 sworn local police officers and sheriffs' deputies (Hyland and Davis, 2019). Together, jurisdictions covered in our data serve about 23% of the U.S. population. Each dot is scaled by the number of sworn officers.

To put our dataset in context, Appendix Table B1 compares officers in our data to (1) officers nationwide and (2) the U.S. population (Hyland and Davis, 2019). 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 and thus constitute a diverse recruitment pool for agencies. As a result, we recommend caution in extrapolating from our study to U.S. law enforcement more generally, and we emphasize that expanding these data and analyses is a critical direction for future research. 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.[7]

[7] To generate these numbers we take the sum of murders and arrests, respectively, for the studied agencies, divided by the number of murders and arrests reported by all agencies in 2019.

Variable	Description	N (Mean)	Percent (SD)
Political Party	Republican	68,702	34.63
	Democratic	65,964	33.25
	Other	63,701	32.11
Gender	Male	144,985	73.09
	Female	38,766	19.54
Race/Ethnicity	White	98,200	49.50
	Hispanic	42,099	21.22
	Black	20,454	10.31
	Asian	6,782	3.42
	Other	4,537	2.29
Most Common Primary Party	Democratic	41,079	48.74
	Republican	43,202	51.26
Most Recent Primary Party	Democratic	42,690	50.94
	Republican	41,111	49.06
Age	-	45.08	14.46

Table 1: **Officer Descriptive Statistics.**

Note: All parties other than Republican or Democratic are grouped together as 'Other' party. "Most Common Primary Party" percentage is out of all officers who participated in at least two primary elections. "Most Recent Primary Party" percent is out of all officers who participated in at least one primary election.

3 Measuring Officer Attributes

Employee rosters provide 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. First, to reduce misidentification of people with common names, 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—such as the New York Police Department, which spans the city's five boroughs—the set of candidate matches covers all of the agency's counties and all their adjacent counties.) Once we identify these pools of potential matches, we 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 (2017*b*), using the *fastlink* R package (Enamorado, Fifield and Imai, 2017*a*)[8]. See Appendix Sections A.2 and C 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.[9] We divide officers 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).[10] 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.[11] 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 C to address potential measurement error in party identification: we compute bounds that substitute extreme assumptions for the covariates of unobserved individuals; we re-compute our core results using an alternate measure of party identification, namely, the party of the primary in which voters most recently participated; and we report results using only states in which both ma-

[8]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 C4.

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

[10]See Appendix A.3 for details on L2's imputation of party identification.

[11]For example, Hersh and Goldenberg (2016*a*) 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.

jor parties held closed presidential/congressional primary elections in 2020, where party identification data may be most accurate. Our core conclusions, e.g. that officers are more likely to be White and Republican, remain supported across nearly all of these robustness checks.[12]

To measure the share of officers of various racial, ethic and gender identities, we primarily rely on the 2019 Law Enforcement Officers Killed and Assaulted data (LEOKA) (Kaplan, 2021), which contains the gender breakdown for officers in each reporting agency, and the 2016 Law Enforcement Management and Administrative Statistics (LEMAS, 2016), a survey of law enforcement agencies which contains the number of officers by race 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.4 for additional details on these measures.[13]

4 Do Police Descriptively Represent Civilians?

We now compare the average levels of officers and civilians in their jurisdictions on the following dimensions: race, ethnicity, gender, household income, age, political party affiliation 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.[14]

Table 2 displays these core 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 Figures 2–3 and in Appendix Figures B1–B8. 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

[12]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 C.2.

[13]See Tables C1 and C2 for robustness checks related to potential mismeasurement of race/ethnicity.

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

of each agency fixed.[15] Subsequent columns display officer-civilian differences and 95% confidence intervals.[16]

Results show police officers diverge from the populations they serve on every attribute we measure. Turning first to race and ethnicity, roughly 56% of officers in our data are White—an enormous overrepresentation of this group. 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. 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). Since decades of prior research has demonstrated a robust correlation between voter turnout and the strength of party identification (Campbell et al., 1960; Prior, 2007), this suggests officers are more likely to be strong partisans than their civilian counterparts. We also find officers are markedly 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 far less likely to identify with the Democratic party than civilians (31% vs. 43%).

In some cases, we find smaller political gaps between Black officers and Black civilians in their jurisdictions, compared to officer-civilian gaps among White and Hispanic individuals (see Table B2). Black officers are 52% Democratic (2% Republican); in contrast, if each Black officer was replaced with a representatively sampled Black civilian from their jurisdiction, the resulting group would be to 66% Democratic (1% Republican; gaps of −14 p.p. and +1 p.p). White officers are 19% Democratic (40% Republican), versus 35% Democratic (22% Republican) among representative White civilians (−19 p.p. and +18 p.p.). Hispanic officers are 43% Democratic (23% Republican) compared to 38% Democratic (7% Republican) among representative civilians (+5 p.p. and +16 p.p.).

To put these results in context, we compare to gaps in descriptive representation previously found in other professions. For example, using a similar approach to ours, Spenkuch,

[15] 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.

[16] 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.

Teso and Xu (2021) estimate that around 50% of civil servants are Democrats and 26% are Republicans—gaps of +15 p.p and −6 p.p., respectively, when compared to the 35% Democrats and 32% Republicans among ANES respondents in 2020. Similarly, Hersh and Goldenberg (2016*b*) finds that 36% of medical doctors are Democrats and 32% are Republicans. Relative to ANES respondents in that study's year of publication, a group that was 35% Democrats and 28% Republicans, this represents near parity (+1 p.p.) for Democrats and +4 p.p. for Republicans (*ANES Time Series Cumulative Data File*, 2021). Using data from Bonica and Sen (2017) and subsetting to the Census tracts in our study, we also observe that roughly 56% of lawyers donate exclusively to Democrats, 20% donate exclusively to Republicans, and about 25% either donate to both parties or not at all—rough proxies for party identification. Although precise comparisons are complicated by measurement and data-availability differences across occupations, on the whole these results suggest stronger Republican overrepresentation among police than in other professions, including in another sector of the criminal justice system.

By far the largest representation gap pertains to gender: roughly 83% of officers in our data are male. This is perhaps unsurprising, as agencies have struggled to recruit female candidates into law enforcement (Kringen, 2014). However, this result 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 provide striking evidence that police officers differ from the populations they serve, but they also mask considerable heterogeneity across agencies. To explore this variation, Figure 2 plots average officer and civilian shares of White individuals 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 race/ethnicity and party identification. Consider Rochester, N.Y.: 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 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.

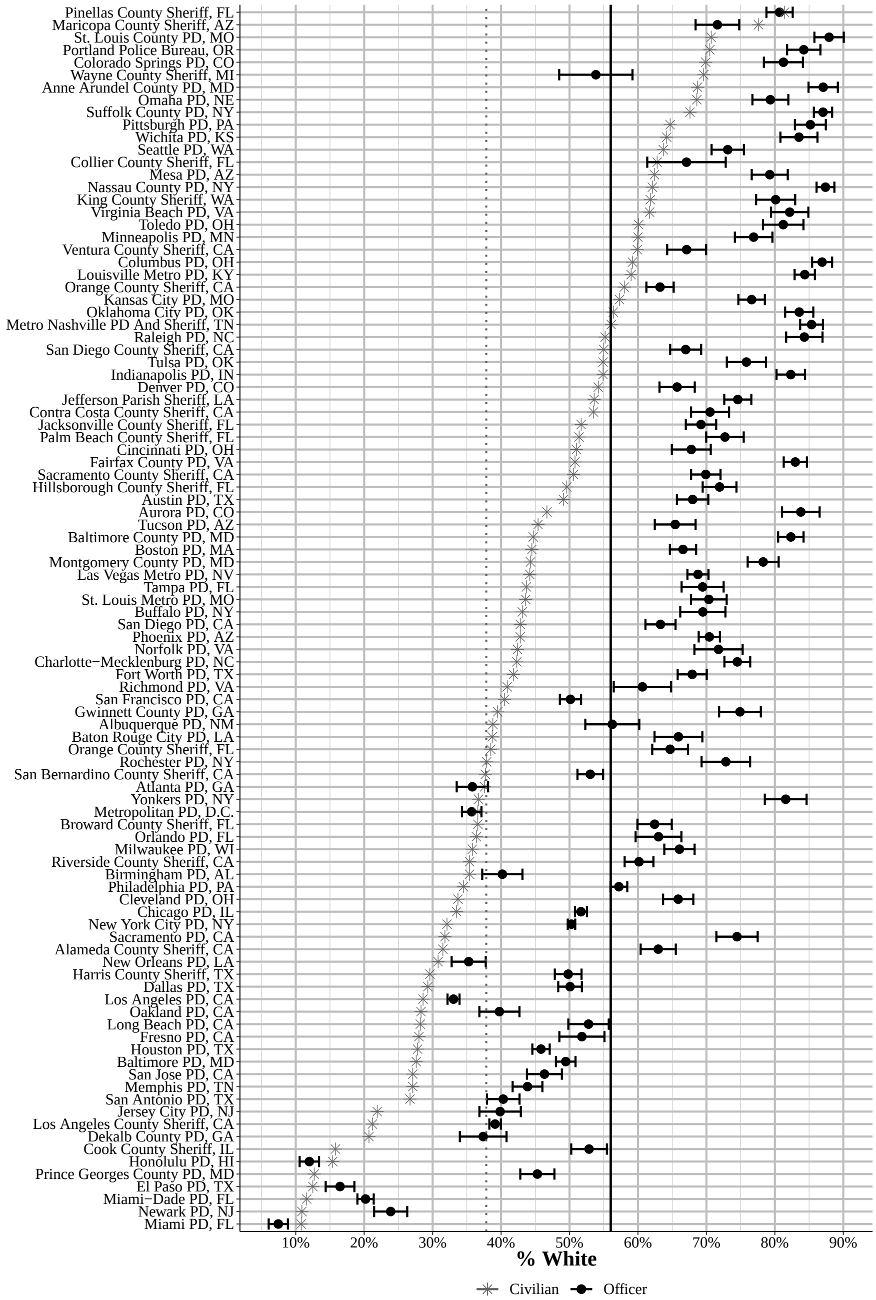

Figure 2: **Average Shares of White Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEMAS (2016) and L2 with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions. See Appendix Table B10 for numeric results.

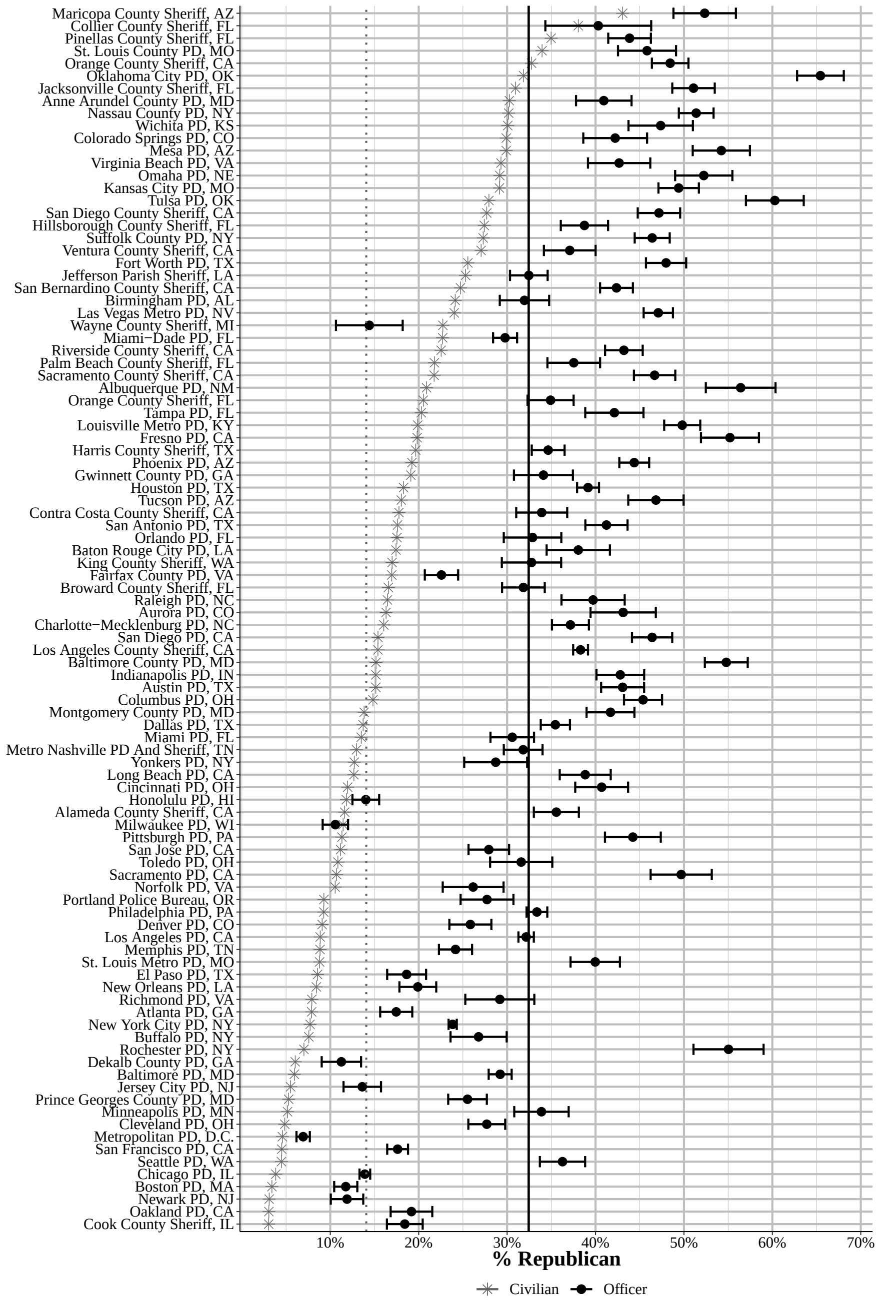

Figure 3: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions. See Appendix Table B11 for numeric results.

4.1 Officers' Places of Residence

Even if police do not themselves reflect the communities they serve, it is possible they live in representative neighborhoods, which could facilitate awareness of and empathy for the issues experienced by civilians they encounter on the job (Pettigrew, 1998; Hopkins, 2010; Key, 1949; Oliver and Wong, 2003). In addition, recent work theorizes that the groups officers socialize with when off the clock can distort beliefs about group behavior and lead 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 a close examination of police union contracts, hiring webpages, and personnel policies for each jurisdiction.[17] It is clear that numerous top agencies regard officer residency as an important consideration.

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 then compared the traits of these tracts to the overall jurisdiction. The results are displayed in Appendix Table B12.[18] 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.

5 The Chicago Police Department: A Micro-Level Case Study

In this section, we use rare 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 are representative of the civilians with whom they likely interact. Second,

[17] Appendix Table B4 reports residency rules for each agency. Appendix Table B22 reports officer-civilian comparisons for agencies with and without residency requirements. We caution readers against interpreting these cross-sectional results as the causal effect of having a residency requirement. We thank an anonymous reviewer for suggesting this analysis.

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

we directly assess whether officers of different racial, ethnic and political backgrounds behave differently when facing common circumstances.

5.1 Representation in Police-Civilian Interactions

We associated each officer in the Chicago data set 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 discussed in Section 4, to characterize officers and civilians in those districts. Figure 4 shows the share of officers assigned to each district who are White according to CPD personnel records (dots with confidence intervals), as well as the share of civilians who are White in those same districts based on Census data (asterisks). 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).

Beyond these aggregate results, 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—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. (For additional numeric results, see Table B14.)

Figure 5 shows another striking mismatch. Overall, 15% of CPD officers are Republican. However, even in the most right-leaning district civilians are no more than 9% Republican (full numeric results given in Table B15). If each officer was replaced with a representative draw from the 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 Figure B12, we present additional results showing Democrats are underrepresented in almost every district, indicating these results are not simply driven by increased political engagement and lower rates of nonpartisanship among officers. (See Appendix C for robustness tests).[19]

[19]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.

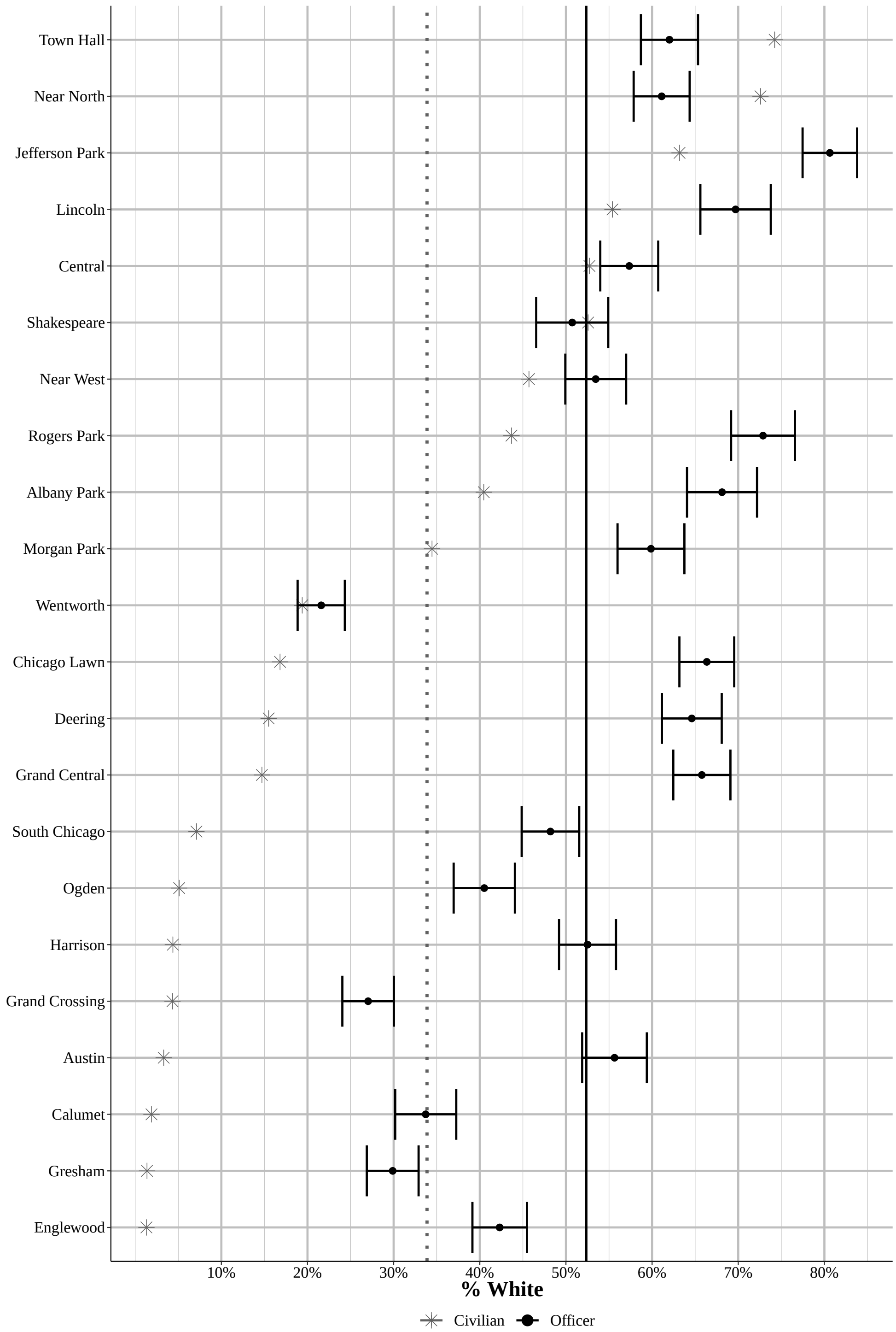

Figure 4: **Average Shares of White Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district. See Appendix Table B14 for numeric results.

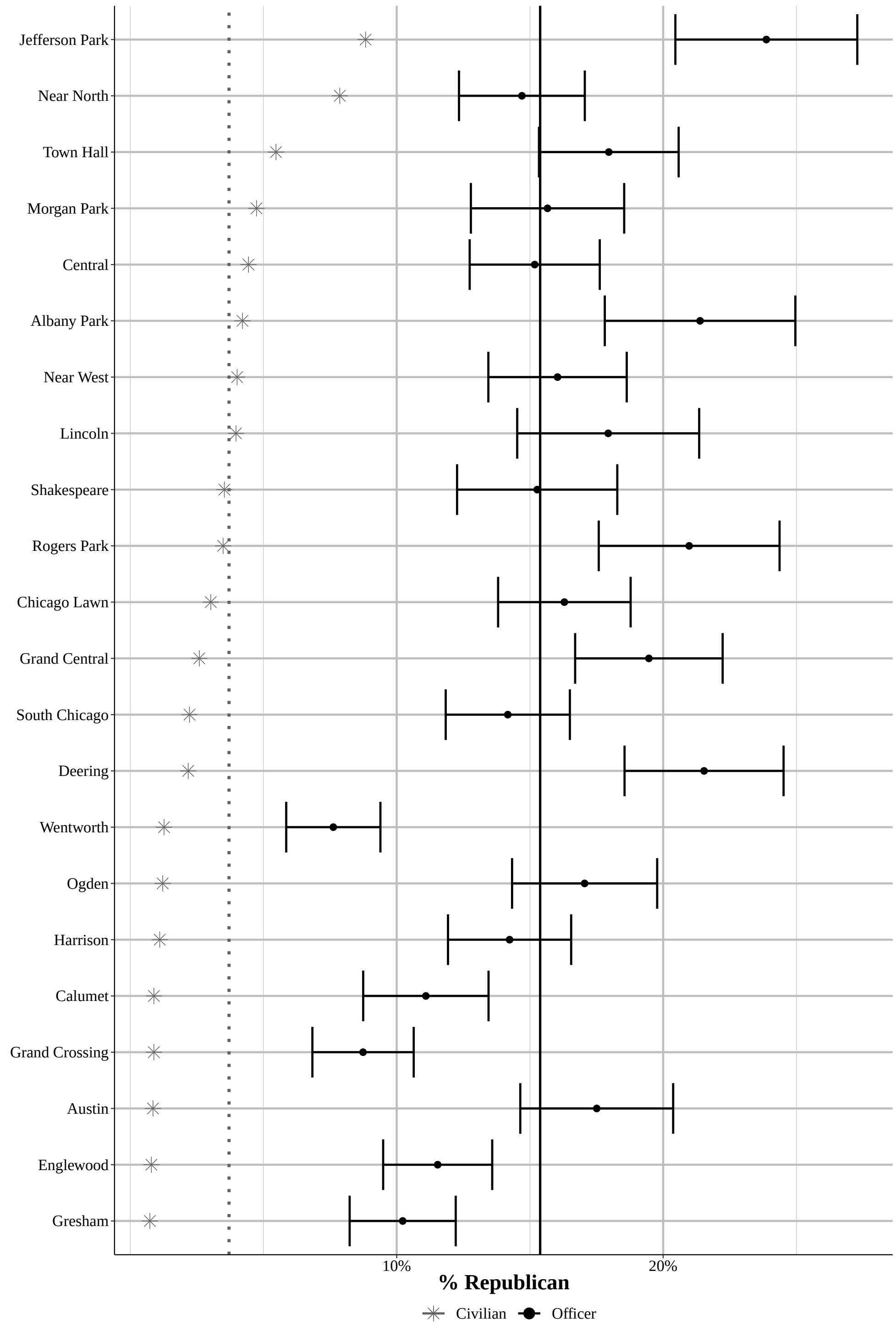

Figure 5: **Average Shares of Republican Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district. See Appendix Table B15 for numeric results.

5.2 Deploying Officers of Different Racial and Political Groups

In this section, we employ a research design, first developed by Ba et al. (2021), which identifies differences in officer behavior that cannot be explained by differential working environments (e.g. neighborhoods or times of day with more or less violent crime). From a theoretical perspective, this analysis probes a key assumption underlying the claimed benefits of representative bureaucracy—i.e., whether officers from different racial, ethnic and political groups treat civilians differently when facing common situations. We note that our analysis is limited to measured officer behaviors that occur during police-civilian encounters. Our data do not allow us to assess whether the deployment of various officer groups has second-order effects on social outcomes such as community trust in police, crime rates or public safety. However, in light of concerns over excessive enforcement and force, particularly in communities of color, we view this analysis as a crucial first step in the empirical evaluation of longstanding theories of descriptive representation in the policing context. If officers of different backgrounds do not exhibit behavioral differences, descriptive representation is unlikely to produce claimed benefits. But if behavioral disparities are present, there is reason to continue investigating officer-level attributes as a partial solution to abusive policing practices.

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.

	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. Within each MDSB, we compute differences in discretionary enforcement between officer groups of various profiles, 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.5 for additional details on estimation). 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 Black, White, Democratic, and Republican officers appear at least once.[20] This ensures that cross-race and cross-party comparisons are based on the same sets of times and places. A second set of analyses subsets to MDSBs with Hispanic, White, Democratic, and Republican 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 B.6 for an examination of these feasibility constraints.

Figures 6–7 display the results of these behavioral analyses (see Appendix B.5 for full numeric results; all p-values adjusted for multiple testing Benjamini and Hochberg, 1995). Turning first to Figure 6, 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 B7–B9). While substantial, these Democrat-Republican officer gaps in discretionary policing are smaller than the corresponding Black-White officer gaps for stops (by a factor of roughly 1.8x; $p_{\text{diff}} < 0.001$). 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 Democrat, Black Republican, and White Democrat officers all make fewer stops than White Republican officers facing similar circumstances. However, we caution that this difference in disparities may be due in part to 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.

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

[20] 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.

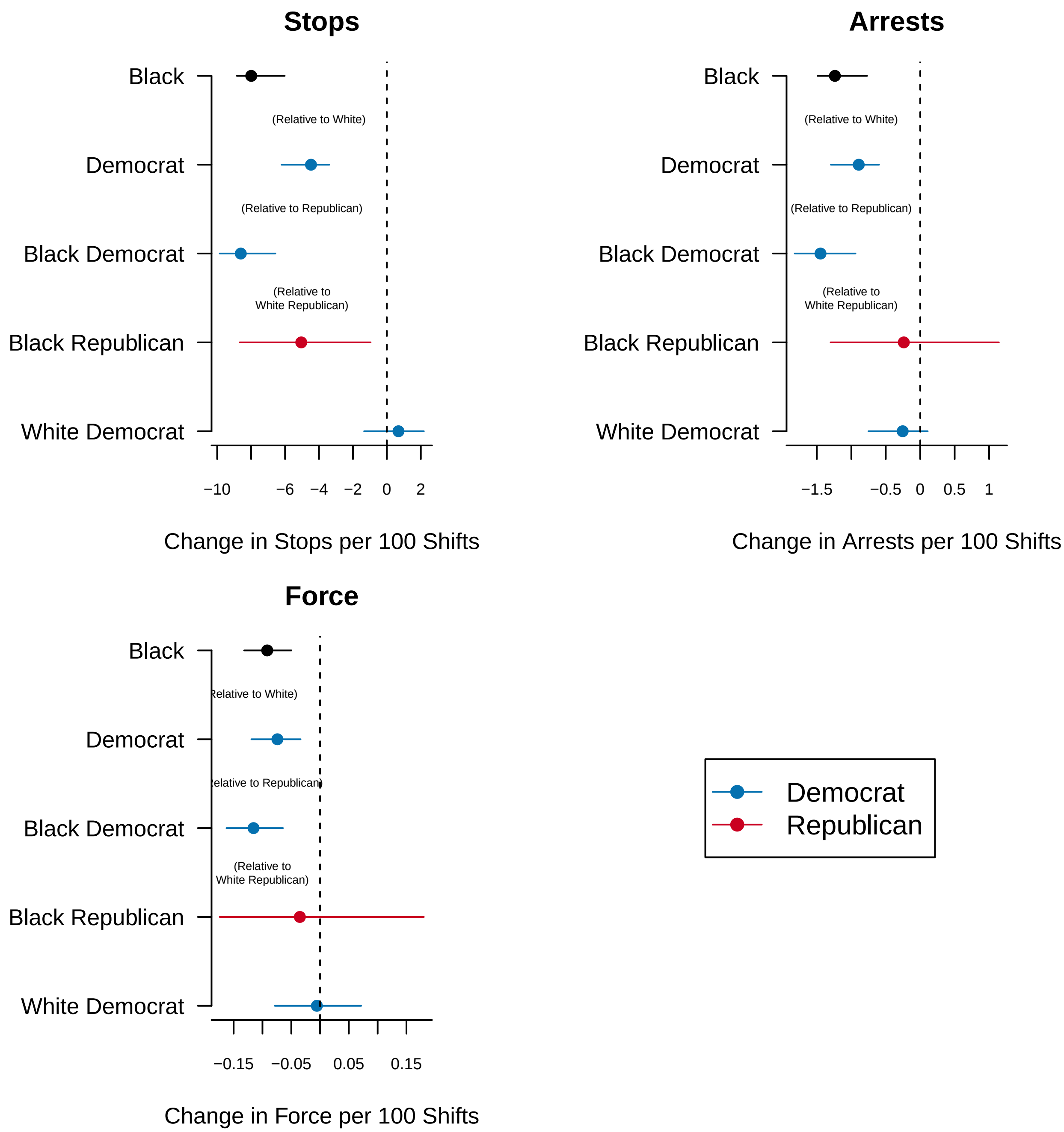

Figure 6: **Race and Party Deployment Effects, Black vs. White Officers**. The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to otherwise common circumstances. Estimates computed using only places and times where at least one Black, White, Republican and Democratic officer was deployed. See Appendix Table B16 for numeric results.

from their Republican counterparts in terms of stops, arrests and uses of force. However, as Figure 7 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 $p_{\text{adj}} < 0.046$).

To investigate how different groups of civilians are impacted by these deployments, Figures B13–B14 and Tables B20–B21 present results by civilian race/ethnicity. In MDSBs where Black, White, Democratic and Republican officers all worked at least one shift, both race- and party-based deployments yield significant reductions, which are concentrated in encounters with Black civilians. Specifically, deploying a Black officer yields reductions of 6.26 stops of, 0.86 arrests of and 0.07 uses of force against Black civilians per 100 shifts. Deploying a Democratic 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). As in the previous analysis, race- and party-based deployment effects are indistinguishable for arrests and use of force, though again, both effects are most pronounced in interactions with Black civilians. When deploying Black instead of White officers, we also see significant reductions in stops and arrests of Hispanic and White civilians, but they are much smaller in magnitude (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 $p_{\text{adj}} = 0.046$). 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 $p_{\text{adj}} \leq 0.008$).

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.

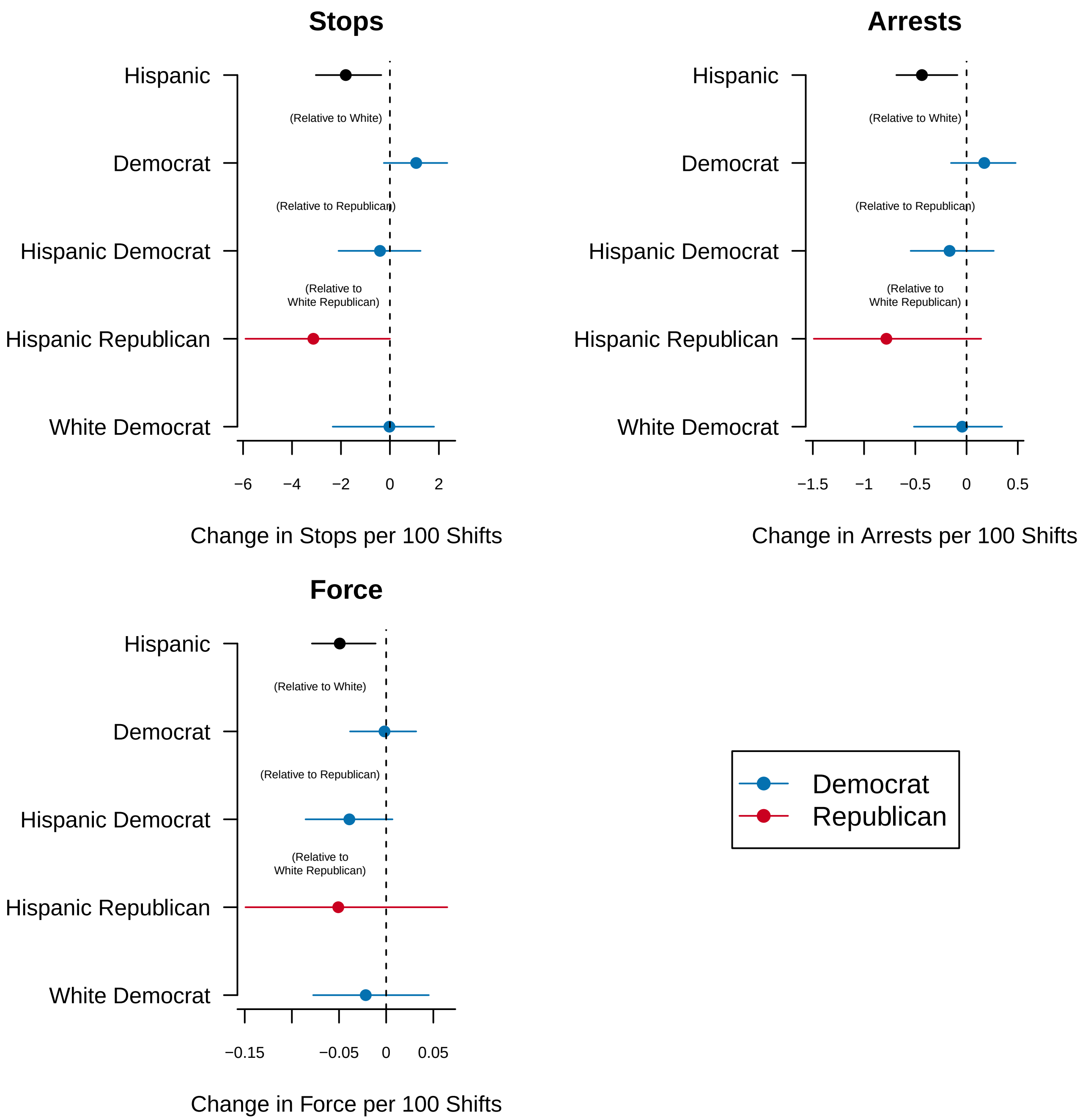

Figure 7: **Race and Party Deployment Effects, Hispanic vs. White Officers**. The figure displays the average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to otherwise common circumstances. Estimates computed using only places and times where at least one Hispanic, White, Republican and Democratic officer was deployed. See Appendix Table B17 for numeric results.

6 Discussion and Conclusion

Scholars and activists have asserted for decades that a representative bureaucracy which resembles the civilians it serves would promote competence and fairness in government. But assessing the prevalence of such descriptive representation in the context of policing remains a challenging task due to data constraints. This is especially true at the subnational level, where differences in record-keeping and data-sharing policies between numerous agencies pose a substantial obstacle to both scholarship and oversight. 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 diversity in policing. Improving on prior work in this area, which tends to focus on just one or two officer traits, we present a multi-dimensional analysis that allows us to characterize the degree to which officers share common demographic, political, 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 White, male, Republican and have higher household income than the average civilian in their jurisdiction, and they tend to live in areas that are similarly outlying on these dimensions. Police are also far more politically active than civilians, turning out to vote at extremely high rates. By analyzing political affiliations within racial groups, we further find the political mismatch between officers and civilians is more pronounced among White and Hispanic individuals, with officers from these groups identifying as Republican at far higher rates than their civilian counterparts.

Our micro-level analysis in Chicago shows the relative importance of these traits for police behavior, using detailed data on officer shift assignments and enforcement activities to compare officers facing common circumstances. Our results paint a complex portrait of the consequences of diversity in law enforcement that varies with the race/ethnicity of officers and with the outcome being studied. We first show deploying Black officers (relative to White) to otherwise similar circumstances corresponds to much larger reductions in stops than deploying Democratic officers (relative to Republican) in the same scenarios, but the two effects are similar in terms of arrests and force; both strategies result in generally reduced enforcement toward Black and Hispanic civilians. 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. The resulting lack of data on law enforcement personnel has stymied not only research, but also public oversight. Because law enforcement agencies operate independently, police officers fired for misconduct are often rehired by other agencies (Grunwald and Rappaport, 2019; Lalwani and Johnston, 2020), and tracking officers across jurisdictions is often infeasible without data similar to ours. However, our efforts demonstrate the feasibility of obtaining such information in the vast majority of cases.

Using these records, our study provides one of the most comprehensive answers to date for a basic question: who are the police? 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 differently. 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

A Additional Details on Data and Estimation

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 data from the American Community Survey (ACS) 2015–2019 data.[21] The ACS surveys approximately 1% of the US population each year, meaning that this data is a Census estimate of the true population.

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, due to the possibility that officers may commute from outside the jurisdiction. For civilian data, however, we only include people who live within the jurisdiction of each agency. We define a jurisdiction as the area for which each agency claims primary responsibility. More specifically, the area is the county or Census Place (typically a city) where the agency claims authority. In the case of city police departments, this is the city itself. The jurisdiction for the Philadelphia Police Department, for example, is the census place called the City of Philadelphia. For sheriffs' offices, we use self-described jurisdictions per official websites. For example, Wayne County Sheriff's Office in Michigan defines their jurisdiction as "unincorporated villages and townships within Wayne County," [22] 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.[23] 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

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

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

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

primarily in extremely rural areas with low population density.

Each individual in the L2 data is associated with an address (including tract, county and state). For computational efficiency, we operate at the tract level when processing L2 data. Tracts with fewer than 100 entries in L2 were excluded. We spatially join the remaining L2 tracts with Census Place shapefiles from the US Census. Tracts that were not in any Place were considered to be in an unincorporated part of that county. We then used the jurisdiction for each agency, as defined above, to identify all tracts for which an agency has at least partial jurisdiction. For example, an agency whose jurisdiction is only a single Census Place (e.g. City of Philadelphia) 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 Section C for a series of robustness checks gauging the impact of potential mismatches.

A.3 Imputed Data on Party ID

L2 describes their method for labeling party identification as follows: "L2 has partnered with academic analysts to create party models for states lacking such registration information. The modeling is based on a great many public and private data sources including demographics available through the voter file, exit polling from presidential elections, commercial lifestyle indicators, census data, self-reported party preferences from private polling and more. Combining all of these data sets through Bayesian analysis and other statistical techniques has resulted in the 'likely' party affiliations we have applied to the voter files in these states. L2 cannot guarantee that any single voter will self-identify as being associated with the assigned 'likely' party. We believe that the accuracy level is 85% or better but make no guarantees. Users of the data should remember that this is a probability-only indicator of preferences. L2 is offering these probability indicators at no additional charge and we hope that you'll find them useful in your targeting. We invite customers' comments about their experiences with the accuracy of the models so that the feedback can be used in future refinements."

See Section C.2 for a suite of robustness checks relating to the accuracy of these imputations.

A.4 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.5 Estimation of Behavioral Differences

Our approach to estimating multi-dimensional behavioral differences is based on an extension of Ba et al. (2021), which computes average differences in counts of various police behaviors using ordinary least squares regressions with fixed effects for MDSBs. We report 95% confidence intervals based on block bootstrapping at the officer level, ensuring that inferences are robust to arbitrary within-officer dependence, including the following: overwork in one shift leading to less effort exerted in the following shift, life events leading to fluctuation in officer behavior on a timescale of a few months, or discontinuous life events like birth of a child leading to long-term changes in officer 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 that deployment effect estimates are always based on within-MDSB comparisons.

B Additional Results

B.1 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 B1: **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 2). 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.

Race	Party	Actual Officer %	Hypothetical Representative Officer %	Difference	N
White	Republican	40.05	21.94	18.11 *** [17.83, 18.39]	111,646
	Democrat	19.25	34.67	-15.42 *** [-15.65, -15.19]	111,646
Hispanic	Republican	23.07	7.49	15.57 *** [15.18, 15.97]	41,974
	Democrat	43.35	37.98	5.37 *** [4.91, 5.84]	41,974
Black	Republican	2.20	1.36	0.83 *** [0.68, 0.99]	33,468
	Democrat	52.23	66.16	-13.92 *** [-14.45, -13.39]	33,468

Table B2: **Average Officer and Civilian Party Membership by Race.** The table displays, from left to right, the share of officers that are Republicans or Democrats; 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 officer share. Officer values are generated by the number of officers in each race that are Republican or Democrat, based on L2 data, out of the total number of officers of that race according to LEMAS 2016 data. This is a subset of the total data and includes the 83 agencies in our data that are in LEMAS. Hypothetical officer shares are generated by taking the share of civilians of each race that are Republican or Democrat, based on L2 data, among the 83 jurisdictions used for the officers data and dividing it by the number of adults in these jurisdictions of each race, according to American Community Survey 5-year 2015-2019 Census data. White and Black refer to non-Hispanic White and non-Hispanic Black, respectively. Stars denote $p < .001$

Race	Party	Actual Officer %	Hypothetical Representative Officer %	Difference	N
White	Republican	40.05	21.65	18.40 *** [18.12, 18.68]	108,770
	Democrat	19.37	34.96	-15.60 *** [-15.83, -15.36]	108,770
Hispanic	Republican	22.97	7.48	15.49 *** [15.09, 15.89]	41,874
	Democrat	43.32	37.96	5.35 *** [4.89, 5.82]	41,874
Black	Republican	2.15	1.34	0.81 *** [0.65, 0.96]	32,757
	Democrat	51.36	66.16	-14.80 *** [-15.33, -14.26]	32,757

Table B3: **Average Officer and Civilian Party Membership by Race (Excluding Agencies with Data Discrepancies).** This table follows the same format and data processing as Table B2 but excludes data from four agencies—Baton Rouge City Police, Honolulu Police Department, Jefferson Parish Sheriff's Office, and St. Louis County Police Department—where the number of registered Black or Hispanic officers, based on L2 data, exceeded the number of officers of that race as measured by LEMAS 2016 data. These agencies accounted for approximately 2% of all officers included among the 83 agencies that are in LEMAS data. The table displays, from left to right, the share of officers that are Republicans or Democrats; 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 officer share. Officer values are generated by the number of officers in each race that are Republican or Democrat, based on L2 data, out of the total number of officers of that race according to LEMAS 2016 data. This is a subset of the total data and includes the 83 agencies in our data that are in LEMAS. Hypothetical officer shares are generated by taking the share of civilians of each race that are Republican or Democrat, based on L2 data, among the 83 jurisdictions used for the officers data and dividing it by the number of adults in these jurisdictions of each race, according to American Community Survey 5-year 2015-2019 Census data. White and Black refer to non-Hispanic White and non-Hispanic Black, respectively. Stars denote $p < .001$

Table B4: **Residency Requirements and Incentives by Agency.** Based on a close review of 229 hyperlinked sources. "Incentive" indicates that residency in the jurisdiction is incentivized but not mandated (coded as "yes"). "State" indicates that residency in the state is required (coded as "no"). Ambiguous cases with conflicting sources are adjudicated by majority rule. We code Kansas City P.D. as "yes," per the agency's hiring statement, but we note that a bill lifting residency requirements was signed into law by the governor on July 14, 2021. We code Las Vegas Metro P.D. as "yes" based on the union's collective bargaining agreement, which describes an incentive, but note that agency's stated conditions of employment (the sole other source identified) does not mention residency.

Agency	**Res.**	**Sources**	**Notes**
NEW YORK CITY P.D.	Y	Sources: 1, 2, 3	Or neighboring county
CHICAGO P.D.	Y	Sources: 1, 2, 3	
LOS ANGELES P.D.	N	Sources: 1, 2, 3	
LOS ANGELES COUNTY S.D.	N	Sources: 1	
PHILADELPHIA CITY P.D.	Y	Sources: 1, 2, 3	
COOK COUNTY S.O.	Y	Sources: 1	
HOUSTON P.D.	N	Sources: 1, 2, 3	
METROPOLITAN P.D., DC	N	Sources: 1, 2, 3	
DALLAS P.D.	N	Sources: 1, 2, 3	
PHOENIX P.D.	N	Sources: 1, 2, 3	
MIAMIDADE P.D.	N	Sources: 1, 2	State
BALTIMORE CITY POLICE	N	Sources: 1, 2, 3	
LAS VEGAS METRO P.D.	Y	Sources: 1, 2	Incentive, state
NASSAU COUNTY P.D.	Y	Sources: 1, 2	Or neighboring county
SUFFOLK COUNTY P.D.	N	Sources: 1, 2, 3	State
HARRIS COUNTY S.O.	N	Sources: 1	
DETROIT P.D.	N	Sources: 1, 2, 3	
BOSTON P.D.	Y	Sources: 1, 2, 3	
RIVERSIDE COUNTY S.O.	N	Sources: 1	
SAN ANTONIO P.D.	N	Sources: 1, 2, 3	State
MILWAUKEE P.D.	Y	Sources: 1, 2, 3	Within 15 miles of city limits
SAN DIEGO P.D.	N	Sources: 1, 2, 3	State
SAN FRANCISCO P.D.	N	Sources: 1, 2, 3	
HONOLULU P.D.	N	Sources: 1, 2	
BALTIMORE COUNTY POLICE	N	Sources: 1	
COLUMBUS P.D.	N	Sources: 1, 2, 3	
SAN BERNARDINO COUNTY S.O.	N	Sources: 1	
ORANGE COUNTY S.D.	N	Sources: 1	State
ATLANTA P.D.	N	Sources: 1, 2, 3	

CHARLOTTEMECKLENBURG P.D.	Y	Sources: 1, 2, 3	Within 45 miles of CMPD headquarters
JACKSONVILLE S.O.	N	Sources: 1, 2	
BROWARD COUNTY S.O.	N	Sources: 1	
CLEVELAND P.D.	N	Sources: 1, 2	
INDIANAPOLIS POLICE	Y	Sources: 1, 2	Within 50 miles of city limits
PRINCE GEORGES COUNTY POLICE	N	Sources: 1, 2	
MEMPHIS P.D.	Y	Sources: 1, 2, 3	Within shelby county
DENVER P.D.	N	Sources: 1, 2, 3	State
AUSTIN P.D.	Y	Sources: 1, 2, 3	Incentive
FORT WORTH P.D.	Y	Sources: 1, 2, 3	Within 30 minutes of report-in station
PALM BEACH COUNTY S.O.	N	Sources: 1	
NEW ORLEANS P.D.	N	Sources: 1, 2, 3	
KANSAS CITY P.D.	Y	Sources: 1, 2, 3	
FAIRFAX COUNTY P.D.	N	Sources: 1, 2, 3	
SACRAMENTO COUNTY S.O.	N	Sources: 1, 2	
ORANGE COUNTY S.O.	N	Sources: 1	
SAN JOSE P.D.	N	Sources: 1, 2, 3	
SAINT LOUIS METRO P.D.	N	Sources: 1, 2, 3	
SAN DIEGO COUNTY S.O.	N	Sources: 1, 2	State
METRO NASHVILLE P.D.	N	Sources: 1, 2, 3	
NEWARK POLICE	N	Sources: 1, 2	
SEATTLE P.D.	N	Sources: 1, 2, 3	
HILLSBOROUGH COUNTY S.O.	Y	Sources: 1	Within 50 miles of Falkenburg Road Jail
MONTGOMERY COUNTY POLICE	N	Sources: 1, 2, 3	
LOUISVILLE METRO P.D.	N	Sources: 1, 2, 3	
EL PASO P.D.	N	Sources: 1, 2, 3	
MIAMI P.D.	N	Sources: 1	
CINCINNATI P.D.	Y	Sources: 1, 2, 3	Or neighboring county
DEKALB COUNTY P.D.	N	Sources: 1, 2	
WAYNE COUNTY S.O.	N	Sources: 1	
OKLAHOMA CITY P.D.	N	Sources: 1, 2, 3	State
TUCSON P.D.	N	Sources: 1, 2	
ALBUQUERQUE P.D.	N	Sources: 1, 2, 3	
TAMPA P.D.	N	Sources: 1, 2	
LONG BEACH P.D.	N	Sources: 1, 2, 3	
ALAMEDA COUNTY S.D.	N	Sources: 1	
PORTLAND POLICE BUREAU	N	Sources: 1, 2	
MINNEAPOLIS P.D.	N	Sources: 1, 2	
JERSEY CITY P.D.	Y	Sources: 1, 2, 3	

PITTSBURGH CITY P.D.	Y	Sources: 1, 2, 3	Within 25 miles of downtown
PINELLAS COUNTY S.O.	Y	Sources: 1	Or neighboring county
MESA P.D.	N	Sources: 1, 2, 3	State
FRESNO P.D.	N	Sources: 1, 2, 3	
TULSA P.D.	Y	Sources: 1, 2, 3	
JEFFERSON PARISH S.O.	N	Sources: 1	
BIRMINGHAM P.D.	N	Sources: 1, 2	State
VIRGINIA BEACH P.D.	N	Sources: 1, 2, 3	State
OAKLAND COUNTY S.O.	N	Sources: 1	
BUFFALO CITY P.D.	Y	Sources: 1, 2, 3	
SAINT LOUIS COUNTY P.D.	N	Sources: 1, 2	
OAKLAND P.D.	N	Sources: 1, 2, 3	Incentive, state
NORFOLK P.D.	N	Sources: 1, 2, 3	
MARICOPA COUNTY S.O.	N	Sources: 1	
ORLANDO P.D.	Y	Sources: 1, 2	Within 35 miles of downtown
VENTURA COUNTY S.O.	N	Sources: 1	
RICHMOND P.D.	N	Sources: 1, 2	
OMAHA P.D.	N	Sources: 1, 2, 3	
KING COUNTY S.O.	N	Sources: 1	
ROCHESTER CITY P.D.	Y	Sources: 1, 2, 3	Or neighboring county
RALEIGH P.D.	N	Sources: 1, 2	
SACRAMENTO P.D.	Y	Sources: 1, 2, 3	Incentive
GWINNETT COUNTY P.D.	N	Sources: 1	
CONTRA COSTA COUNTY S.O.	N	Sources: 1	
COLORADO SPRINGS P.D.	N	Sources: 1, 2, 3	
WICHITA P.D.	Y	Sources: 1, 2, 3	Within 30 minutes of city limits
YONKERS CITY P.D.	Y	Sources: 1, 2	Or neighboring county
TOLEDO P.D.	N	Sources: 1, 2	
ANNE ARUNDEL COUNTY POLICE	N	Sources: 1	
BATON ROUGE CITY POLICE	N	Sources: 1, 2, 3	
COLLIER COUNTY S.O.	N	Sources: 1	
AURORA P.D.	N	Sources: 1, 2, 3	

Variable	Description	N	Percent
Political Party	Republican	70,882	37.61
	Democratic	68,360	36.27
	Non-Partisan	43,606	23.13
	American Independent	1,474	0.78
	Independence	932	0.49
	Libertarian	832	0.44
	Conservative	721	0.38
	Registered Independent	569	0.30
	Other	476	0.25
	Unknown	187	0.10
	Green	180	0.10
	Peace And Freedom	116	0.06
	Working Family Party	76	0.04
	Constitution	21	0.01
	Reform	16	0.01
	Natural Law	11	0.01
	Constitutional	7	0.00
	Socialist	7	0.00
	Women's Equality Party	7	0.00
	Worker's Party	3	0.00
	American	2	0.00
	Bread And Roses	2	0.00
	Independent Democrat	1	0.00
	Tea	1	0.00
	Whig	1	0.00

Table B5: **Descriptive Statistics on Officer Partisanship.** Number and percentage of officers in each political party, as reported in L2 data.

Table B6: **Party Membership by Police Agency.** Percentage of officers in each political party as reported in L2 data, by agency.

Agency	% Republican	% Democratic	% Other	% Registered to Vote
Alameda County Sheriff	41.64	32.67	25.69	85.42
Albuquerque Police Department	60.71	21.42	17.88	92.93
Anne Aroundel County Police	52.59	27.93	19.48	77.84
Atlanta Police Department	20.90	62.76	16.35	83.55
Aurora Police Department	50.25	9.95	39.80	85.82
Austin Police Department	48.93	35.38	15.69	88.01
Baltimore County Police	58.09	23.18	18.73	94.32
Baltimore Police Department	35.56	43.87	20.56	82.15
Baton Rouge City Police	40.45	36.84	22.71	94.06
Birmingham Police Department	33.30	64.75	1.95	95.98
Boston Police Department	12.60	28.64	58.76	93.27
Broward County Sheriffs Office	36.60	32.66	30.74	87.01
Buffalo Police Department	28.74	47.70	23.56	93.17
Charlotte-Mecklenburg Police Department	44.97	19.89	35.14	82.64
Chicago Police Department	14.55	57.76	27.69	95.6
Cincinnati Police Department	45.43	25.51	29.06	89.59
Cleveland Police Department	30.12	34.91	34.97	91.97
Collier County Sheriffs Office	65.82	15.82	18.35	61.24
Colorado Springs Police Department	51.61	10.87	37.52	81.81
Columbus Police Department	49.87	18.73	31.41	90.99
Contra Costa County Sheriff	39.98	33.37	26.65	84.83
Cook County Sheriffs Office	19.55	55.19	25.26	94.26
Dallas Police Department	45.19	42.46	12.35	78.45
Dekalb County Police Department	13.68	67.77	18.55	82.28
Denver Police Department	33.20	27.59	39.21	77.84
El Paso Police Department	19.91	75.64	4.44	93.59
Fairfax County Police Department	32.30	45.11	22.59	69.9
Fort Worth Police Department	51.65	33.43	14.92	92.88
Fresno Police Department	59.73	20.07	20.20	92.42
Gwinnett County Police Department	36.60	23.07	40.33	93.18
Harris County Sheriff Office	38.87	48.26	12.87	89.13
Hillsborough County Sheriffs Office	55.63	17.00	27.36	69.65
Honolulu Police Department	16.70	26.73	56.58	83.95
Houston Police Department	41.67	43.90	14.44	93.97
Indianapolis Police Department	54.00	19.82	26.17	79.26
Jacksonville County Sheriff	62.32	18.70	18.99	81.97
Jefferson Parish Sheriff's Office	37.68	35.68	26.64	86.14

Jersey City Police Department	16.12	48.00	35.88	84.49
Kansas City Police Department	53.51	24.99	21.51	92.33
King County Sheriff Office	34.94	38.07	26.99	93.74
Las Vegas Metro Police Department	54.24	17.24	28.52	86.84
Long Beach Police Department	43.12	30.26	26.62	90.06
Los Angeles County Sheriff	43.68	31.12	25.21	87.71
Los Angeles Police Department	34.60	36.96	28.45	92.93
Louisville Metro Police Department	53.97	32.57	13.47	92.29
Maricopa County Sheriff Office	55.68	16.62	27.70	94.01
Memphis Police Department	26.61	35.62	37.77	90.81
Mesa Police Department	65.00	11.18	23.82	83.42
Metro Nashville Police Department And Sheriff	39.15	17.38	43.48	81.27
Metropolitan Police Department, D.c.	9.73	69.11	21.16	71.26
Miami Police Department	34.80	32.77	32.43	87.87
Miami-Dade Police Department	40.25	32.59	27.16	73.97
Milwaukee Police Department	32.92	46.19	20.88	32.12
Minneapolis Police Department	39.79	24.29	35.92	85.15
Montgomery County Police	48.90	28.86	22.24	85.27
Nassau County Police Department	53.65	18.44	27.91	95.78
New Orleans Police Department	23.32	47.55	29.13	85.34
New York City Police Department	29.00	42.25	28.74	82.2
Newark Police Department	14.31	47.38	38.31	83.08
Norfolk Police Department	32.80	39.40	27.80	79.74
Oakland Police Department	27.07	42.97	29.96	70.86
Oklahoma City Police Department	72.21	14.78	13.01	90.62
Omaha Police Department	60.51	14.94	24.56	86.34
Orange County Sheriff, CA	52.59	21.94	25.47	92.12
Orange County Sheriffs Office, FL	48.70	21.04	30.26	71.7
Orlando Police Department	44.20	23.53	32.27	74.38
Palm Beach County Sheriff Office	48.72	23.79	27.49	77.04
Philadelphia Police Department	35.20	50.14	14.66	94.81
Phoenix Police Department	50.41	19.74	29.85	88.03
Pinellas County Sheriff	53.33	19.37	27.30	82.23
Pittsburgh Police Department	46.26	42.42	11.32	95.59
Portland Police Bureau	33.33	29.01	37.66	83.18
Prince Georges County Police Department	29.38	50.79	19.83	86.88
Raleigh Police Department	41.94	16.72	41.35	94.72
Richmond Police Department	34.55	51.82	13.64	84.45
Riverside County Sheriff	46.37	24.52	29.11	93.18
Rochester Police Department	57.61	15.40	26.99	95.54
Sacramento County Sheriff	51.32	23.96	24.72	90.96

Sacramento Police Department	54.81	17.99	27.20	90.66
Saint Louis Metro Police Department	42.79	42.88	14.32	93.4
San Antonio Police Department	44.41	43.95	11.64	92.85
San Bernardino County Sheriff	45.51	29.39	25.10	93.1
San Diego County Sheriff	51.85	21.63	26.52	90.97
San Diego Police Department	49.06	22.10	28.85	94.59
San Francisco Police Department	25.72	40.61	33.67	68.5
San Jose Police Department	31.98	37.36	30.66	87.33
Seattle Police Department	42.62	34.98	22.40	85.08
St Louis County Police Department	48.10	33.06	18.84	95.26
Suffolk County Police Department	47.36	16.08	36.56	97.99
Tampa Police Department	55.49	17.99	26.52	75.93
Toledo Police Department	37.86	28.21	33.93	83.46
Tucson Police Department	55.11	16.61	28.28	84.97
Tulsa Police Department	73.93	13.82	12.25	81.53
Ventura County Sheriff	39.29	33.84	26.87	94.38
Virginia Beach Police Department	47.02	24.60	28.38	90.75
Wayne County Sheriffs Office	15.38	69.55	15.06	93.69
Wichita Police Department	61.96	11.96	26.09	76.45
Yonkers Police Department	37.71	26.69	35.59	76.13

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 B7: **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 B8: **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 B9: **Uses of force per 100 shifts, by officer and civilian group.**

B.2 Within-Jurisdiction Comparisons

Table B10: **Average Shares of White Officers and White Civilians in the Same Jurisdictions.** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers at the lower bound of a 95% confidence interview; the share of officers at the upper end of a 95% confidence interview; and the share of officers who would have the attribute if taken as a random draw from their jurisdictions.

Agency	Officer	Officer Lower Bound	Officer Upper Bound	Civilian
Alameda County Sheriff, CA	62.96	60.39	65.53	31.50
Albuquerque PD, NM	56.25	52.31	60.19	38.80
Anne Arundel County PD, MD	87.06	84.92	89.20	68.70
Atlanta PD, GA	35.81	33.52	38.10	37.60
Aurora PD, CO	83.79	81.04	86.54	46.70
Austin PD, TX	67.98	65.69	70.28	49.10
Baltimore County PD, MD	82.33	80.48	84.19	44.70
Baltimore PD, MD	49.45	48.02	50.88	27.60
Baton Rouge City PD, LA	65.91	62.42	69.41	38.70
Birmingham PD, AL	40.19	37.25	43.12	35.40
Boston PD, MA	66.58	64.67	68.50	44.50
Broward County Sheriff, FL	62.43	59.92	64.94	36.60
Buffalo PD, NY	69.48	66.18	72.78	43.10
Charlotte-Mecklenburg PD, NC	74.51	72.63	76.40	42.30
Chicago PD, IL	51.67	50.80	52.55	33.50
Cincinnati PD, OH	67.79	64.95	70.64	51.00
Cleveland PD, OH	65.88	63.67	68.09	33.70
Collier County Sheriff, FL	67.09	61.35	72.82	62.80
Colorado Springs PD, CO	81.25	78.40	84.10	69.90
Columbus PD, OH	86.90	85.44	88.36	59.20
Contra Costa County Sheriff, CA	70.53	67.75	73.31	53.50
Cook County Sheriff, IL	52.86	50.25	55.46	15.80
Dallas PD, TX	50.08	48.35	51.80	29.30
Dekalb County PD, GA	37.39	33.98	40.80	20.70
Denver PD, CO	65.72	63.14	68.30	54.20
El Paso PD, TX	16.47	14.38	18.57	12.50
Fairfax County PD, VA	82.99	81.29	84.68	50.80
Fort Worth PD, TX	67.92	65.80	70.05	41.80
Fresno PD, CA	51.81	48.52	55.10	28.00
Gwinnett County PD, GA	74.90	71.85	77.95	39.50
Harris County Sheriff, TX	49.80	47.85	51.75	29.60
Hillsborough County Sheriff, FL	71.92	69.45	74.39	49.60
Honolulu PD, HI	11.99	10.57	13.40	15.40
Houston PD, TX	45.84	44.57	47.10	27.80

Indianapolis PD, IN	82.32	80.24	84.40	54.90
Jacksonville County Sheriff, FL	69.21	66.99	71.43	51.70
Jefferson Parish Sheriff, LA	74.58	72.61	76.56	53.60
Jersey City PD, NJ	39.86	36.84	42.89	21.90
Kansas City PD, MO	76.61	74.67	78.54	57.30
King County Sheriff, WA	80.11	77.26	82.97	61.80
Las Vegas Metro PD, NV	68.76	67.22	70.30	44.20
Long Beach PD, CA	52.78	49.83	55.73	28.20
Los Angeles County Sheriff, CA	39.13	38.29	39.97	21.20
Los Angeles PD, CA	33.05	32.18	33.93	28.60
Louisville Metro PD, KY	84.37	82.88	85.85	59.00
Maricopa County Sheriff, AZ	71.61	68.42	74.80	77.60
Memphis PD, TN	43.86	41.69	46.04	27.10
Mesa PD, AZ	79.25	76.62	81.89	62.40
Metro Nashville PD And Sheriff, TN	85.36	83.70	87.02	56.10
Miami PD, FL	7.45	6.05	8.86	10.80
Miami-Dade PD, FL	20.20	19.01	21.39	11.60
Milwaukee PD, WI	66.06	63.85	68.27	35.80
Minneapolis PD, MN	76.90	74.16	79.64	60.00
Montgomery County PD, MD	78.29	76.03	80.55	44.30
Nassau County PD, NY	87.39	86.09	88.70	62.10
New Orleans PD, LA	35.27	32.78	37.76	30.80
New York City PD, NY	50.29	49.74	50.83	32.10
Newark PD, NJ	23.87	21.45	26.29	10.90
Norfolk PD, VA	71.77	68.25	75.29	42.40
Oakland PD, CA	39.76	36.83	42.68	28.30
Oklahoma City PD, OK	83.56	81.50	85.62	56.40
Omaha PD, NE	79.34	76.72	81.97	68.60
Orange County Sheriff, CA	63.22	61.23	65.22	58.00
Orange County Sheriff, FL	64.70	62.08	67.31	38.50
Orlando PD, FL	63.00	59.65	66.35	36.40
Palm Beach County Sheriff, FL	72.71	69.97	75.45	51.40
Philadelphia PD, PA	57.21	55.98	58.44	34.50
Phoenix PD, AZ	70.42	68.87	71.97	42.80
Pinellas County Sheriff, FL	80.69	78.77	82.61	81.40
Pittsburgh PD, PA	85.19	82.93	87.45	64.70
Portland Police Bureau, OR	84.22	81.79	86.66	70.50
Prince Georges County PD, MD	45.30	42.81	47.79	12.70
Raleigh PD, NC	84.31	81.65	86.96	55.20
Richmond PD, VA	60.65	56.46	64.85	40.90
Riverside County Sheriff, CA	60.15	58.05	62.26	35.40

Rochester PD, NY	72.84	69.29	76.38	37.90
Sacramento County Sheriff, CA	69.91	67.76	72.06	50.60
Sacramento PD, CA	74.47	71.45	77.49	31.80
St. Louis Metro PD, MO	70.35	67.75	72.96	43.60
San Antonio PD, TX	40.32	37.94	42.69	26.70
San Bernardino County Sheriff, CA	53.03	51.16	54.91	37.70
San Diego County Sheriff, CA	66.97	64.71	69.23	55.00
San Diego PD, CA	63.29	61.09	65.49	42.80
San Francisco PD, CA	50.14	48.59	51.68	40.50
San Jose PD, CA	46.33	43.78	48.88	27.10
Seattle PD, WA	73.12	70.76	75.48	63.70
St. Louis County PD, MO	87.92	85.78	90.07	70.70
Suffolk County PD, NY	87.03	85.70	88.37	67.60
Tampa PD, FL	69.44	66.37	72.52	43.70
Toledo PD, OH	81.22	78.27	84.18	60.10
Tucson PD, AZ	65.44	62.46	68.42	45.40
Tulsa PD, OK	75.84	72.98	78.70	54.90
Ventura County Sheriff, CA	67.11	64.27	69.95	59.90
Virginia Beach PD, VA	82.17	79.44	84.89	61.70
Metropolitan PD, D.C.	35.71	34.29	37.14	36.60
Wayne County Sheriff, MI	53.85	48.49	59.20	69.60
Wichita PD, KS	83.52	80.81	86.22	64.20
Yonkers PD, NY	81.58	78.53	84.63	36.70

Table B11: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions.** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers at the lower bound of a 95% confidence interview; the share of officers at the upper end of a 95% confidence interview; and the share of officers who would have the attribute if taken as a random draw from their jurisdictions.

Agency	Officer	Officer Lower Bound	Officer Upper Bound	Civilian
Alameda County Sheriff, CA	35.57	33.02	38.11	11.63
Albuquerque PD, NM	56.41	52.47	60.36	20.88
Anne Arundel County PD, MD	40.93	37.79	44.07	30.25
Atlanta PD, GA	17.46	15.65	19.27	7.89
Aurora PD, CO	43.13	39.43	46.82	16.31
Austin PD, TX	43.06	40.63	45.50	15.15
Baltimore County PD, MD	54.79	52.36	57.21	15.17
Baltimore PD, MD	29.21	27.91	30.51	5.93
Baton Rouge City PD, LA	38.05	34.47	41.63	17.43
Birmingham PD, AL	31.96	29.17	34.76	24.13
Boston PD, MA	11.75	10.44	13.06	3.40
Broward County Sheriff, FL	31.84	29.43	34.26	16.56
Buffalo PD, NY	26.77	23.60	29.95	7.57
Charlotte-Mecklenburg PD, NC	37.16	35.07	39.25	16.05
Chicago PD, IL	13.91	13.30	14.52	3.83
Cincinnati PD, OH	40.69	37.70	43.68	11.97
Cleveland PD, OH	27.70	25.61	29.78	4.85
Collier County Sheriff, FL	40.31	34.32	46.30	38.05
Colorado Springs PD, CO	42.22	38.61	45.83	29.90
Columbus PD, OH	45.37	43.22	47.53	14.83
Contra Costa County Sheriff, CA	33.91	31.03	36.80	17.77
Cook County Sheriff, IL	18.43	16.40	20.45	3.03
Dallas PD, TX	35.45	33.80	37.11	13.71
Dekalb County PD, GA	11.25	9.03	13.48	6.03
Denver PD, CO	25.84	23.47	28.22	9.08
El Paso PD, TX	18.64	16.43	20.84	8.56
Fairfax County PD, VA	22.58	20.69	24.46	16.95
Fort Worth PD, TX	47.98	45.70	50.25	25.56
Fresno PD, CA	55.20	51.93	58.48	19.82
Gwinnett County PD, GA	34.11	30.77	37.44	19.11
Harris County Sheriff, TX	34.64	32.79	36.50	19.67
Hillsborough County Sheriff, FL	38.75	36.07	41.42	27.41
Honolulu PD, HI	14.02	12.50	15.53	11.82
Houston PD, TX	39.15	37.91	40.39	18.29

Indianapolis PD, IN	42.80	40.10	45.50	15.16
Jacksonville County Sheriff, FL	51.08	48.68	53.48	30.95
Jefferson Parish Sheriff, LA	32.46	30.33	34.58	25.30
Jersey City PD, NJ	13.62	11.50	15.74	5.51
Kansas City PD, MO	49.40	47.12	51.69	29.13
King County Sheriff, WA	32.76	29.40	36.11	16.99
Las Vegas Metro PD, NV	47.10	45.44	48.76	24.02
Long Beach PD, CA	38.83	35.95	41.72	12.67
Los Angeles County Sheriff, CA	38.31	37.47	39.15	15.39
Los Angeles PD, CA	32.15	31.28	33.02	8.86
Louisville Metro PD, KY	49.81	47.77	51.84	19.89
Maricopa County Sheriff, AZ	52.34	48.81	55.88	43.07
Memphis PD, TN	24.16	22.29	26.04	8.84
Mesa PD, AZ	54.23	50.99	57.46	29.90
Metro Nashville PD And Sheriff, TN	31.82	29.62	34.01	12.96
Miami PD, FL	30.58	28.12	33.04	13.50
Miami-Dade PD, FL	29.77	28.41	31.13	22.71
Milwaukee PD, WI	10.57	9.14	12.01	11.45
Minneapolis PD, MN	33.88	30.81	36.96	5.17
Montgomery County PD, MD	41.69	38.99	44.40	13.83
Nassau County PD, NY	51.38	49.42	53.35	30.18
New Orleans PD, LA	19.90	17.82	21.98	8.42
New York City PD, NY	23.84	23.38	24.31	7.71
Newark PD, NJ	11.89	10.06	13.73	3.09
Norfolk PD, VA	26.16	22.72	29.60	10.55
Oakland PD, CA	19.18	16.83	21.54	3.05
Oklahoma City PD, OK	65.44	62.80	68.08	31.86
Omaha PD, NE	52.24	49.00	55.48	29.17
Orange County Sheriff, CA	48.44	46.37	50.51	32.76
Orange County Sheriff, FL	34.91	32.31	37.52	20.52
Orlando PD, FL	32.88	29.62	36.13	17.54
Palm Beach County Sheriff, FL	37.54	34.56	40.52	21.77
Philadelphia PD, PA	33.37	32.20	34.54	9.26
Phoenix PD, AZ	44.38	42.69	46.07	19.23
Pinellas County Sheriff, FL	43.85	41.44	46.26	34.97
Pittsburgh PD, PA	44.22	41.07	47.38	11.32
Portland Police Bureau, OR	27.73	24.74	30.71	9.28
Prince Georges County PD, MD	25.52	23.34	27.71	5.29
Raleigh PD, NC	39.72	36.15	43.30	16.47
Richmond PD, VA	29.17	25.27	33.08	7.91
Riverside County Sheriff, CA	43.21	41.08	45.33	22.54

Rochester PD, NY	55.04	51.08	59.01	7.02
Sacramento County Sheriff, CA	46.68	44.34	49.02	21.74
Sacramento PD, CA	49.69	46.23	53.15	10.72
St. Louis Metro PD, MO	39.97	37.17	42.76	8.79
San Antonio PD, TX	41.23	38.85	43.62	17.60
San Bernardino County Sheriff, CA	42.37	40.51	44.22	24.73
San Diego County Sheriff, CA	47.17	44.77	49.57	27.70
San Diego PD, CA	46.40	44.13	48.67	15.39
San Francisco PD, CA	17.62	16.44	18.79	4.51
San Jose PD, CA	27.93	25.63	30.22	11.16
Seattle PD, WA	36.26	33.70	38.82	4.48
St. Louis County PD, MO	45.82	42.54	49.10	33.95
Suffolk County PD, NY	46.41	44.43	48.39	27.29
Tampa PD, FL	42.13	38.84	45.42	20.29
Toledo PD, OH	31.59	28.08	35.11	10.86
Tucson PD, AZ	46.83	43.70	49.96	18.03
Tulsa PD, OK	60.28	57.01	63.55	27.94
Ventura County Sheriff, CA	37.08	34.16	40.01	27.06
Virginia Beach PD, VA	42.67	39.15	46.19	29.31
Metropolitan PD, D.C.	6.93	6.18	7.69	4.58
Wayne County Sheriff, MI	14.41	10.64	18.19	22.73
Wichita PD, KS	47.37	43.73	51.01	30.07
Yonkers PD, NY	28.71	25.15	32.27	12.71

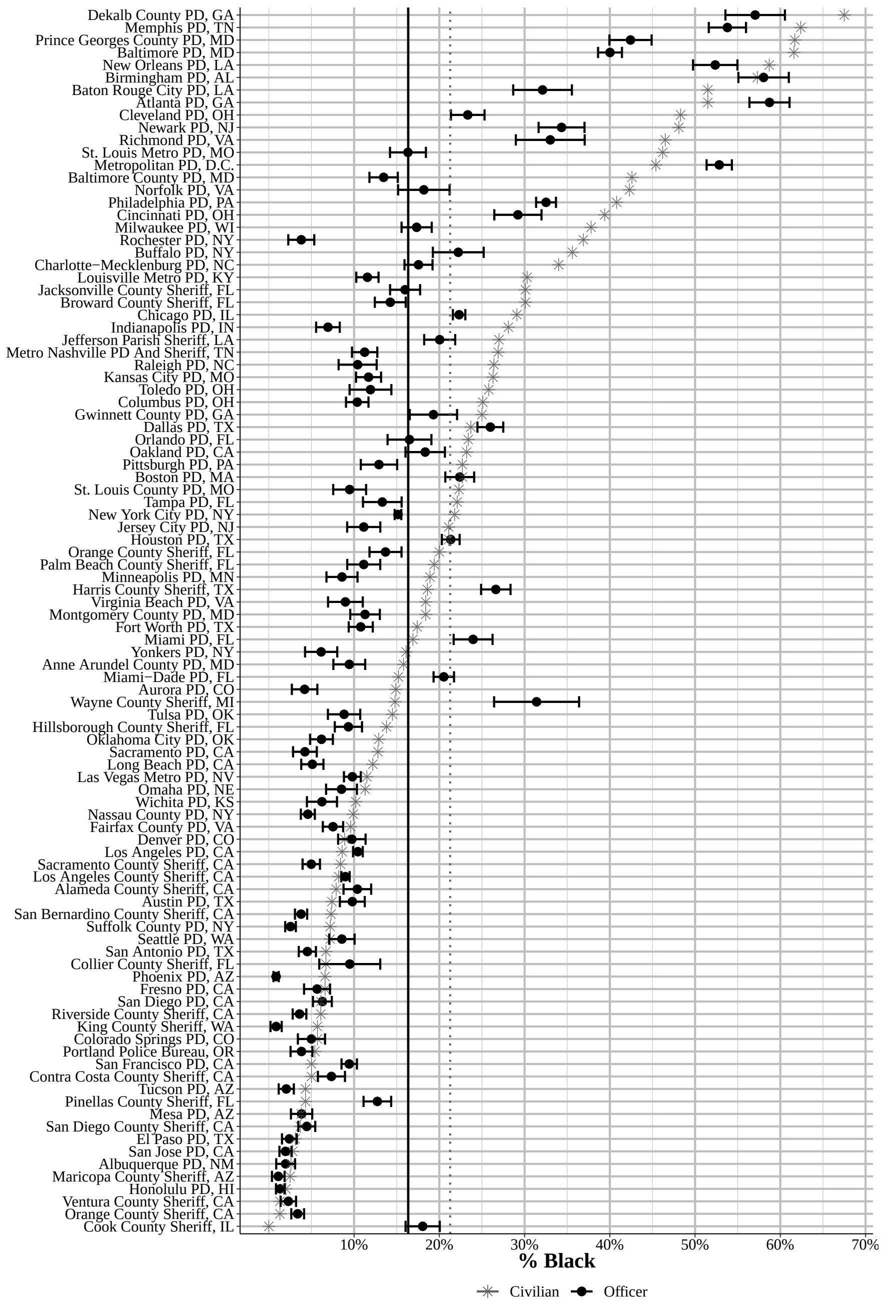

Figure B1: **Average Shares of Black Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEMAS (2016) and L2 with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

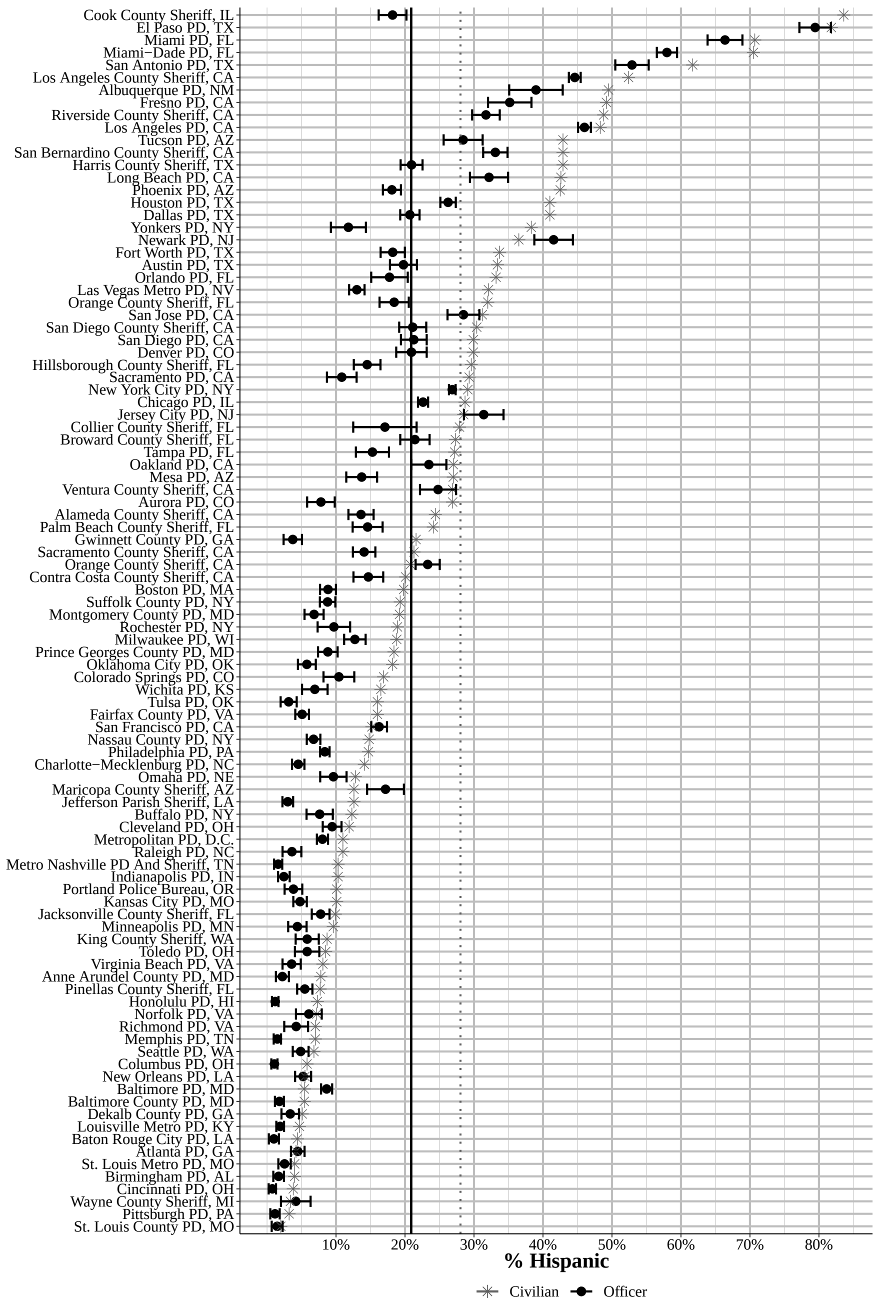

Figure B2: **Average Shares of Hispanic Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEMAS (2016) and L2 with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

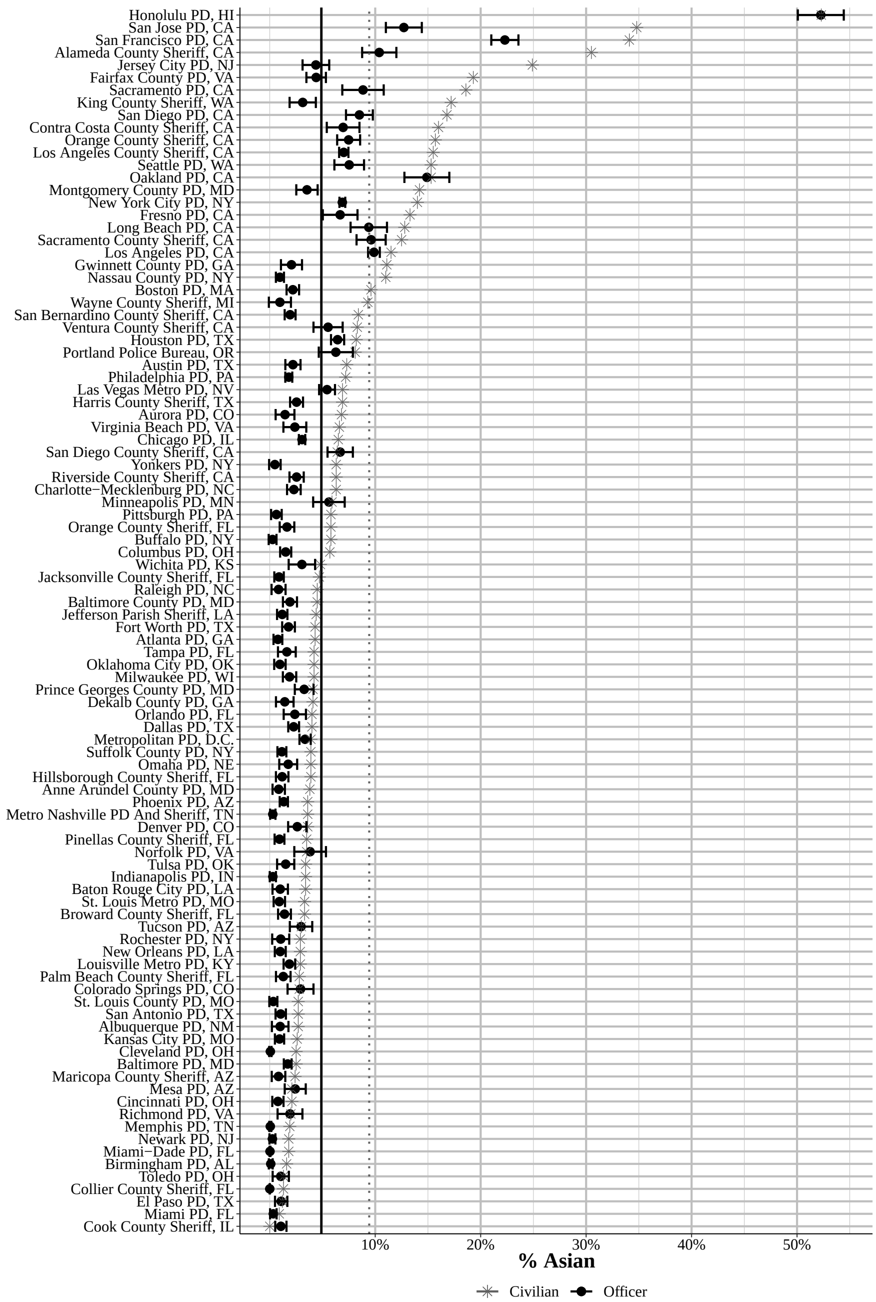

Figure B3: **Average Shares of Asian Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEMAS (2016) and L2 with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

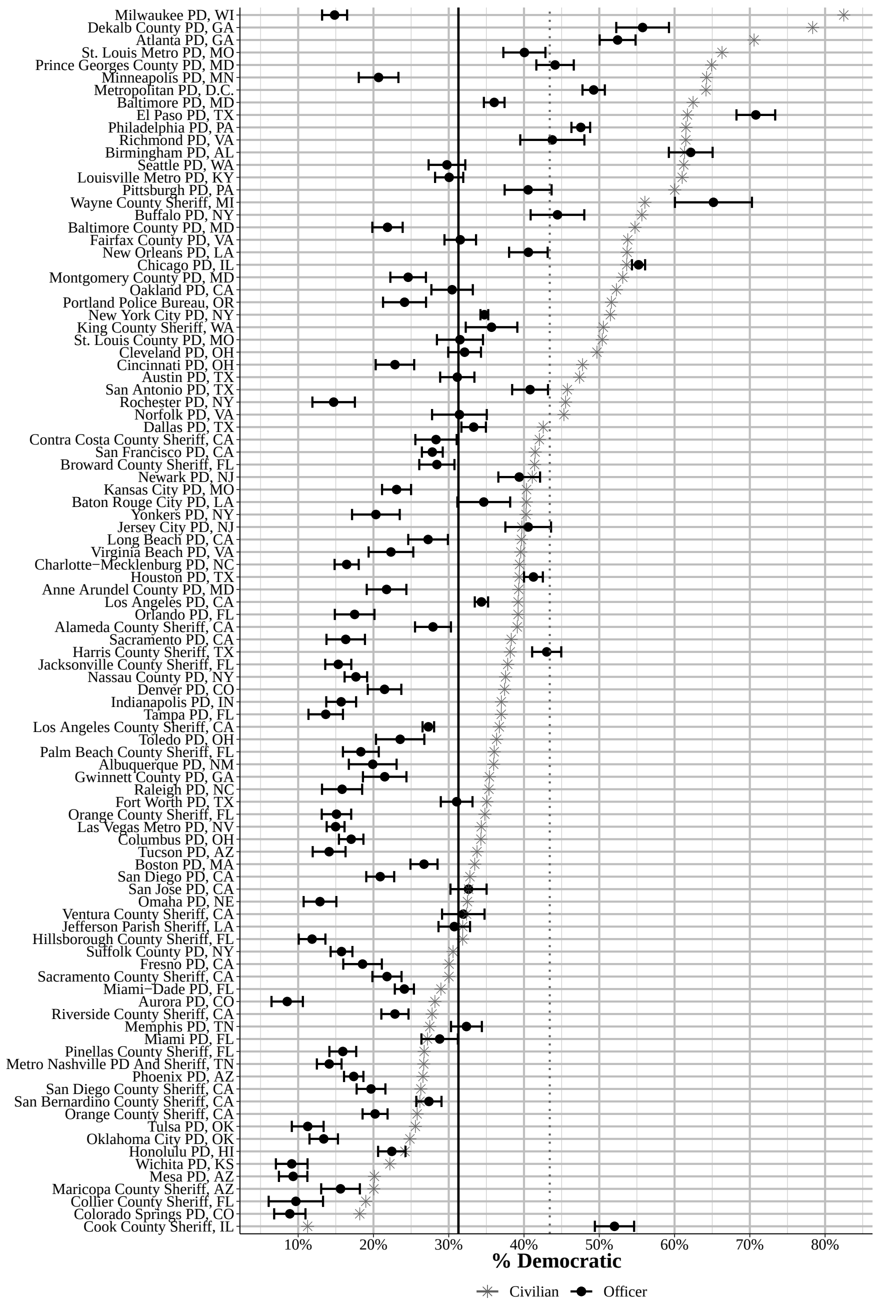

Figure B4: **Average Shares of Democrats Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

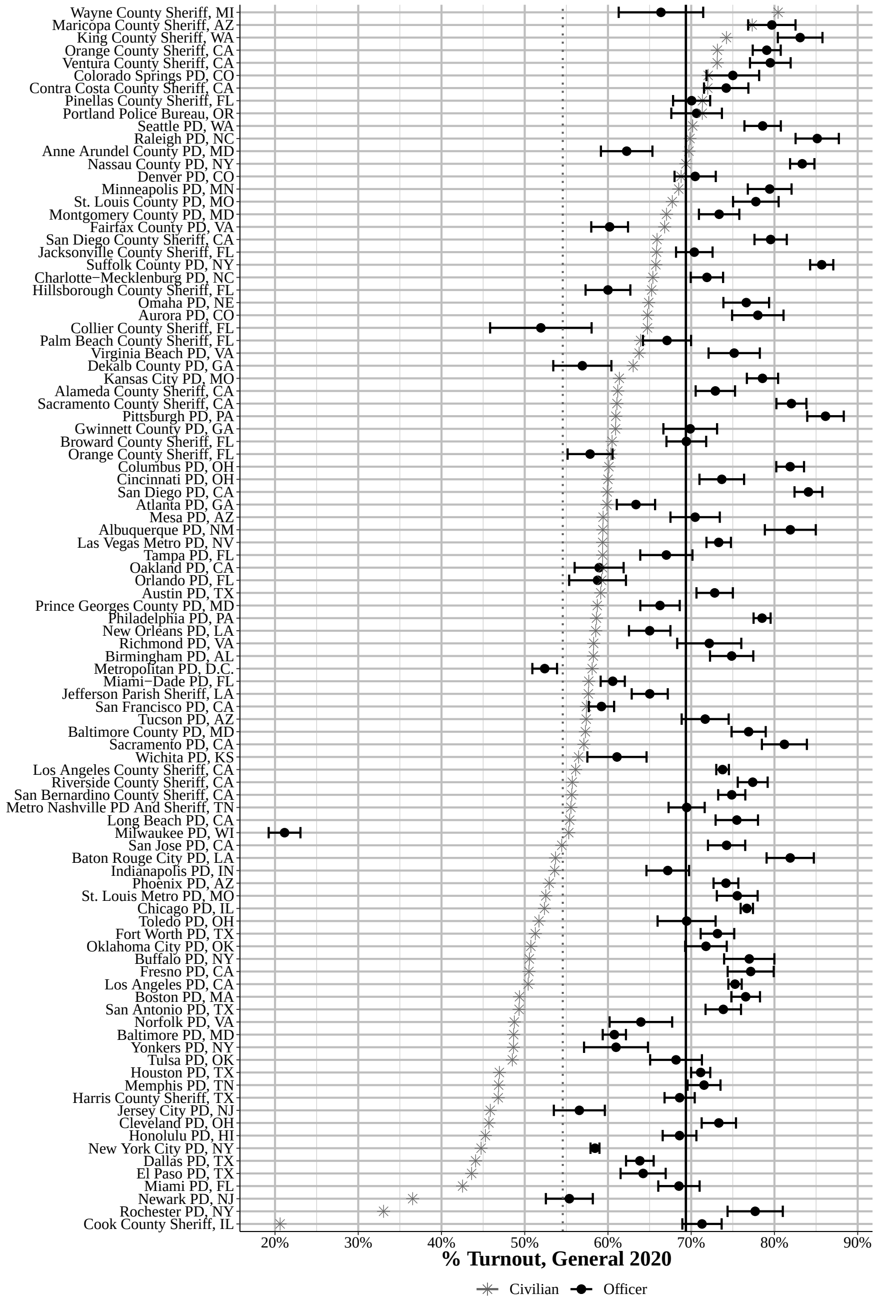

Figure B5: **Average General Election Turnout in 2020 Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

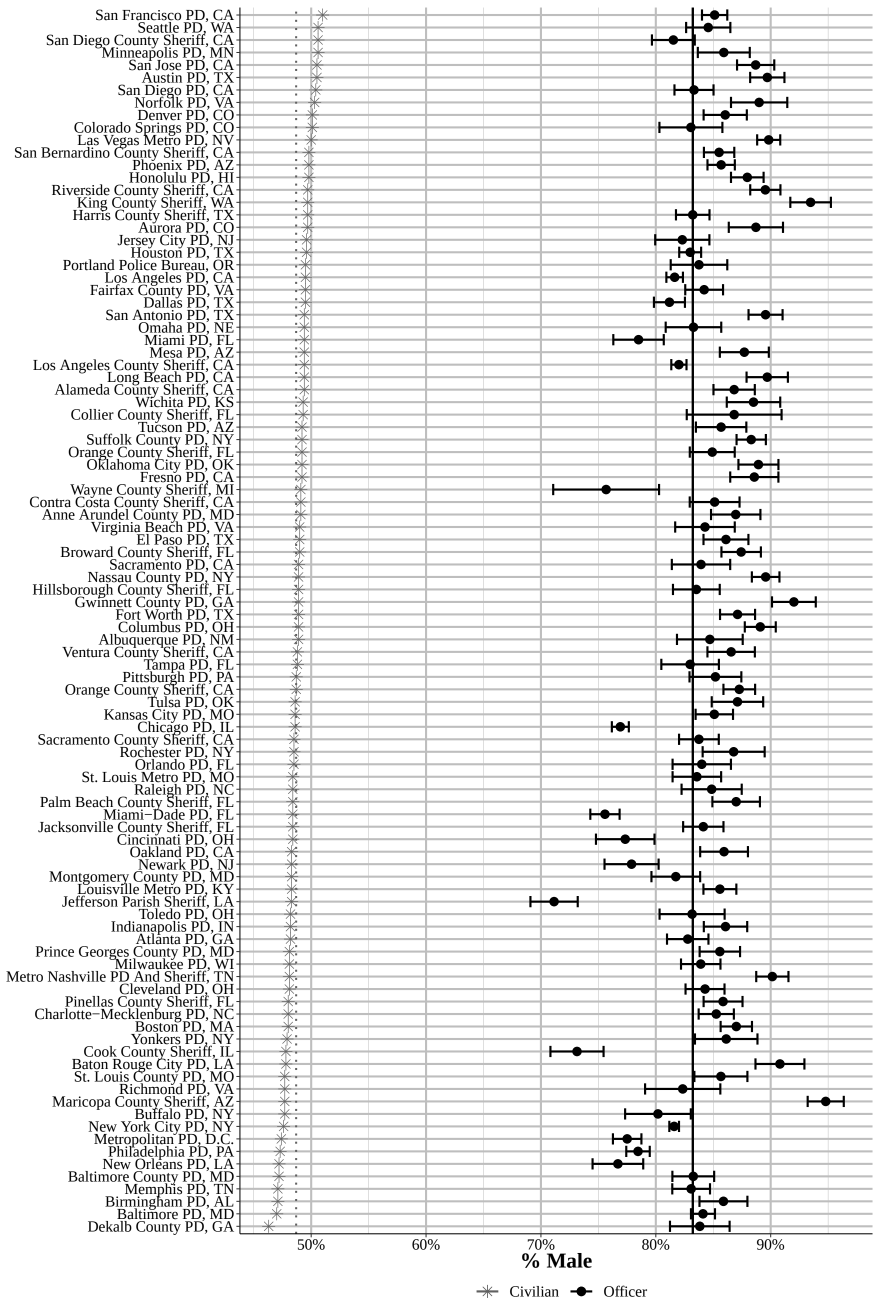

Figure B6: **Average Shares of Males Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from LEOKA 2019 data with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

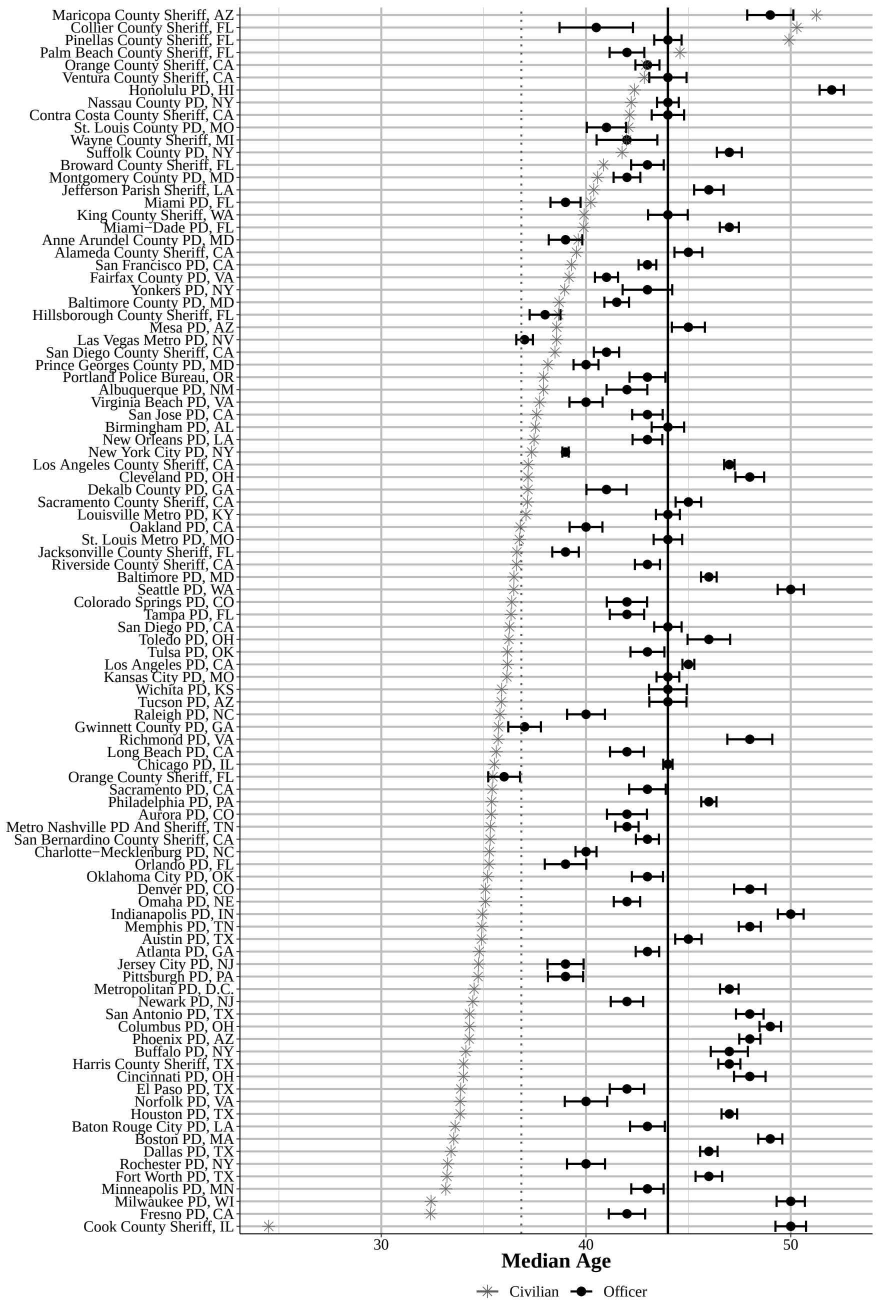

Figure B7: **Median Age Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from L2 voter file (i.e. among registered voters) with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

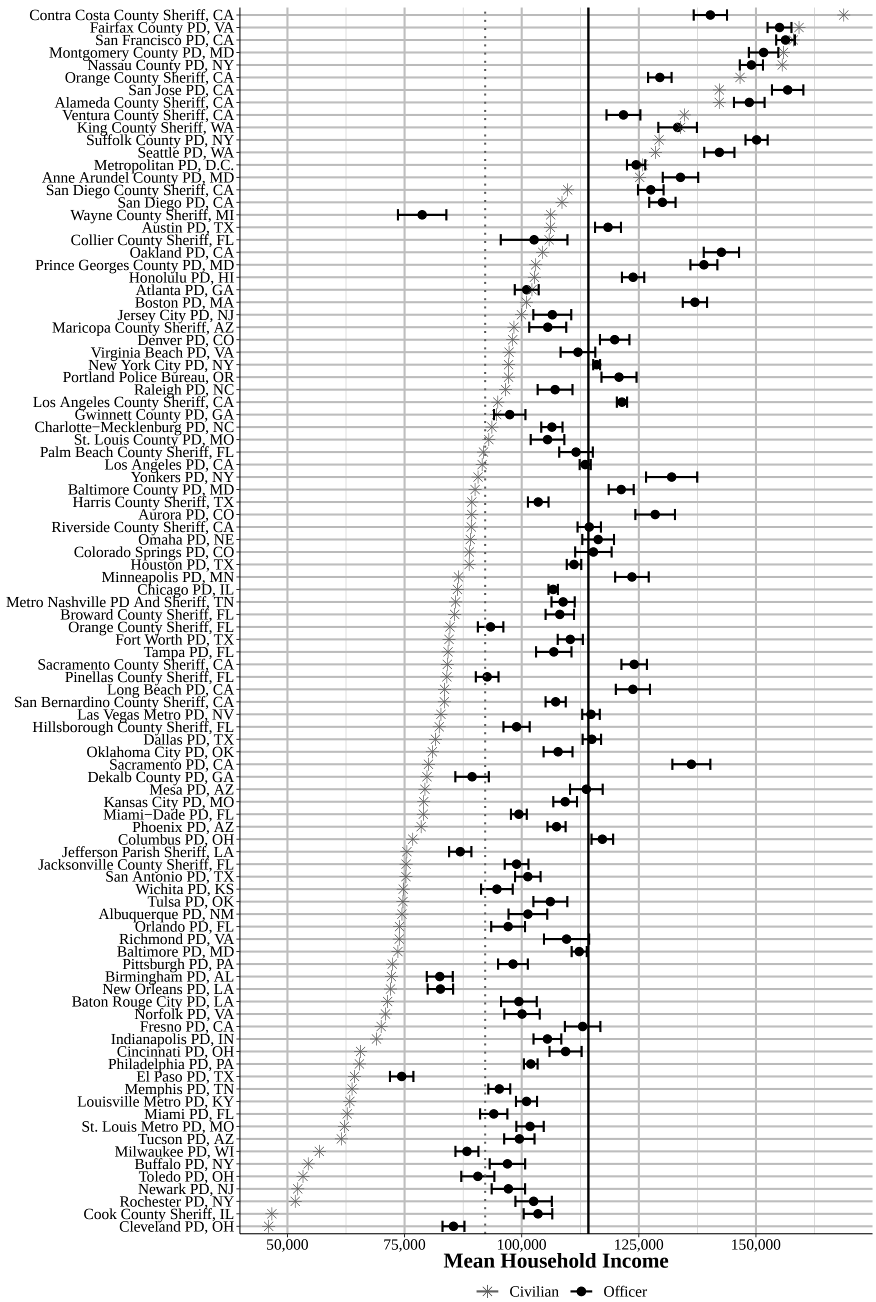

Figure B8: **Median Household Income Among Officers and Civilians in the Same Jurisdictions.** Black dots are officer shares from L2 voter file (i.e. among registered voters) with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

B.3 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 B12: **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.

B.4 Chicago Analysis

Race	Democratic	Other/Unknown Party	Republican
White	52.79	24.71	22.51
Hispanic	49.24	39.24	11.53
Black	84.30	11.11	4.59

Table B13: **Party Membership of Chicago Police Officers.** As reported in L2 voter file.

District	District Name	Officer	95% Confidence Interval		Civilian
1	Central	57.35	53.98	60.71	52.73
2	Wentworth	21.59	18.85	24.33	19.38
3	Grand Crossing	27.04	24.05	30.03	4.32
4	South Chicago	48.20	44.86	51.54	7.11
5	Calumet	33.72	30.18	37.26	1.89
6	Gresham	29.89	26.88	32.90	1.37
7	Englewood	42.31	39.14	45.47	1.30
8	Chicago Lawn	66.35	63.17	69.53	16.81
9	Deering	64.61	61.14	68.08	15.49
10	Ogden	40.52	36.96	44.07	5.10
11	Harrison	52.51	49.20	55.81	4.37
12	Near West	53.46	49.92	56.99	45.71
14	Shakespeare	50.73	46.55	54.91	52.58
15	Austin	55.64	51.89	59.39	3.31
16	Jefferson Park	80.63	77.47	83.80	63.19
17	Albany Park	68.12	64.05	72.18	40.46
18	Near North	61.11	57.86	64.36	72.58
19	Town Hall	62.01	58.70	65.33	74.23
20	Lincoln	69.69	65.60	73.78	55.40
22	Morgan Park	59.87	55.99	63.75	34.46
24	Rogers Park	72.88	69.17	76.58	43.67
25	Grand Central	65.78	62.46	69.09	14.71

Table B14: **Shares of White Chicago Officers and White Chicago Civilians in Officers' Assigned Districts.** The table displays, from left to right, the actual share of officers with a given attribute; the 95% confidence interval on that estimate; and the share of officers who would have the attribute if taken as a random draw from their assigned districts.

District	District Name	Officer	95% Confidence Interval		Civilian
1	Central	15.18	12.74	17.62	4.44
2	Wentworth	7.62	5.85	9.39	1.27
3	Grand Crossing	8.74	6.84	10.64	0.89
4	South Chicago	14.17	11.84	16.50	2.22
5	Calumet	11.09	8.74	13.45	0.89
6	Gresham	10.22	8.23	12.22	0.74
7	Englewood	11.54	9.49	13.59	0.79
8	Chicago Lawn	16.29	13.81	18.78	3.02
9	Deering	21.54	18.55	24.52	2.17
10	Ogden	17.05	14.33	19.78	1.22
11	Harrison	14.24	11.93	16.55	1.11
12	Near West	16.04	13.44	18.63	4.01
14	Shakespeare	15.27	12.27	18.28	3.53
15	Austin	17.51	14.64	20.38	0.85
16	Jefferson Park	23.87	20.46	27.29	8.83
17	Albany Park	21.39	17.81	24.96	4.21
18	Near North	14.70	12.34	17.06	7.86
19	Town Hall	17.96	15.34	20.58	5.47
20	Lincoln	17.94	14.52	21.35	3.97
22	Morgan Park	15.66	12.78	18.54	4.74
24	Rogers Park	20.98	17.58	24.37	3.48
25	Grand Central	19.47	16.70	22.23	2.59

Table B15: **Shares of Republicans Among Chicago Officers and Chicago Civilians in Officers' Assigned Districts.** The table displays, from left to right, the actual share of officers with a given attribute; the 95% confidence interval on that estimate; and the share of officers who would have the attribute if taken as a random draw from their assigned districts.

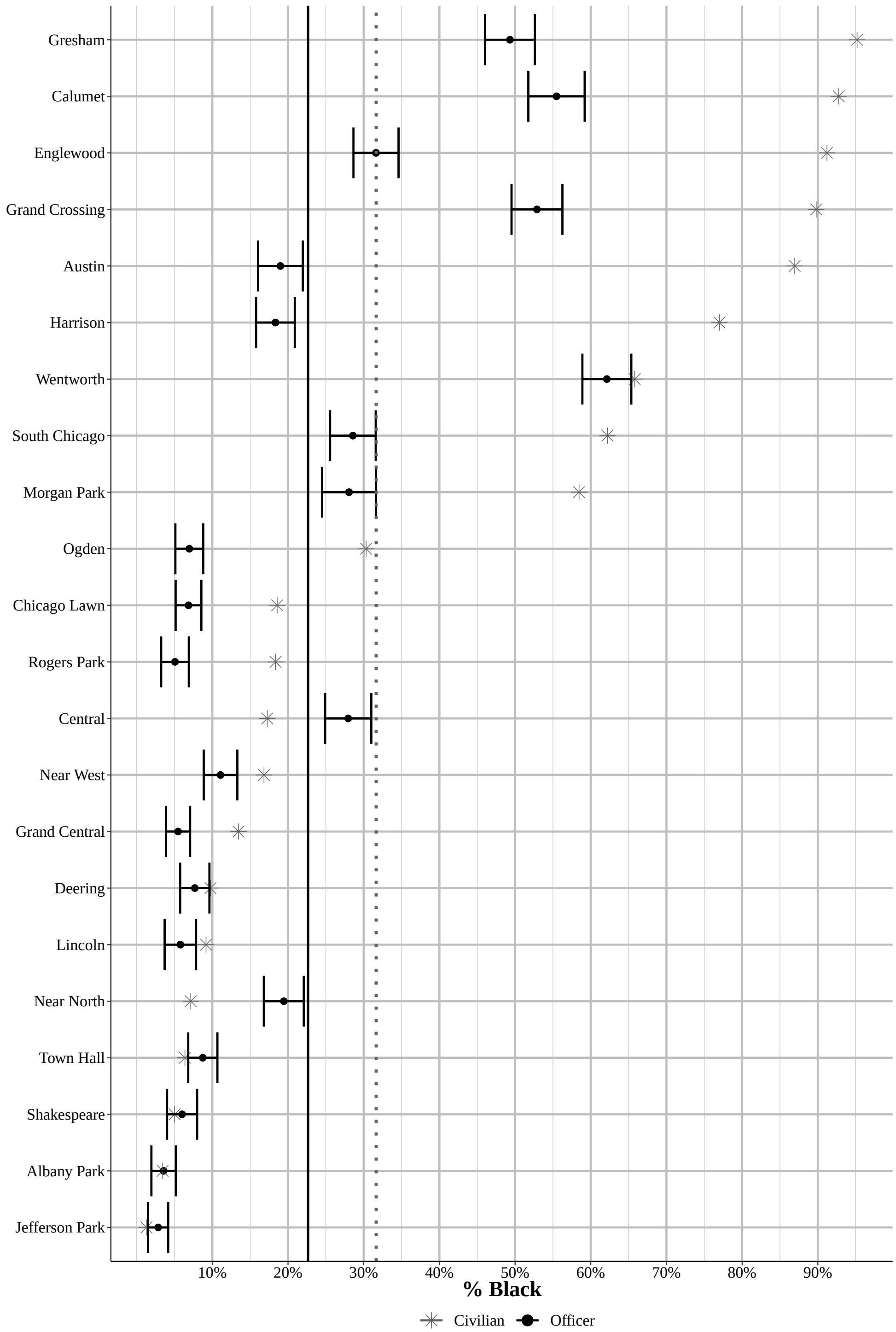

Figure B9: **Shares of Black Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district.

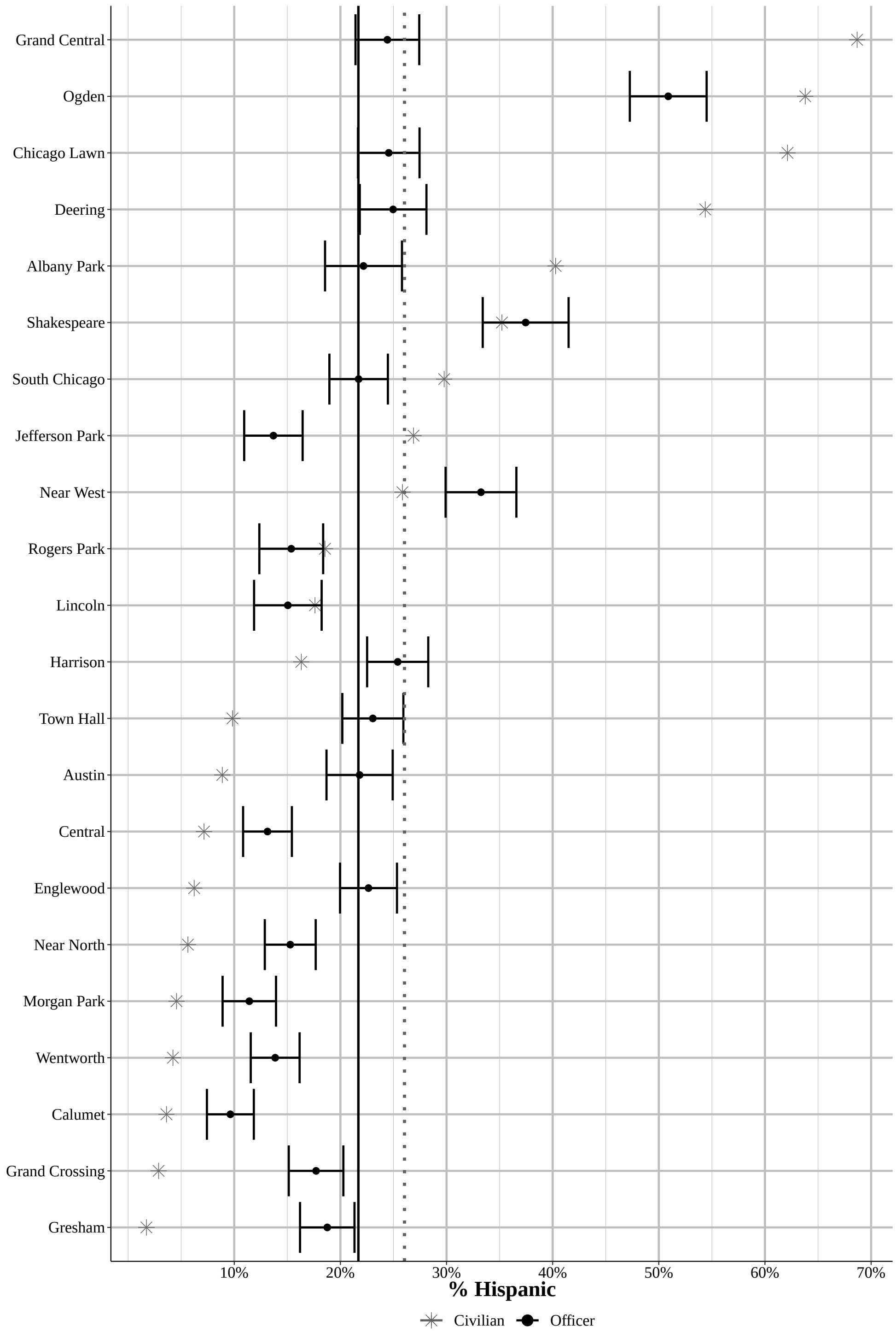

Figure B10: **Shares of Hispanic Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district.

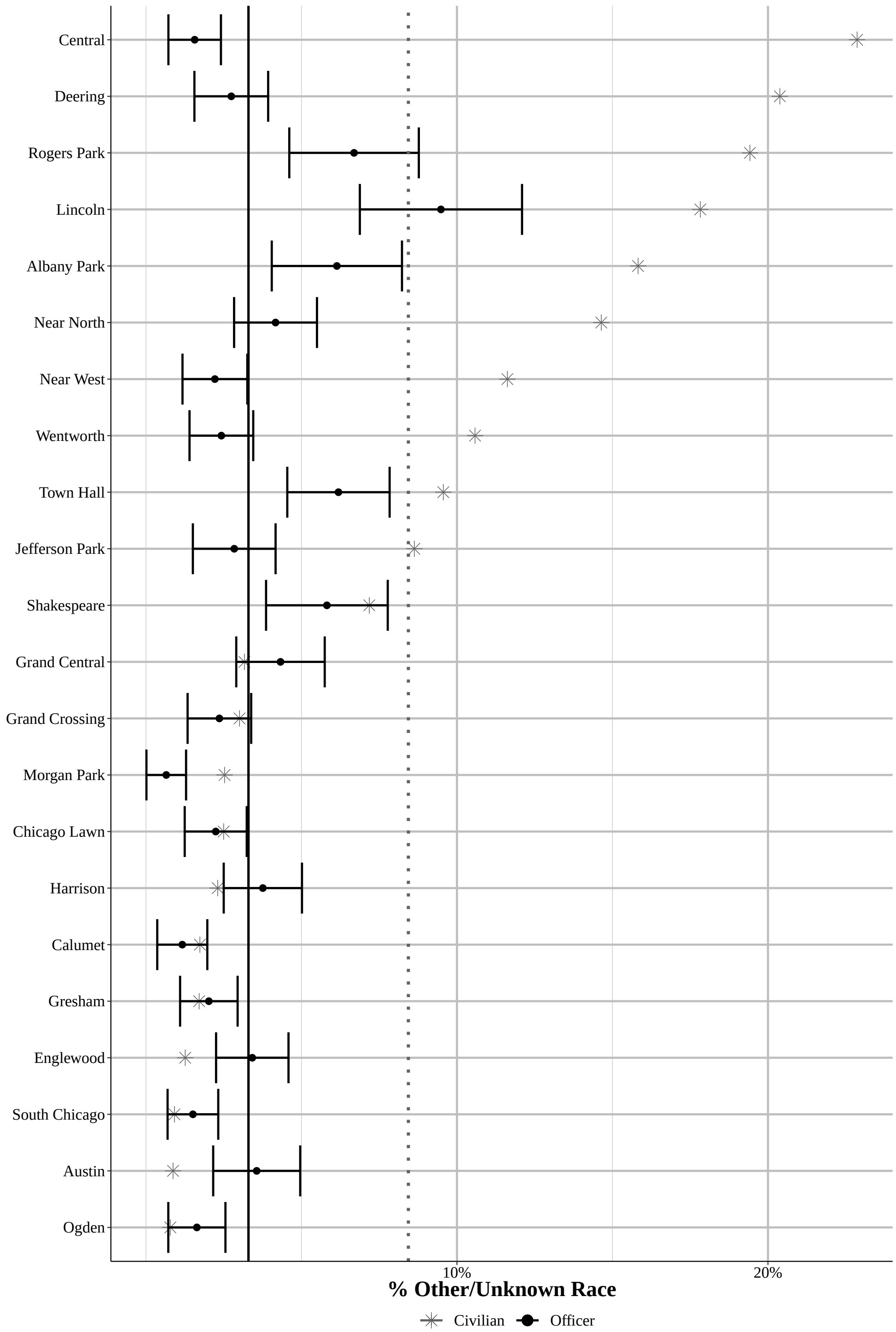

Figure B11: **Shares of Other- or Unknown-Race Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district.

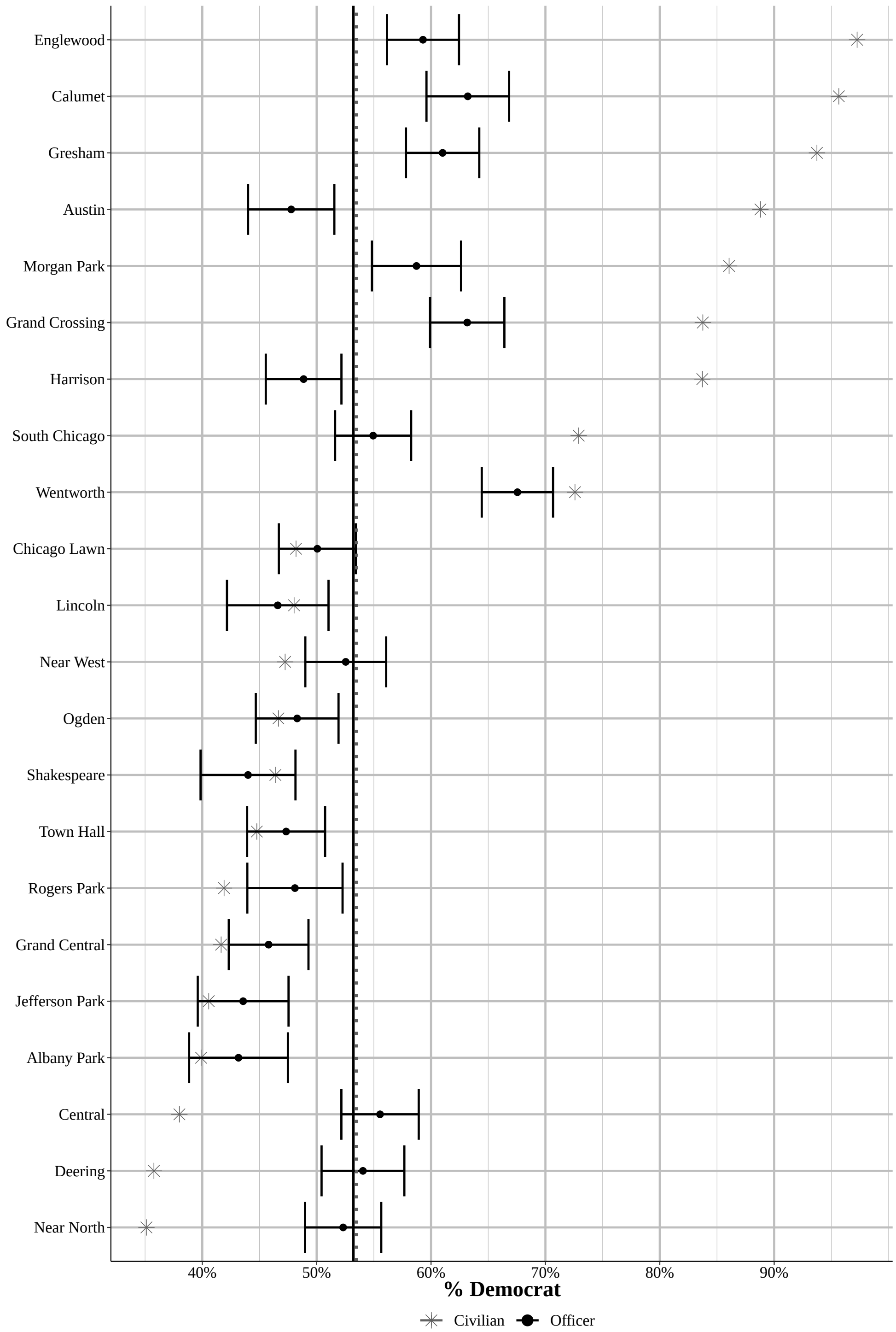

Figure B12: **Shares of Democratic Chicago Officers and Civilians in Officers' Assigned Districts.** Black dots are officer shares with 95% confidence intervals. Grey asterisks are civilian shares from U.S. Census. Vertical solid black line is the pooled officer mean. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective district.

B.5 Deployment Effects

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Black	-7.99	White	0.00	Stops
Democrat	-4.47	Republican	0.00	Stops
Black Democrat	-8.61	White Republican	0.00	Stops
Black Republican	-5.04	White Republican	0.04	Stops
White Democrat	0.68	White Republican	0.74	Stops
Black	-1.24	White	0.00	Arrests
Democrat	-0.89	Republican	0.00	Arrests
Black Democrat	-1.45	White Republican	0.00	Arrests
Black Republican	-0.24	White Republican	0.87	Arrests
White Democrat	-0.26	White Republican	0.26	Arrests
Black	-0.09	White	0.00	Force
Democrat	-0.07	Republican	0.01	Force
Black Democrat	-0.12	White Republican	0.00	Force
Black Republican	-0.04	White Republican	0.98	Force
White Democrat	-0.01	White Republican	0.99	Force

Table B16: **Deployment Effects Per 100 Shifts, Black vs. White Officers.** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. p-values adjusted for multiple testing. Estimated in places and times where at least one Black, White, Democratic and Republican officer present. Table B18 presents robustness checks using an alternate measure of partisanship based on last primary, which yield substantively identical results.

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Hispanic	-1.80	White	0.03	Stops
Democrat	1.07	Republican	0.22	Stops
Hispanic Democrat	-0.41	White Republican	0.80	Stops
Hispanic Republican	-3.13	White Republican	0.11	Stops
White Democrat	-0.02	White Republican	0.98	Stops
Hispanic	-0.44	White	0.05	Arrests
Democrat	0.17	Republican	0.49	Arrests
Hispanic Democrat	-0.17	White Republican	0.74	Arrests
Hispanic Republican	-0.78	White Republican	0.18	Arrests
White Democrat	-0.04	White Republican	0.82	Arrests
Hispanic	-0.05	White	0.03	Force
Democrat	-0.00	Republican	0.94	Force
Hispanic Democrat	-0.04	White Republican	0.18	Force
Hispanic Republican	-0.05	White Republican	0.59	Force
White Democrat	-0.02	White Republican	0.74	Force

Table B17: **Deployment Effects Per 100 Shifts, Hispanic vs. White Officers.** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. *p*-values adjusted for multiple testing. Estimated in places and times where at least one Hispanic, White, Democratic and Republican officer present. Table B19 presents robustness checks using an alternate measure of partisanship based on last primary, which yield substantively identical results.

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Black	-7.56	White	0.00	Stops
Democrat	-3.97	Republican	0.00	Stops
Black Democrat	-8.13	White Republican	0.00	Stops
Black Republican	-5.01	White Republican	0.06	Stops
White Democrat	0.61	White Republican	0.83	Stops
Black	-1.12	White	0.00	Arrests
Democrat	-0.78	Republican	0.00	Arrests
Black Democrat	-1.33	White Republican	0.00	Arrests
Black Republican	-0.31	White Republican	0.87	Arrests
White Democrat	-0.20	White Republican	0.33	Arrests
Black	-0.09	White	0.00	Force
Democrat	-0.07	Republican	0.01	Force
Black Democrat	-0.11	White Republican	0.00	Force
Black Republican	-0.02	White Republican	0.90	Force
White Democrat	0.01	White Republican	0.85	Force

Table B18: **Deployment Effects Per 100 Shifts, Black v. White Officers (Alternate Measure of Partisanship Based on Last Primary Participation).** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. *p*-values adjusted for multiple testing. Estimated in places and times where at least one Black, White, Democratic and Republican officer present. Table B16 presents main analyses using L2 estimates of partisanship, which yield substantively identical results.

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Hispanic	-1.80	White	0.03	Stops
Democrat	1.09	Republican	0.25	Stops
Hispanic Democrat	-0.39	White Republican	0.82	Stops
Hispanic Republican	-3.04	White Republican	0.18	Stops
White Democrat	0.05	White Republican	0.97	Stops
Hispanic	-0.41	White	0.07	Arrests
Democrat	0.19	Republican	0.42	Arrests
Hispanic Democrat	-0.14	White Republican	0.80	Arrests
Hispanic Republican	-0.80	White Republican	0.22	Arrests
White Democrat	-0.03	White Republican	0.82	Arrests
Hispanic	-0.05	White	0.03	Force
Democrat	-0.00	Republican	0.85	Force
Hispanic Democrat	-0.04	White Republican	0.23	Force
Hispanic Republican	-0.05	White Republican	0.54	Force
White Democrat	-0.02	White Republican	0.69	Force

Table B19: **Deployment Effects Per 100 Shifts, Hispanic v. White Officers (Alternate Measure of Partisanship Based on Last Primary Participation).** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. *p*-values adjusted for multiple testing. Estimated in places and times where at least one Hispanic, White, Democratic and Republican officer present. Table B17 presents main analyses using L2 estimates of partisanship, which yield substantively identical results.

Officer Deployed	Estimate	Reference Group	Outcome	Adjusted p-value
Black	-6.26	White	Stop Black Civilian	0.00
Black	-1.13	White	Stop Hispanic Civilian	0.00
Black	-0.65	White	Stop White Civilian	0.00
Democrat	-3.32	Republican	Stop Black Civilian	0.00
Democrat	-0.44	Republican	Stop Hispanic Civilian	0.01
Democrat	-0.49	Republican	Stop White Civilian	0.00
Black	-0.86	White	Arrest Black Civilian	0.00
Black	-0.27	White	Arrest Hispanic Civilian	0.00
Black	-0.11	White	Arrest White Civilian	0.05
Democrat	-0.59	Republican	Arrest Black Civilian	0.00
Democrat	-0.22	Republican	Arrest Hispanic Civilian	0.00
Democrat	-0.08	Republican	Arrest White Civilian	0.07
Black	-0.07	White	Force Black Civilian	0.00
Black	-0.01	White	Force Hispanic Civilian	0.04
Black	-0.01	White	Force White Civilian	0.05
Democrat	-0.05	Republican	Force Black Civilian	0.02
Democrat	-0.01	Republican	Force Hispanic Civilian	0.34
Democrat	-0.01	Republican	Force White Civilian	0.23

Table B20: **Deployment Effects Per 100 Shifts, Black vs. White Officers, by Civilian Race/Ethnicity.** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. *p*-values adjusted for multiple testing. Estimated in places and times where at least one Black, White, Democratic and Republican officer present.

Officer Deployed	Estimate	Reference Group	Outcome	Adjusted p-value
Hispanic	-1.86	White	Stop Black Civilian	0.00
Hispanic	0.22	White	Stop Hispanic Civilian	0.62
Hispanic	-0.09	White	Stop White Civilian	0.83
Democrat	0.89	Republican	Stop Black Civilian	0.14
Democrat	0.20	Republican	Stop Hispanic Civilian	0.64
Democrat	-0.00	Republican	Stop White Civilian	0.97
Hispanic	-0.34	White	Arrest Black Civilian	0.02
Hispanic	-0.08	White	Arrest Hispanic Civilian	0.58
Hispanic	-0.03	White	Arrest White Civilian	0.54
Democrat	0.12	Republican	Arrest Black Civilian	0.54
Democrat	-0.01	Republican	Arrest Hispanic Civilian	0.99
Democrat	0.05	Republican	Arrest White Civilian	0.32
Hispanic	-0.04	White	Force Black Civilian	0.01
Hispanic	0.01	White	Force Hispanic Civilian	0.64
Hispanic	-0.01	White	Force White Civilian	0.04
Democrat	0.00	Republican	Force Black Civilian	0.95
Democrat	0.00	Republican	Force Hispanic Civilian	0.69
Democrat	-0.01	Republican	Force White Civilian	0.50

Table B21: **Deployment Effects Per 100 Shifts, Hispanic vs. White Officers, by Civilian Race/Ethnicity.** The table displays the effect per 100 shifts of deploying a given type of officer on stops, arrests, and uses of force, relative to the listed reference category. p-values adjusted for multiple testing. Estimated in places and times where at least one Hispanic, White, Democratic and Republican officer present.

B.6 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 6. 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.

The strongest predictor of whether cross-officer-group comparisons can feasibly be made in an MDSB is the number of officers assigned to a particular task. Single-officer MDSBs—when only one individual is assigned to a particular beat (patrol task) in a given month, day, and shift—represent 31.3% of all MDSBs available, but these MDSBs are never feasible since mechanically speaking, there exists no other officer to whom valid comparisons can be made. Among two-officer MDSBs (which represent 23.8% of MDSBs), 2.6% are feasible for the BWDR analysis and 4.7% are feasible for the HWDR analysis, as the required comparisons can only be made when the two available officers have certain combinations of traits. However, in five-officer MDSBs (7.9% of MDSBs), 21.1% are feasible for the BWDR analysis and 40.5 are feasible for the HWDR analysis.

These feasible MDSBs are not uniformly distributed throughout the day. Among first-watch MDSBs (shifts starting at 10pm), 12.1% are feasible for the BWDR analysis and 21.8% are feasible for HWDR. During second watch (shifts starting at 6am), 6.0% are feasible for BWDR and 9.0% are feasible for HWDR. During third watch (shifts starting at 2pm), 9.4% are feasible for BWDR and 19.6% are feasible for HWDR. All pairwise differences are significant at $p<0.001$.

Similarly, feasible MDSBs are not uniformly distributed throughout the city. To examine how feasibility varies by local resident racial/ethnic group, we use areal interpolation (interpolating from Census block group boundaries to beat boundaries) to estimate the proportion of residents that are Black and Hispanic. This procedure relies on the assumption that residents are uniformly distributed within Census block groups. To examine how feasibility varies by local political orientation, we assign geocoded L2 records of registered voters to the beat in which they are contained, then compute the proportion of records that are predicted to be Democrats. We note that these analyses are necessarily limited to patrol tasks for which CPD reports the geographic boundaries (i.e. contained in the beat map). During the period of our behavioral analysis, 2012–2019, CPD officers are assigned to over 10,000 distinct patrol tasks, each represented by a beat code. Roughly half of these assignments (49%) involve known geographic boundaries that average less than

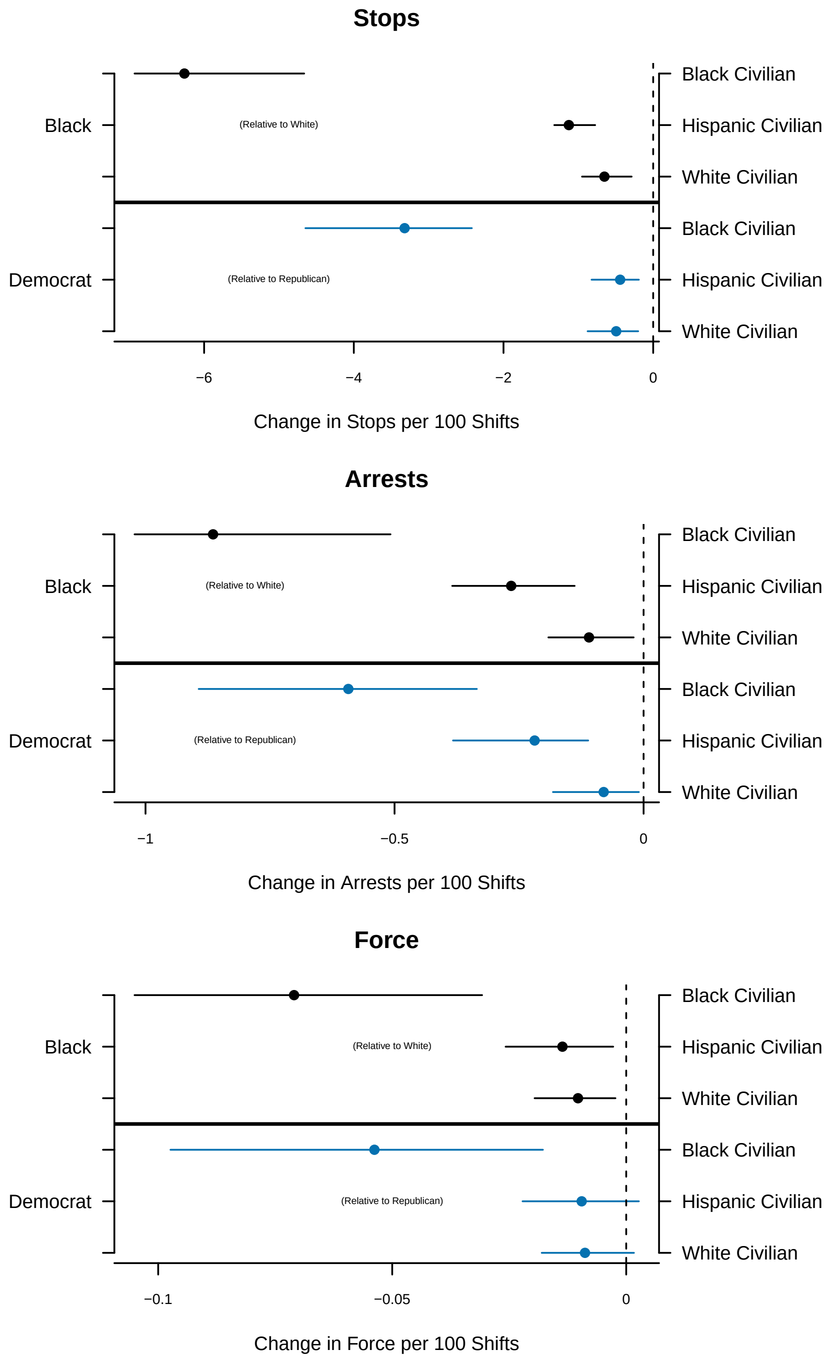

Figure B13: **Race and Party Deployment Effects, Black vs. White Officers by Civilian Race.** The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian characteristics. These estimates are computed using only places and times where at least one Black, White, Republican and Democratic officer was deployed.

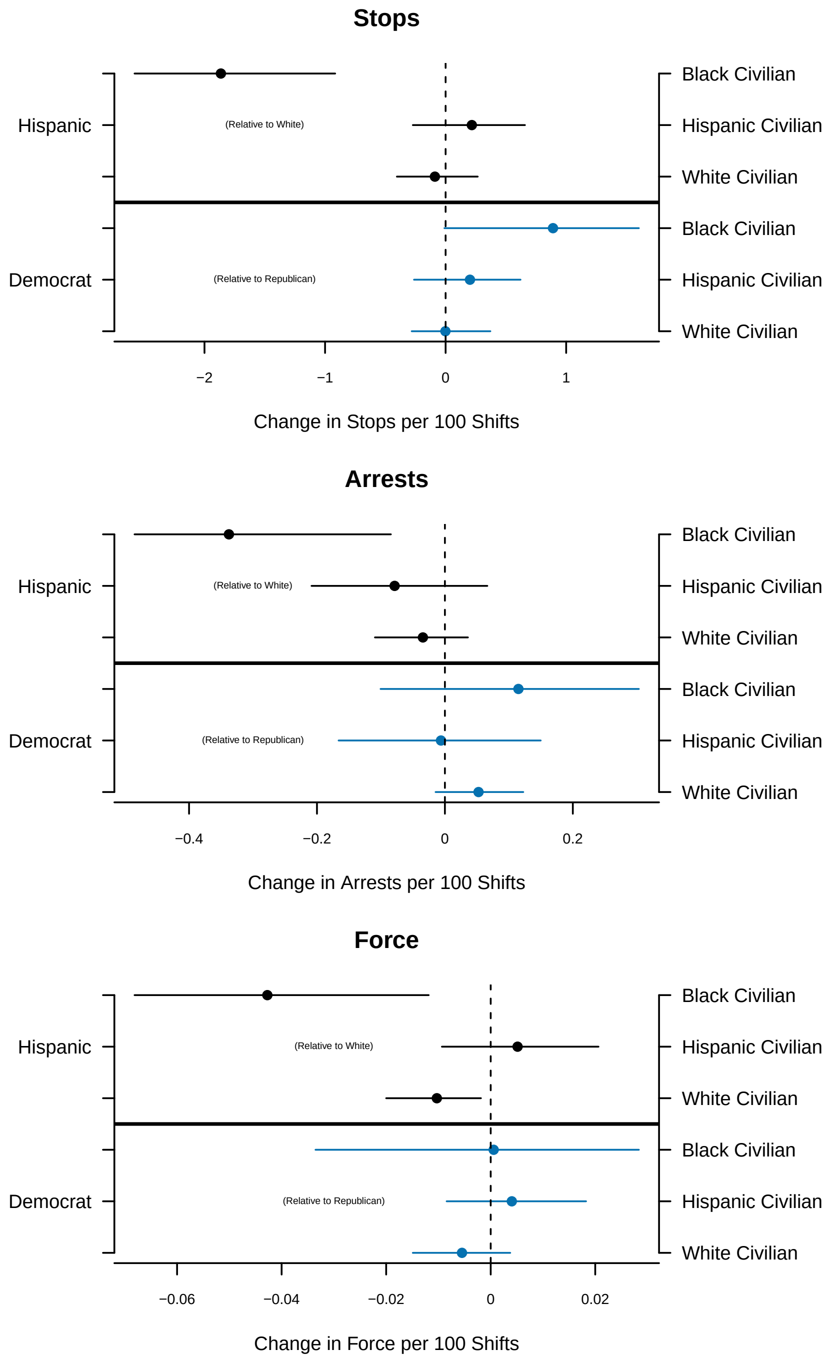

Figure B14: **Race and Party Deployment Effects, Hispanic vs. White Officers by Civilian Race.** The figure displays the average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian characteristics. These estimates are computed using only places and times where at least one Hispanic, White, Republican and Democratic officer was deployed.

one square mile. For example, area 1431 corresponds to a known collection of city blocks in the CPD's Shakespeare district, to which over 6,000 officer-shift slots were assigned. Within this geographic area, our patrol assignment data distinguishes between standard patrol tasks (indicated with beat code such as "1431", roughly 7,500 shifts) and additional patrol tasks distinguished by an alphabetical suffix (e.g., beat code "1431R", roughly 4,100 shifts). Here, beat code 1431 is assigned for second and third watch, whereas 1431R indicates a relief assignment and is always assigned for first shift (this relief assignment overlaps with the end of third watch to ensure no gap in service exists). We ensure that one officer's behavior during a 1431 assignment is compared only to other officers with 1431 assignments in the same month, shift, and day; by the same token, one officer's behavior during a 1431R assignment is only compared to similar 1431R assignments. However, MDSBs involving the 1431 and 1431R task are both associated with residents of the same geographic area when computing resident demographics. Though we cannot always pinpoint the geographic locations of patrol task assignments using CPD-provided beat maps, our hyper-granular assignment data makes it highly plausible to assume that officers working under the same assignment code are tasked with similar jobs and face common circumstances.

Across the city, we find that the median beat's residents are 22.8% Black, 10.3% Hispanic, and 67.1% Democrat. Where local resident composition can be computed, we find that 11.7% of MDSBs in areas with below-median Black resident proportion are feasible for the BWDR analysis; in contrast, MDSBs are significantly more likely to be feasible in above-median Black areas (18.2% feasible for the BWDR analysis, $p < 0.001$). This is partly due to selection in the districts where officers work and partly because beats with a higher proportion of Black residents tend to have more officers assigned to work in a given MDSB. When grouping MDSBs according to local political orientation, we find that 18.3% of MDSBs are feasible for the BWDR analysis in below-median Democratic areas, compared to 11.7% feasibility in above-median Democratic areas. Results are depicted graphically in Figure B15.

Turning to the HWDR analysis of Figure 7, we find that 23.6% of MDSBs in areas with below-median Hispanic resident proportion are feasible for the HWDR analysis; while MDSBs are significantly more likely to be feasible in above-median Hispanic areas (33.9% feasible for the BWDR analysis, p<0.001). When grouping MDSBs according to local political orientation, we find that 26.3% of MDSBs are feasible in below-median Democratic areas, compared to 30.9% feasibility in above-median Democratic areas. Results are de-

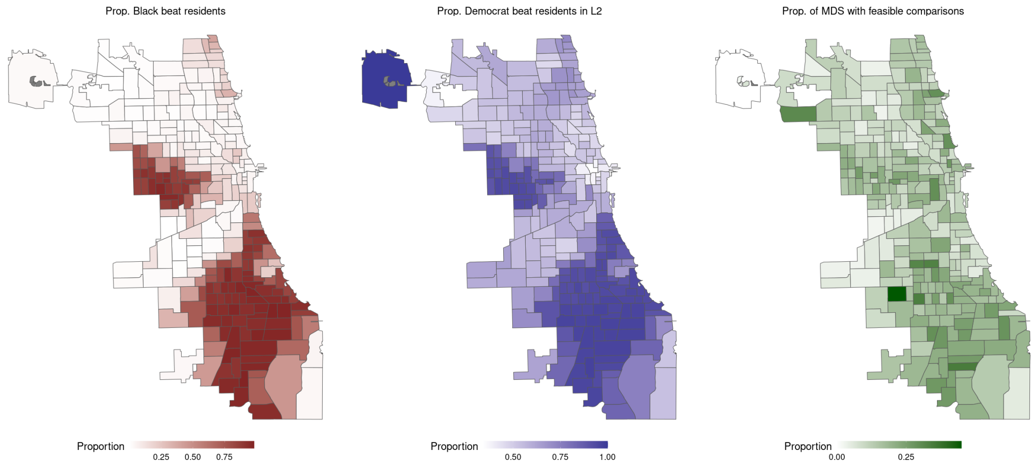

Figure B15: **Feasibility in BWDR Analyses.** Left panel depicts the proportion of Black residents in each geographic beat, based on areal interpolation from 2015–2019 Census American Community Survey block-group-level data. Center panel shows the proportion of geocoded L2 records in each beat that are characterized as Democratic. Right panel shows the proportion of MDSBs associated with a geographic beat in which comparisons across Black, White, Democrat, and Republican officers are feasible.

picted graphically in Figure B16.

To informally assess the extent to which deployment effects vary with local resident composition, we conduct exploratory BWRD subgroup analyses in which we restrict to MDSBs in areas with (1) above-median proportions of Black residents, (2) below-median proportions of Black residents, (3) above-median proportions of Democrat records in L2, and (4) below-median proportions of Democrats. Within each group, we then repeat the BWDR analysis. We find that the estimated effect of deploying an available Black officer is markedly larger (more negative, a further reduction of 9.9 stops; heterogeneity $p < 0.001$) in areas with more Black residents, compared to areas with fewer Black residents. In the BWDR analysis, we also find that the effect of deploying an available Democratic officer is larger in more Democratic areas (more negative, a further reduction of 5.1 stops per 100 shifts; $p = 0.030$). We find no evidence of heterogeneity in arrests and uses of force. See Figure B17 for additional details.

We repeat this exercise in exploratory HWRD subgroup analyses in which we restrict to MDSBs in areas with (1) above-median proportions of Hispanic residents and (2) below-median proportions of Hispanic residents, as well as (3) above-median proportions of Democrat records in L2 and (4) below-median proportions of Democrats as before. Within each group, we then repeat the HWDR analysis. We find that the estimated effect

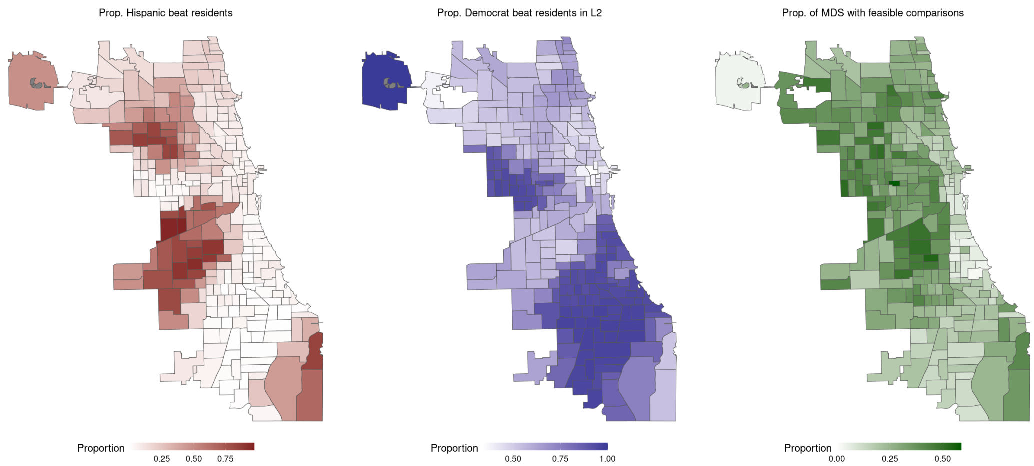

Figure B16: **Feasibility in HWDR Analyses.** Left panel depicts the proportion of Hispanic residents in each geographic beat, based on areal interpolation from 2015–2019 Census American Community Survey block-group-level data. Center panel shows the proportion of geocoded L2 records in each beat that are characterized as Democratic. Right panel shows the proportion of MDSBs associated with a geographic beat in which comparisons across Hispanic, White, Democrat, and Republican officers are feasible.

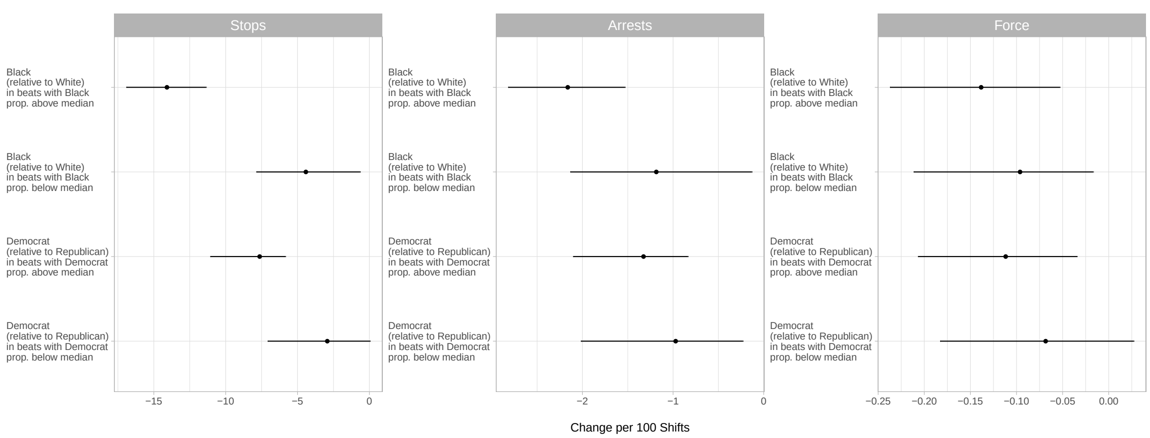

Figure B17: **Heterogeneity in BWRD deployment effects.** Black-White and Democrat-Republican deployment effects from Figure 6 are re-estimated in subgroups of geographically linkable beats that are above and below the median proportions of Black residents and Democrat registered voters.

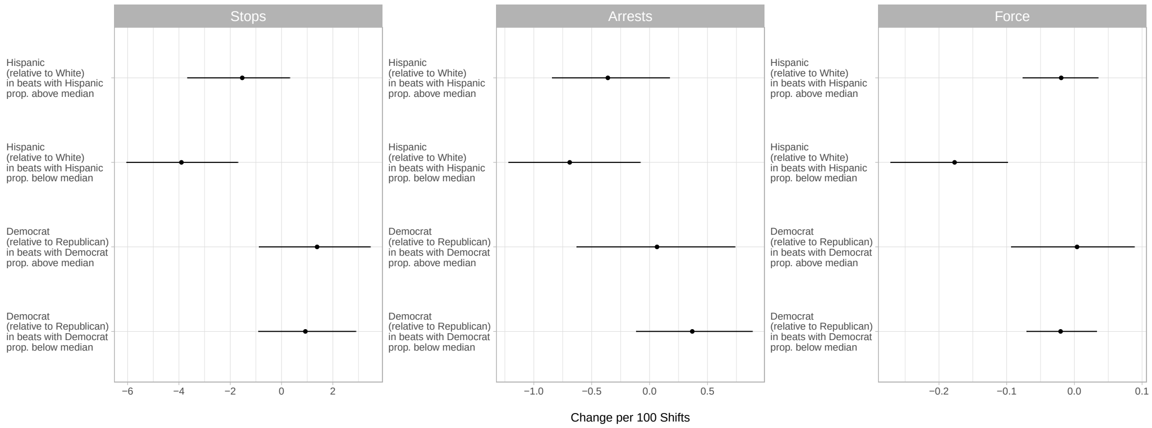

Figure B18: **Heterogeneity in HWRD deployment effects.** Hispanic-White and Democrat-Republican deployment effects from Figure 7 are re-estimated in subgroups of geographically linkable beats that are above and below the median proportions of Hispanic residents and Democrat registered voters.

of deploying an available Hispanic officer on stops and arrests is statistically indistinguishable when comparing areas with different Hispanic resident populations. However, reductions in force when deploying Hispanic officers were concentrated entirely in areas with low Hispanic populations; areas with above-median Hispanic resident proportions had no detectable deployment effect. All other comparisons were insignificant in this analysis. For details, see Figure B18.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	58.23	37.55	20.68*** [20.35, 21.02]	79,924
	Hispanic	18.25	24.58	-6.33*** [-6.59, -6.06]	79,924
	Black	17.99	25.50	-7.50*** [-7.77, -7.24]	79,924
	Other/Unknown Race	1.54	2.98	-1.44*** [-1.53, -1.35]	79,924
	Asian	3.98	9.40	-5.42*** [-5.55, -5.28]	79,924
Party (Voting Age Pop.)	Republican	27.40	10.59	16.81*** [16.51, 17.11]	80,378
	Democratic	35.15	48.26	-13.11*** [-13.45, -12.78]	80,378
	Other/Unknown Party	37.45	41.81	-4.36*** [-4.69, -4.02]	80,378
General Turnout, 2020	Voting Age Pop.	66.85	50.76	16.10*** [15.77, 16.42]	80,378
Gender	Male	81.71	48.01	33.71*** [33.44, 33.97]	80,378
	Female	18.29	51.99	-33.71*** [-33.97, -33.44]	80,378
Median Age (Years)	-	42.00	36.36	7.80*** [7.69, 7.90]	68,909
Mean Household Income ($)	-	111539.85	87935.86	23616.06*** [23150.69, 24081.43]	68,314

(a) **Agencies with residency requirement**

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	54.72	38.00	16.71*** [16.47, 16.96]	136,443
	Hispanic	22.45	30.07	-7.62*** [-7.83, -7.42]	136,443
	Black	15.39	18.80	-3.40*** [-3.58, -3.22]	136,443
	Other/Unknown Race	2.01	3.68	-1.67*** [-1.74, -1.59]	136,443
	Asian	5.43	9.45	-4.03*** [-4.14, -3.91]	136,443
Party (Voting Age Pop.)	Republican	35.38	16.10	19.27*** [19.03, 19.52]	138,099
	Democratic	29.04	40.60	-11.56*** [-11.80, -11.32]	138,099
	Other/Unknown Party	35.58	43.30	-7.72*** [-7.98, -7.47]	138,099
General Turnout, 2020	Voting Age Pop.	70.84	56.83	14.01*** [13.77, 14.25]	135,790
Gender	Male	84.10	49.09	35.01*** [34.82, 35.20]	138,099
	Female	15.90	50.91	-35.01*** [-35.20, -34.82]	138,099
Median Age (Years)	-	44.00	37.12	8.24*** [8.15, 8.32]	117,639
Mean Household Income ($)	-	115807.99	94691.43	21093.98*** [20752.23, 21435.73]	117,639

(b) **Agencies without residency requirement**

Table B22: **Comparison of Average Officer and Civilian Traits by Residency Requirements.** The top (bottom) panel represents agencies that have (do not have) residency requirements. 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.

C Robustness Checks

C.1 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 C1, 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 C2 shows the comparison between officers and civilians after adjusting for the measurement error shown in Table C1 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 C1: **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 C2: **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 C1 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 C1 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.

C.2 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. We detail each of these exercises below for convenience.

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 C9 below). This exercise demonstrates that 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. Specifically, Table C9 shows that the lower bound for percent Republican among officers produced by this exercise is 32%, 18 points higher than the share among civilians ($p_{\text{diff}} < .001$). 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. (See Figures C5–C7 for bounding results for each agency.)

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 C3: **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 $p < .001$

To address measurement error due to mismatching, we take several approaches. First, we re-compute our core results using an alternate threshold for the posterior probability of a correct match of 0.95 (see Table C4 below). As the table shows, our core conclusions remain virtually unaffected.

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 C4: **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.

Second, we employ an alternate measure of party identification: the most recent party primary a voter participated in, according to L2 (see Table C5 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. The table below 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 identification, our overall conclusion that Republicans are substantially overrepresented (here, by 12.40 percentage points) holds. We note that this measurement strategy would be contaminated if voters engaged in insincere primary registrations in order to sabotage out-party elections. However, Frank Stephenson (2011) demonstrates that even in an election where an influential figure encouraged Republican voters to engage in crossover voting in order to sabotage a specific candidate, this rarely occurred.

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 C5: **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.

We also conducted this same robustness check within the jurisdiction of Chicago, where our behavioral analysis is conducted. The results, displayed in Table C6, are remarkably similar for both our original estimates (top table) and alternate estimates (bottom table) both in terms of rates and differences. We believe this is because Illinois is a closed primary state, meaning L2 is less reliant on imputational measures there.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Party (Voting Age Pop.)	Republican	13.91	3.83	10.08*** [9.47, 10.68]	12,509
	Democratic	55.22	53.65	1.57*** [0.70, 2.44]	12,509
	Other/Unknown Party	30.87	42.52	-11.65*** [-12.46, -10.84]	12,509

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

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Party (Voting Age Pop.)	Republican	14.29	3.75	10.53*** [9.92, 11.15]	12,509
	Democratic	52.56	43.59	8.97*** [8.10, 9.85]	12,509
	Other/Unknown Party	33.15	52.66	-19.51*** [-20.33, -18.68]	12,509

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

Table C6: **Comparison of Officer and Civilian Party Identification in Chicago.** 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.

As a further check on the degree to which imputed partisanship is driving our key results, we also re-compute core results after subsetting to states with closed primaries, in which citizens must register with a political party to participate and where L2 is less reliant on imputation. These results, shown in Table C7 and Table C8 below, are consistent with our core conclusions in terms of the disparities between officers and civilians.

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 C7: **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 C8: **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.

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 new 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 the table 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.

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 C9: **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 $p < .001$

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 C10). In addition, we conduct the same exercise now using the three agencies which include the officer's exact date of birth (Table C11). We find that results are nearly identical when using name-only as when using name+age or name+date-of-birth.

Incorporating this additional information substantially reduces the number of duplicate matches. Among the name and age matches, 15.9% had more than one match. Of these officers with multiple matches, 48.3% had two matches, 17.3% had three matches, 9.5% had four matches, 6.1% had five matches, 4.1% had six matches, 3.0% had seven matches, 2.2% had eight matches, 1.5% had nine matches, and fewer than eight percent had 10 or more matches. In addition, we conduct the same exercise now using the three agencies which include the officer's date of birth (Table C11). In this group only 2.5% of officers had more than one match.

Finally, our core results are virtually unchanged when incorporating age or DOB into the merge procedure (see Table C10 and Table C11). 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	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 C10: **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 C11: **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.

Finally, Section C.3 displays the results of bounding exercises assuming conservative assumptions about the attributes of officers not matched to L2, including party identification.

C.3 Estimated Bounds Accounting for Unmatched Officers

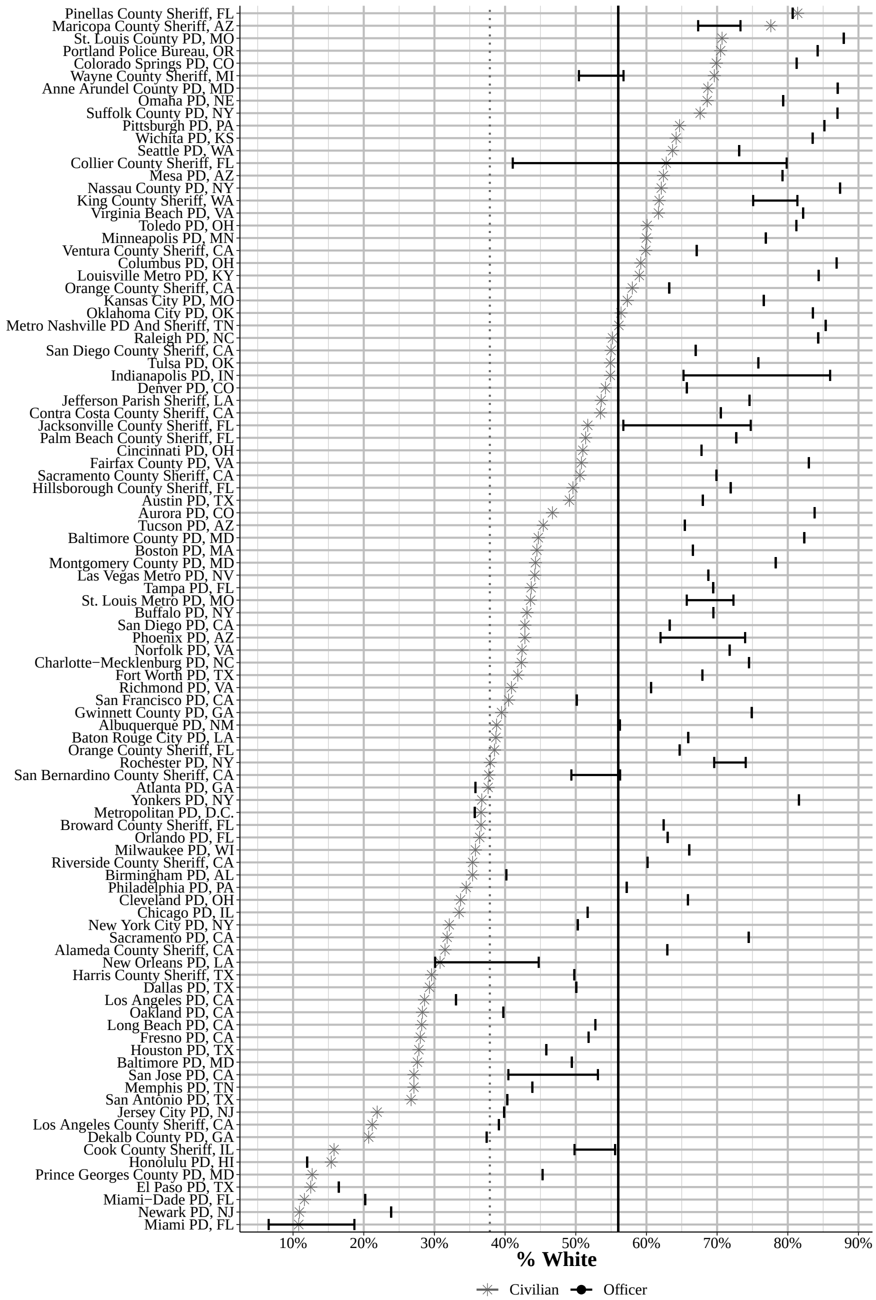

Figure C1: **Average Shares of White Officers and White Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

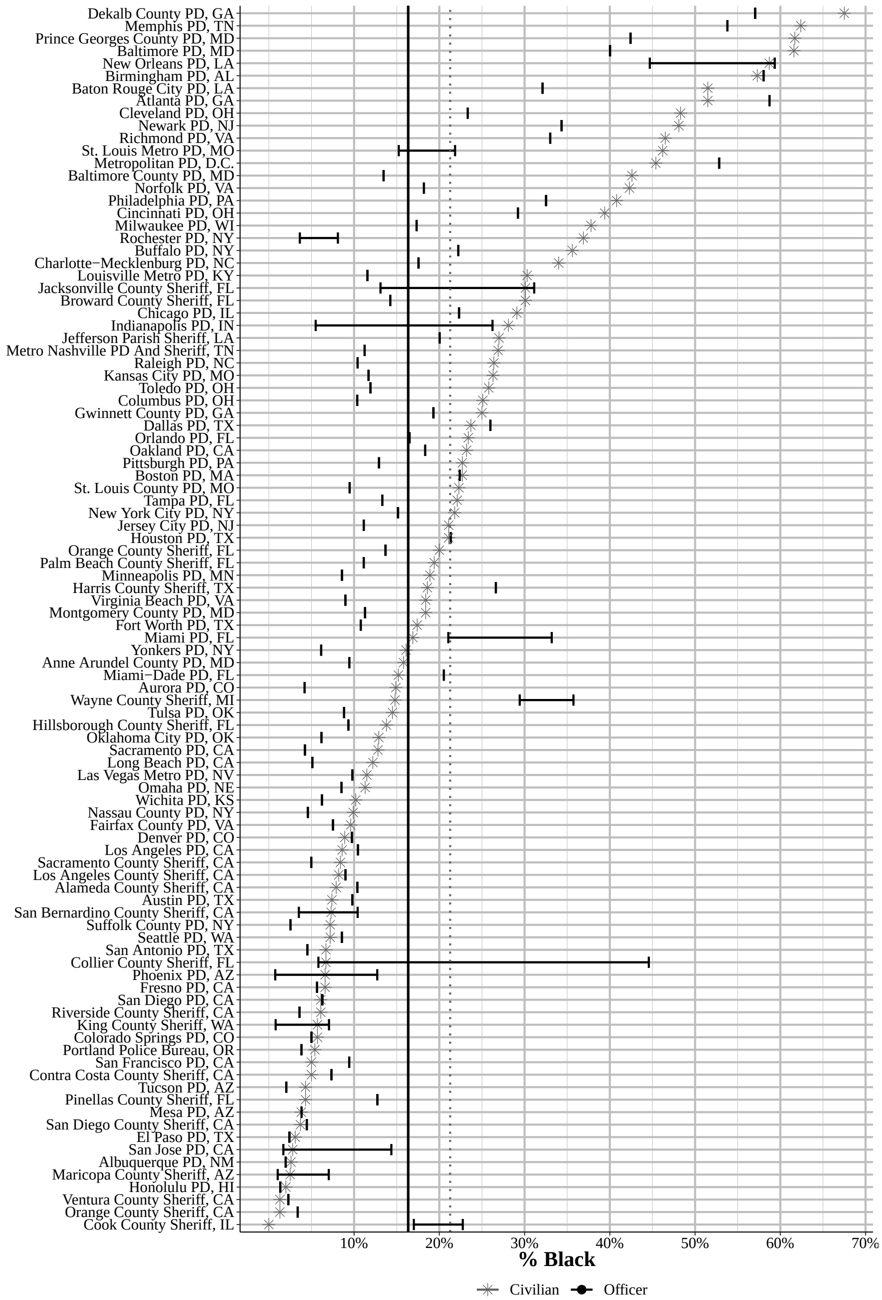

Figure C2: **Average Shares of Black Officers and Black Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officers was randomly drawn from their respective jurisdiction.

Figure C3: **Average Shares of Asian Officers and Asian Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

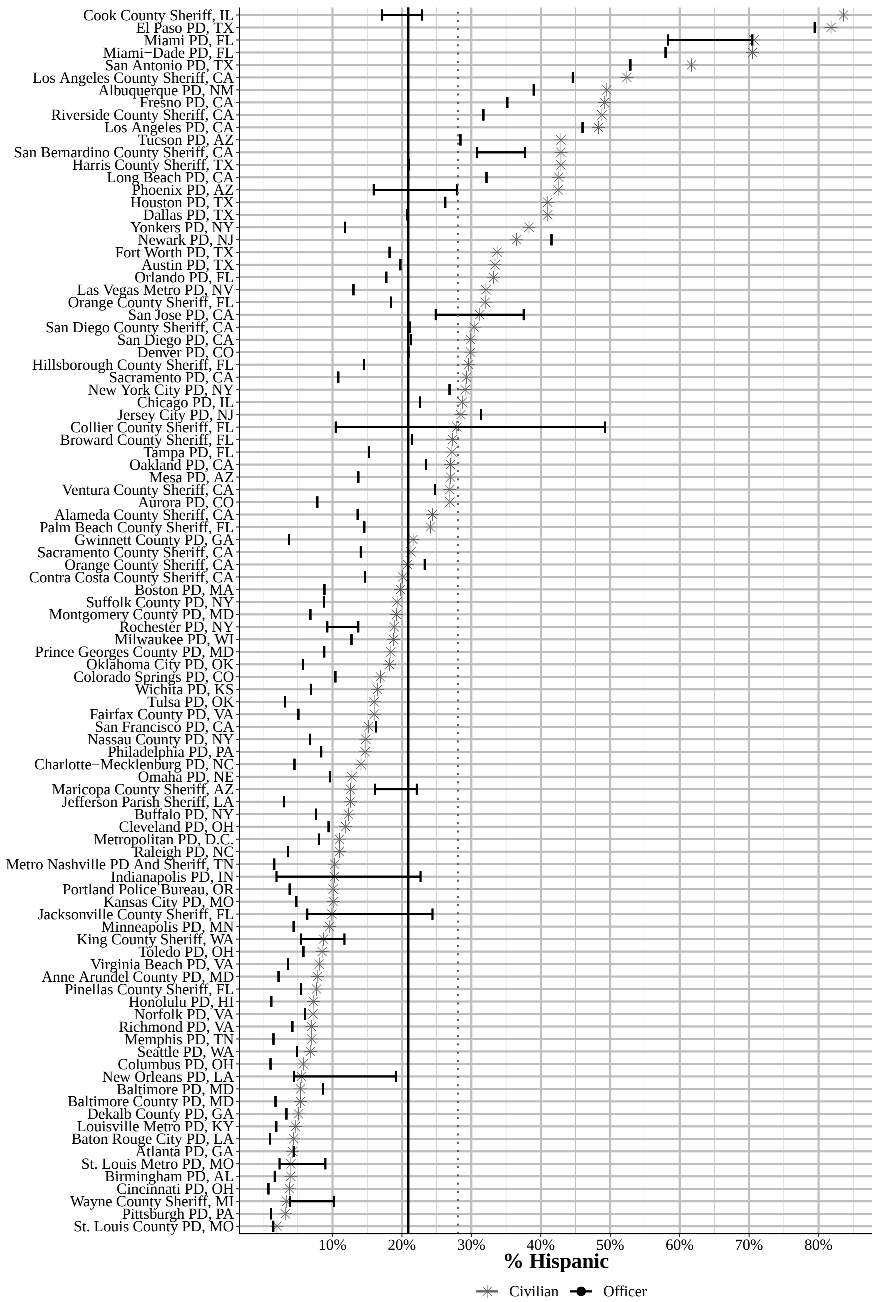

Figure C4: **Average Shares of Hispanic Officers and Hispanic Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

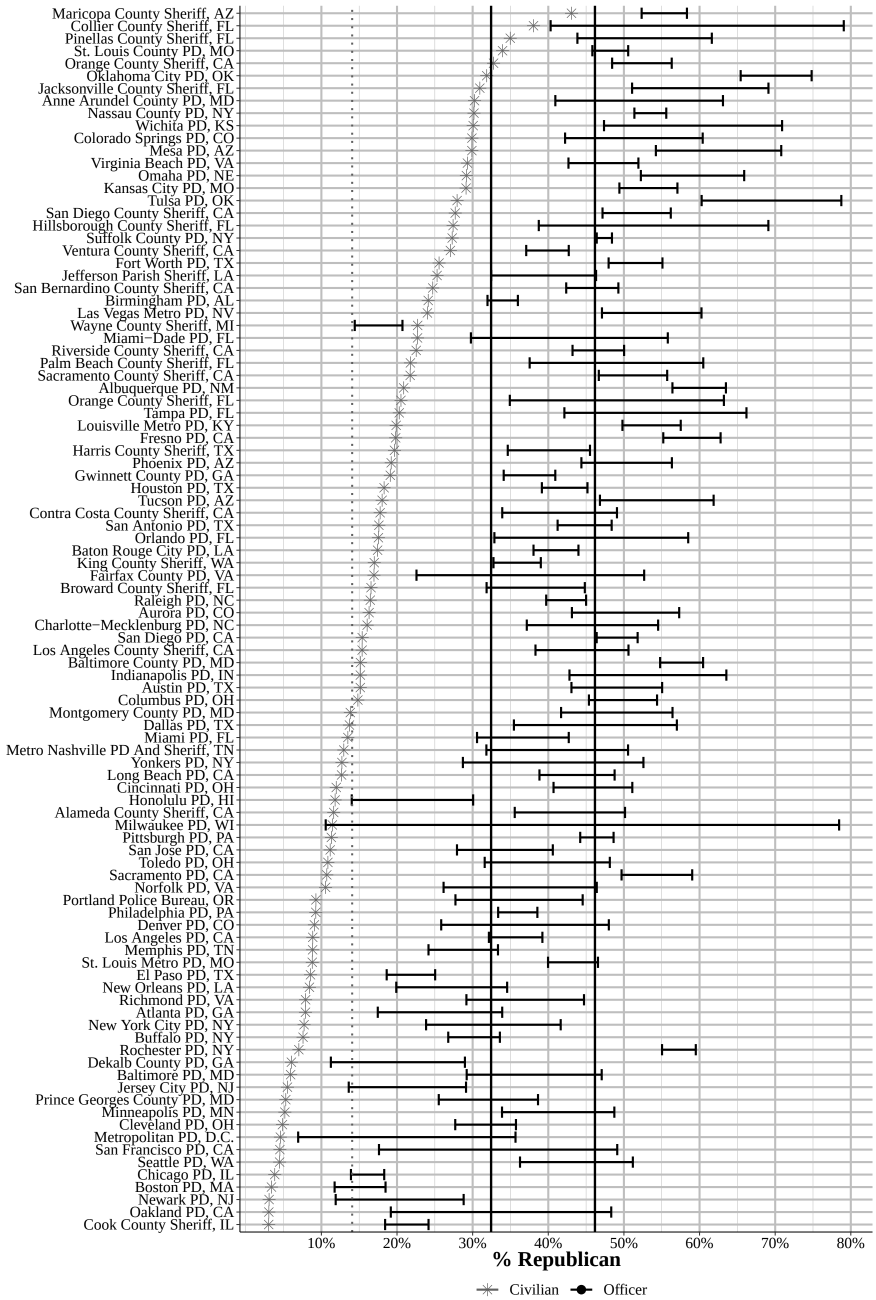

Figure C5: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

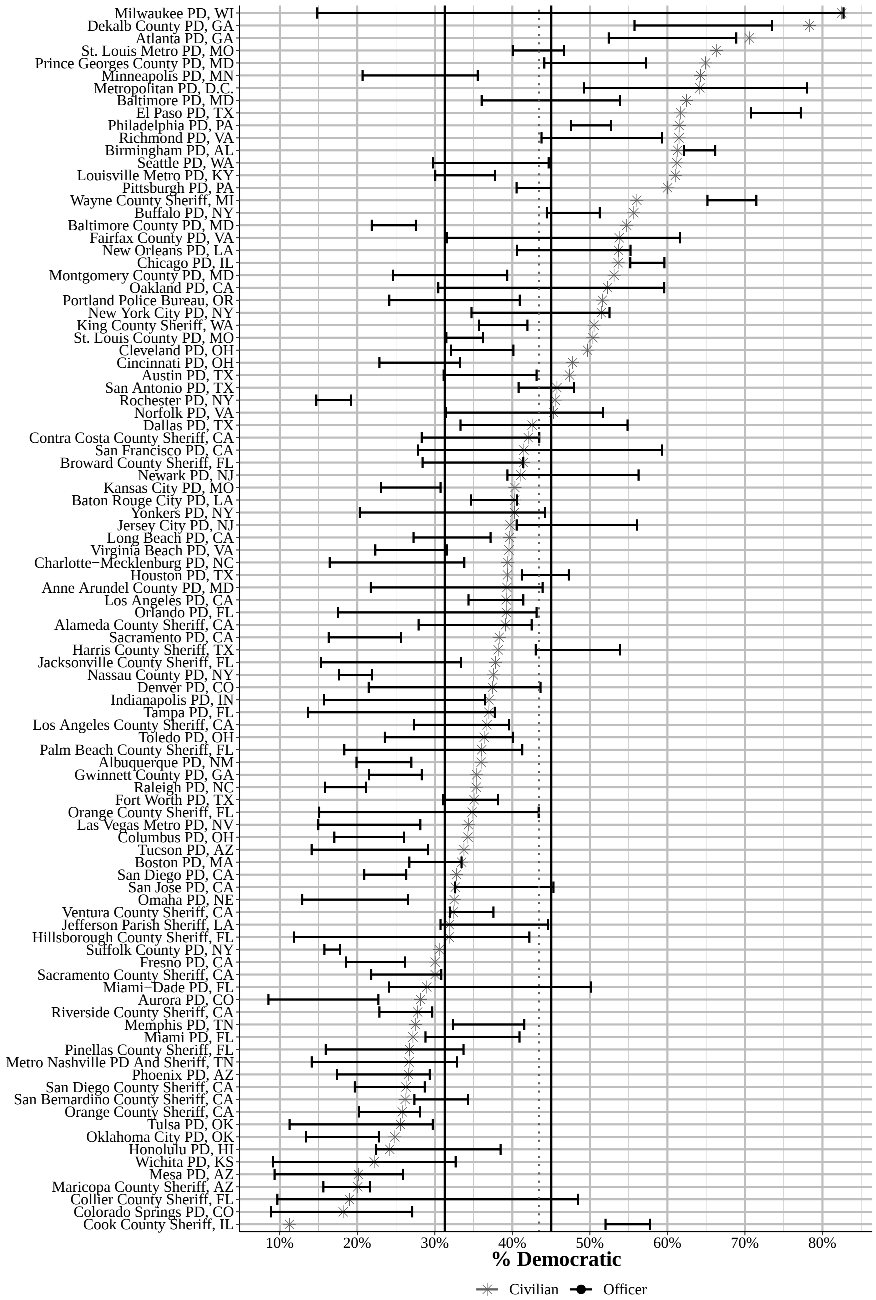

Figure C6: **Average Shares of Democrats Among Officers and Civilians in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

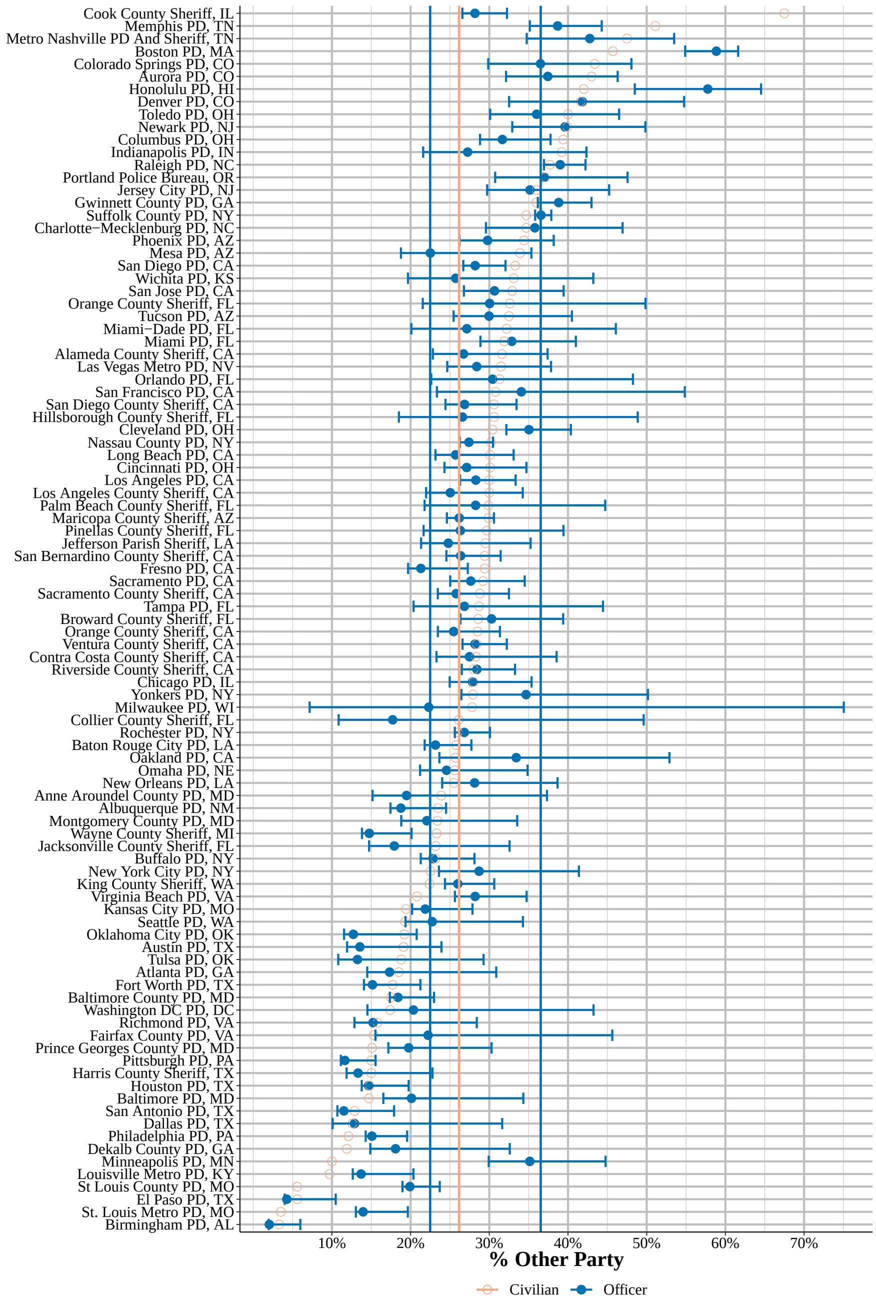

Figure C7: **Average Shares of Individuals Not Identifying With Either Major Political Party in the Same Jurisdictions: Estimated Bounds.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

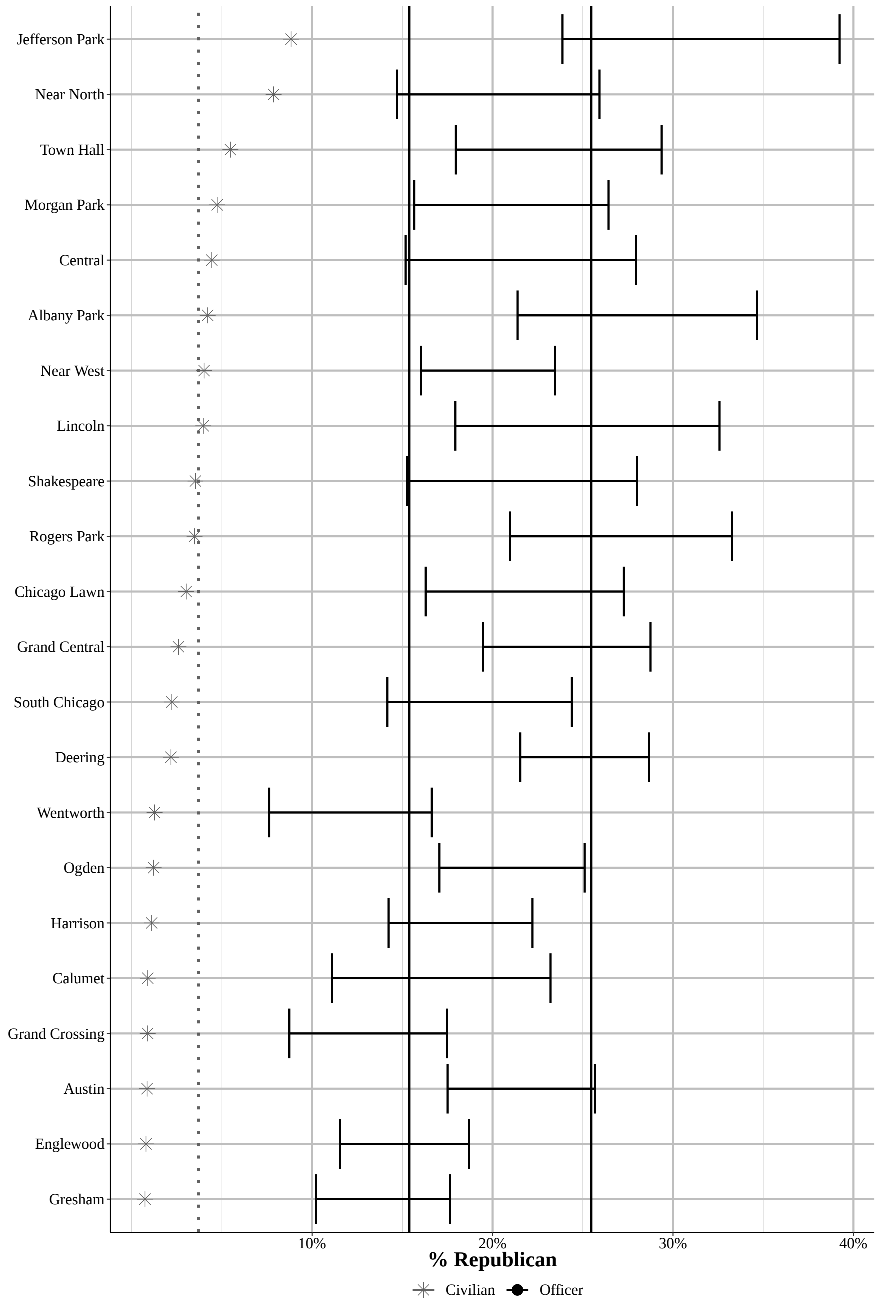

Figure C8: **Average Shares of Republican Chicago Officers and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

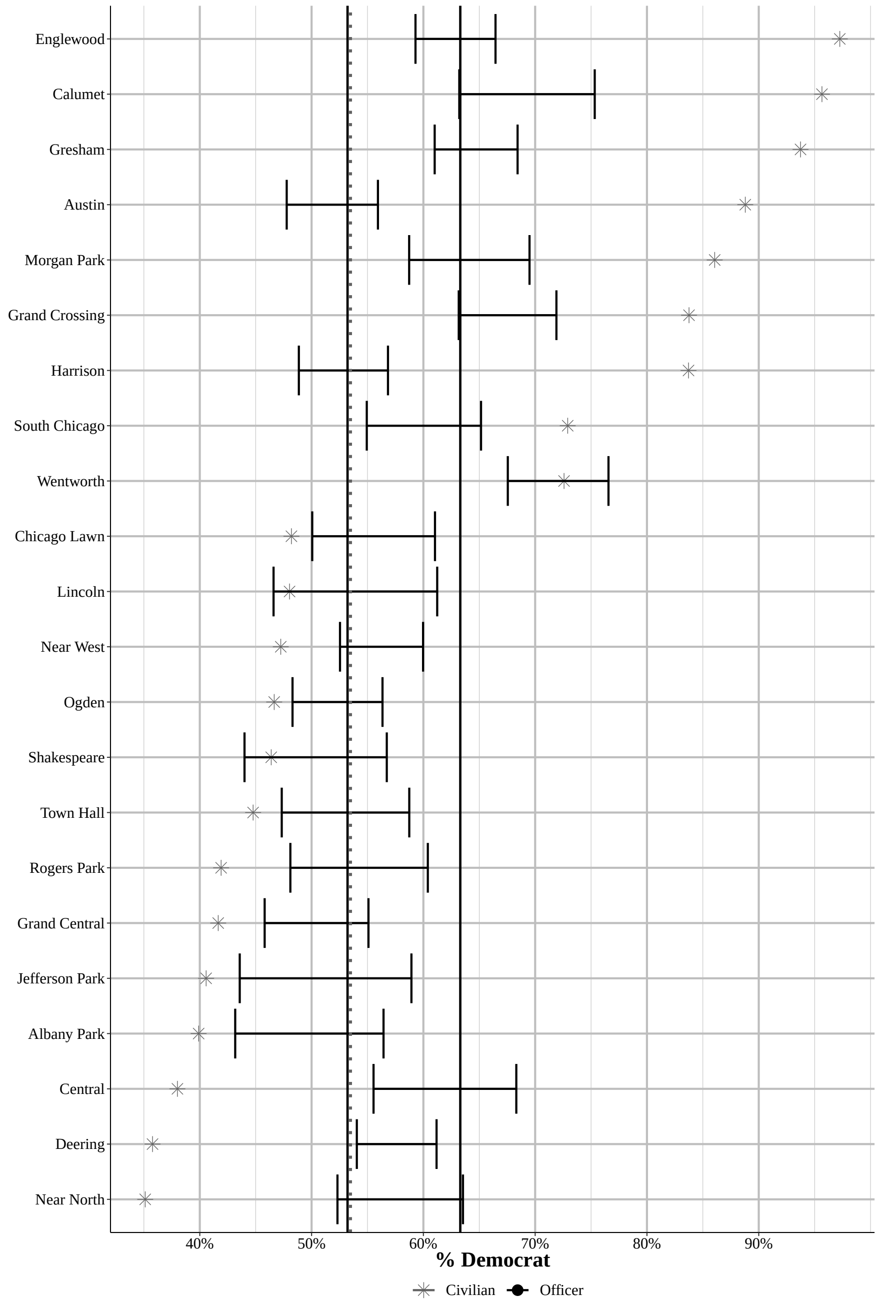

Figure C9: **Average Shares of Democratic Chicago Officers and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical pooled officer mean if each officer was randomly drawn from their respective jurisdiction.

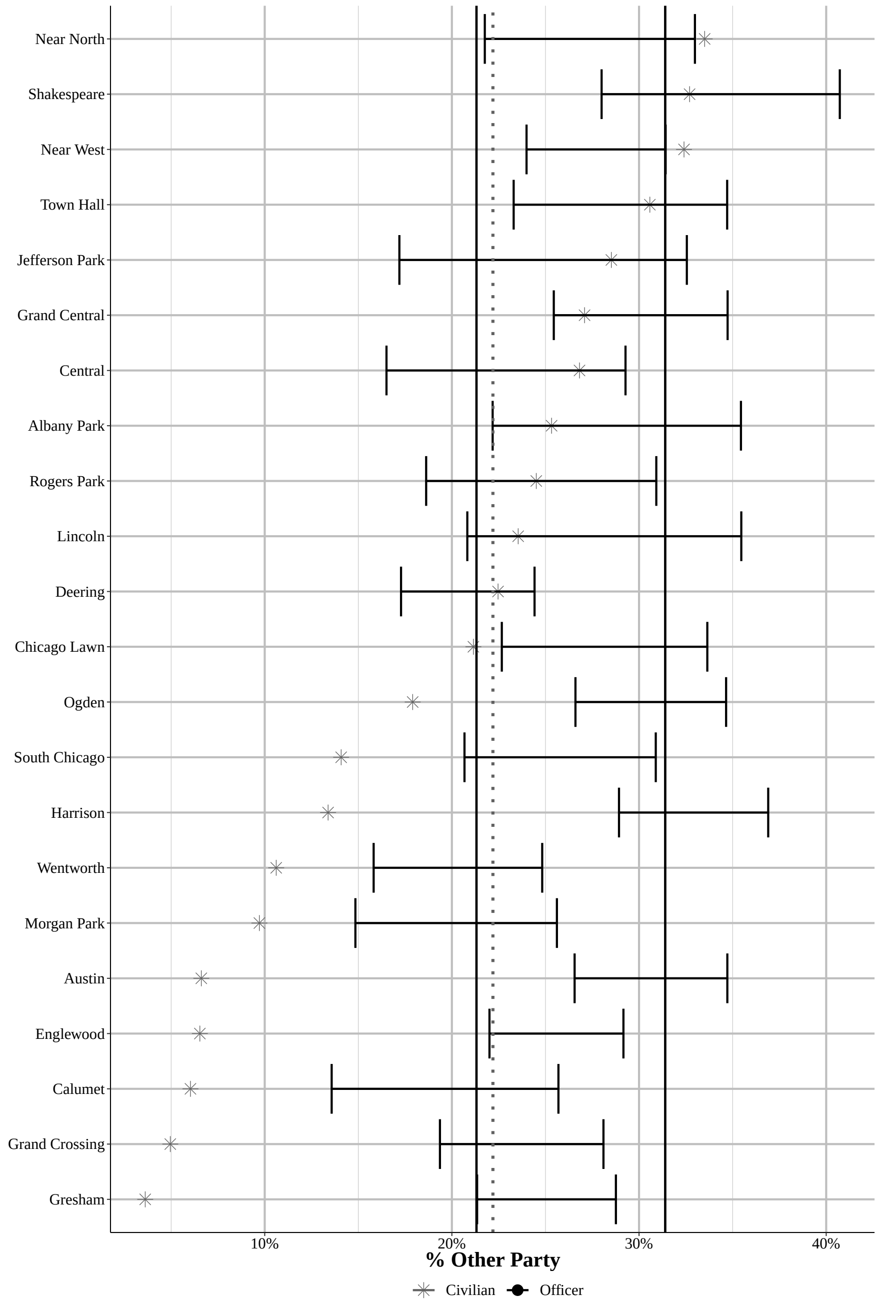

Figure C10: **Average Shares of "Other Party" Chicago Officers and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Black dots are officer shares from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Grey asterisks are civilian shares from U.S. Census. Vertical solid black lines are the pooled officer means under "best" and "worst" case scenarios, assuming all officers not found in L2 do/do not possesses the attribute. Vertical dotted grey line is the hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

C.4 Balance Tests for Behavioral Analysis in Chicago

We conduct a series of propensity balance tests to validate that we are comparing officers working in common circumstances in the Chicago behavioral analysis. To conduct these tests, 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) using 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. In other words, local conditions should not predict officer assignments within MDSBs. 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. Both binarized (above/below median) and continuous linear specifications are used for each non-discretionary incident type. The results of these tests are reported in Tables C12–C19. 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.

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 rows of Tables C12 (binarized forgery incidents) and C13 (continuous measure), respectively p=0.02 and 0.03. 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 Binary	0.00	0.47
Forgery/Counterfeiting Binary	0.02	0.02
Manslaughter Binary	0.18	0.39
Murder Binary	0.01	0.39
Sexual Abuse Binary	0.00	0.88
Sexual Assault Binary	-0.01	0.58
Vandalism Binary	0.01	0.08
Simes: 0.159		

Table C12: **Propensity to Assign Black Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with binarized crime levels. Simes *p*-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Black, White, Democratic and Republican officer.

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 C13: **Propensity to Assign Black Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with crime levels used as a linear predictor. Simes p-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Black, White, Democratic and Republican officer.

Crime	Coef	p
Burglary Binary	0.00	0.70
Forgery/Counterfeiting Binary	0.01	0.56
Manslaughter Binary	-0.20	0.29
Murder Binary	0.00	0.85
Sexual Abuse Binary	-0.00	0.73
Sexual Assault Binary	-0.01	0.43
Vandalism Binary	0.00	0.60
Simes: 0.849		

Table C14: **Propensity to Assign Democrat Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with binarized crime levels. Simes p-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Black, White, Democratic and Republican officer.

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 C15: **Propensity to Assign Democrat Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with crime levels used as a linear predictor. Simes p-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Black, White, Democratic and Republican officer.

Crime	Coef	p
Burglary Binary	0.00	0.66
Forgery/Counterfeiting Binary	-0.00	0.59
Manslaughter Binary	-0.02	0.86
Murder Binary	-0.03	0.05
Sexual Abuse Binary	-0.00	0.81
Sexual Assault Binary	0.00	0.94
Vandalism Binary	-0.00	0.06
Simes: 0.211		

Table C16: **Propensity to Assign Hispanic Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with binarized crime levels. Simes p-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Hispanic, White, Democratic and Republican officer.

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 C17: **Propensity to Assign Hispanic Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with crime levels used as a linear predictor. Simes *p*-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Hispanic, White, Democratic and Republican officer.

Crime	Coef	p
Burglary Binary	0.00	0.29
Forgery/Counterfeiting Binary	0.01	0.11
Manslaughter Binary	-0.05	0.68
Murder Binary	-0.00	0.78
Sexual Abuse Binary	0.00	0.78
Sexual Assault Binary	-0.00	0.86
Vandalism Binary	0.00	0.23
Simes: 0.684		

Table C18: **Propensity to Assign Democrat Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with binarized crime levels. Simes *p*-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Hispanic, White, Democratic and Republican officer.

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 C19: **Propensity to Assign Democrat Officer to MDSB.** Coefficients represent predicted changes in propensity score of officer assignment as a function of crime counts within MDSB, with crime levels used as a linear predictor. Simes p-value Sarkar and Chang (1997) is reported for the joint null hypothesis of zero association with officer assignment, accounting for multiple dependent tests. Estimates are among MDSBs with at least one Hispanic, White, Democratic and Republican officer.