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

Bocar Ba, Jacob Kaplan, Dean Knox, Mayya Komisarchik, Rachel Mariman
Jonathan Mummolo, Roman Rivera, & Michelle Torres

March 21, 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 97 of the 100 largest local U.S. agencies—over one third of local law enforcement agents nationwide. We show officers skew more White, Republican, politically active, male, and high-income than their jurisdictions; they also surround themselves with similarly unrepresentative neighbors. In a quasi-experimental analysis in Chicago, we find Democratic and minority officers initiate fewer stops, arrests, and uses of force than Republican and White counterparts facing common circumstances. The Black-White behavioral gap is often far larger than the Democratic-Republican gap, a pattern not observed among Hispanic officers. Our results complicate conventional understandings of descriptive representation, highlighting the importance of multi-dimensional perspectives of diversity.

*Bocar Ba, Assistant Professor, Economics, Duke University, bocar.ba@duke.edu. Jacob Kaplan, Professional Specialist, School of Public and International Affairs, Princeton University, jk7785@princeton.edu. Dean Knox, Assistant Professor, Operations, Information and Decisions, University of Pennsylvania, dcknox@upenn.edu. Mayya Komisarchik, Assistant Professor, Political Science, University of Rochester, mayya.komisarchik@rochester.edu. Rachel Mariman, Research Project Manager, Analytics at Wharton, University of Pennsylvania, rmariman@wharton.upenn.edu. Jonathan Mummolo, Assistant Professor, Politics and Public Affairs, Princeton University, jmummolo@princeton.edu, corresponding author. Roman Rivera, PhD student, Economics, Columbia University, r.g.rivera@columbia.edu. Michelle Torres, Assistant Professor, Political Science, Rice University, smtorres@rice.edu. Authors listed alphabetically.

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" (p. 701).

In this paper, we analyze nearly a quarter million officers,[1] covering 97 of America's 100 largest local agencies[2] 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. It draws 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 (Hyland and Davis, 2019).

Our analysis is motivated by the fact that race and ethnicity alone may be relatively crude indicators of how officers relate to civilians or behave on the job. This is a particular concern given the politicization of policing in the United States, with Democrats and Republicans strongly disagreeing on policing policy (Eckhouse, 2019; Pew, 2017; Kim

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

[2]We have obtained commitments to provide data on the remaining three agencies but have not yet received these data.

Parker and Kiley Hurst, 2021). 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). The intersection of multiple identities may affect police behavior in important ways undetectable in prior work. In the words of Dolan and Rosenbloom (2003, p. 77), "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."

Progress on this question, like many others in the study of policing, has been stymied by a scattered, incomplete and heterogeneous landscape of administrative data (Knox and Mummolo, 2020). Assembling even basic facts about law enforcement agencies, such as whom they employ, remains remarkably difficult in many jurisdictions—much less information on officers' demographics, preferences or activities. Agencies rarely share this information proactively and, in our experience, sometimes even seek to defy freedom-of-information laws in violation of the near-universal requirement to disclose government employee rosters upon request. National surveys of police officers offer some insights (BJS, 2016; 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. Conversely, studies which closely scrutinize single jurisdictions (Ba et al., 2021; Hoekstra and Sloan, 2020) leave open questions of generalizability.

To address this gap, we first leverage our data to 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 more often. However, the degree of nonrepresentativeness is highly heterogeneous. Among Black individuals, officers and civilians in the same jurisdictions are both roughly 1-3% Republican while officers are nearly 52% Democrat compared to 66% among civilians.. Among White and Hispanic individuals, however, officers skew far more Republican than their respective local civilian counterparts.

Next, we broaden our notion of identity to account for the context of where officers live and work. 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 (Eisinger, 1983) (though evidence remains mixed (Smith, 1980a; Murphy and Worrall, 1999; Hauck and Nichols, 2020)). In a thorough examination of personnel policies for the nation's 100 largest agencies, we find that over a quarter mandate or encourage local residency. In light of this, we examine where officers reside and find these neighborhoods also differ systematically from civilians at large. Census tracts where officers live tend to have higher shares of White residents, higher shares of Republicans, higher rates of voter turnout and higher household income than their jurisdictions writ large. In other words, officers do not only differ from their jurisdictions on a range of social identities; they also choose to surround themselves with other individuals who are closer to themselves and further from their jurisdictions, suggesting divergences in lived experiences.

To probe these patterns at a finer-grained level, we then turn to a micro-level dataset, acquired from the Chicago Police Department (CPD) after 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 police districts to which police officers are assigned to work. This allows us to evaluate whether officers resemble civilians in the specific areas where they work—that is, the civilians with whom they most frequently interact—rather than simply analyzing representation at the coarser level of jurisdictions. 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.

Finally, having established these descriptive patterns, we conduct a deep analysis of hyper-granular CPD data to evaluate the real-world impact of the highly salient attributes of race, ethnicity, and party affiliation. Using datasets 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 test whether officers from various groups choose to treat civilians differently when facing common circumstances. This strategy closely mirrors the research design of Ba et al. (2021), allowing analysts to estimate what police commanders can expect when deploying an officer of one group (e.g., Democratic officers, drawn from all officers in the unit available for deployment) and how the average behavior of this group differs from another (e.g., Republican officers).

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, commanders can expect fewer stops, arrests, and uses of force (compared to White or Republican officers, respectively). However, the Black-White gap is roughly double the size of the Democratic-Republican gap—with the sole exception of force, where race- and- party-based deployment effects are similar. At first glance, these results suggest officer race is a more salient divide than personal politics, corresponding to larger differences in the treatment of civilians. However, we see a very different pattern when examining Hispanic officers, where we find the effects of ethnicity- and- party-based deployments are generally indistinguishable (at least in scenarios where both ethnic and political comparisons can be made, as before). We also find the aforementioned effects of deploying Black and (to a lesser degree) Democratic officers primarily benefits Black civilians, who are much less likely to be stopped, arrested or subject to force than when White or Republican officers are deployed.

Our analysis underscores the complex nature of descriptive representation in the bureaucracy. Police officers are as multi-faceted 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. Our paper also illustrates that data access remains a substantial obstacle for the study of policing, but not an insurmountable one. The dataset we assembled on officers from 97 of the country's 100 largest agencies, to be made public, is a valuable resource not only for the study of bureaucracy but also for the expansion of police oversight. Police watchdog groups have long noted the difficulty of tracking officers accused of misconduct because they often quietly gain employment in different agencies in the rare occasions when they are terminated (Grunwald and Rappaport, 2019; Lalwani and Johnston, 2020). And even in the absence of misconduct, many civilians would currently find it exceedingly difficult to learn which individuals are endowed with coercive powers by their communities, even though this information is generally public by law. Our dataset offers the beginnings of a solution and, with expansion and maintenance, can facilitate the creation of a comprehensive registry that sheds light on a critically important but often opaque segment of the "second face of the American State" (Soss and Weaver, 2017).

1 Representative Bureaucracy

Since Kingsley (1944) introduced the concept of "representative bureaucracy," many scholars have extolled the theoretical virtues of staffing public agencies with workers who resemble their clients (Dolan and Rosenbloom, 2003). In general, theories of representative bureaucracy are premised on several key assertions: bureaucratic oversight is incapable of ensuring bureaucrats will exercise discretion in desirable ways (Huber and Shipan, 2002; Krause, 2010); 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"? 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 (Wilson, 1989), could easily lead to the selection of particular group members who hold atypical policy preferences relative to group members at large (Linos, 2017). This may be especially true of racial minorities in law enforcement: in order to perpetuate current norms, policing agencies may select unusually conservative members of minority communities, who tend to support status-quo policing practices more than their liberal counterparts (Eckhouse, 2019; Forman Jr., 2017; Pew, 2017; Kim Parker and Kiley Hurst, 2021). Second, recent work underscores that such conservative segments of minority communities, African Americans in particular, may be more prevalent than previously thought (White and Raganella, 2010). Of course, it is also possible White civilians are politically misrepresented by bureaucrats: they occupy substantial shares of both major parties, creating an ample pool from which to fill the relatively few positions available and potentially producing an agency that does not reflect the political views of White residents at large. If such politically atypical members of groups are disproportionately selected, the logic of representative bureaucracy may be upended. The notion of bureaucrats, "colored by their political outlook and by the climate of opinion in their social group," (Lipset, 1975, p. 80) is an incoherent concept if non-representative members of each group assume government posts.

We have relatively little empirical evidence to adjudicate these possibilities in policing because most empirical studies of descriptive representation tend to focus on race and gender, which may only crudely proxy for relevant social views. Decades of empirical studies have sought to quantify the effects of racial—and to a lesser extent, gender-based—

diversity on the nature of police-civilian interactions. For most of that time, results have been ambiguous (Sklansky, 2005). Some provide correlational evidence consistent with the hypothesis that more diversity is associated with improvements of such interactions. 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) finds force is more likely to be used in encounters involving 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 outcomes, at least in the times and places where adequate data exists. Leveraging the scattered implementation of affirmative action rulings forcing police agencies to racially diversify in the 1970s and 1980s, Harvey and Mattia (2019) finds hiring more Black police officers reduces racial disparities in crime victimization. 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 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; Clinton et al., 2012), 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[3] 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 or 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 three agencies—the Detroit Police Dept. and the Oakland County Sheriff's Office, both in Michigan, and the Norfolk Police Dept. in Virginia—remain pending.

Ultimately, we received data covering roughly 220,000 officers from 97 police agencies. 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 38 states and the District of Columbia. In all, the roughly 218,000 officers we successfully merged with L2 voter file data represent over one third of the roughly 642,000 local police officers and sheriffs' deputies nationwide (Hyland and Davis, 2019), making this—to our knowledge—the largest-ever examination of descriptive representation in policing.

To put our dataset in context, Appendix Table B1 reports basic descriptive statistics comparing officers in our data to (1) officers nationwide and (2) the U.S. population. These statistics show our officers skew heavily male (73%) and have much higher household income than the average American household ($114,331 vs. $92,310, respectively). Officers in our data are more racially and ethnically diverse than both officers nationwide and

[3] 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.

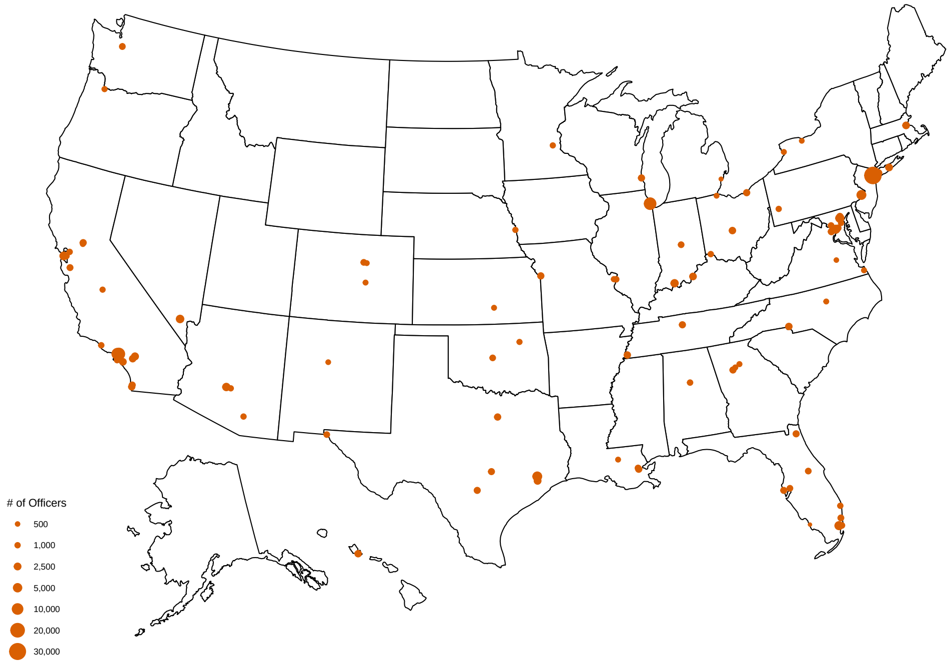

Figure 1: **Agency Locations.** Our agency rosters cover roughly 220,000 officers across 38 states and the District of Columbia, representing 34% of the nation's estimated 641,628 sworn local police officers and sheriffs' deputies (Hyland and Davis, 2019). Together, jurisdictions covered in our data serve 23% of the U.S. population. Each dot is scaled by the number of sworn officers.

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 our registry and analysis is a critical direction for future research. Even so, the jurisdictions we study—which cover 23% of the U.S. population and were responsible for investigating 41% of all murders and conducting 17% of all arrests reported to the FBI in 2019 (Kaplan, 2020, 2018)—are important to study in their own right.

3 Measuring Officer Attributes

Each employee roster provides 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 the firm L2. To match police roster data with voting data, we employ 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 in which their agency lies, 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 in the voter file, 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 name matches only, we employ the probabilistic technique in Enamorado, Fifield and Imai (2017*b*), using the *fastlink* R package (Enamorado, Fifield and Imai, 2017*a*)[4].

The L2 voter file database contains a number of individual-level covariates including race, ethnicity, party identification, gender, 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 Census American Community Survey data.[5] We divide officers and civilians into three categories based on L2's labels: Democrat, Republican, and an aggregate of numerous other party affiliations and individuals not appearing in the L2 data. These categories rely on proprietary L2 algorithms to characterize the party affiliation of officers and civilians, which introduces potential bias due to error in machine-learning based proxies (Knox, Lucas and Cho, 2022).[6] While error in these imputations may result in biased estimates of mean levels of party affiliation, it is less plausible they would severely bias estimates of *di erences* between officers and civilians (our primary quantity of interest) because the same imputation method is applied to both groups. Nevertheless, we compute bounds that substitute extreme assumptions for the covariates of unobserved individuals to demonstrate the robustness of our results. As an additional check, Appendix B.1 reports similar results using only states in which both major parties held closed presidential/congressional primary elections in 2020.[7]

To measure the share of officers of various racial, ethic and gender identities, we rely

[4]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 B19.

[5]See Appendix A.1 for details on jurisdiction geography and Census merges.

[6]See Appendix A.2 for details on L2's imputation of party ID.

[7]Turnout analyses exclude voter turnout for agencies in Kentucky, which account for about 1% of officers, due to missing data in L2.

on the 2020 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 BJS, 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 close to 100% and roughly 86% of the agencies in our study, respectively. For missing agencies, we rely on imputed values of race and ethnicity from the L2 data set. We similarly rely on L2 for measures of officers' household income and age. See Appendix A.3 for additional details on these measures.

We note that L2 does not cover every officer; across all agencies, we were able to match 86% of officers with at least 90% confidence. In analyses where L2 is used only as a fallback measure for agencies not appearing in alternative datasets, differential missingness is a lesser concern; in analyses of household income and age, where L2 is our sole source of information, it poses a greater threat. To ensure reported results are robust to any possible missingness pattern, we apply a simple bounding procedure across all analyses to characterize the range of possible agency-level averages on each attribute given hypothetical extreme values for the unobserved officers (e.g., reporting a series of estimates assuming all missing officers are female, male, Democratic, Republicans). We discuss these bounds below and report them in Appendix B.

4 Do Police Descriptively Represent Civilians?

We now present an in-depth comparison between police officers and the civilians they serve. To accomplish this, we 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 American Community Survey data, aggregating all tracts for which the agency has jurisdiction.[8] Officer attributes are measured with a multi-pronged approach. For certain analyses, we are able to use agency-level race, ethnicity, and gender information from LEMAS and LEOKA data, where missingness of officers within an agency is not a concern. However, not all of our agencies appear in LEMAS; moreover, neither source reports age, income, or political attributes. To conduct these analyses, we rely on L2 voter files—meaning key

[8]See Appendix A.1 for details on matching tracts to jurisdictions.

variables are missing for officers who are not registered to vote. This challenge, while substantial, is less severe in our context than many voter-file analyses due to the high political engagement of police officers. We are able to match 86% of officers with high confidence (match probability exceeding 90%), meaning missingness affects at most 14% of officers (with far lower levels in many analyses due to use of LEMAS and LEOKA where possible). To probe the robustness of our results under the most extreme possible patterns of selective missingness, Appendix Section B re-computes all estimates using best- and worst-case assumptions about the characteristics of missing officers. Due to the sheer magnitude of differences between police officers and civilians, the interpretation of our results remain similar even under these extreme scenarios.

Table 1 compares officers in our data to the civilians in their jurisdictions. The left estimates correspond to officers in our data, aggregating across our 97 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.) The next column corresponds to the hypothetical value for perfectly representative police agencies—for example, the proportion of Republican officers or the median age that could be expected if each officer was replaced with a representative draw from their respective jurisdiction, holding the size of each agency fixed.[9] Subsequent columns display officer-civilian differences and 95% confidence intervals.

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 5 and 7 percentage points, respectively. Officers are also much more politically active than a representative group of civilians: 86% of officers are registered to vote (compared to 77% of voting-age civilians), and 69% of officers voted in the 2020 general election (compared to 54% of civilians).

We also find officers are markedly more likely to be Republican than civilians in their jurisdictions: as a share of the voting-age population at least 32% of officers are Republican, vs. 14% if officers represented civilians. Decades of prior research has demonstrated a

[9] Specifically, this hypothetical value is computed as $\frac{1}{\sum_{\square} \#\{\text{agency}_{\square}\}} \sum_{\square} \square_{\square} \cdot \#\{\text{agency}_{\square}\}$, where $\square$ indexes agencies, $\square_{\square}$ refers to the average civilian in the agency's jurisdiction, and $\#\{\text{agency}_{\square}\}$ is the number of officers employed by the agency.

robust correlation between voter turnout and the strength of party identification (Campbell et al., 1960; Prior, 2007), suggesting officers are also more likely to be strong partisans. We also find similar results when subsetting to states with closed primaries where measures of party identification are arguably more reliable (see Appendix B.1).

Within racial and ethnic groups, politically speaking, we find Black civilians are better-represented by officers of their own race than are White and Hispanic civilians (see Table B2). Black officers are 52% Democratic. Among Black voting age civilians drawn from the same jurisdictions, 66% appear in L2 as Democratic (officer-to-civilian ratio of 0.79; modest underrepresentation). Black officers are also 2% Republican, versus 1% among representative Black civilians. However, White and Hispanic officers diverge more sharply from their civilian counterparts. White officers are 19% Democratic, versus 35% among a representative set of White civilians (ratio of 0.54; severe underrepresentation). They are 40% Republican, versus 22% among White civilians (ratio of 1.81; severe overrepresentation). Similarly, Hispanic officers are 43% Democratic compared to 38% among representative civilians (ratio of 1.13) and 23% Republican, compared to 7% among representative civilians (ratio of 3.28).

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 far less likely to use force than their male counterparts (Ba et al., 2021). Officers are also older than the average civilian in their jurisdictions (44 vs. 37 years old), and 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.

We note some officers cannot be identified with sufficient certainty in the L2 data—defined as a match probability of at least 90%—meaning some covariates are missing for these individuals. Nevertheless, most of the disparities we find are so severe that the most extreme possible missingness scenarios, substituting "best-" and "worst-case" values for missing officers, would not alter their substantive interpretation (see Appendix B.2). For example, if—implausibly—every single officer not found in L2 and from a non-BJS (2016) agency happened to be non-White, then officers would be 46.1% White (the lowest possible value under any missingness pattern). Conversely, if every missing officer were White, the highest possible value is 59.7%. Regardless, either extreme remains far higher than the White share of representative civilians, 37.9%. Likewise, under similarly extreme scenarios, we can conclude that between 32.4% and 46.5% of officers must be Republican; under any possible missingness pattern, this number is far larger than the 14% figure among representative civilians. Even under the wildest possible assumptions about data we cannot observe, officers substantially diverge from civilians in their jurisdictions on a host of salient social and political dimensions.[10]

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 global means from Table 1 are plotted as vertical lines for reference). Consider the City of Sacramento, capital of California and home to more than half a million people, (roughly 32% White). We estimate 74% of Sacramento Police Dept. officers are White. Similarly, Figure 3 shows Rochester, N.Y., an upstate community with more than 200,000 residents, about 8% of whom are Republican. We estimate at least 56% of police officers there are Republican.

Conversely, our data also reveal some police forces are quite representative of their jurisdictions. For example, the Miami Police Dept. is 8% White (67% Hispanic), closely aligned with the composition of city residents at 11% (71%). Similarly, 13% (22%) of officers in the Honolulu Police Dept. are Republican (Democratic), close to the 12% (24%) of adult civilians there overall (see Appendix B.2 for additional within-jurisdiction comparisons). However on the whole, we find police officers are very different from the civilians they are tasked with protecting, differences which classic theories of representative bureaucracy suggest could lead to subpar performance (Kingsley, 1944; Mosher, 1968).

[10]Exceptions include analyses of Black, Hispanic, and Asian officers, those of other or unknown race/ethnicity, and Democratic party members. For these analyses, average lower and upper bounds overlap the hypothetical shares that agencies would exhibit if officers were replaced with representative draws from their respective jurisdictions.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	55.99	37.82	18.18*** [17.98, 18.38]	215,935
	Hispanic	20.96	28.12	-7.16*** [-7.32, -7.00]	215,935
	Black	16.32	21.20	-4.88*** [-5.03, -4.73]	215,935
	Other/Unknown Race	1.83	3.42	-1.58*** [-1.64, -1.53]	215,935
	Asian	4.90	9.45	-4.55*** [-4.64, -4.46]	215,935
Party (Voting Age Pop.)	Republican	32.44	14.00	18.44*** [18.25, 18.64]	218,041
	Democratic	31.03	43.32	-12.30*** [-12.49, -12.10]	218,041
	Other/Unknown Party	36.53	42.92	-6.39*** [-6.60, -6.19]	218,041
General Turnout, 2020	Voting Age Pop.	69.03	54.41	14.62*** [14.43, 14.82]	215,646
Gender	Male	83.20	48.69	34.51*** [34.35, 34.67]	218,041
	Female	16.80	51.31	-34.51*** [-34.67, -34.35]	218,041
Median Age (Years)	-	44.00	36.85	8.03*** [7.97, 8.10]	185,431
Mean Household Income ($)	-	114330.56	92309.78	22007.62*** [21730.44, 22284.80]	184,844

Table 1: **Comparison of Average Officer and Civilian Traits.** The table displays, from left to right, the actual share of officers with a given attribute; the share of officers who would have the attribute if taken as a random draw from their jurisdictions; and the difference between the two. Stars denote $p<.001$; brackets contain 95% confidence intervals.

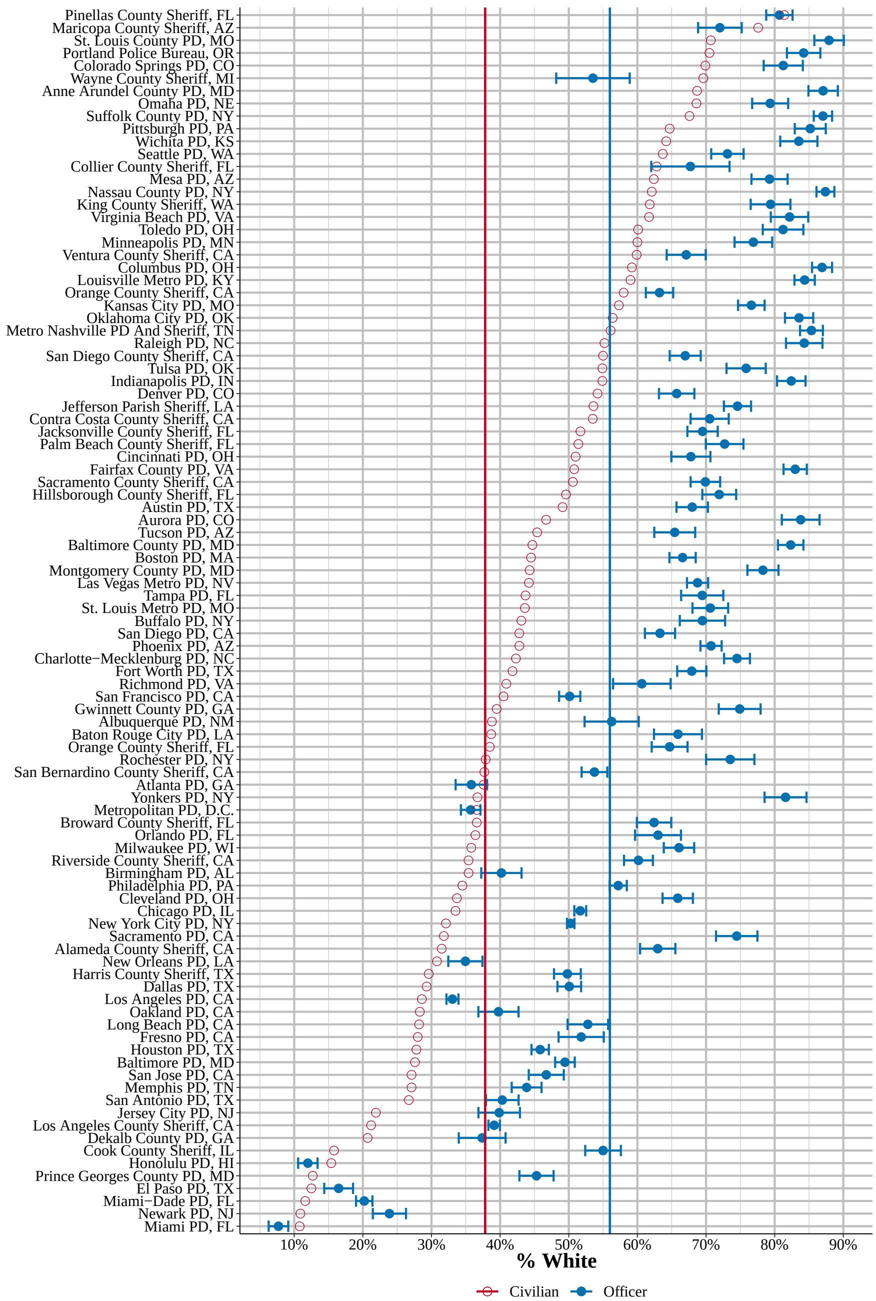

Figure 2: **Average Shares of White Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from BJS (2016) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions. See Appendix Table B11 for numeric results.

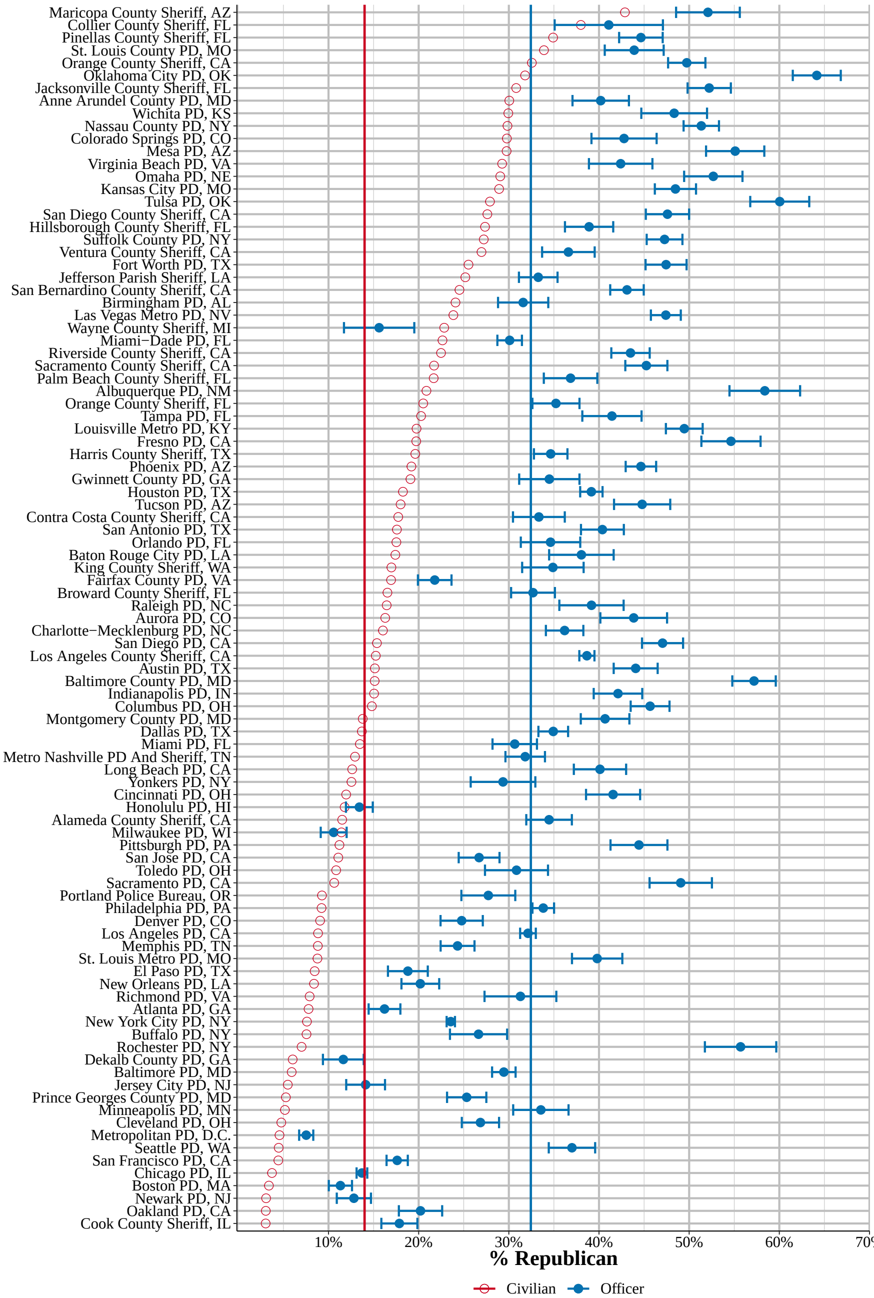

Figure 3: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdictions. See Appendix Table B12 for numeric results.

4.1 Officers' Places of Residence

Even if police do not themselves reflect the communities they serve, it is still possible they are rooted in those communities in ways that facilitate awareness of and empathy for the issues experienced by civilians they encounter on the job. An individual's place of residence is a close proxy for the social interactions they engage in on a day-to-day basis outside the work context, correlating strongly with social attitudes (Hopkins, 2010; Key, 1949; Oliver and Mendelberg, 2000; Oliver and Wong, 2003). Past work on intergroup contact theory has hypothesized such non-threatening interactions foster positive attitudes toward out-group members (Pettigrew, 1998). Often citing this same 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. There is wide variation in these policies: the precise terms span within-city-limits requirements and home-to-work distance thresholds, and policy instruments vary from financial incentives to employment conditions (for agency-specific rules, see Appendix Table B4). Nevertheless, it is clear that numerous top agencies regard officer residency as an important consideration.

To evaluate the possibility officers live among neighbors who more or less represent their jurisdictions writ large, we used officer home addresses in the L2 database—redacted from our replication data for security reasons—to match them with U.S. Census tracts. The characteristics of these home tracts, which approximate the neighborhoods in which officers choose to live, are then compared to the overall jurisdiction. The results are displayed in Table 2.[11]

As the table shows, areas in which officers live tend to have higher shares of Republicans (+9.0 percentage points, p.p. among the voting age population) and White residents (+13 p.p.). They also tend to have a higher median household annual income (+$12,908) and participate in elections at greater rates (+9 p.p. among voting age population). In the same vein, officers tend to live in areas with lower shares of Black (-7.0 p.p.) and Hispanic (-5 p.p.) residents than the jurisdiction-wide average.

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

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	50.54	37.82	12.83*** [12.71, 12.94]	200,302
	Hispanic	23.36	28.12	-5.06*** [-5.15, -4.98]	200,302
	Black	14.21	21.20	-6.90*** [-6.99, -6.80]	200,302
	Other/Unknown Race	3.40	3.42	0.01 [-0.00, 0.02]	200,302
	Asian	8.49	9.45	-0.88*** [-0.93, -0.84]	200,302
Party (Voting Age Pop.)	Republican	23.35	14.00	9.31*** [9.25, 9.38]	201,018
	Democratic	38.74	43.32	-4.49*** [-4.57, -4.42]	201,018
	Other/Unknown Party	39.97	42.92	-3.01*** [-3.07, -2.96]	201,018
General Turnout, 2020	Voting Age Pop.	63.77	54.41	9.43*** [9.35, 9.50]	198,780
Gender	Male	48.82	48.69	0.13*** [0.11, 0.14]	201,033
	Female	51.18	51.31	-0.13*** [-0.14, -0.11]	201,033
Median Age (Years)	-	38.80	36.87	2.33*** [2.30, 2.36]	201,030
Mean Household Income ($)	-	105215.82	92628.27	12908.40*** [12716.03, 13100.77]	201,004

Table 2: **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.

5 The Chicago Police Dept.: A Micro-Level Case Study

The officer-level analyses presented above paint a broad portrait of the state of descriptive representation across America's largest law-enforcement agencies. However, certain aspects of descriptive representation cannot be studied without more granular information. In this section, we consider two such questions using rare micro-level data on officer shift assignments and behavior, obtained via years of records requests in Chicago.

First, to account for enormous variation within each jurisdiction—both in terms of local resident traits and in agencies' deployment of officers—we conduct a disaggregated analysis of representation across precincts ("districts") of the Chicago Police Department (CPD). Past work has shown Black and Hispanic officers disproportionately serve in Black- and Hispanic-majority parts of Chicago (Ba et al., 2021), respectively, suggesting failures in citywide representation may be in part blunted by allocating police officers to precincts where they resemble the local population. On the other hand, on a per-capita basis, police agencies often allocate greater numbers of officers to policing minority communities (Kane, 2003; Briggs and Keimig, 2017), which may exacerbate representational gaps between predominantly White police officers and the civilians with whom they most frequently interact. In Section 5.1, we use detailed precinct-level staffing rosters to probe this important question in terms of racial and ethnic representation and political party affiliation.

Second, while some have advanced normative justifications for descriptively representative police forces—reasons that hold regardless of representation's ultimate impact—many proponents of diversification ground their advocacy in assertions that representation would lead to tangible benefits for civilians, such as reductions in the use of force (Sklansky, 2005; Legewie and Fagan, 2016). After decades of mixed empirical results, several recent studies using careful causal designs and newly available data have supported these assertions with respect to race, ethnicity and gender (Harvey and Mattia, 2019; Hoekstra and Sloan, 2020; West, 2018). However, despite the strong link between political ideology and policing philosophy, prior work has not assessed whether conservative officers in fact choose to enforce the law differently than liberal officers faced with similar circumstances. In Section 5.2, we use newly expanded data on micro-level shift assignments and officer behavior to estimate the magnitude of these enforcement gaps and place them in context with comparisons along other dimensions of officer identity.

5.1 Representation in Police-Civilian Interactions

Much of our analysis is based on one reasonable definition of descriptive representation in policing: the degree to which officers resemble civilians residing in their agency's jurisdiction, broadly defined. However, at least one meaningful alternative definition exists: the degree to which officers resemble the civilians *with whom they interact*. Unfortunately, the vast majority of police-civilian interactions go undocumented (Knox, Lowe and Mummolo, 2020), making it impossible to directly evaluate this alternative form of representation. However, using our micro-level data in Chicago, we can provide a detailed examination of the degree to which officers resemble a set of civilians that they frequently encounter.

To do this, we associated each officer in the Chicago data set with the district, or precinct, in which they most frequently worked, as measured in month-level unit assignment data. 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 (blue dots), according to CPD personnel records, as well as the share of civilians who are White in those same districts (red dots), based on Census data. The vertical blue line shows that, aggregating over all CPD districts, 52% of officers are White according to CPD personnel records. If officers perfectly matched civilians in their districts, however, that figure would be 33%.

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.

Figure 5 shows another striking mismatch. Overall, 15% of CPD officers are Republican. If each officer was replaced with a representative draw from the local district population, this group would be 3% Republican. However, even in the most right-leaning district civilians are no more than 9% Republican; in more than half of districts, this figure is below 3%. Strikingly, 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 B for robustness tests).

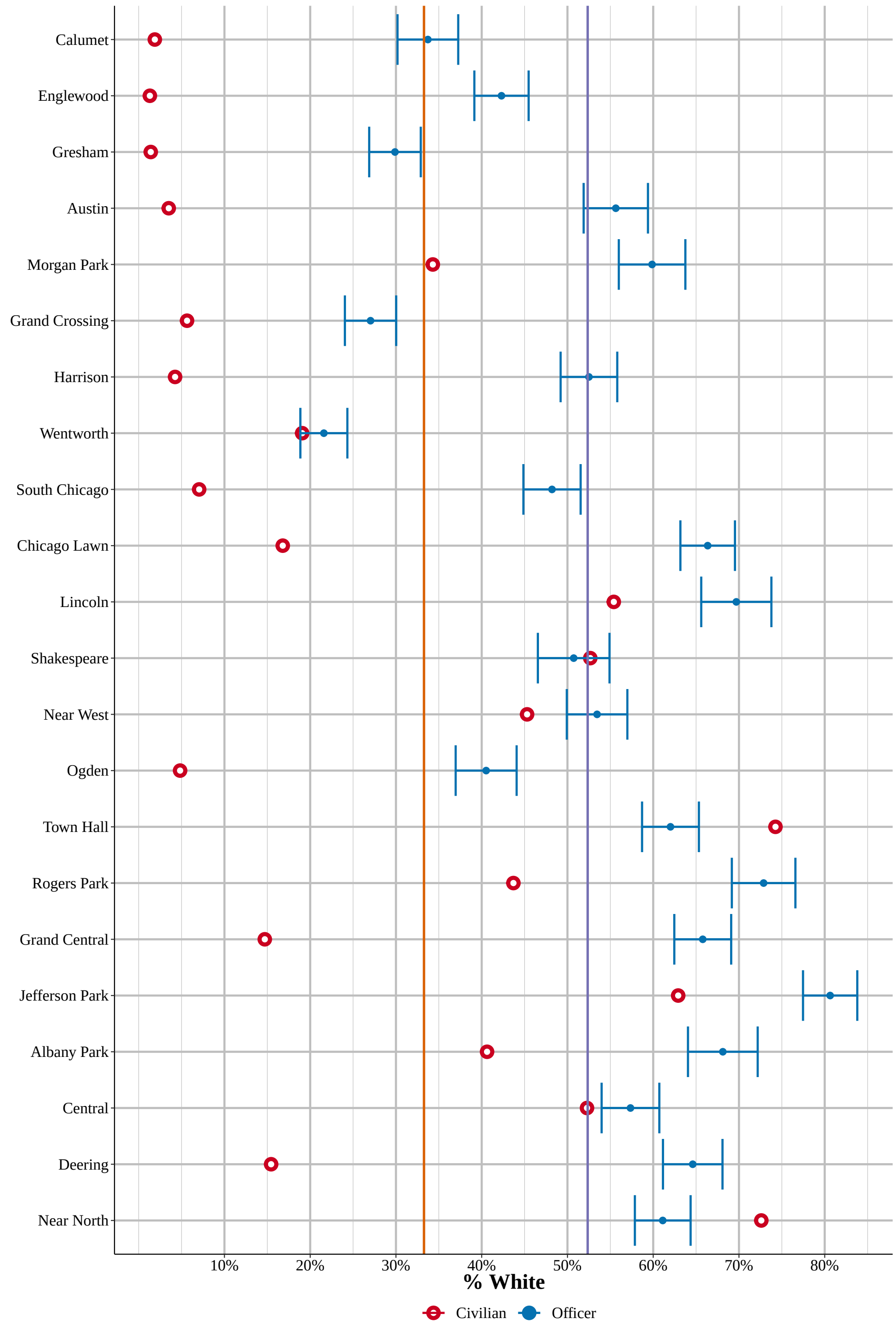

Figure 4: **Average Shares of White Chicago Officers and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective district. See Appendix B13 for numeric results.

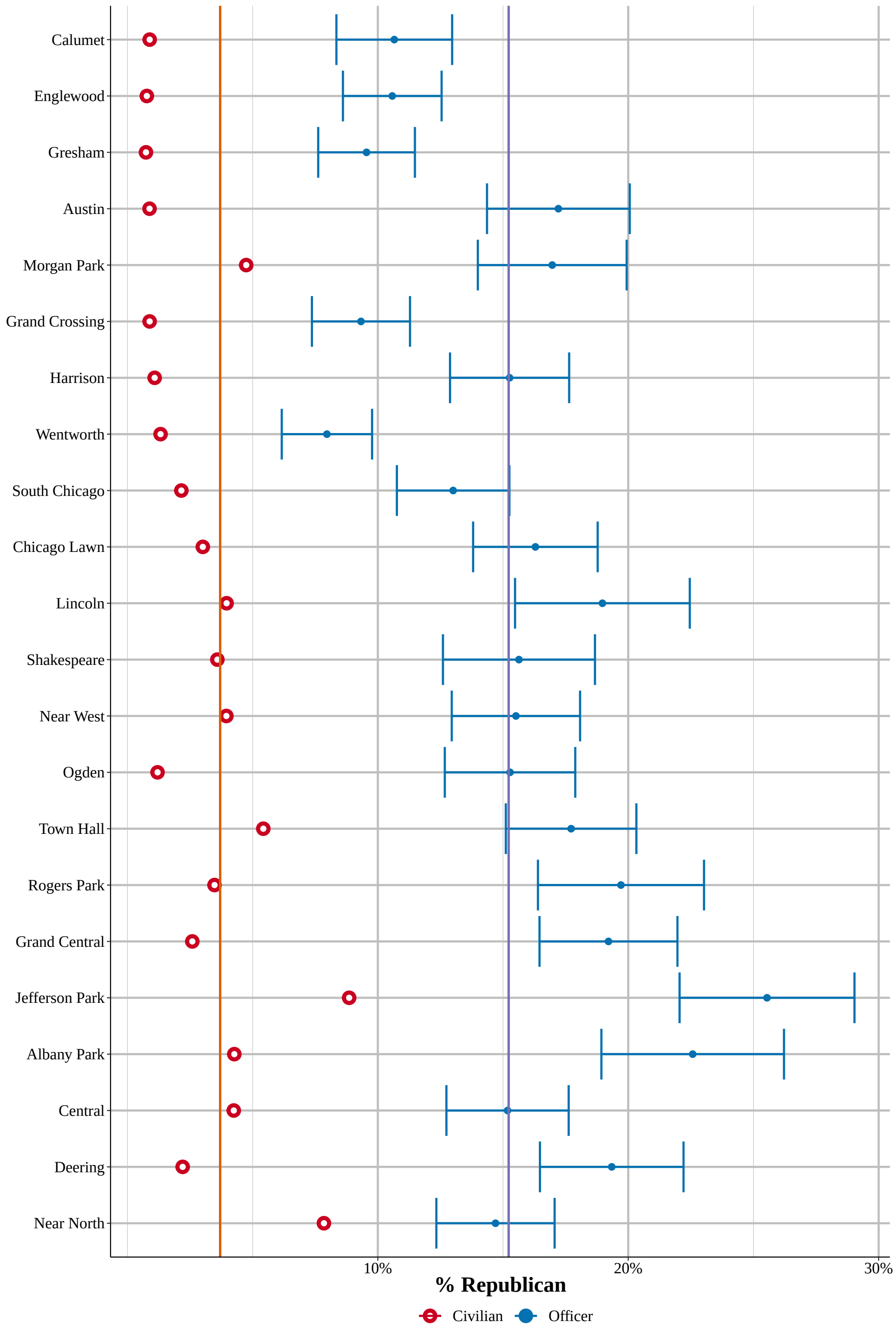

Figure 5: **Average Shares of Republican Chicago Officers and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective district. See Appendix Table B14 for numeric results.

As this analysis shows, not only do officers diverge from their jurisdictions as a whole, they also substantially diverge from civilians living in the areas of the city they are assigned to serve—at least, in Chicago. At multiple institutional layers, descriptive representation in policing appears deficient.

5.2 Deploying Officers of Different Racial and Political Groups

In this section, we use micro-level data on officer decisions to stop, arrest, and use force against Chicago civilians to study the impact of descriptive representation. To do so, we leverage fine-grained information on officer shift assignments to compare officers in similar times and places, ensuring external circumstances, including civilian behavior, are held fixed. This research design, first developed by Ba et al. (2021), allows us to compare groups of officers and attribute differences in their enforcement patterns to differences in their decision-making. We analyze CPD shift-assignment and enforcement records covering the years 2012–2019, using extensive new data collection that doubles the temporal coverage of Ba et al. (2021), which spanned 2012–2015. Table 3 describes our sample for this analysis. As the table shows, our data include observations on the behavior of more than 12,000 officers across more than 7 million shifts. Using new data on officer-level partisan affiliation, we probe "deployment effects"—the differences in behavior police commanders can expect when assigning Republican and Democratic officers to conduct the same task, based on how these individuals exercise the considerable discretion officers possess—and contrast these with previously demonstrated race- and ethnicity-based effects.

	White	Black	Hispanic	Male	Female	Republican	Democrat	Other Party
Stops	1096510	377310	553736	1630886	396670	360515	1160143	506898
Arrests	248327	88222	142373	392220	86702	80407	262776	135739
Force	11143	3739	5566	17566	2882	3620	11419	5409
Shifts	3489841	1697719	1842828	5458569	1571819	1144951	4173863	1711574
Officers	6215	2859	3354	9296	3132	1891	7168	3373

Table 3: **Summary of data on officer behavior (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 typically 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 effect estimate by taking the weighted average according to the number of patrol slots within each MDSB (see Appendix A.4 for additional details on estimation). Among the pool of officers eligible to work a beat and shift, predetermined "day-off group" rotations create exogeneous variation in the specific individuals available on any particular date. Thus, within these small slivers of time and space, we can plausibly assume officers are facing common circumstances, and therefore differences in policing outcomes can be attributed to differences in how two groups of officers exercise discretion.

Importantly, this research design estimates the effects of "bundled" treatments. When commanders deploy a Black officer, for example, they deploy that individual along with all their other identities and beliefs. Our analysis therefore does not offer us purchase on the precise *mechanism* driving behavioral differences. For example, if we observe Black and White officers make different numbers of arrests when facing common circumstances, we cannot conclude that difference is due to an officer's race rather than some officer-level correlate of race. Rather, we simply estimate differences in what commanders can expect when deploying members of each group to the same environment. As Ba et al. (2021) explain, this is the policy-relevant quantity of interest, since commanders must deploy whole officers, not isolated officer attributes net of their correlates.

To facilitate comparison between political deployment effects with previously demonstrated racial/ethnic effects, we focus on scenarios in which both contrasts can be made. For example, we first present results based on the subset of MDSBs in which Black, White, Democratic, and Republican officers appear.[12] This ensures 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 can differ substantially, meaning that effects should not be directly compared.

Figures 6–7 display the results of these behavioral analyses (see Appendix B.4 for full numeric results; all p-values adjusted for multiple testing using the Benjamini-Hochberg procedure (Ferreira and Zwinderman, 2006)). Turning first to Figure 6, we find Democratic officers detain 3.8 fewer civilians, make 0.77 fewer arrests and engage in 0.09 fewer uses of force per 100 shifts, compared to Republican officers faced with the same circumstances (all adjusted p-values<0.01). To put their magnitude in perspective, these effects represent reductions equal to 12%, 11% and 28% of the citywide average volume of stops, arrests and uses of force among Republican officers per 100 shifts citywide, respectively (see

[12]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.

Appendix Tables B8-B10). 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 2.1x) and arrests (1.6x; adjusted p-values of both differences < 0.012). They are comparable in size for use of force. When examining all combinations of race and party, we see a similar dynamic: Black officers tend to make fewer stops and arrests than White officers of the same political party.

We next turn to scenarios where Democratic-Republican officer deployment effects can be contrasted with Hispanic-White officer differences, estimated in MDSBs where at least one individual in each group was present. In these circumstances—which we emphasize can differ substantially from those considered above—Democratic officers are not significantly different from their Republican counterparts in terms of stops, arrests and uses of force. As Figure 7 shows, the deployment effects associated with ethnicity and party are, in this case, quite comparable in magnitude.

To investigate how different groups of civilians are impacted by these deployments, Figures B13 and B14 display results broken out 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 on encounters with Black civilians. Specifically, deploying a Black officer yields reductions of 6.0 and 0.8 stops and arrests of Black civilians per 100 shifts, and deploying a Democratic officer yields reductions of 3.2 and 0.6 stops and arrests of Black civilians per 100 shifts, respectively (all marginal $p_{\text{adj}} < 0.01$; p of differences in effects < 0.001 for stops and 0.036 for arrests). As in the previous analysis, race and party-based deployments yield very similar effects when it comes to the use of force, though again, effects are most pronounced in interactions with Black civilians. Deploying a Black (relative to White) officer or a Democratic (relative to a Republican) officer produces an expected reduction in 0.07–0.08 force per 100 shifts (both $p_{\text{adj}} < 0.01$). We also see significant reductions in stops and arrests of Hispanic and White civilians when deploying Black officers, but they are much smaller in magnitude (1.1 and 0.3 fewer stops and arrests of Hispanic civilians per 100 shifts when deploying Black officers; 0.7 and 0.1 fewer stops and arrests of White civilians per 100 shifts; $p < 0.01$ in all cases.) However, deploying a Democrat rather than a Republican yields no significant effects on enforcement for these groups, apart from a reduction of 0.2 Hispanic-civilian arrests per 100 shifts ($p_{\text{adj}} < 0.01$).

Consistent with the results in the previous section, we see a different pattern when comparing Hispanic and White officers. For all outcomes involving Hispanic officers,

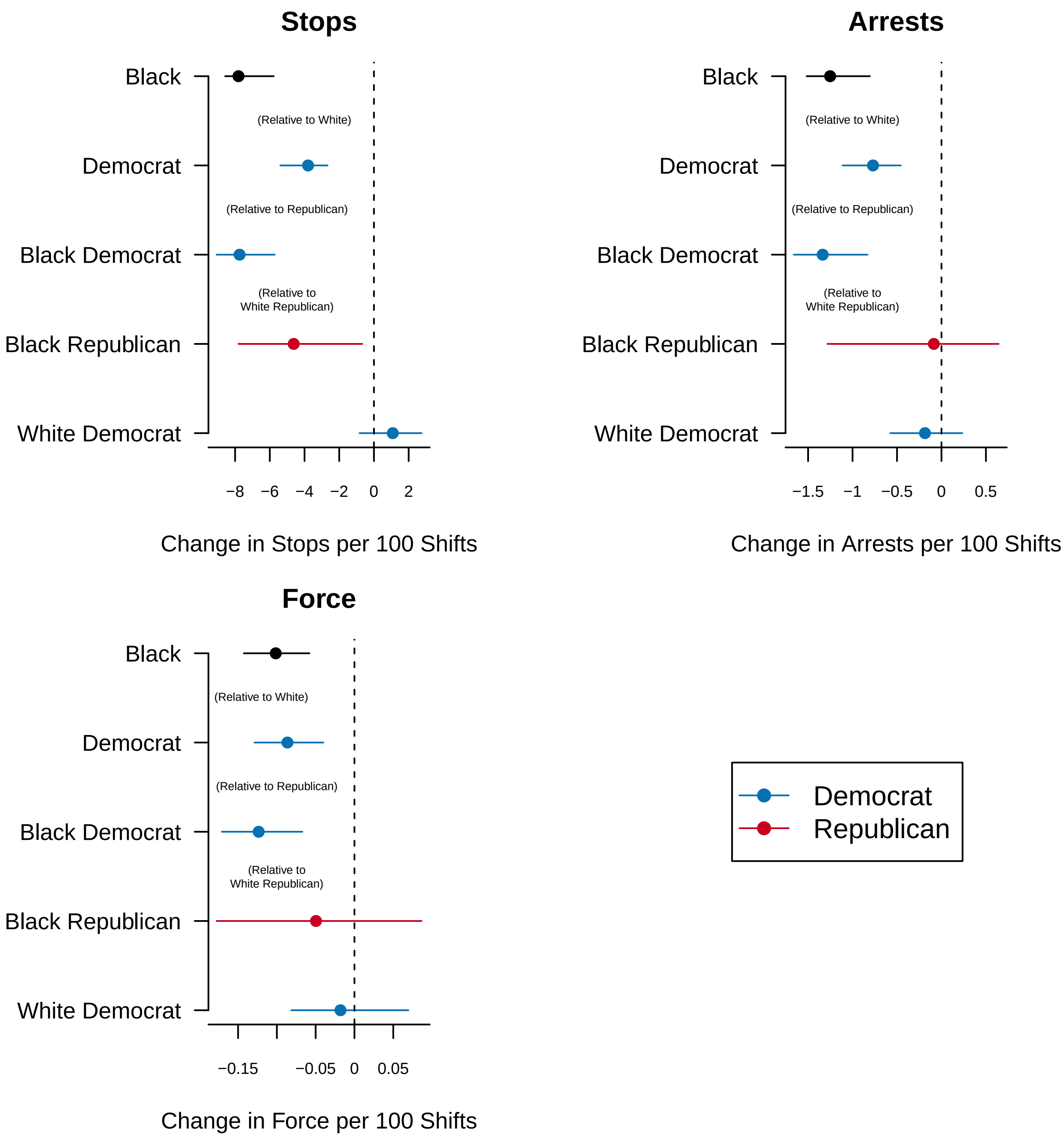

Figure 6: **Race and Party Deployment Effects, Black v. White Officers**. The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to otherwise common circumstances. Estimates computed using only places and times where at least one Black, White, Republican and Democratic officer was deployed. See Appendix Table B15 for numeric results.

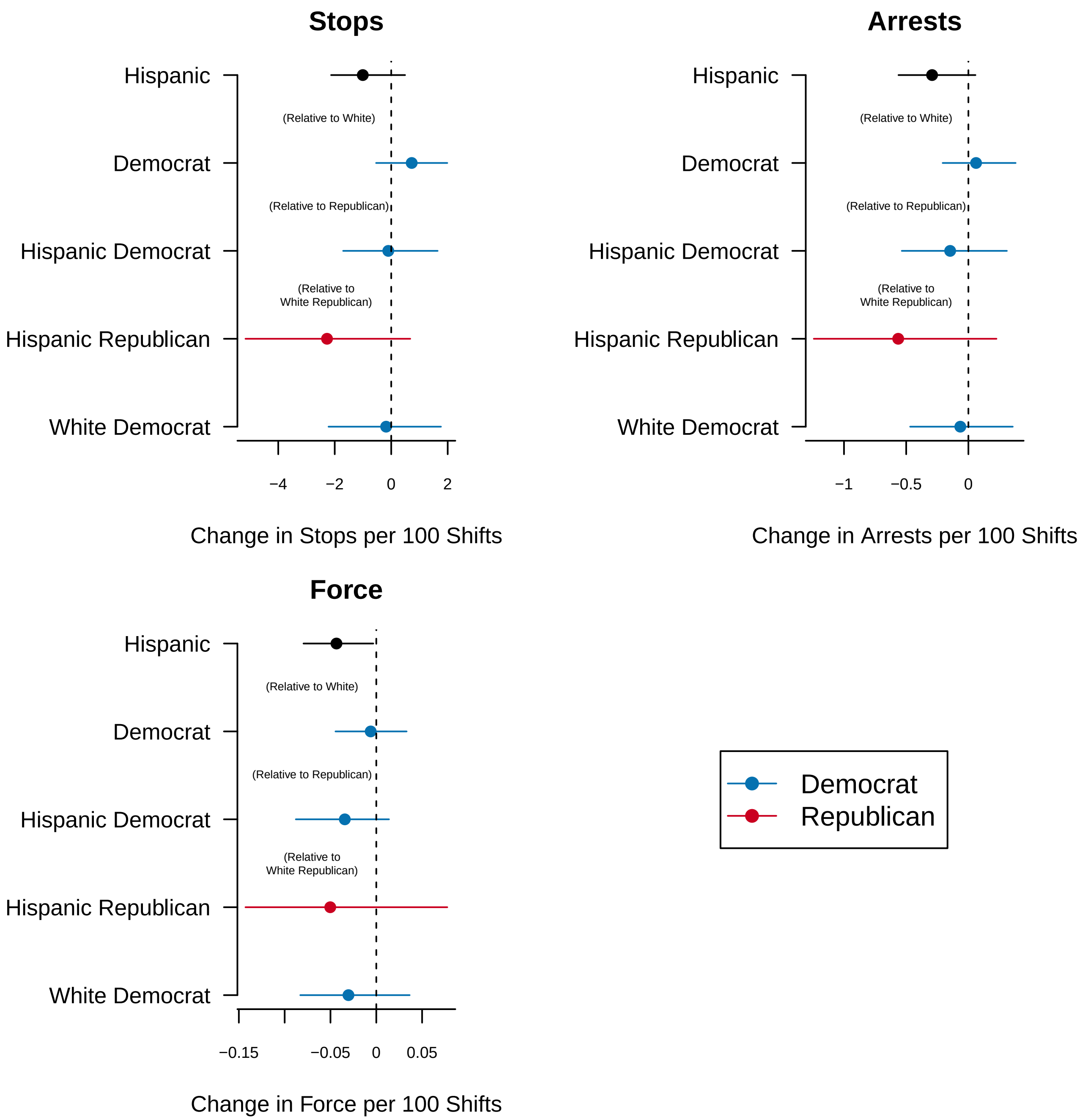

Figure 7: **Race and Party Deployment Effects, Hispanic v. White Officers**. The figure displays the average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican); and race-party combinations (relative to White Republicans) to otherwise common circumstances. Estimates computed using only places and times where at least one Hispanic, White, Republican and Democratic officer was deployed. See Appendix Table B16 for numeric results.

while significant reductions manifest for stops of Black civilians, after multiple-testing corrections we see no other statistically significant changes in police behavior, including outcomes involving Hispanic civilians.

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 a large and scattered network of agencies with different record keeping and sharing policies poses a substantial obstacle to both scholarship and oversight. In this paper, we draw on an original data set containing information on police officers from 97 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 the critical area of policing. Improving on prior work in this area that 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 tend to live in sections of localities that also exhibit higher levels of these features. Police are also much more politically active than civilians, turning out to vote at extremely high rates. By analyzing political affiliations within racial groups, we also find the political mismatch between officers and civilians is much more pronounced among White and Hispanic individuals than among Black individuals, with White and Hispanic officers identifying as Republican at levels far higher than those of their civilian counterparts.

To assess the relative importance of these traits for police behavior, we turn to a micro-level analysis in Chicago where detailed data on officer shift assignments and enforcement activities allow us to compare officers from different groups who are 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 a Black officer (relative to White) to otherwise similar circumstances yields much larger reductions in stops and arrests than deploying a Democrat (relative to a Republican), but the two effects are very similar in magnitude in terms of reductions in the use of force. However, we also find deploying a Hispanic officer (relative to White) yields effects very similar in magnitude to deploying a Democrat (relative to a Republican). These results complicate conventional narratives surrounding diversity initiatives, and illustrate how race and ethnicity are imperfect proxies for the political orientations of officers.

In addition to providing valuable empirical evidence to the study of representative bureaucracy, our paper also illustrates the feasibility of enhanced data collection efforts on the personal attributes of bureaucrats. This is especially important in the context of law enforcement, where a lack of data on law enforcement personnel has not only stymied the study of policing, but public oversight. Because law enforcement agencies operate independently, it is often the case that police officers fired for misconduct are rehired by other agencies (Grunwald and Rappaport, 2019; Lalwani and Johnston, 2020). A registry of the officers working in the 100 largest U.S. police agencies, which we will release publicly, provides a template for needed data collection efforts, and with some expansion can seed a national registry of officers vital for accountability.

Using these records, our study provides one of the most comprehensive answers to date to a basic question: who are the police? But important questions remain. For one, due to the difficulty of obtaining shift assignment data, our analysis of how officer attributes map to officer behavior is limited to a single city. Much more research is needed before we can generalize broadly about how deploying officers from different groups affects the nature and volume of police-civilian interactions. In addition, more research is needed on the causes of the disparities we observe between the features of 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 represents an important frontier in the study of representative bureaucracy.

References

Alexander, Michelle. 2010. *The New Jim Crow: Mass Incarceration in the Age of Colorblindness*. New York: The New Press.

Ba, Bocar A., Dean Knox, Jonathan Mummolo and Roman G. Rivera. 2021. "The Role of Officer Race and Gender in Police-Civilian Interactions in Chicago." *Science* 371(6530):696–702.

Bendor, Jonathan and Adam Meirowitz. 2004. "Spatial models of delegation." *American Political Science Review* 98(2):293–310.

BJS. 2016. Law Enforcement Management and Administrative Statistics. Technical report United States Department of Justice. Office of Justice Programs. Bureau of Justice Statistics. Inter-university Consortium for Political and Social Research Maryland: .
URL: *https://doi.org/10.3886/ICPSR37323.v1*

Brehm, John and Scott Gates. 1999. *Working, Shirking, and Sabotage: Bureaucratic Response to a Democratic Public*. University of Michigan Press.

Briggs, Steven J and Kelsey A Keimig. 2017. "The impact of police deployment on racial disparities in discretionary searches." *Race and Justice* 7(3):256–275.

Campbell, Angus, Philip E. Converse, Warren E. Miller and Donald E. Stokes. 1960. *The American Voter*. University of Chicago Press.

Clinton, Joshua D., Anthony Bertelli, Christian R. Grose, David E. Lewis and David C. Nixon. 2012. "Separated powers in the United States: The ideology of agencies, presidents, and congress." *American Journal of Political Science* 56(2):341–354.

Clinton, Joshua D. and David E. Lewis. 2008. "Expert opinion, agency characteristics, and agency preferences." *Political Analysis* 16(1):3–20.

DOJ. 2016. Law Enforcement Agency Roster (LEAR), 2016. Technical report United States Department of Justice. Office of Justice Programs. Bureau of Justice Statistics. http://doi.org/10.3886/ICPSR30766.v1.

Dolan, Julie. 2001. "Political appointees in the United States: Does gender make a difference?" *Political Science & Politics* 34.

Dolan, Julie and David H. Rosenbloom. 2003. *Representative bureaucracy: Classic readings and continuing controversies*. Routledge.

Eckhouse, Laurel. 2019. “Race, party, and representation in criminal justice politics.” *The Journal of Politics* 81(3):1143–1152.

Eisinger, Peter K. 1983. “Municipal residency requirements and the local economy.” *Social Science Quarterly* 64(1):85.

Enamorado, Ted, Benjamin Fifield and Kosuke Imai. 2017*a*. “fastLink: Fast Probabilistic Record Linkage with Missing Data.”.
URL: *https://github.com/kosukeimai/fastLink*

Enamorado, Ted, Benjamin Fifield and Kosuke Imai. 2017*b*. “Using a Probabilistic Model to Assist Merging of Large-scale Administrative Records.” *Working Paper* .

Ferreira, JA and AH Zwinderman. 2006. “On the benjamini–hochberg method.” *The Annals of Statistics* 34(4):1827–1849.

Forman Jr., James. 2017. *Locking up our own: Crime and punishment in Black America*. Farrar, Straus and Giroux.

Fyfe, James J. 1981. “Who shoots? A look at officer race and police shooting.” *Journal of Police Science & Administration* .

Glaser, Jack. 2014. *Suspect Race: Causes and Consequences of Racial Pro ling*. Oxford University Press.

Goldstein, Herman. 1977. *Policing a Free Society*. Ballinger Pub. Co.

Grunwald, Ben and John Rappaport. 2019. “The Wandering Officer.” *Yale Law Journal* 129.
URL: *https://www.washingtonpost.com/politics/2020/06/16/what-happens-when-police-o cer-gets- red-very-often-another-police-agency-hires-them/*

Hainmueller, Jens, Daniel J Hopkins and Teppei Yamamoto. 2014. “Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments.” *Political analysis* 22(1):1–30.

Harrell, Erika and Elizabeth Davis. 2020. “Contacts between police and the public, 2018–statistical tables.” *Bureau of Justice Statics Report, NCJ* 255730.

Harris. 2021. Reimagining Chicago’s Public Safety. Technical report.
URL: *https://theharrispoll.com/reimagining-chicago-public-safety-macarthur-foundation/*

Harvey, Anna and Taylor Mattia. 2019. “Reducing Racial Disparities in Crime Victimization.” *Working Paper* .
URL: *https://s18798.pcdn.co/annaharvey/wp-content/uploads/sites/6417/2019/12/Victimization[illegible].[illegible]*

Hauck, Grace and Mark Nichols. 2020. “Should police officers be required to live in the cities they patrol? There’s no evidence it matters.” *USA TODAY* .
URL: *https://www.usatoday.com/story/news/nation/2020/06/13/police-residency-data/5327640002/*

Hoekstra, M. and C. Sloan. 2020. “Does Race Matter for Police Use of Force? Evidence from 911 Calls.” *National Bureau of Economic Research, Working Paper (26774)* .
URL: *https://econrails.uzh.ch/api/agenda/event[illegible]/269*

Hopkins, Daniel J. 2010. “Politicized Places: Explaining Where and When Immigrants Provoke Local Opposition.” *American Political Science Review* 104(1):40–60.

Huber, John D. and Charles R. Shipan. 2002. *Deliberate Discretion? The Institutional Foundations of Bureaucratic Autonomy*. Cambridge University Press.

Hyland, Shelley S and Elizabeth Davis. 2019. “Local police departments, 2016: Personnel.” *Washington, DC: Bureau of Justice Statistics (BJS) US Dept of Justice, O ce of Justice Programs, Bureau of Justice Statistics* .

Kane, Robert J. 2003. “Social control in the metropolis: A community-level examination of the minority group-threat hypothesis.” *Justice Quarterly* 20(2):265–295.

Kaplan, Jacob. 2018. “Jacob Kaplan’s Concatenated Files: Uniform Crime Reporting (UCR) Program Data: Arrests by Age, Sex, and Race, 1974-2020.” *Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor]* pp. 12–29.

Kaplan, Jacob. 2020. "Jacob Kaplan's Concatenated Files: Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest, 1960-2020." *Ann Arbor, MI: Interuniversity Consortium for Political and Social Research [distributor]* .

Kaplan, Jacob. 2021. "Uniform Crime Reporting Program Data: Law Enforcement Officers Killed and Assaulted (LEOKA) 1960-2020." *Ann Arbor, MI: Inter-university Consortium for Political and Social Research* .

Key, V.O. 1949. *Southern Politics in State and Nation*. A.A. Knopf.

Kim Parker and Kiley Hurst. 2021. "Growing share of Americans say they want more spending on police in their area.".
URL: *https://www.pewresearch.org/fact-tank/2021/10/26/growing-share-of-americans-say-they-want-more-spending-on-police-in-their-area/*

Kingsley, Donald. 1944. *Representative Bureaucracy*. Antioch Press.

Knox, Dean, Christopher Lucas and Wendy K Tam Cho. 2022. "Testing Causal Theories with Learned Proxies." *Annual Review of Political Science* 25.

Knox, Dean and Jonathan Mummolo. 2020. "Toward a general causal framework for the study of racial bias in policing." *Journal of Political Institutions and Political Economy* 1(3):341–378.

Knox, Dean, Will Lowe and Jonathan Mummolo. 2020. "Administrative records mask racially biased policing." *American Political Science Review* 114(3):619–637.

Krause, George A. 2010. Legislative delegation of authority to bureaucratic agencies. In *The Oxford handbook of American Bureaucracy*.

Kringen, Anne Li. 2014. *Understanding barriers that a ect recruiting and retaining female police o cers: A mixed method approach*. Texas State University-San Marcos.

Kropf, Martha, Timothy Vercellotti and David C. Kimball. 2013. "Representative bureaucracy and partisanship: The implementation of election law." *Public Administration Review* 73:242–252.

Lalwani, Nikita and Mitchell Johnston. 2020. "What happens when a police officer gets fired? Very often another police agency hires them." *The Washington Post* .

URL: *https://www.washingtonpost.com/politics/2020/06/16/what-happens-when-police-o cer-gets- red-very-often-another-police-agency-hires-them/*

Legewie, Joscha and Jeffrey Fagan. 2016. "Group threat, police officer diversity and the deadly use of police force." *Columbia Public Law Research Paper* (14-512).

Lerman, Amy and Vesla Weaver. 2014. *Arresting Citizenship: The Democratic Consequences of American Crime Control*. University of Chicago Press.

Linos, Elizabeth. 2017. "More Than Public Service: A Field Experiment on Job Advertisements and Diversity in the Police." *Journal of Public Administration Research and Theory* 28(1):67–85.
URL: *https://doi.org/10.1093/jopart/mux032*

Lipset, Seymour Martin. 1975. *Representative Bureaucracy: Classic Readings and Continuing Controversies*. Routledge chapter Bureaucracy and Social Change, pp. 80–84.

McCrary, Justin. 2007. "The effect of court-ordered hiring quotas on the composition and quality of police." *American Economic Review* 97(1):318–353.

Meier, Kenneth J and Jill Nicholson-Crotty. 2006. "Gender, representative bureaucracy, and law enforcement: The case of sexual assault." *Public Administration Review* 66(6):850–860.

Meier, Kenneth J, Robert D Wrinkle and Jerry L Polinard. 1999. "Representative bureaucracy and distributional equity: Addressing the hard question." *The Journal of Politics* 61(4):1025–1039.

Meier, Kenneth John. 1975. "Representative bureaucracy: An empirical analysis." *American Political Science Review* 69(2):526–542.

Miller, Amalia R and Carmit Segal. 2012. "Does temporary affirmative action produce persistent effects? A study of black and female employment in law enforcement." *Review of Economics and Statistics* 94(4):1107–1125.

Miller, Amalia R and Carmit Segal. 2018. "Do Female Officers Improve Law Enforcement Quality? Effects on Crime Reporting and Domestic Violence." *The Review of Economic Studies* 86(5):2220–2247.

Morin, Rich, Kim Parker, Renee Stepler and Andrew Mercer. 2017. Behind the Badge: Amid protests and calls for reform, how police view their jobs, key issues and recent fatal encounters between blacks and police. Technical report Pew Research Center.

Mosher, Frederick Camp. 1968. *Democracy and the public service*. Vol. 53 New York: Oxford University Press.

Murphy, David W and John L Worrall. 1999. "Residency requirements and public perceptions of the police in large municipalities." *Policing: An international journal of police strategies & management* .

Oliver, J. Eric and Janelle Wong. 2003. "Intergroup Prejudice in Multiethnic Settings." *American Journal of Political Science* 47(4):567–82.

Oliver, J. Eric and Tali Mendelberg. 2000. "Reconsidering the Environmental Determinants of White Racial Attitudes." *American Journal of Political Science* 44(3):574–89.

Pettigrew, Thomas F. 1998. "Intergroup contact theory." *Annual review of psychology* 49(1):65–85.

Pew. 2017. "Republicans more likely than Democrats to have confidence in police.".
URL: *https://www.pewresearch.org/fact-tank/2017/01/13/republicans-more-likely-than-democrats-to-have-con dence-in-police/*

Potter, Rachel and Craig Volden. 2021. "A Female Policy Premium? Agency Context and Women's Leadership in the U.S. Federal Bureaucracy." *Journal of Public Administration Research and Theory* 31:91–107.

Prior, Markus. 2007. *Post-Broadcast Democracy*. Cambridge University Press.

Sen, Maya and Omar Wasow. 2016. "Race as a bundle of sticks: Designs that estimate effects of seemingly immutable characteristics." *Annual Review of Political Science* 19:499–522.

Sklansky, David Alan. 2005. "Not your father's police department: Making sense of the new demographics of law enforcement." *J. Crim. L. & Criminology* 96:1209–1244.

Smith, Dennis C. 1980*a*. "Police attitudes and performance: The impact of residency." *Urban a airs quarterly* 15(3):317–334.

Smith, Russell L. 1980*b*. "Representative bureaucracy: A research note on demographic representation in state bureaucracies." *Review of Public Personnel Administration* 1(1):1–13.

Soss, Joe and Vesla Weaver. 2017. "Police are our government: Politics, political science, and the policing of race–class subjugated communities." *Annual Review of Political Science* 20:565–591.

Walker, Samuel, Cassia Spohn and Miriam DeLone. 2016. *The color of justice: Race, ethnicity, and crime in America*. Cengage Learning.

West, Jeremy. 2018. "Racial Bias in Police Investigations.". Working Paper.
URL: *https://people.ucsc.edu/ jwest1/articles/West[illegible].[illegible]*

White, Ismail K, Chryl N Laird and Troy D Allen. 2014. "Selling Out?: The politics of navigating conflicts between racial group interest and self-interest." *American Political Science Review* 108(4):783–800.

White, Michael D., Jonathon A. Cooper Jessica Saunders and Anthony J. Raganella. 2010. "Motivations for becoming a police officer: Re-assessing officer attitudes and job satisfaction after six years on the street." *Journal of Criminal Justice* 38(4):520–530.

Wilson, James Q., ed. 1989. *Bureaucracy: What government agencies do and why they do it*.

Wright II, James E. and Andrea M. Headley. 2020. "Police Use of Force Interactions: Is Race Relevant or Gender Germane?" *The American Review of Public Administration* 50(8):851–864.
URL: *https://doi.org/10.1177/0275074020919908*

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.[13] The ACS surveys approximately 1% of the US population each year, meaning that this data is a Census estimate of the true population.

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" [14] 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's rough approximation of a neighborhood.[15] Census tracts are fully contained within counties, but can extend to cover multiple Census Places (e.g. cities, towns) meaning that different parts of a single tract may lie inside and outside of an agency's jurisdiction. This is rare and occurs primarily in extremely rural areas with low population density.

Each individual in the L2 data is associated with an address (including tract, county

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

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

[15] urlhttps://www2.census.gov/geo/pdfs/reference/GARM/Ch1GARM.pdf

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.

A.2 Imputed Data on Party ID

L2 describes their method for labeling party ID 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 B.1 for estimates of core results after subsetting to states with closed primary elections in 2020.

A.3 Data on Officer Race/Ethnicity and Gender

As explained in the main text, we rely on 2019 LEOKA data (Kaplan, 2021) for gender data on agencies, due to its near-complete coverage. Two exceptions are the Columbus

Police Department, in Ohio, and the Jefferson Parish Sheriff's Office, in Louisiana, which do not report officer gender in 2019; here we use 2018 LEOKA data which did include officer gender. In addition, because LEOKA data does not contain racial/ethnic measures, we obtain those from the 2016 LEMAS data for 86% of agencies, and use L2 estimates of officers' racial and ethnic identities for the remaining agencies.

A.4 Estimation of Behavioral Differences

Our approach to estimating multi-dimensional behavioral differences is based on an extension of Ba et al. (2021). We index MDSBs by $\square \square F$, where F is the set of MDSBs in some feasible set of interest (i.e., MDSBs in which officers with minority, White, Democratic, and Republican identities appear; note that depending on the analysis, "minority" can denote either Black or Hispanic identity). Patrol assignment slots within an MDSB are indexed by $\square \square \{1, \dots, \square_{\square}\}$. We denote shift-level outcomes—stop, arrest, and force counts, potentially broken out by civilian category—as $\square_{\square,\square}$. For each slot, the officer's multi-dimensional demographic profile (including race, ethnicity, and party) is $\square_{\square,\square}$, which can potentially take on as many values as there are officers available for deployment in a particular MDSB. We assume that $\square_{\square,\square}$ is exogeneously selected within the pool of officers eligible for deployment to each MDSB (importantly, the distribution of $\square_{\square,\square}$ is not assumed to be constant across MDSBs, as different officer types can select into differing districts or shifts). This relaxes the stable unit treatment value assumption of Ba et al. (2021) to allow for officer profiles that share a common dimension of interest, $\square$, but vary on other dimensions. It implicitly assumes stability of potential outcomes across officers sharing identical profiles, though we note that these profiles can be made arbitrarily rich.

Our estimands are defined in terms of aggregations of and contrasts between MDSB-level attribute-specific potential outcomes, $\square_{\square}[\square_{\square,\square}(\square_{\square,\square})|\square_{\square,\square} \square \square]$, where $\square_{\square,\square} \square \square$ indicates that multi-dimensional identity $\square_{\square,\square}$ includes aspect $\square$, which can take on the values Black, Hispanic, Democratic, or Republican. Here, the expectation is taken over officer profiles that are available for assignment, indicating the average potential outcome when deploying a randomly drawn $\square$-type officer into the slot.

We study estimands of the following form:

$$\square_{\square,\square}\left[\square_{\square,\square'}[\square_{\square,\square}(\square_{\square,\square}) - \square_{\square,\square}(\square'_{\square,\square})|\square_{\square,\square} \square \square, \square'_{\square,\square} \square \square']\right].$$

The inner expectation is what we refer to as the within-MDSB deployment effect. This quantity is the difference in enforcement volume that a commander can expect when deploying a single randomly drawn officer from the pool available into the MDSB, if that pool is first subset to officer type g as opposed to type g'. The outer expectation aggregates these within-MDSB effects over all MDSBs in CPD and patrol slots in the MDSB (i.e., over i and t). This estimand marginalizes over the "bundle of sticks" associated with identities g and g' (Sen and Wasow, 2016), much as marginalization occurs in the average marginal component effects studied in conjoint analyses (AMCE, Hainmueller, Hopkins and Yamamoto, 2014).

An important challenge is that, due to the granularity at which we define MDSBs, not every MDSB is served by officers of every identity group of interest. Given this fundamental limitation, and the need to compare differences between political and racial/ethnic deployment effects, we therefore restrict ourselves to studying the feasible set of MDSBs, $\mathcal{F}$, in which all officer groups of interest appear. We then examine three estimands:

$$\mathbb{E}_{i,t}\left[\mathbb{E}_{g,g'}\left[Y_{i,t}(g_{i,t}) - Y_{i,t}(g'_{i,t}) \mid g_{i,t} \in \text{Dem.}, g'_{i,t} \in \text{Rep.}\right] \mid i \in \mathcal{F}\right], \tag{1}$$

$$\mathbb{E}_{i,t}\left[\mathbb{E}_{g,g'}\left[Y_{i,t}(g_{i,t}) - Y_{i,t}(g'_{i,t}) \mid g_{i,t} \in \text{minority}, g'_{i,t} \in \text{White}\right] \mid i \in \mathcal{F}\right], \text{ and} \tag{2}$$

$$\begin{aligned} &\mathbb{E}_{i,t}\left[\mathbb{E}_{g,g'}\left[Y_{i,t}(g_{i,t}) - Y_{i,t}(g'_{i,t}) \mid g_{i,t} \in \text{Dem.}, g'_{i,t} \in \text{Rep.}\right] \mid i \in \mathcal{F}\right] \\ &\quad - \mathbb{E}_{i,t}\left[\mathbb{E}_{g,g'}\left[Y_{i,t}(g_{i,t}) - Y_{i,t}(g'_{i,t}) \mid g_{i,t} \in \text{minority}, g'_{i,t} \in \text{White}\right] \mid i \in \mathcal{F}\right]. \end{aligned} \tag{3}$$

An key consideration in consistently estimating the above quantities is that in the presence of heterogeneous within-MDSB deployment effects, ordinary least squares (OLS) will not consistently recover the causal quantities defined above. Rather, it will produce the weighted average of within-MDSB deployment effects, with weights corresponding to the variance of group identities. Importantly, these variance weights differ when examining political divides and racial/ethnic divides. As a result, OLS estimates for the Democratic-Republican deployment effect and the minority-White deployment effect cannot be directly compared, even when restricted to the same set of jointly feasible MDSBs, because the implicit weights on those MDSBs will generally differ. To address this issue, we employ the following simple and direct estimator

$$\sum_{i \in \mathcal{F}} \frac{T_i}{\sum_{i' \in \mathcal{F}} T_{i'}} \sum_{t=1}^{T_i} \left(\frac{\sum_{j=1}^{N_i} Y_{i,j} \cdot \mathbf{1}(g_{i,j} \in g)}{\sum_{j=1}^{N_i} \mathbf{1}(g_{i,j} \in g)} - \frac{\sum_{j=1}^{N_i} Y_{i,j} \cdot \mathbf{1}(g_{i,j} \in g')}{\sum_{j=1}^{N_i} \mathbf{1}(g_{i,j} \in g')} \right).$$

where g = Democratic and g' = Republican for political deployment effects, and g =

minority and [illegible]$'$ = White for racial/ethnic deployment effects (where "minority" can indicate Black or Hispanic, depending on the analysis). This approach computes within-MDSB means for each identity group, takes the within-MDSB difference between identity groups, and then averages these across MDSBs with weights based on the number of patrol slots for each MDSB. Finally, differences between the above deployment effects are taken.

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, ensuring that deployment effects are always based on within-MDSB comparisons.

B Additional Results

B.1 Descriptive Statistics

Variable	Values	Police in Data	All U.S. Police	All U.S. Pop.
Race (%)	White	56.0	71.5	60.7
	Hispanic	21.0	12.5	18.0
	Black	16.3	11.4	12.3
	Other/Unknown	1.8	4.7	3.6
	Asian	4.9	-	5.5
Party (% of Registered Voters)	Republican	37.7	-	31.5
	Democratic	36.1	-	34.7
	Other Party	26.2	-	33.7
Gender	Male	83.2	87.7	49.2
	Female	16.8	12.3	50.8
Median Age (Years)	-	44	-	38.1
Mean Household Income ($)	-	114,331	-	62,843
N		218,041	701,000	330,000,000

Table B1: **Police Officers in Our Data, Compared to All U.S. Officers and U.S. Population.** Estimates for officers in our data are obtained from various sources described in Section 2. Estimates for police nationwide are from Hyland and Davis (2019). National political affiliation estimates are from the 2020 American National Election Studies; "other" includes partisan leaners. National race, gender, age, and income averages are based on American Community Survey 2015–2019 estimates.

Race	Party	Actual Officer %	Hypothetical Representative Officer %	Difference	N
White	Republican	40.09	21.83	18.26 *** [17.98, 18.54]	111,282
	Democrat	19.12	34.58	-15.46 *** [-15.69, -15.23]	111,282
Hispanic	Republican	23.06	7.44	15.62 *** [15.23, 16.02]	42,012
	Democrat	42.89	37.83	5.06 *** [4.60, 5.52]	42,012
Black	Republican	2.18	1.35	0.84 *** [0.68, 0.99]	33,374
	Democrat	51.61	66.09	-14.47 *** [-15.01, -13.94]	33,374

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. Among the 83 jurisdictions used for the officers data, hypothetical officer shares are generated by taking the number of civilians of each race that are Republican or Democrat, based on L2 data, then dividing by the number of adults in these jurisdictions of each race, according to American Community Survey 5-year 2015-2019 Census data. Likely due to "dead wood" in L2—a known issue with voter files that are only periodically cleaned—in five jurisdictions (accounting for 2.5% of officers in the 83 LEMAS agencies), this number exceeds 100% by no more than 2 percentage points. In these jurisdictions, we manually cap party shares to 100%, a workaround that we viewed as preferable to excluding the far larger portion of unregistered voting-age residents from the denominator of these shares. (In Table B3, we conduct an additional robustness test that excludes these agencies, finding similar results.) 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	40.11	21.48	18.64 *** [18.35, 18.92]	107,702
	Democrat	19.21	34.92	-15.71 *** [-15.95, -15.48]	107,702
Hispanic	Republican	22.94	7.39	15.56 *** [15.16, 15.95]	41,652
	Democrat	42.82	37.85	4.97 *** [4.51, 5.44]	41,652
Black	Republican	2.13	1.33	0.80 *** [0.64, 0.96]	32,639
	Democrat	50.67	66.13	-15.46 *** [-15.99, -14.92]	32,639

Table B3: **Average officer and civilian party membership by race, subset of agencies**. This table follows the same format and data processing as Table B2 but excludes data from five agencies—Baton Rouge City Police, Honolulu Police Department, Jefferson Parish Sheriff's Office, St. Louis County Police Department, and Ventura County Sheriff's Office—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 2.5% 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	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	55.99	38.01	17.98*** [17.78, 18.18]	207,961
	Hispanic	20.74	27.33	-6.59*** [-6.75, -6.43]	207,961
	Black	16.73	21.77	-5.04*** [-5.20, -4.89]	207,961
	Other/Unknown Race	1.58	3.42	-1.84*** [-1.89, -1.79]	207,961
	Asian	4.96	9.47	-4.51*** [-4.60, -4.41]	207,961
Party (Voting Age Pop.)	Republican	25.39	14.00	11.39*** [11.22, 11.57]	218,041
	Democratic	22.34	43.32	-20.99*** [-21.16, -20.82]	218,041
	Other/Unknown Party	52.27	42.92	9.35*** [9.14, 9.55]	218,041
General Turnout, 2020	Voting Age Pop.	51.24	54.41	-3.17*** [-3.38, -2.96]	215,646
Gender	Male	83.20	48.69	34.51*** [34.35, 34.67]	218,041
	Female	16.80	51.31	-34.51*** [-34.67, -34.35]	218,041
Median Age (Years)	-	44.00	36.95	7.86*** [7.78, 7.93]	136,392
Mean Household Income ($)	-	115337.32	92174.92	23153.72*** [22833.70, 23473.75]	135,932

Table B5: **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. Stars denote $p<.001$; brackets contain 95% confidence intervals.

Variable	Description	N	Percent
Political Party	Republican	70,734	37.74
	Democratic	67,654	36.10
	Non-Partisan	43,332	23.12
	American Independent	1,507	0.80
	Independence	960	0.51
	Libertarian	817	0.44
	Conservative	684	0.36
	Registered Independent	575	0.31
	Other	485	0.26
	Unknown	204	0.11
	Green	179	0.10
	Peace And Freedom	130	0.07
	Working Family Party	68	0.04
	Constitution	20	0.01
	Reform	16	0.01
	Natural Law	13	0.01
	Socialist	8	0.00
	Women's Equality Party	8	0.00
	Constitutional	6	0.00
	Worker's Party	4	0.00
	Bread And Roses	2	0.00
	Independent Democrat	1	0.00
	Independent Republican	1	0.00
	Liberal	1	0.00
	Progressive	1	0.00
	Tea	1	0.00

Table B6: **Distribution of Political Party Affiliation Among Officers in L2**. Among officers registered to vote this shows the number and percent of these officers in every political party available in L2 data.

Agency	% Republican	% Democratic	% Other	% Registered
Alameda County Sheriff	40.34	32.93	26.72	85.42
Albuquerque Police Department	62.83	18.41	18.76	92.93
Anne Arundel County Police	51.63	28.88	19.48	77.84
Atlanta Police Department	19.39	63.28	17.33	83.61
Aurora Police Department	51.10	11.47	37.44	85.82
Austin Police Department	50.07	36.38	13.55	88.01
Baltimore County Police	60.60	21.01	18.39	94.38
Baltimore Police Department	35.82	44.07	20.11	82.21
Baton Rouge City Police	40.45	36.39	23.16	94.06
Birmingham Police Department	32.91	65.04	2.04	95.98
Boston Police Department	12.14	29.01	58.85	93.27
Broward County Sheriffs Office	37.59	32.13	30.28	86.94
Buffalo Police Department	28.59	48.56	22.84	93.17
Charlotte-Mecklenburg Police Department	43.79	20.42	35.79	82.64
Chicago Police Department	15.30	56.84	27.86	89.6
Cincinnati Police Department	46.39	26.48	27.13	89.59
Cleveland Police Department	29.25	35.71	35.04	91.8
Collier County Sheriffs Office	67.09	15.19	17.72	61.24
Colorado Springs Police Department	52.29	11.21	36.50	81.81
Columbus Police Department	50.16	18.18	31.66	91.04
Contra Costa County Sheriff	39.34	33.18	27.48	84.73
Cook County Sheriffs Office	18.93	52.89	28.17	94.33
Dallas Police Department	44.52	42.62	12.86	78.45
Dekalb County Police Department	14.15	67.77	18.08	82.28
Denver Police Department	31.85	26.33	41.81	77.76
El Paso Police Department	20.11	75.62	4.27	93.51
Fairfax County Police Department	31.16	46.63	22.21	69.9
Fort Worth Police Department	51.10	33.74	15.16	92.83
Fresno Police Department	59.12	19.58	21.30	92.42
Gwinnett County Police Department	37.02	24.17	38.81	93.18
Harris County Sheriff Office	38.89	47.80	13.32	89.09
Hillsborough County Sheriffs Office	55.86	17.57	26.58	69.65

Agency	% Republican	% Democratic	% Other	% Registered
Honolulu Police Department	15.99	26.25	57.76	83.95
Houston Police Department	41.64	43.71	14.66	94.04
Indianapolis Police Department	53.12	19.63	27.25	79.26
Jacksonville County Sheriff	63.57	18.51	17.92	82.15
Jefferson Parish Sheriff's Office	38.64	36.58	24.78	86.08
Jersey City Police Department	16.71	48.12	35.18	84.49
Kansas City Police Department	52.50	25.63	21.86	92.33
King County Sheriff Office	37.22	36.79	25.99	93.74
Las Vegas Metro Police Department	54.62	16.98	28.40	86.81
Long Beach Police Department	44.53	29.76	25.71	90.06
Los Angeles County Sheriff	44.07	30.89	25.04	87.72
Los Angeles Police Department	34.56	37.16	28.28	92.95
Louisville Metro Police Department	53.59	32.71	13.70	92.29
Maricopa County Sheriff Office	55.40	18.42	26.18	94.01
Memphis Police Department	26.76	34.56	38.68	90.86
Mesa Police Department	66.05	11.45	22.50	83.42
Metro Nashville Police Department and Sheriff	39.15	18.09	42.77	81.27
Metropolitan Police Department, D.C.	10.56	69.08	20.35	71.26
Miami Police Department	34.89	32.26	32.85	87.87
Miami-Dade Police Department	40.66	32.20	27.15	74.01
Milwaukee Police Department	32.92	44.78	22.30	32.12
Minneapolis Police Department	39.41	25.45	35.14	85.15
Montgomery County Police	47.70	30.24	22.06	85.27
Nassau County Police Department	53.60	18.99	27.41	95.78
New Orleans Police Department	23.65	48.22	28.13	85.34
New York City Police Department	28.66	42.64	28.70	82.22
Newark Police Department	15.42	44.96	39.62	83.08
Oakland Police Department	28.55	38.03	33.42	70.76
Oklahoma City Police Department	70.67	16.61	12.72	90.78
Omaha Police Department	61.01	14.43	24.56	86.34
Orange County Sheriff, CA	53.99	20.54	25.47	92.12
Orange County Sheriffs Office, FL	49.13	20.82	30.04	71.7

Agency	% Republican	% Democratic	% Other	% Registered
Orlando Police Department	46.55	23.03	30.42	74.38
Palm Beach County Sheriff Office	47.83	23.91	28.26	77.04
Philadelphia Police Department	35.70	49.21	15.09	94.73
Phoenix Police Department	50.72	19.50	29.78	88.03
Pinellas County Sheriff	54.30	19.37	26.33	82.23
Pittsburgh Police Department	46.48	41.87	11.65	95.59
Portland Police Bureau	33.33	29.71	36.96	83.18
Prince Georges County Police Department	29.15	51.09	19.76	86.88
Raleigh Police Department	41.35	19.65	39.00	94.72
Richmond Police Department	37.05	47.73	15.23	84.45
Riverside County Sheriff	46.65	24.92	28.42	93.23
Rochester Police Department	58.30	14.88	26.82	95.54
Sacramento County Sheriff	49.75	24.47	25.79	90.96
Sacramento Police Department	54.20	18.16	27.65	90.54
Saint Louis Metro Police Department	42.61	43.43	13.96	93.4
San Antonio Police Department	43.52	44.96	11.52	92.79
San Bernardino County Sheriff	46.30	27.34	26.36	93.1
San Diego County Sheriff	52.31	20.83	26.85	90.97
San Diego Police Department	49.71	22.08	28.20	94.64
San Francisco Police Department	25.72	40.21	34.07	68.5
San Jose Police Department	30.58	38.77	30.66	87.33
Seattle Police Department	43.49	33.77	22.74	85.08
St Louis County Police Department	46.09	34.00	19.91	95.26
Suffolk County Police Department	48.26	15.17	36.57	97.95
Tampa Police Department	54.57	18.60	26.83	75.93
Toledo Police Department	36.90	27.09	36.01	83.61
Tucson Police Department	52.71	17.33	29.96	84.97
Tulsa Police Department	73.65	13.11	13.25	81.53
Ventura County Sheriff	38.79	33.03	28.18	94.38
Virginia Beach Police Department	46.66	25.15	28.20	90.89
Wayne County Sheriffs Office	16.67	68.59	14.74	93.69
Wichita Police Department	63.22	11.05	25.72	76.45

Agency	% Republican	% Democratic	% Other	% Registered
Yonkers Police Department	38.48	26.85	34.67	76.29

Table B7: **Political party membership by agency.**The share of registered officers in each party, by agency, as well as the percent of officers that are registered to vote.

	All Off.	White Off.	Black Off.	Hispanic Off.	Male Off.	Female Off.	Republican Off.	Democrat Off.	Other Party Off.
Black Civ.	18.49	19.16	18.29	17.40	19.13	16.27	18.58	18.19	19.16
White Civ.	3.70	4.66	1.84	3.59	3.75	3.52	4.73	3.54	3.41
Hispanic Civ.	5.46	6.19	1.38	7.81	5.79	4.29	6.63	4.96	5.88
Total Civ.	28.84	31.42	22.22	30.05	29.88	25.24	31.49	27.80	29.62

Table B8: **Stops per 100 Shifts in CPD, 2012-2019**

	All Off.	White Off.	Black Off.	Hispanic Off.	Male Off.	Female Off.	Republican Off.	Democrat Off.	Other Party Off.
Black Civ.	4.66	4.58	4.48	4.97	4.90	3.82	4.43	4.42	5.38
White Civ.	0.71	0.87	0.30	0.79	0.74	0.62	0.84	0.64	0.80
Hispanic Civ.	1.38	1.59	0.38	1.90	1.48	1.02	1.67	1.17	1.69
Total Civ.	6.81	7.12	5.20	7.73	7.19	5.52	7.02	6.30	7.93

Table B9: **Arrest per 100 Shifts in CPD, 2012-2019.**

	All Off.	White Off.	Black Off.	Hispanic Off.	Male Off.	Female Off.	Republican Off.	Democrat Off.	Other Party Off.
Black Civ.	0.21	0.23	0.19	0.21	0.24	0.13	0.22	0.20	0.23
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	0.18	0.32	0.27	0.32

Table B10: **Force per 100 Shifts in CPD, 2012-2019**.

B.2 Within-Jurisdiction Comparisons

Table B11: **Average Shares of White Officers and Civilians in the Same Jurisdictions.** Numeric results depicted in Figure 2.

Agency	Officer Mean	Officer 95% CI Lower	Officer 95% CI Upper	Civilian Mean
Alameda County Sheriff, CA	62.96	60.39	65.53	31.50
Albuquerque PD, NM	56.25	52.31	60.19	38.80
Anne Aroundel 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	50.81	52.54	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	67.72	62.02	73.43	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	55.00	52.40	57.59	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	82.42	80.35	84.50	54.90
Jacksonville County Sheriff, FL	69.50	67.28	71.71	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	79.40	76.51	82.30	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	72.02	68.85	75.20	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	7.71	6.28	9.13	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	34.94	32.45	37.42	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
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	57.20	55.95	58.46	34.50
Phoenix PD, AZ	70.73	69.18	72.28	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	73.53	70.01	77.04	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	70.63	68.03	73.22	43.60
San Antonio PD, TX	40.32	37.94	42.69	26.70
San Bernardino County Sheriff, CA	53.74	51.87	55.61	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	46.72	44.17	49.28	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	53.53	48.17	58.88	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 B12: **Average Shares of Republican Officers and Civilians in the Same Jurisdictions.** Numeric results depicted in Figure 3.

Agency	Officer Mean	Officer 95% CI Lower	Officer 95% CI Upper	Civilian Mean
Alameda County Sheriff, CA	34.46	31.93	36.99	11.51
Albuquerque PD, NM	58.39	54.47	62.31	20.86
Anne Aroundel County PD, MD	40.19	37.06	43.32	30.05
Atlanta PD, GA	16.21	14.45	17.97	7.79
Aurora PD, CO	43.85	40.15	47.55	16.29
Austin PD, TX	44.07	41.63	46.51	15.14
Baltimore County PD, MD	57.20	54.79	59.61	15.12
Baltimore PD, MD	29.45	28.14	30.75	5.92
Baton Rouge City PD, LA	38.05	34.47	41.63	17.41
Birmingham PD, AL	31.59	28.80	34.37	24.09
Boston PD, MA	11.32	10.03	12.61	3.39
Broward County Sheriff, FL	32.68	30.25	35.11	16.54
Buffalo PD, NY	26.64	23.47	29.81	7.56
Charlotte-Mecklenburg PD, NC	36.19	34.11	38.26	16.04
Chicago PD, IL	13.71	13.11	14.30	3.73
Cincinnati PD, OH	41.56	38.56	44.56	11.96
Cleveland PD, OH	26.85	24.79	28.92	4.76
Collier County Sheriff, FL	41.09	35.08	47.09	37.99
Colorado Springs PD, CO	42.78	39.16	46.39	29.78
Columbus PD, OH	45.67	43.51	47.82	14.81
Contra Costa County Sheriff, CA	33.33	30.46	36.21	17.73
Cook County Sheriff, IL	17.86	15.86	19.86	3.03
Dallas PD, TX	34.93	33.28	36.57	13.70
Dekalb County PD, GA	11.64	9.38	13.90	6.03
Denver PD, CO	24.77	22.43	27.11	9.07
El Paso PD, TX	18.80	16.59	21.01	8.47
Fairfax County PD, VA	21.78	19.92	23.64	16.94
Fort Worth PD, TX	47.44	45.17	49.71	25.53
Fresno PD, CA	54.64	51.36	57.92	19.73

Gwinnett County PD, GA	34.49	31.15	37.83	19.09
Harris County Sheriff, TX	34.64	32.79	36.50	19.62
Hillsborough County Sheriff, FL	38.90	36.23	41.58	27.36
Honolulu PD, HI	13.42	11.94	14.91	11.79
Houston PD, TX	39.15	37.91	40.39	18.25
Indianapolis PD, IN	42.11	39.41	44.80	15.05
Jacksonville County Sheriff, FL	52.22	49.82	54.62	30.82
Jefferson Parish Sheriff, LA	33.26	31.12	35.40	25.17
Jersey City PD, NJ	14.12	11.96	16.27	5.49
Kansas City PD, MO	48.48	46.19	50.76	28.92
King County Sheriff, WA	34.89	31.48	38.30	16.98
Las Vegas Metro PD, NV	47.41	45.75	49.07	23.85
Long Beach PD, CA	40.11	37.21	43.01	12.63
Los Angeles County Sheriff, CA	38.66	37.82	39.50	15.25
Los Angeles PD, CA	32.12	31.25	32.99	8.84
Louisville Metro PD, KY	49.46	47.42	51.50	19.77
Maricopa County Sheriff, AZ	52.08	48.55	55.62	42.88
Memphis PD, TN	24.31	22.43	26.19	8.82
Mesa PD, AZ	55.10	51.87	58.33	29.75
Metro Nashville PD And Sheriff, TN	31.82	29.62	34.01	12.94
Miami PD, FL	30.65	28.19	33.12	13.48
Miami-Dade PD, FL	30.09	28.73	31.45	22.64
Milwaukee PD, WI	10.57	9.14	12.01	11.43
Minneapolis PD, MN	33.55	30.48	36.62	5.17
Montgomery County PD, MD	40.67	37.98	43.37	13.79
Nassau County PD, NY	51.34	49.38	53.31	29.85
New Orleans PD, LA	20.18	18.09	22.28	8.39
New York City PD, NY	23.56	23.10	24.03	7.61
Newark PD, NJ	12.81	10.92	14.71	3.08
Oakland PD, CA	20.20	17.80	22.61	3.05
Oklahoma City PD, OK	64.15	61.49	66.82	31.80
Omaha PD, NE	52.68	49.44	55.91	29.05
Orange County Sheriff, CA	49.73	47.67	51.80	32.56
Orange County Sheriff, FL	35.23	32.61	37.84	20.51

Orlando PD, FL	34.62	31.33	37.92	17.53
Palm Beach County Sheriff, FL	36.85	33.88	39.82	21.67
Philadelphia PD, PA	33.82	32.62	35.02	9.23
Phoenix PD, AZ	44.65	42.96	46.34	19.20
Pinellas County Sheriff, FL	44.65	42.23	47.07	34.91
Pittsburgh PD, PA	44.43	41.28	47.59	11.21
Portland Police Bureau, OR	27.73	24.74	30.71	9.28
Prince Georges County PD, MD	25.33	23.15	27.50	5.27
Raleigh PD, NC	39.17	35.60	42.73	16.46
Richmond PD, VA	31.29	27.30	35.27	7.91
Riverside County Sheriff, CA	43.49	41.37	45.62	22.48
Rochester PD, NY	55.70	51.74	59.66	7.02
Sacramento County Sheriff, CA	45.25	42.92	47.59	21.71
Sacramento PD, CA	49.07	45.61	52.52	10.63
St. Louis Metro PD, MO	39.80	37.01	42.59	8.77
San Antonio PD, TX	40.38	38.00	42.76	17.59
San Bernardino County Sheriff, CA	43.10	41.24	44.96	24.52
San Diego County Sheriff, CA	47.59	45.19	49.99	27.62
San Diego PD, CA	47.05	44.77	49.33	15.37
San Francisco PD, CA	17.62	16.44	18.79	4.44
San Jose PD, CA	26.70	24.44	28.97	11.09
Seattle PD, WA	37.00	34.43	39.57	4.48
St. Louis County PD, MO	43.91	40.64	47.17	33.90
Suffolk County PD, NY	47.27	45.29	49.25	27.22
Tampa PD, FL	41.44	38.15	44.72	20.27
Toledo PD, OH	30.85	27.35	34.34	10.85
Tucson PD, AZ	44.79	41.67	47.90	18.00
Tulsa PD, OK	60.05	56.77	63.32	27.91
Ventura County Sheriff, CA	36.61	33.69	39.52	26.97
Virginia Beach PD, VA	42.40	38.88	45.92	29.26
Metropolitan PD, D.C.	7.53	6.74	8.31	4.57
Wayne County Sheriff, MI	15.62	11.72	19.51	22.83
Wichita PD, KS	48.34	44.69	51.98	29.94

Yonkers PD, NY	29.35	25.77	32.94	12.55

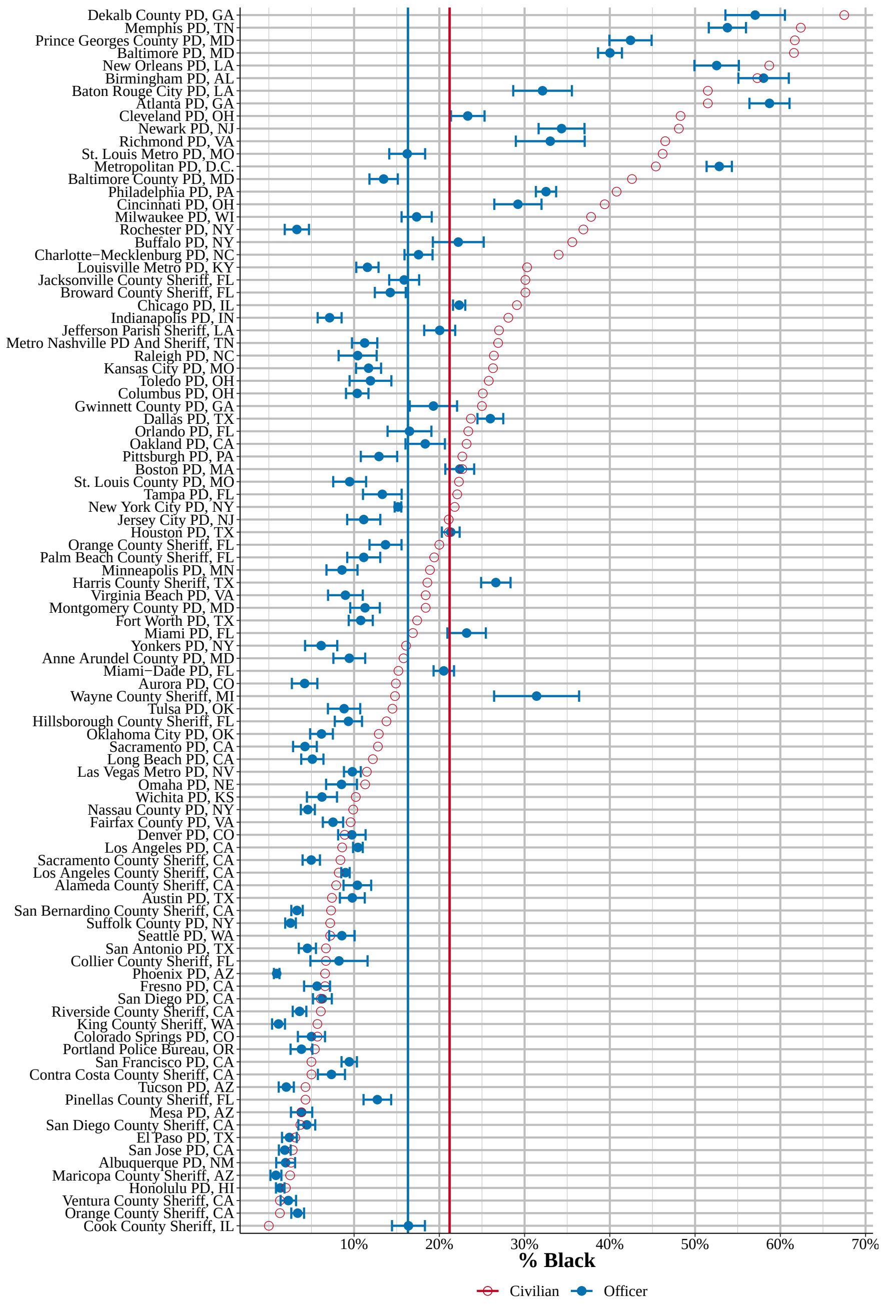

Figure B1: **Average Shares of Black Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from BJS (2016) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

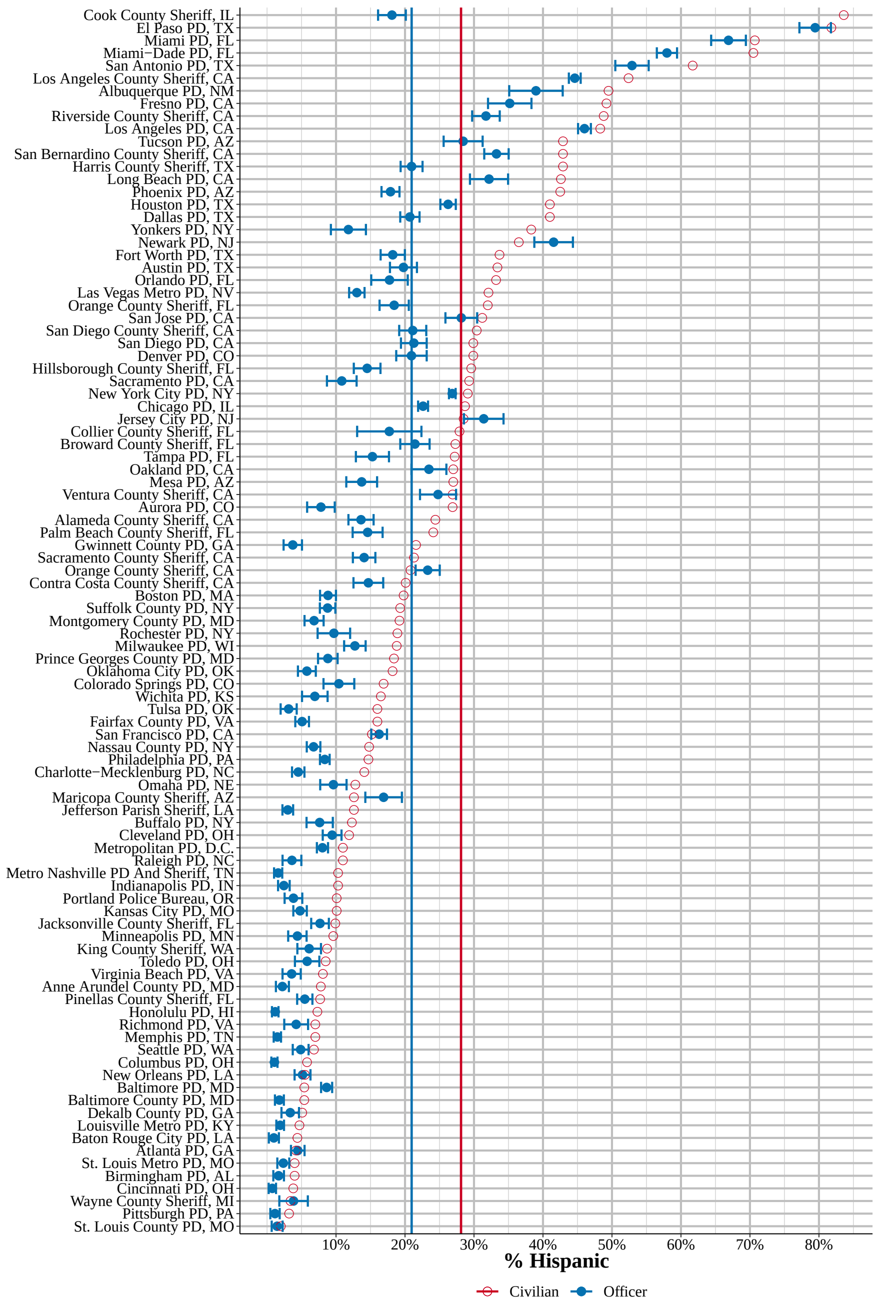

Figure B2: **Average Shares of Hispanic Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from BJS (2016) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

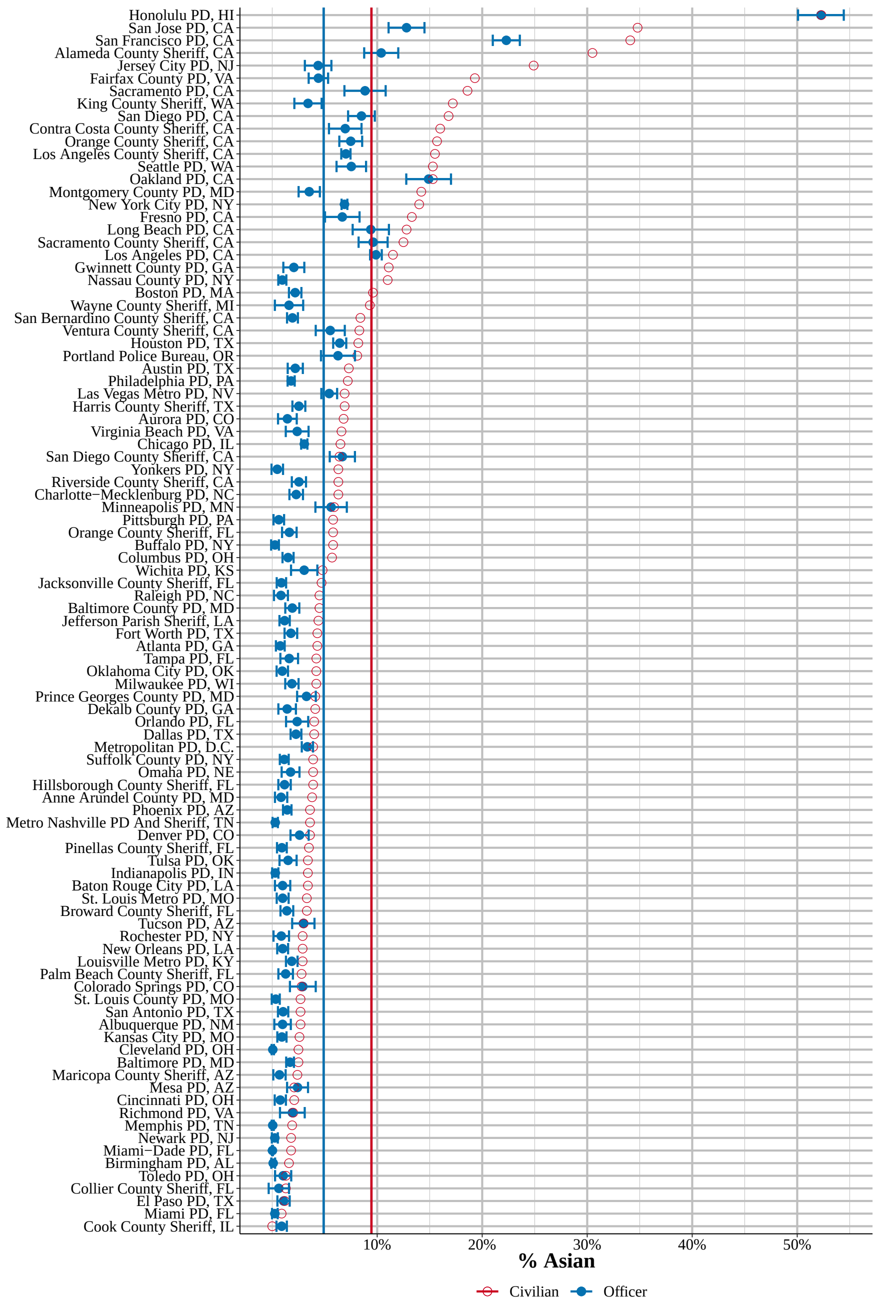

Figure B3: **Average Shares of Asian Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from BJS (2016) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

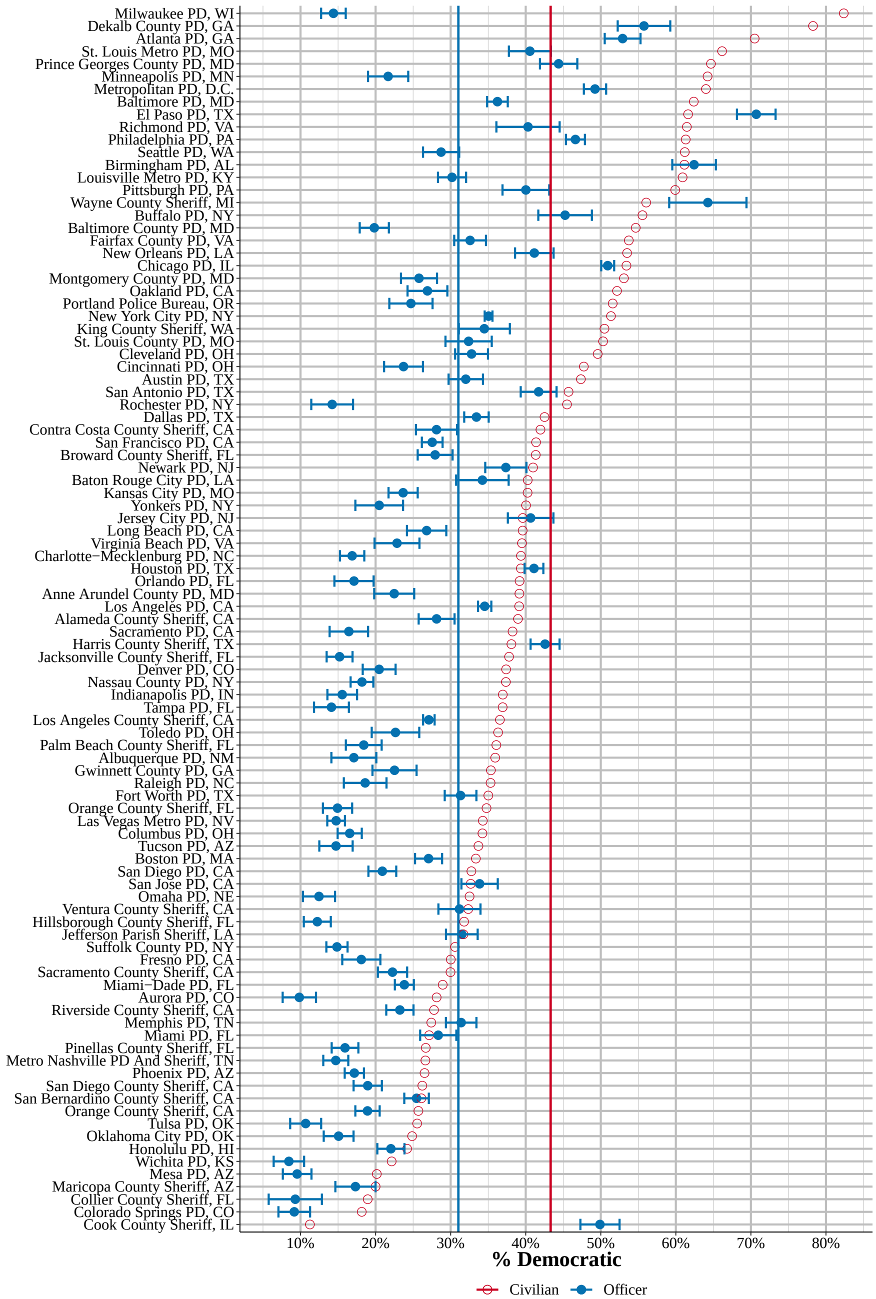

Figure B4: **Average Shares of Democrats Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares.Red dots are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

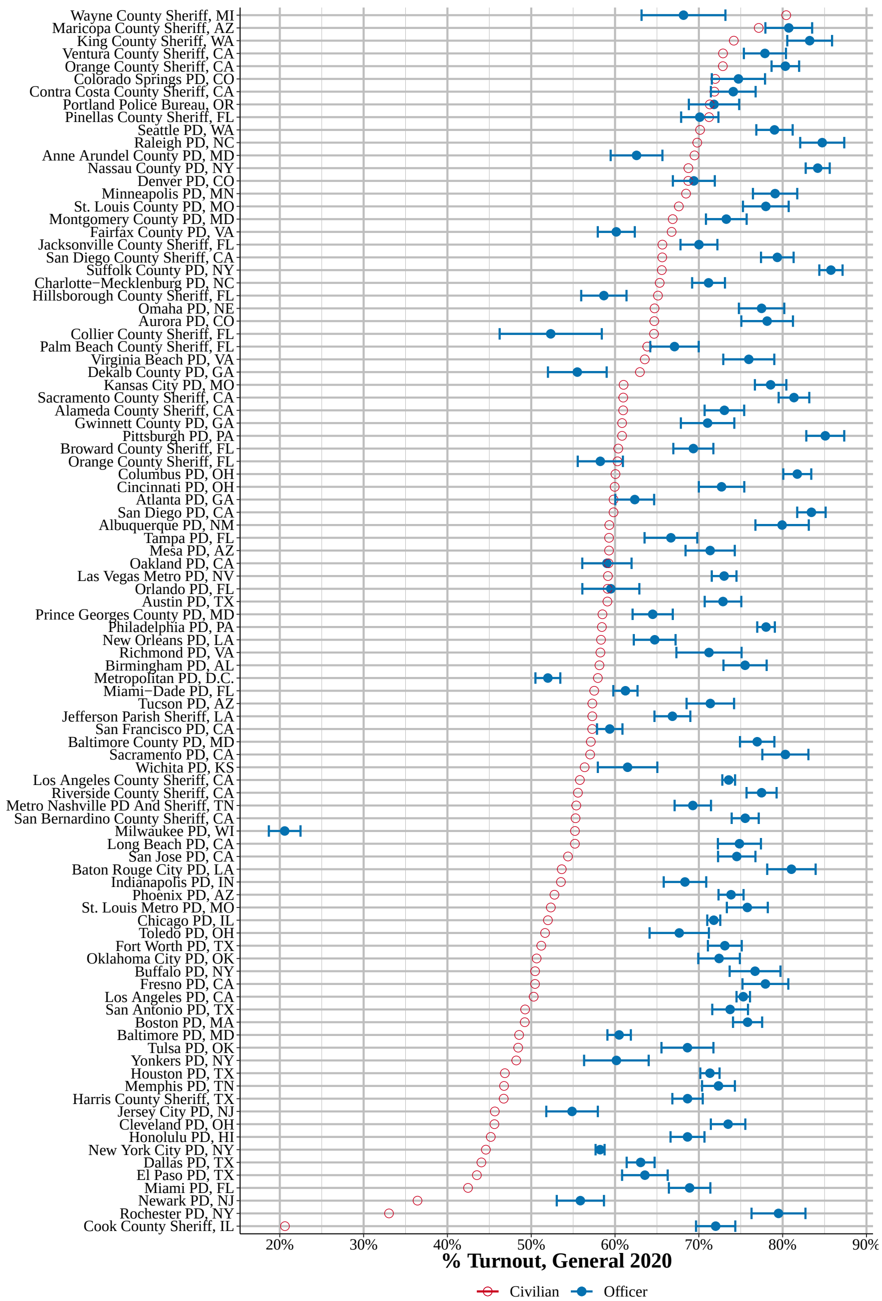

Figure B5: **Average General Election Turnout in 2020 Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian Republicans from L2 as a share of voting-age population from Census ACS. Vertical blue line is the pooled officer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

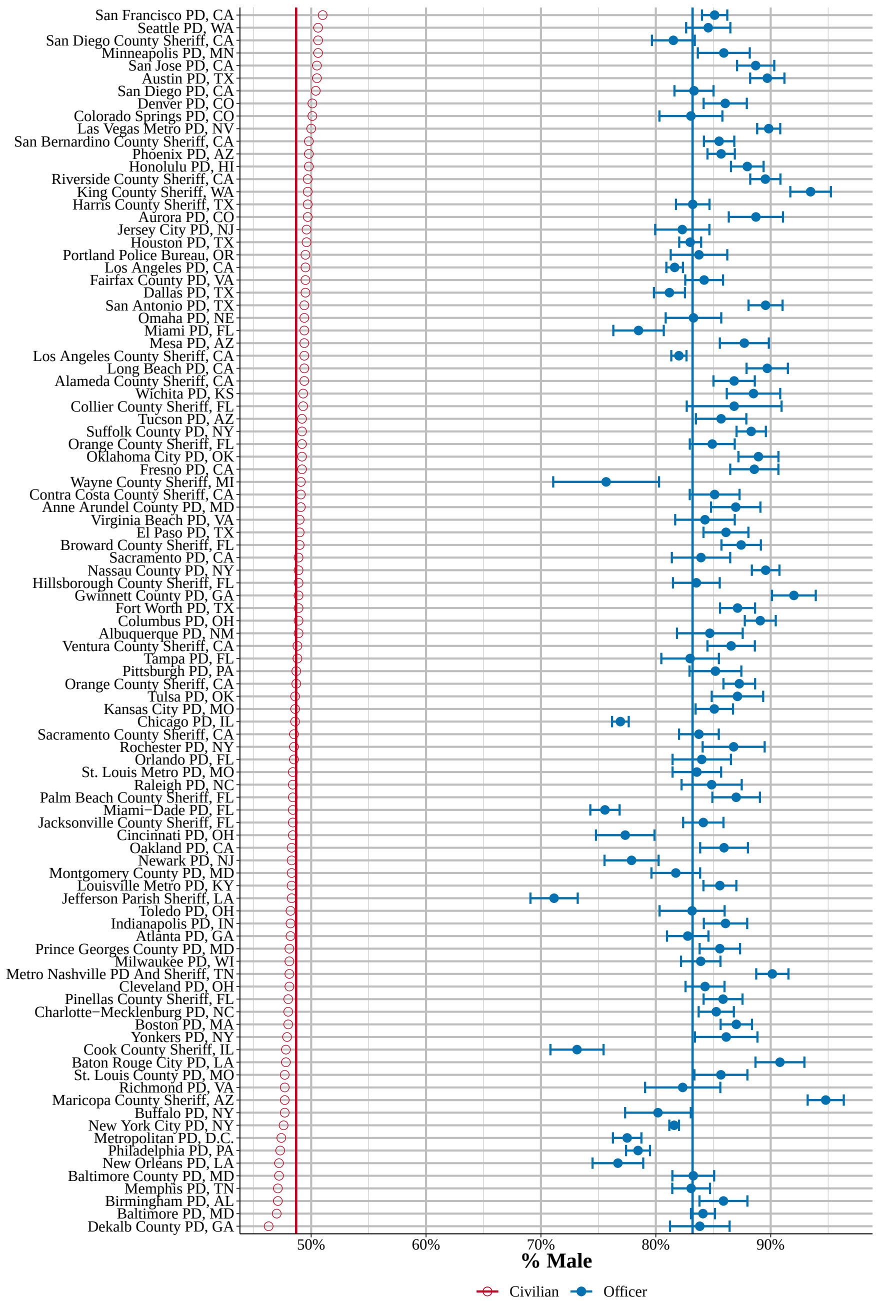

Figure B6: **Average Shares of Males Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from LEOKA 2019 data with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical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

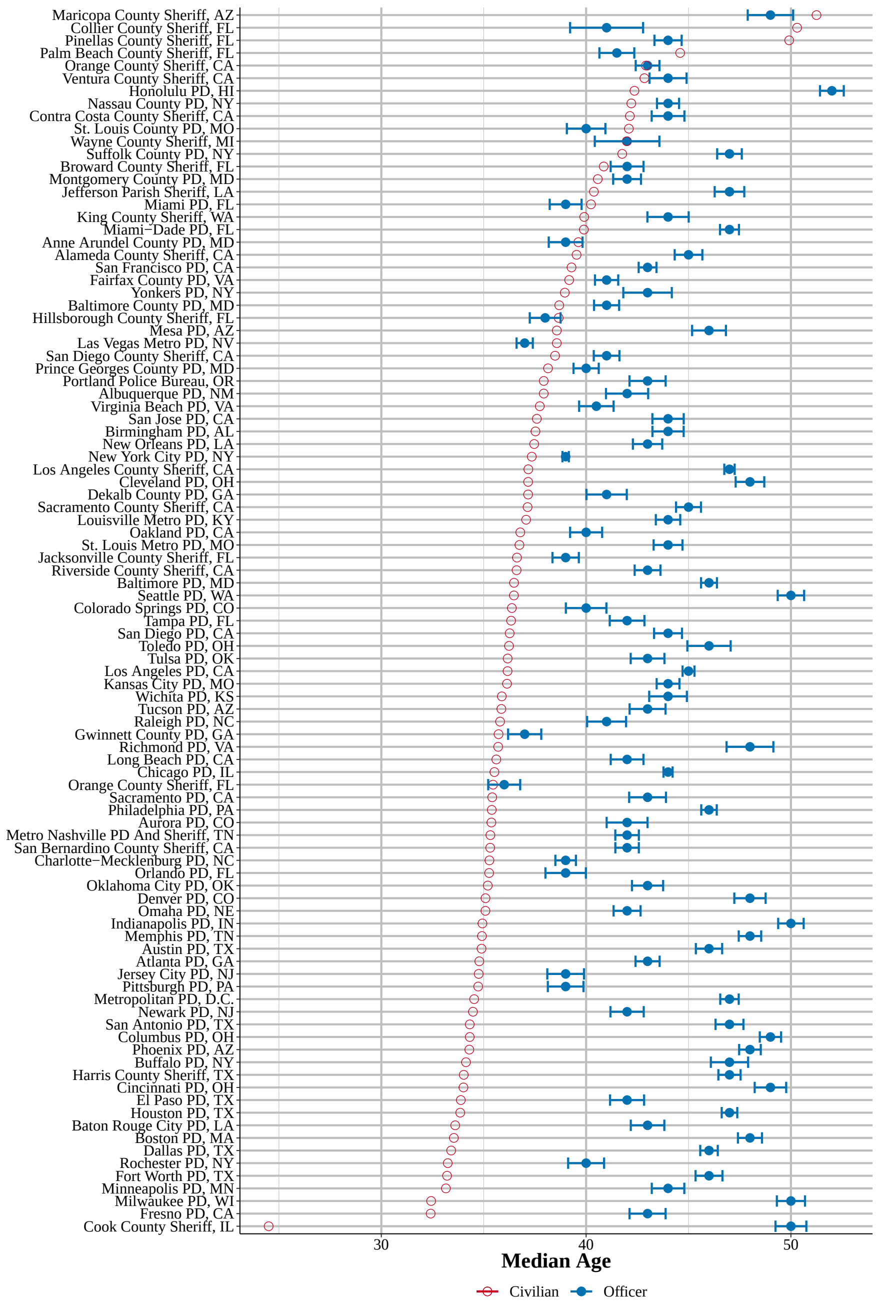

Figure B7: **Median Age Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from L2 voter file (i.e. among registered voters) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line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

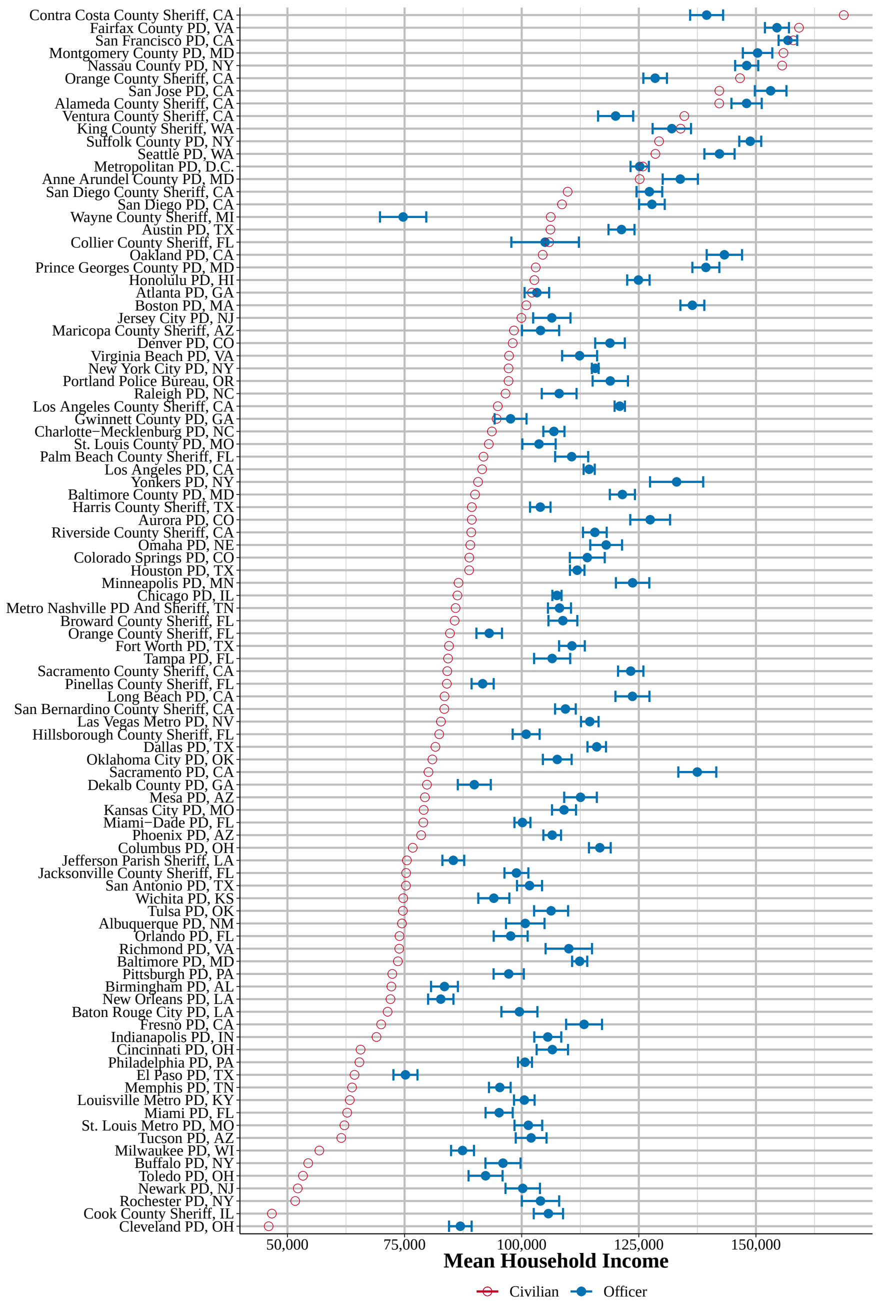

Figure B8: **Median Household Income Among Officers and Civilians in the Same Jurisdictions.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters) with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean.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

B.3 District-Level Analysis in Chicago

District	District Name	Officer	Officer Lower Bound	Officer Upper Bound	Civilian
1	Central	57.35	53.98	60.71	52.28
2	Wentworth	21.59	18.85	24.33	19.06
3	Grand Crossing	27.04	24.05	30.03	5.64
4	South Chicago	48.20	44.86	51.54	7.05
5	Calumet	33.72	30.18	37.26	1.88
6	Gresham	29.89	26.88	32.90	1.41
7	Englewood	42.31	39.14	45.47	1.31
8	Chicago Lawn	66.35	63.17	69.53	16.80
9	Deering	64.61	61.14	68.08	15.44
10	Ogden	40.52	36.96	44.07	4.83
11	Harrison	52.51	49.20	55.81	4.24
12	Near West	53.46	49.92	56.99	45.29
14	Shakespeare	50.73	46.55	54.91	52.66
15	Austin	55.64	51.89	59.39	3.51
16	Jefferson Park	80.63	77.47	83.80	62.91
17	Albany Park	68.12	64.05	72.18	40.63
18	Near North	61.11	57.86	64.36	72.61
19	Town Hall	62.01	58.70	65.33	74.26
20	Lincoln	69.69	65.60	73.78	55.40
22	Morgan Park	59.87	55.99	63.75	34.30
24	Rogers Park	72.88	69.17	76.58	43.70
25	Grand Central	65.78	62.46	69.09	14.70

Table B13: **Proportion White in Chicago Districts. Numeric results for Figure 4.**

District	District Name	Officer	Officer Lower Bound	Officer Upper Bound	Civilian
1	Central	15.18	12.74	17.62	4.25
2	Wentworth	7.97	6.16	9.77	1.32
3	Grand Crossing	9.33	7.37	11.29	0.89
4	South Chicago	13.01	10.76	15.26	2.15
5	Calumet	10.66	8.35	12.97	0.89
6	Gresham	9.55	7.62	11.48	0.74
7	Englewood	10.58	8.61	12.55	0.78
8	Chicago Lawn	16.29	13.81	18.78	3.01
9	Deering	19.34	16.47	22.21	2.21
10	Ogden	15.28	12.67	17.88	1.20
11	Harrison	15.26	12.88	17.64	1.09
12	Near West	15.51	12.95	18.08	3.95
14	Shakespeare	15.64	12.60	18.67	3.59
15	Austin	17.21	14.36	20.06	0.88
16	Jefferson Park	25.54	22.05	29.04	8.86
17	Albany Park	22.57	18.93	26.22	4.27
18	Near North	14.70	12.34	17.06	7.85
19	Town Hall	17.72	15.11	20.33	5.43
20	Lincoln	18.97	15.48	22.46	3.96
22	Morgan Park	16.97	13.99	19.94	4.74
24	Rogers Park	19.71	16.39	23.03	3.48
25	Grand Central	19.21	16.46	21.97	2.59

Table B14: **Proportion Republican in Chicago Districts. Numeric results for Figure 4.**

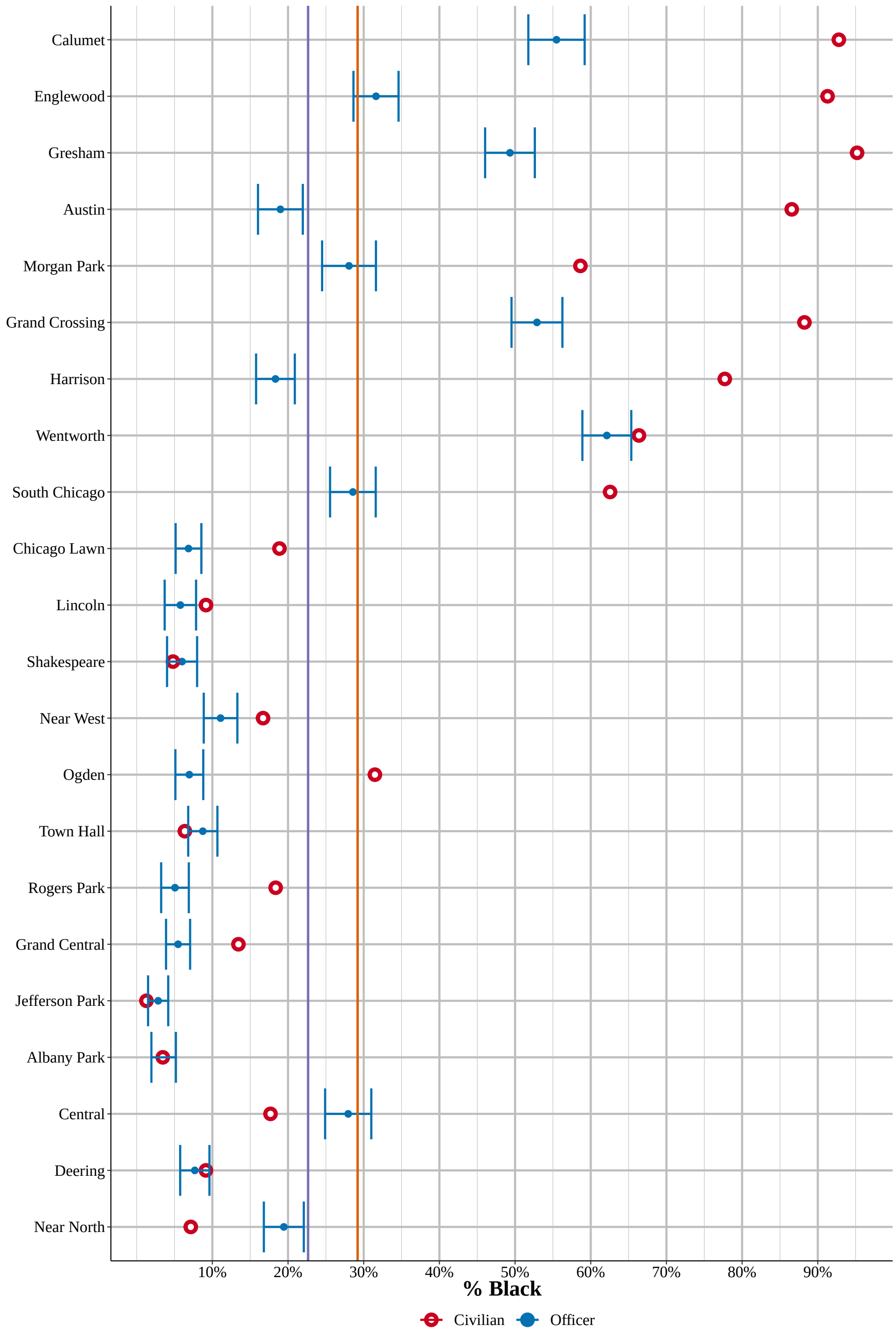

Figure B9: **Average Shares of Black Chicago Officers and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean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

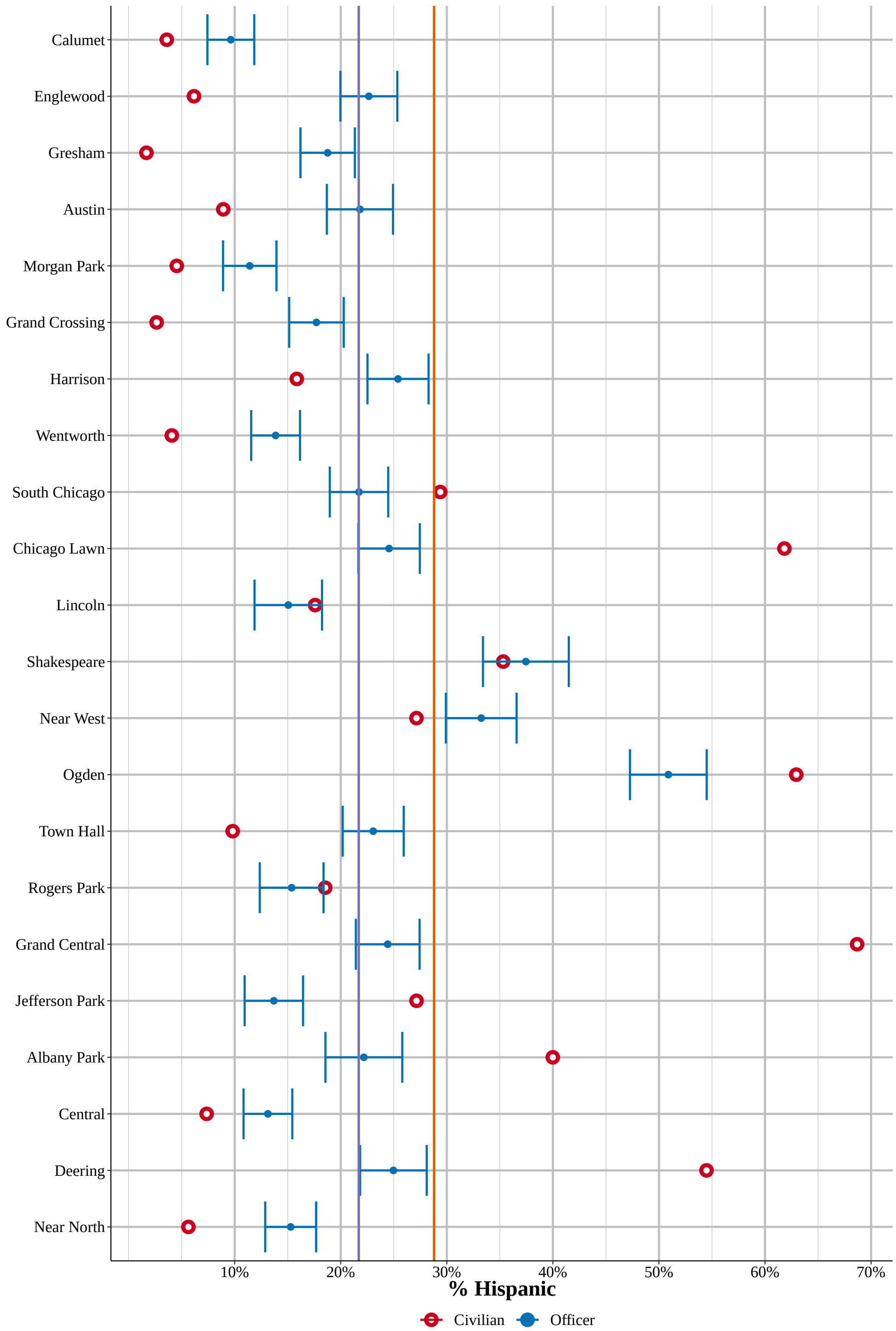

Figure B10: **Average Shares of Hispanic Chicago Officers and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective district.

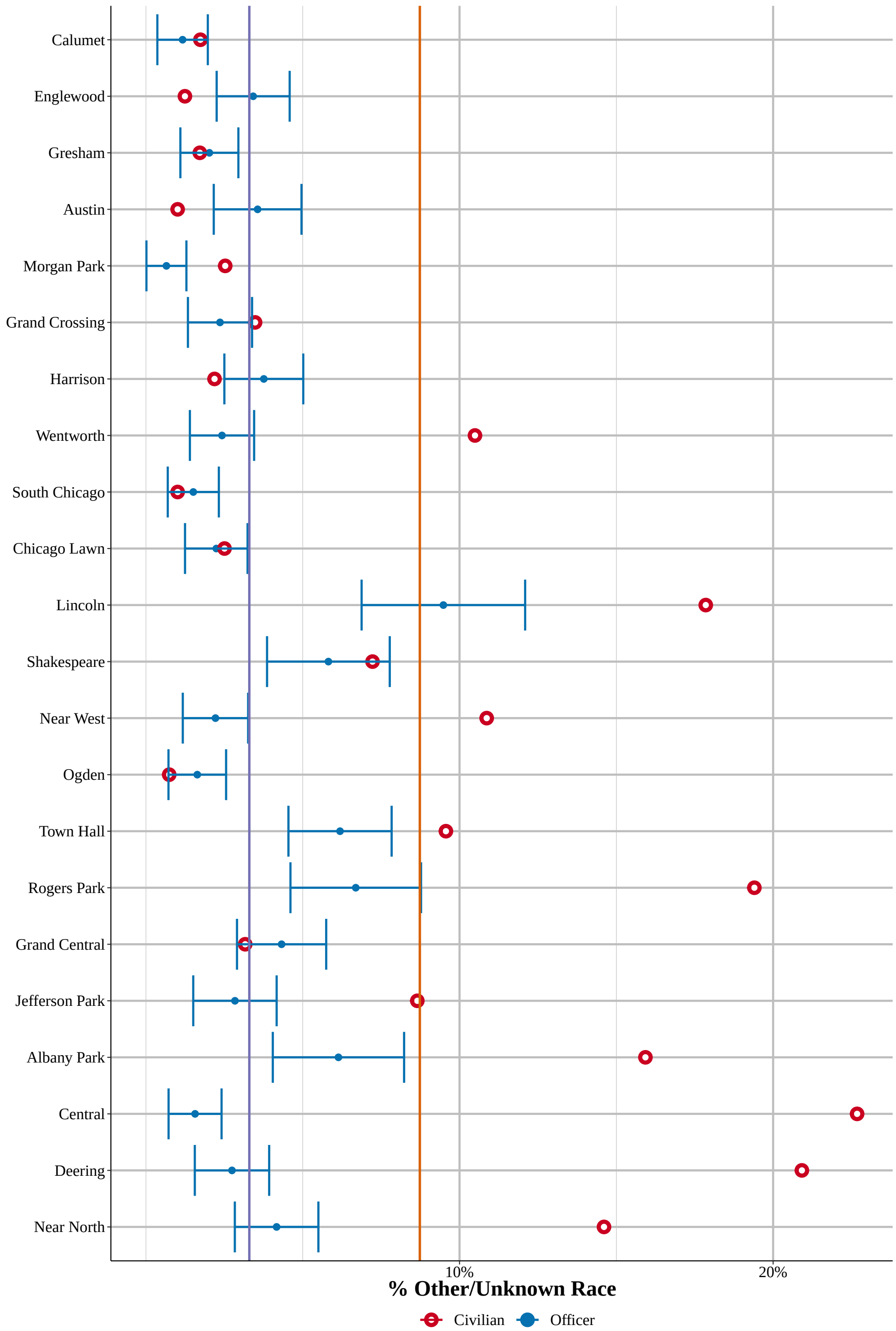

Figure B11: **Average Shares of Chicago Officers of Other Race and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective district.

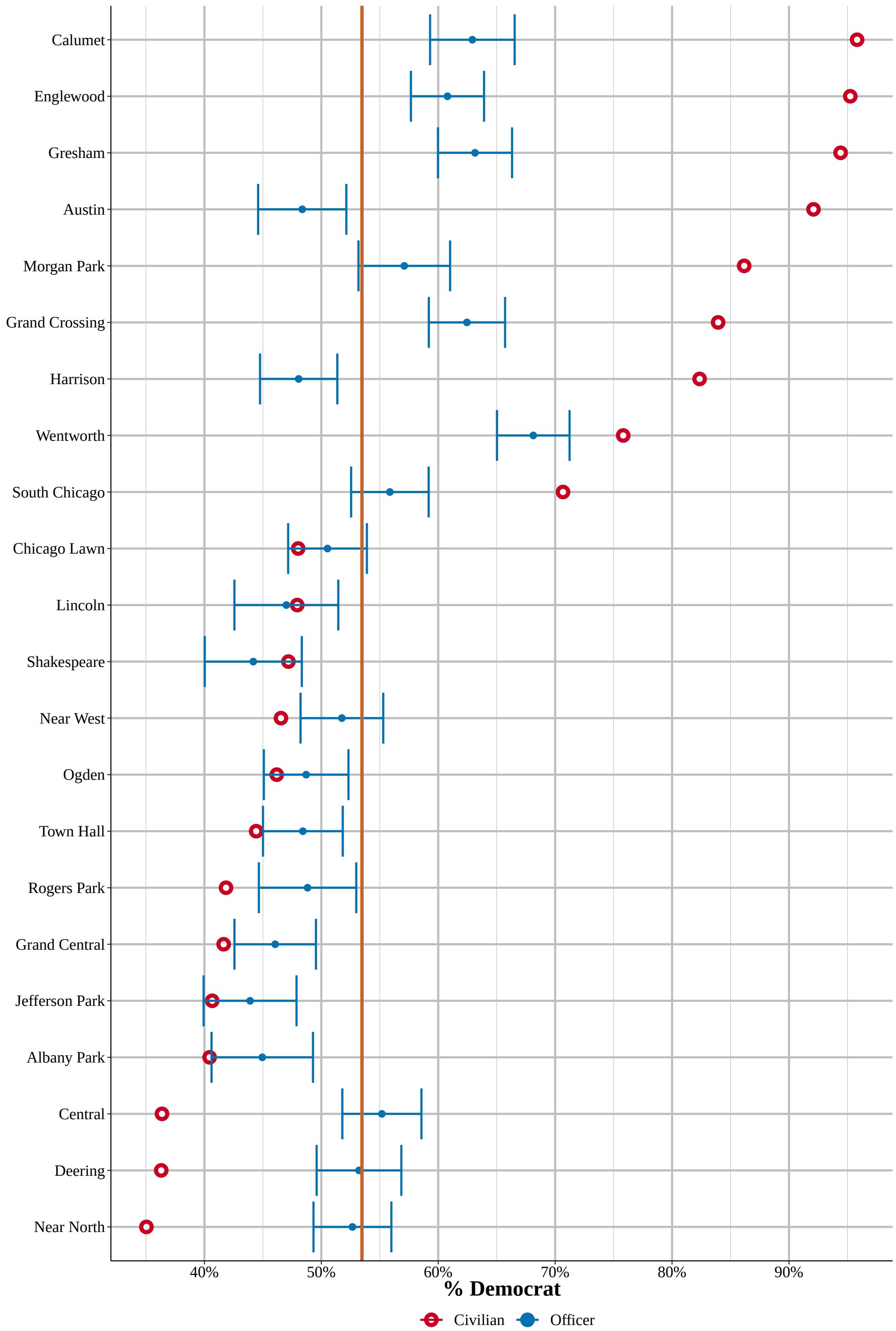

Figure B12: **Average Shares of Democratic Chicago Officers and Civilians in Officers' Assigned Districts.** Blue dots are officer shares with 95% confidence intervals. Red dots are civilian shares from U.S. Census. Vertical blue line is the pooled officer mean. Vertical red line is hypothetical officer mean if each officer was randomly drawn from their respective district.

B.4 Deployment Effects

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Black	-7.80	White	0.00	Stops
Democrat	-3.80	Republican	0.00	Stops
Black Democrat	-7.74	White Republican	0.00	Stops
Black Republican	-4.62	White Republican	0.05	Stops
White Democrat	1.09	White Republican	0.42	Stops
Black	-1.25	White	0.00	Arrests
Democrat	-0.77	Republican	0.00	Arrests
Black Democrat	-1.34	White Republican	0.00	Arrests
Black Republican	-0.09	White Republican	0.82	Arrests
White Democrat	-0.18	White Republican	0.66	Arrests
Black	-0.10	White	0.00	Force
Democrat	-0.09	Republican	0.00	Force
Black Democrat	-0.12	White Republican	0.00	Force
Black Republican	-0.05	White Republican	0.66	Force
White Democrat	-0.02	White Republican	0.93	Force

Table B15: **Deployment Effects Per 100 Shifts, Black v. 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.

Officer Deployed	Estimate	Reference Group	Adjusted p-value	Outcome
Hispanic	-1.01	White	0.31	Stops
Democrat	0.72	Republican	0.49	Stops
Hispanic Democrat	-0.10	White Republican	0.96	Stops
Hispanic Republican	-2.27	White Republican	0.31	Stops
White Democrat	-0.18	White Republican	0.98	Stops
Hispanic	-0.29	White	0.30	Arrests
Democrat	0.06	Republican	0.76	Arrests
Hispanic Democrat	-0.15	White Republican	0.73	Arrests
Hispanic Republican	-0.56	White Republican	0.31	Arrests
White Democrat	-0.07	White Republican	0.87	Arrests
Hispanic	-0.04	White	0.10	Force
Democrat	-0.01	Republican	0.87	Force
Hispanic Democrat	-0.03	White Republican	0.31	Force
Hispanic Republican	-0.05	White Republican	0.66	Force
White Democrat	-0.03	White Republican	0.73	Force

Table B16: **Deployment Effects Per 100 Shifts, Hispanic v. 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.

Officer Deployed	Estimate	Reference Group	Outcome	Adjusted p-value
Black	-5.99	White	Stop Black Civilian	0.00
Black	-1.07	White	Stop Hispanic Civilian	0.00
Black	-0.70	White	Stop White Civilian	0.00
Democrat	-3.23	Republican	Stop Black Civilian	0.00
Democrat	-0.28	Republican	Stop Hispanic Civilian	0.08
Democrat	-0.27	Republican	Stop White Civilian	0.07
Black	-0.83	White	Arrest Black Civilian	0.00
Black	-0.28	White	Arrest Hispanic Civilian	0.00
Black	-0.14	White	Arrest White Civilian	0.00
Democrat	-0.57	Republican	Arrest Black Civilian	0.00
Democrat	-0.17	Republican	Arrest Hispanic Civilian	0.00
Democrat	-0.04	Republican	Arrest White Civilian	0.44
Black	-0.08	White	Force Black Civilian	0.00
Black	-0.01	White	Force Hispanic Civilian	0.02
Black	-0.01	White	Force White Civilian	0.04
Democrat	-0.07	Republican	Force Black Civilian	0.00
Democrat	-0.01	Republican	Force Hispanic Civilian	0.59
Democrat	-0.01	Republican	Force White Civilian	0.12

Table B17: **Deployment Effects Per 100 Shifts, Black v. 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	-1.46	White	Stop Black Civilian	0.03
Hispanic	0.44	White	Stop Hispanic Civilian	0.10
Hispanic	0.05	White	Stop White Civilian	0.92
Democrat	0.47	Republican	Stop Black Civilian	0.59
Democrat	0.19	Republican	Stop Hispanic Civilian	0.59
Democrat	0.03	Republican	Stop White Civilian	0.89
Hispanic	-0.21	White	Arrest Black Civilian	0.35
Hispanic	-0.07	White	Arrest Hispanic Civilian	0.59
Hispanic	-0.02	White	Arrest White Civilian	0.70
Democrat	0.04	Republican	Arrest Black Civilian	0.82
Democrat	-0.02	Republican	Arrest Hispanic Civilian	0.92
Democrat	0.04	Republican	Arrest White Civilian	0.49
Hispanic	-0.04	White	Force Black Civilian	0.08
Hispanic	0.00	White	Force Hispanic Civilian	0.82
Hispanic	-0.01	White	Force White Civilian	0.22
Democrat	-0.01	Republican	Force Black Civilian	0.82
Democrat	0.01	Republican	Force Hispanic Civilian	0.48
Democrat	-0.01	Republican	Force White Civilian	0.58

Table B18: **Deployment Effects Per 100 Shifts, Hispanic v. 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.

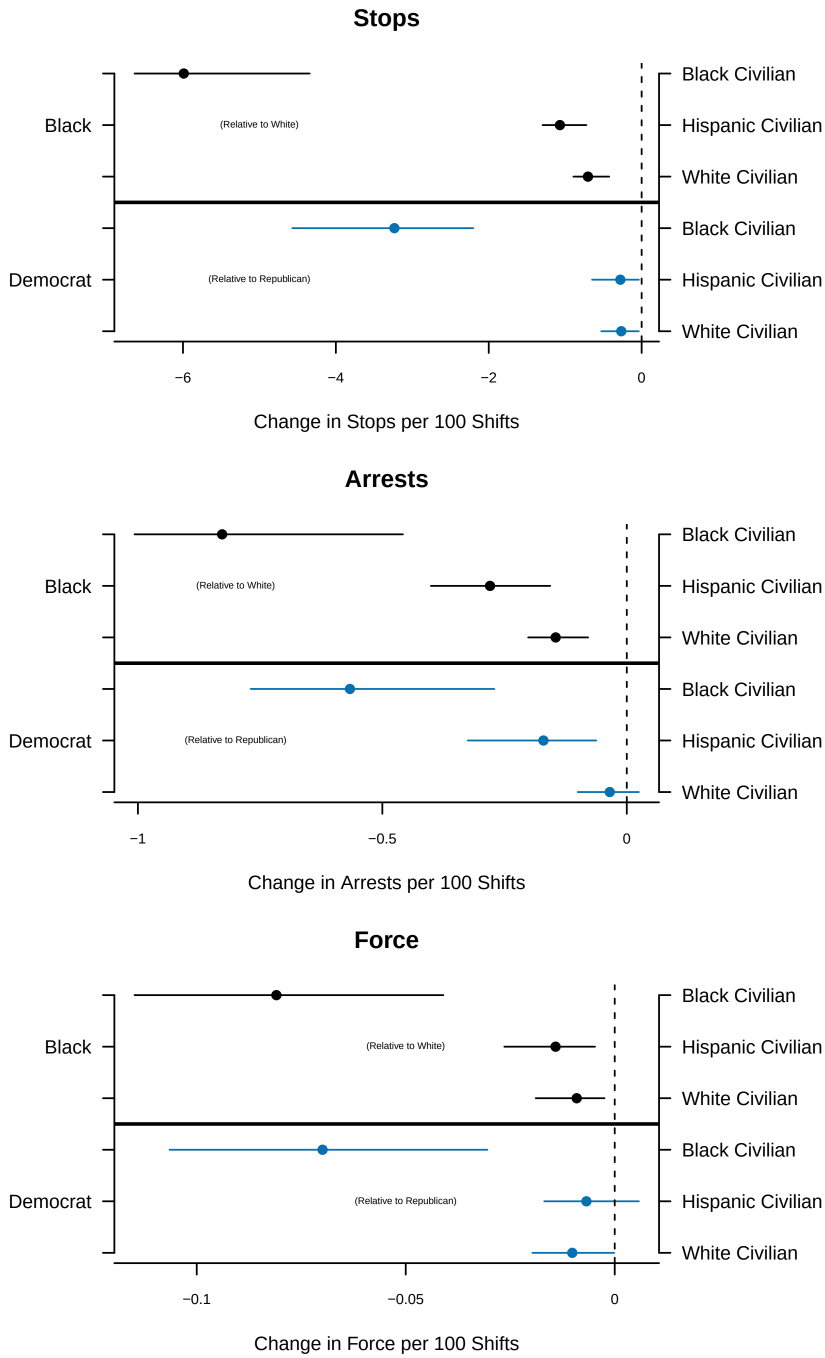

Figure B13: **Race and Party Deployment Effects, Black v. White Officers by Civilian Race**. The figure displays the average effects of deploying Black officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian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

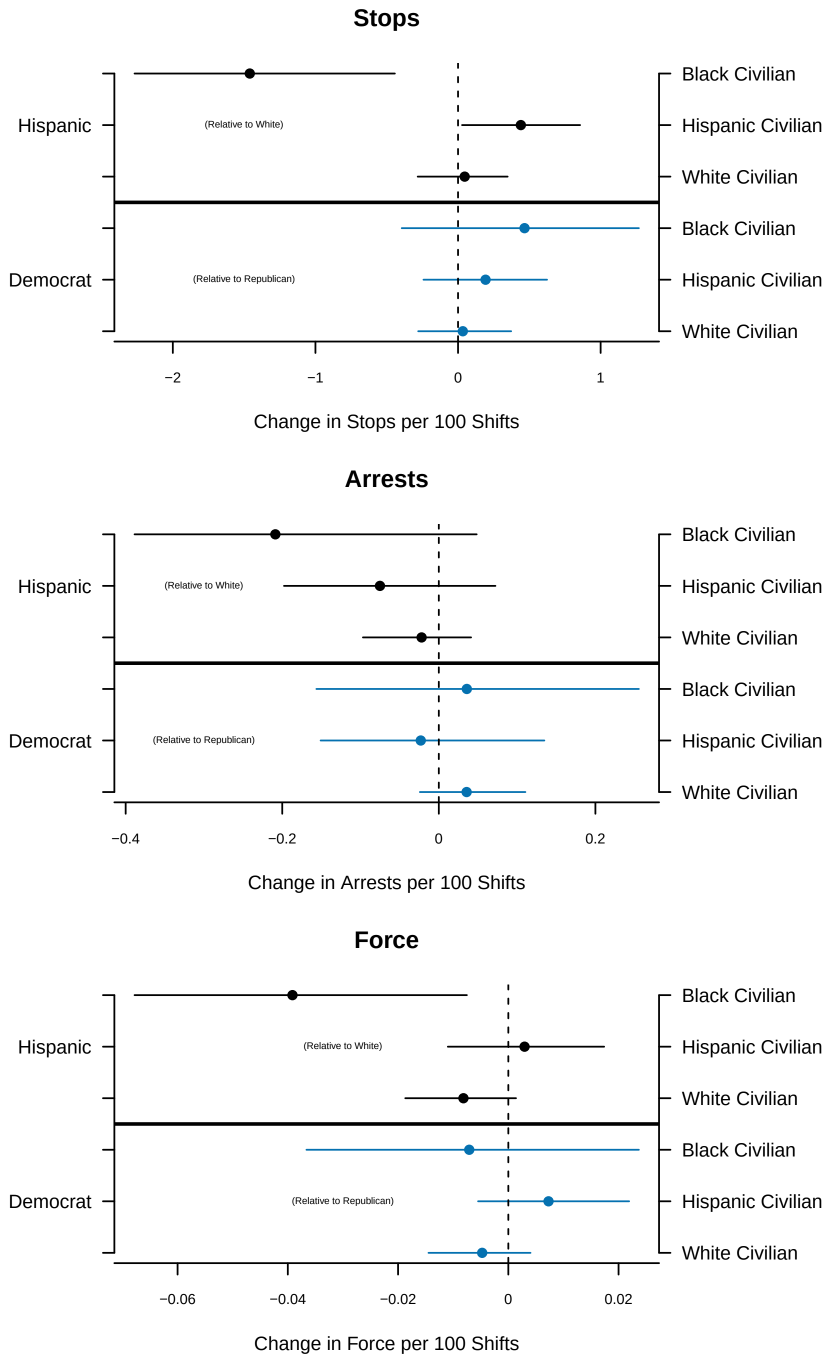

Figure B14: **Race and Party Deployment Effects, Hispanic v. White Officers by Civilian Race**. The figure displays the average effects of deploying Hispanic officers (relative to White); Democratic officers (relative to Republican) to otherwise common circumstances, with separate outcomes based on civilian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

B Robustness Checks

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	55.99	38.01	17.98*** [17.78, 18.18]	207,961
	Hispanic	20.74	27.33	-6.59*** [-6.75, -6.43]	207,961
	Black	16.73	21.77	-5.04*** [-5.20, -4.89]	207,961
	Other/Unknown Race	1.58	3.42	-1.84*** [-1.89, -1.79]	207,961
	Asian	4.96	9.47	-4.51*** [-4.60, -4.41]	207,961
Party (Voting Age Pop.)	Republican	25.39	14.00	11.39*** [11.22, 11.57]	218,041
	Democratic	22.34	43.32	-20.99*** [-21.16, -20.82]	218,041
	Other/Unknown Party	52.27	42.92	9.35*** [9.14, 9.55]	218,041
General Turnout, 2020	Voting Age Pop.	51.24	54.41	-3.17*** [-3.38, -2.96]	215,646
Gender	Male	83.20	48.69	34.51*** [34.35, 34.67]	218,041
	Female	16.80	51.31	-34.51*** [-34.67, -34.35]	218,041
Median Age (Years)	-	44.00	36.95	7.86*** [7.78, 7.93]	136,392
Mean Household Income ($)	-	115337.32	92174.92	23153.72*** [22833.70, 23473.75]	135,932

Table B19: **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. Stars denote $p<.001$; brackets contain 95% confidence intervals.

B.1 Restricting to States with Closed Primaries

The L2 database uses modeled estimates of party identification for voters residing in states that do not require registration with a political party to participate in elections. As a robustness check, we replicate our core results from Table 1 below after subsetting to states that had closed primaries in congressional/state-level elections (Table B20) or in presidential elections (Table B21) in 2020 according to `https://ballotpedia.org/Closed_primary`.

Variable	Value	Actual Officer %	Hypothetical Representative Officer %	Difference	N
Race	White	53.42	37.79	15.63*** [15.28, 15.97]	71,709
	Hispanic	21.78	25.33	-3.55*** [-3.84, -3.27]	71,709
	Black	20.55	25.55	-4.99*** [-5.28, -4.71]	71,709
	Other/Unknown Race	0.34	2.97	-2.63*** [-2.68, -2.59]	71,709
	Asian	3.91	8.37	-4.46*** [-4.60, -4.32]	71,709
Party (Voting Age Pop.)	Republican	35.67	13.63	22.04*** [21.69, 22.38]	71,945
	Democratic	34.28	47.97	-13.69*** [-14.03, -13.35]	71,945
	Other/Unknown Party	30.05	38.40	-8.35*** [-8.68, -8.02]	71,945
General Turnout, 2020	Voting Age Pop.	71.84	53.44	18.41*** [18.08, 18.75]	69,964
Gender	Male	90.50	48.05	42.45*** [42.23, 42.66]	71,945
	Female	9.50	51.95	-42.45*** [-42.66, -42.23]	71,945
Median Age (Years)	-	41.00	37.98	5.56*** [5.45, 5.68]	65,510
Mean Household Income ($)	-	114021.79	92974.15	21038.28*** [20563.99, 21512.57]	65,874

Table B20: **Comparison of Average Officer and Civilian Traits: States with Closed Congressional Primaries in 2020 Only**. 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	54.83	38.60	16.22*** [15.88, 16.57]	70,389
	Hispanic	21.70	24.52	-2.82*** [-3.11, -2.54]	70,389
	Black	19.41	25.19	-5.78*** [-6.06, -5.50]	70,389
	Other/Unknown Race	0.44	3.02	-2.58*** [-2.63, -2.53]	70,389
	Asian	3.62	8.68	-5.05*** [-5.19, -4.92]	70,389
Party (Voting Age Pop.)	Republican	35.57	13.10	22.48*** [22.13, 22.82]	70,624
	Democratic	34.41	48.78	-14.37*** [-14.71, -14.02]	70,624
	Other/Unknown Party	30.01	38.12	-8.11*** [-8.45, -7.78]	70,624
General Turnout, 2020	Voting Age Pop.	72.41	53.84	18.57*** [18.24, 18.90]	68,643
Gender	Male	90.25	48.07	42.18*** [41.96, 42.40]	70,624
	Female	9.75	51.93	-42.18*** [-42.40, -41.96]	70,624
Median Age (Years)	-	42.00	37.95	5.90*** [5.79, 6.02]	64,799
Mean Household Income ($)	-	114831.25	93876.69	20941.12*** [20465.08, 21417.17]	64,791

Table B21: **Comparison of Average Officer and Civilian Traits: States with Closed Presidential Primaries in 2020 Only**. 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.

B.2 Bounded Estimates Accounting for Unmatched Officers

Variable	Value	Officer Lower Bound %	Officer Upper Bound %	Hypothetical Representative Officer %	Difference Lower Bound	Difference Upper Bound
Race	White	46.61	59.69	37.85	8.76***	21.84***
	Hispanic	19.20	32.28	28.12	-8.92***	4.16***
	Black	14.91	27.99	21.19	-6.28***	6.80***
	Other/Unknown Race	1.82	14.90	3.42	-1.60***	11.48***
	Asian	4.39	17.47	9.42	-5.03***	8.05***
Party (Voting Age Pop.)	Republican	32.44	46.49	14.00	18.44***	32.49***
	Democratic	31.03	45.08	43.32	-12.30***	1.75***
	Other/Unknown Party	22.48	36.53	42.92	-20.44***	-6.39***
General Turnout, 2020	Voting Age Pop.	69.00	83.16	54.41	14.59***	28.75***
Median Age (Years)	-	42.00	45.00	36.87	6.96***	8.88***
Mean Household Income ($)	-	111154.59	119875.16	92628.27	18526.31***	27246.88***

Table B22: **Average Officer Traits Relative to Jurisdictions.** 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 hypothetical “best” and “worst” case values (e.g. all or no Democrats) to officers not observable in any of our data sources. Stars denote $p < .001$

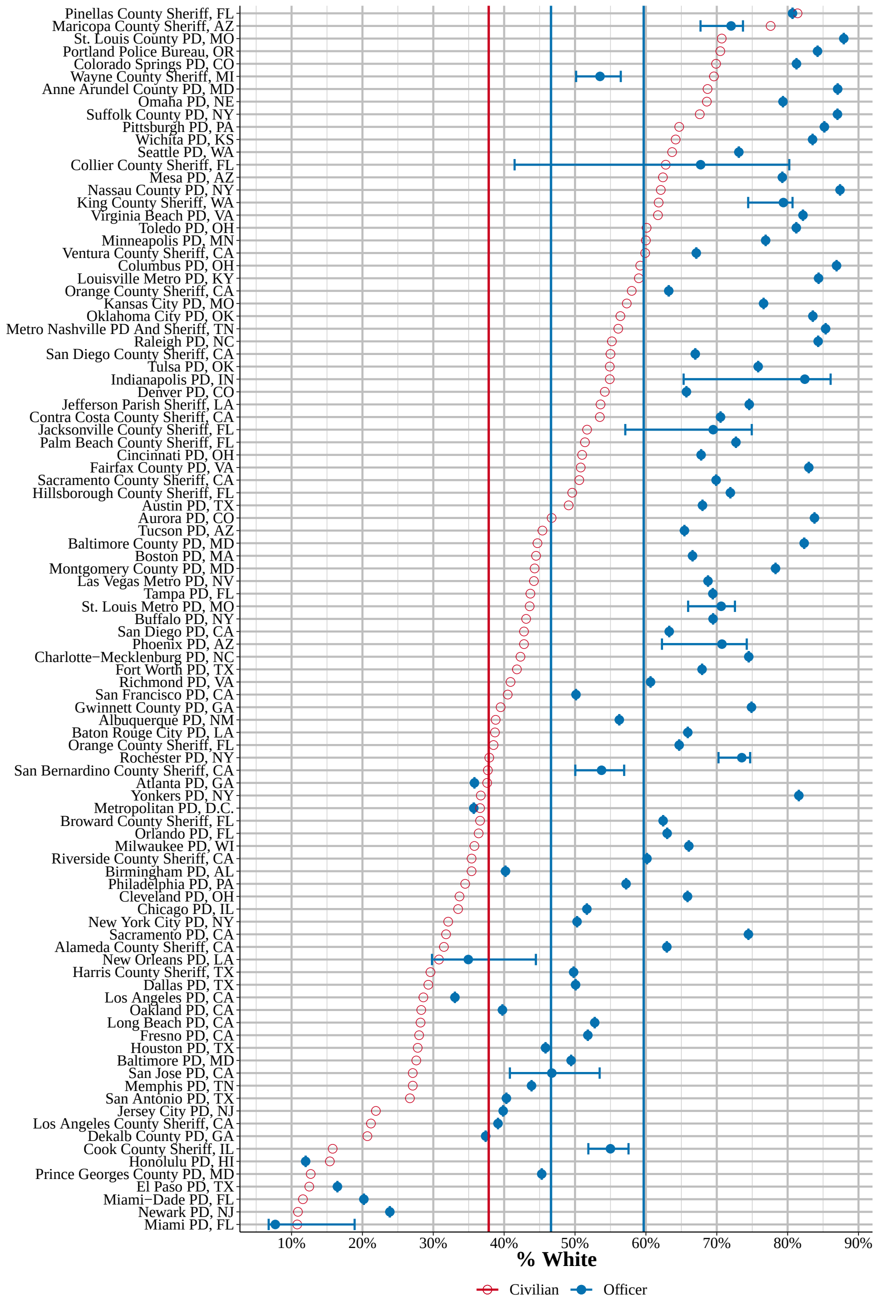

Figure B15: **Average Shares of White Officers and White Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

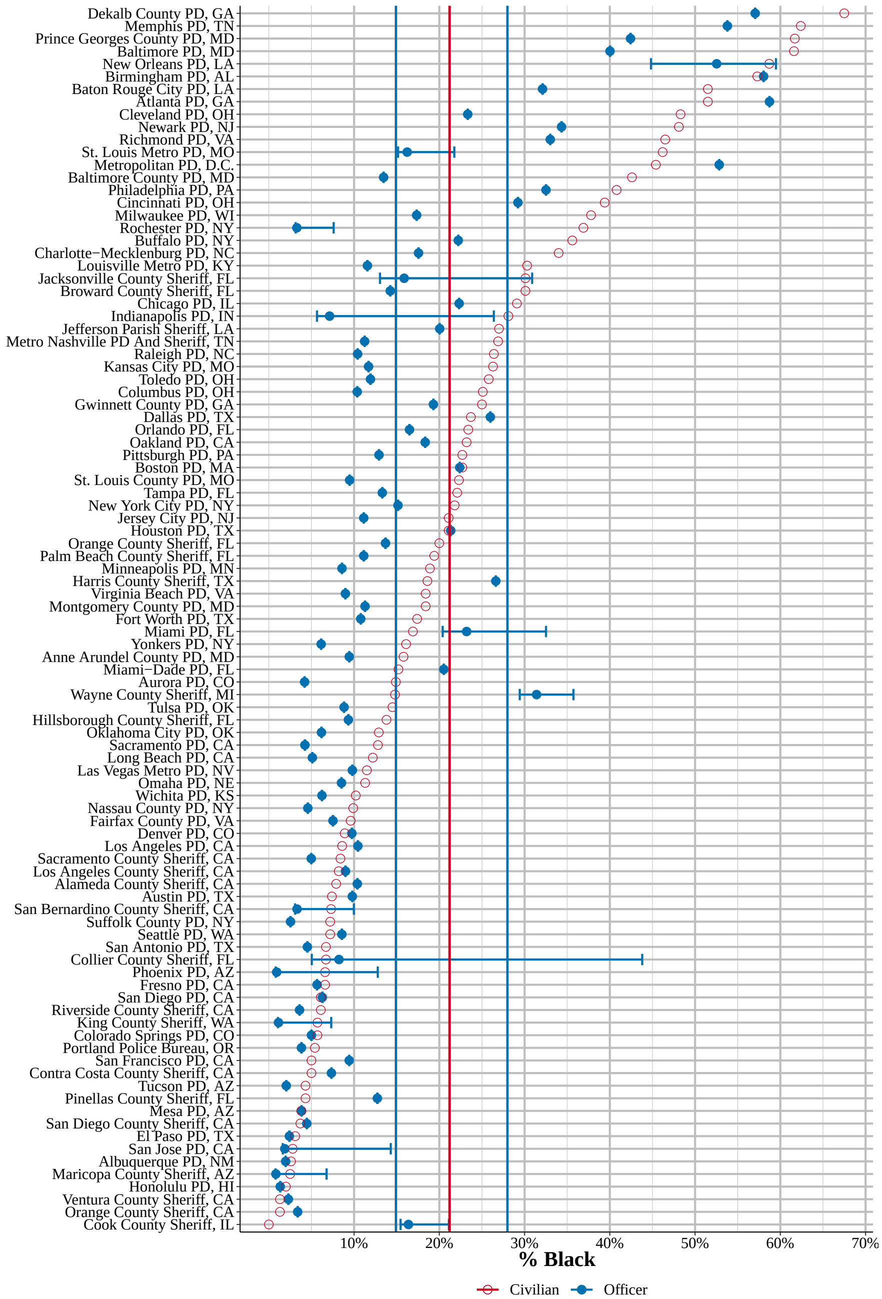

Figure B16: **Average Shares of Black Officers and Black Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officers was randomly drawn from their respective jurisdiction.

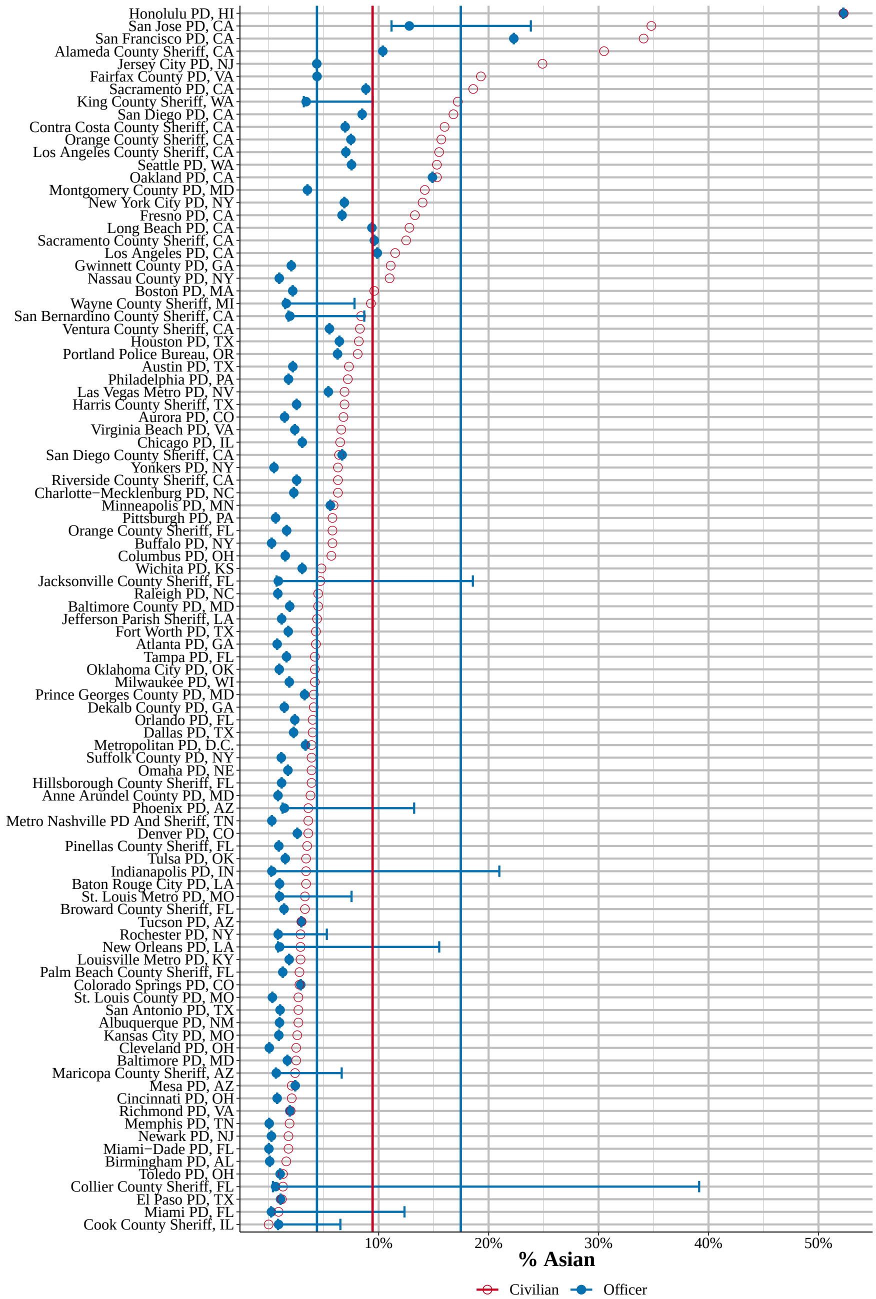

Figure B17: **Average Shares of Asian Officers and Asian Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

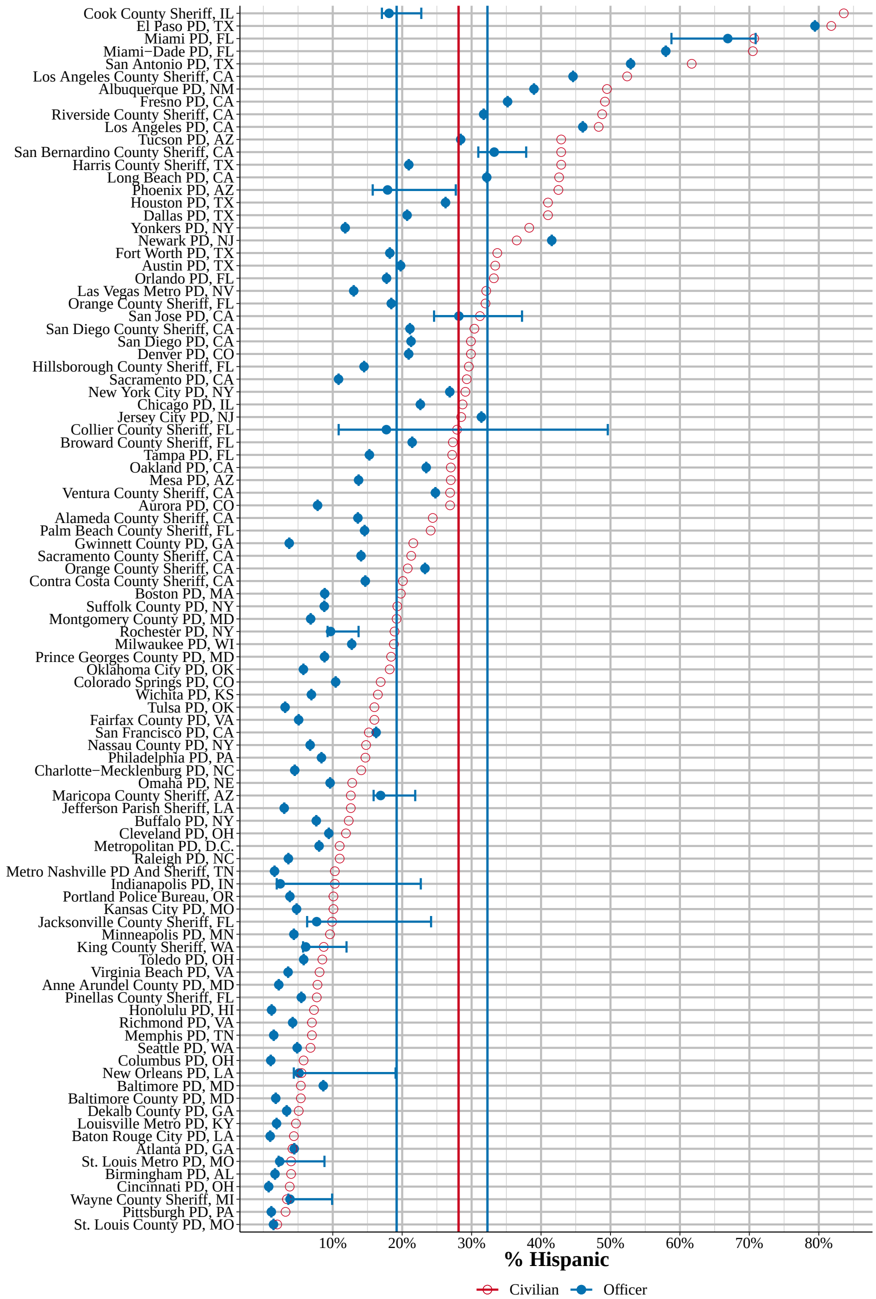

Figure B18: **Average Shares of Hispanic Officers and Hispanic Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

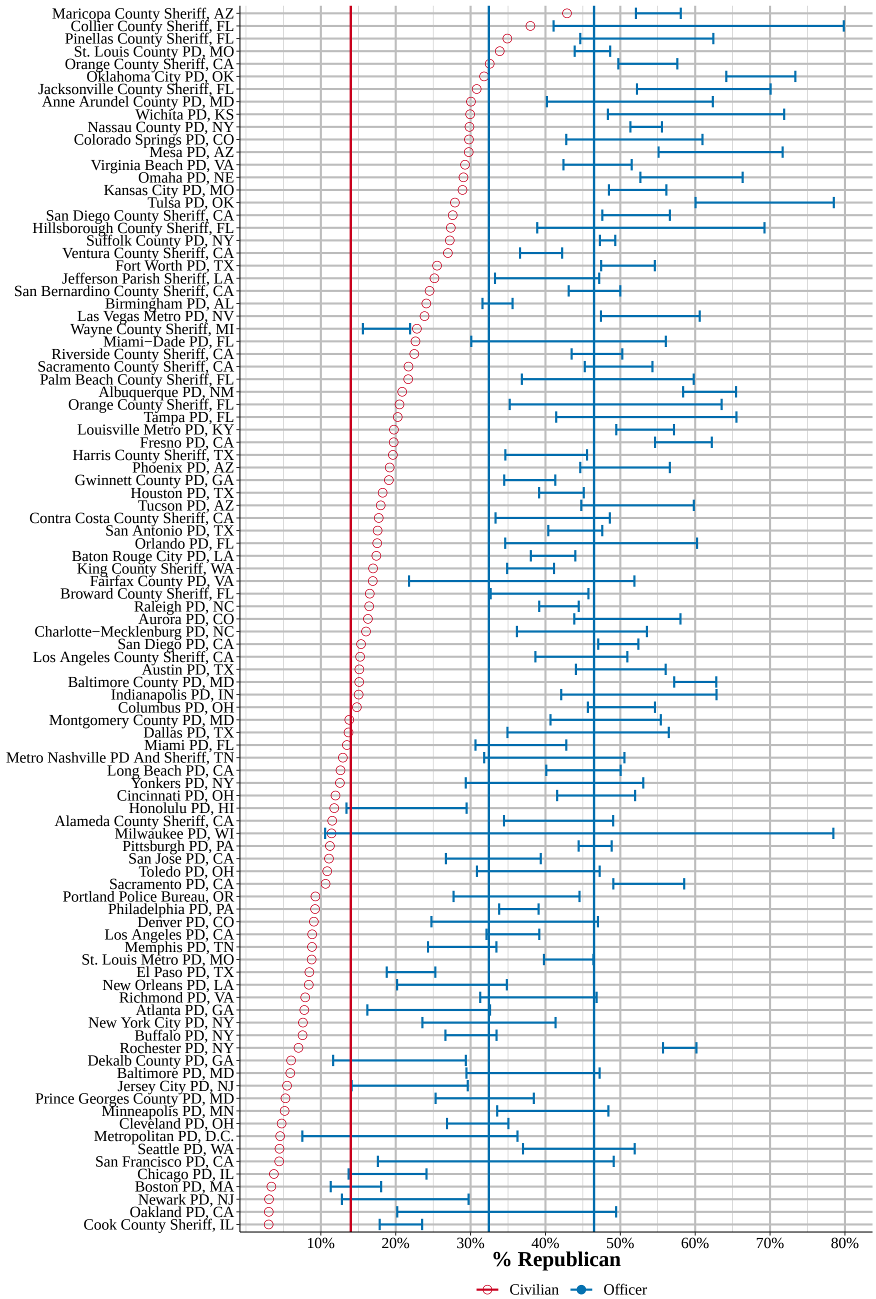

Figure B19: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

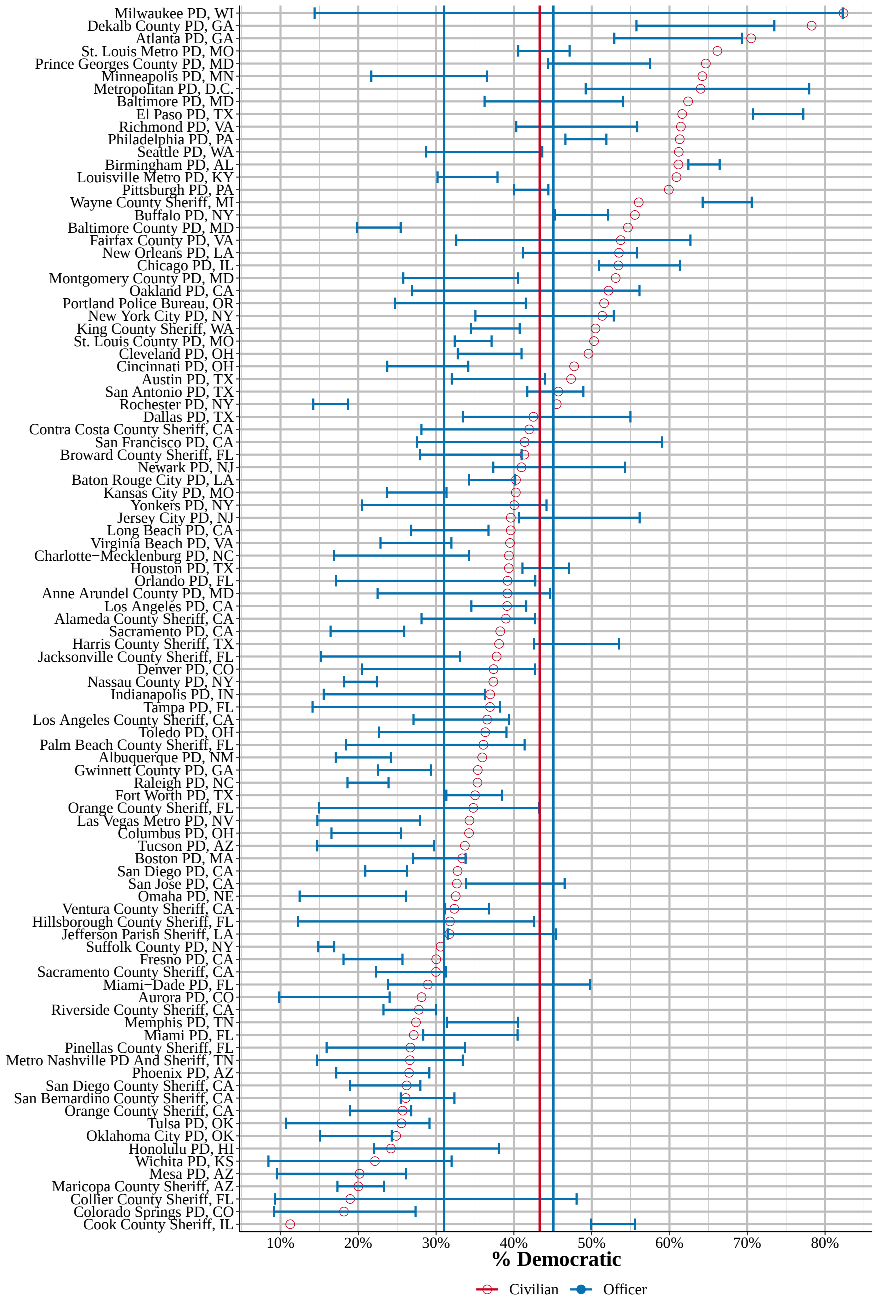

Figure B20: **Average Shares of Democrats Among Officers and Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

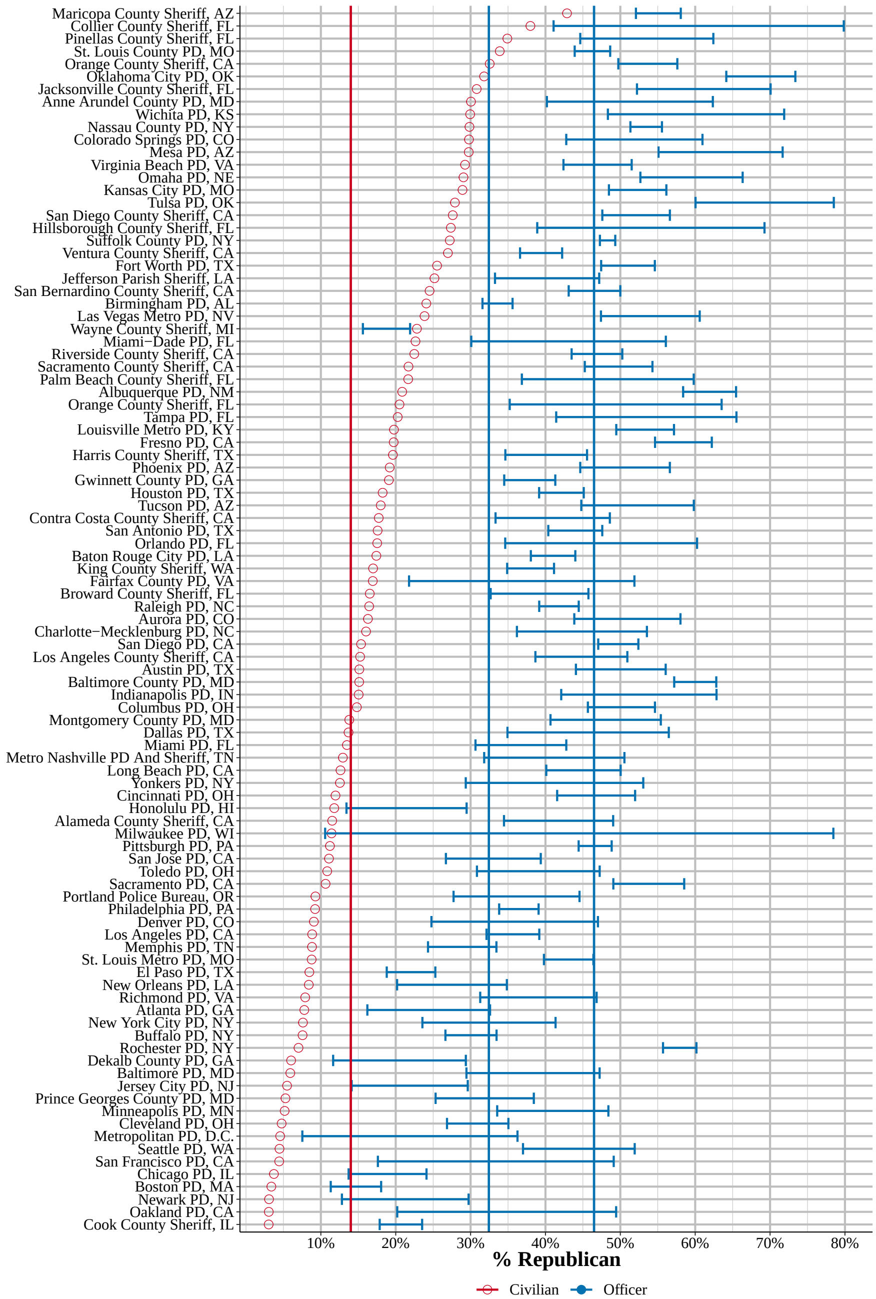

Figure B21: **Average Shares of Republicans Among Officers and Civilians in the Same Jurisdictions: Bounded Estimates.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values for agencies where covariate data is missing for some share of officers. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

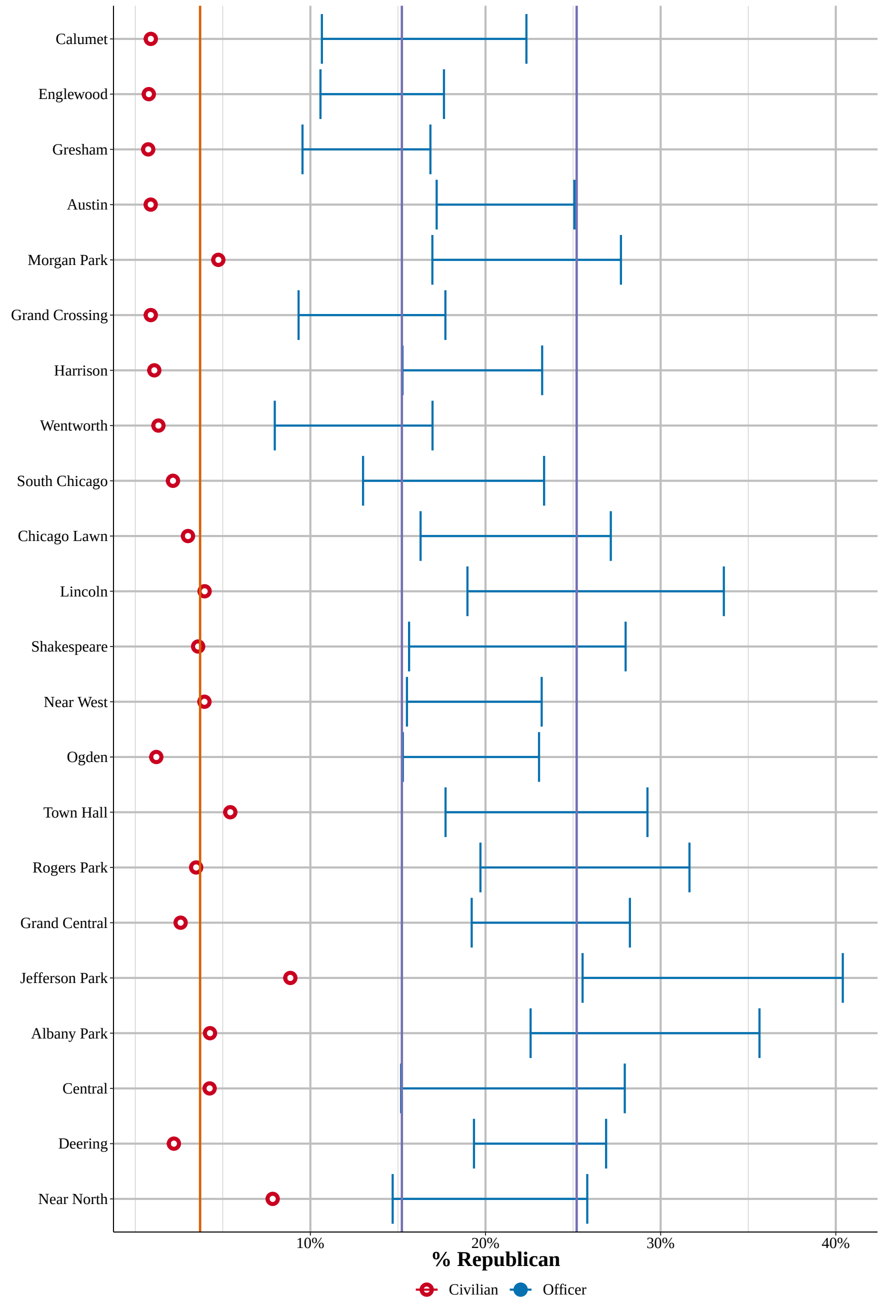

Figure B22: **Average Shares of Republican Chicago Officers and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.

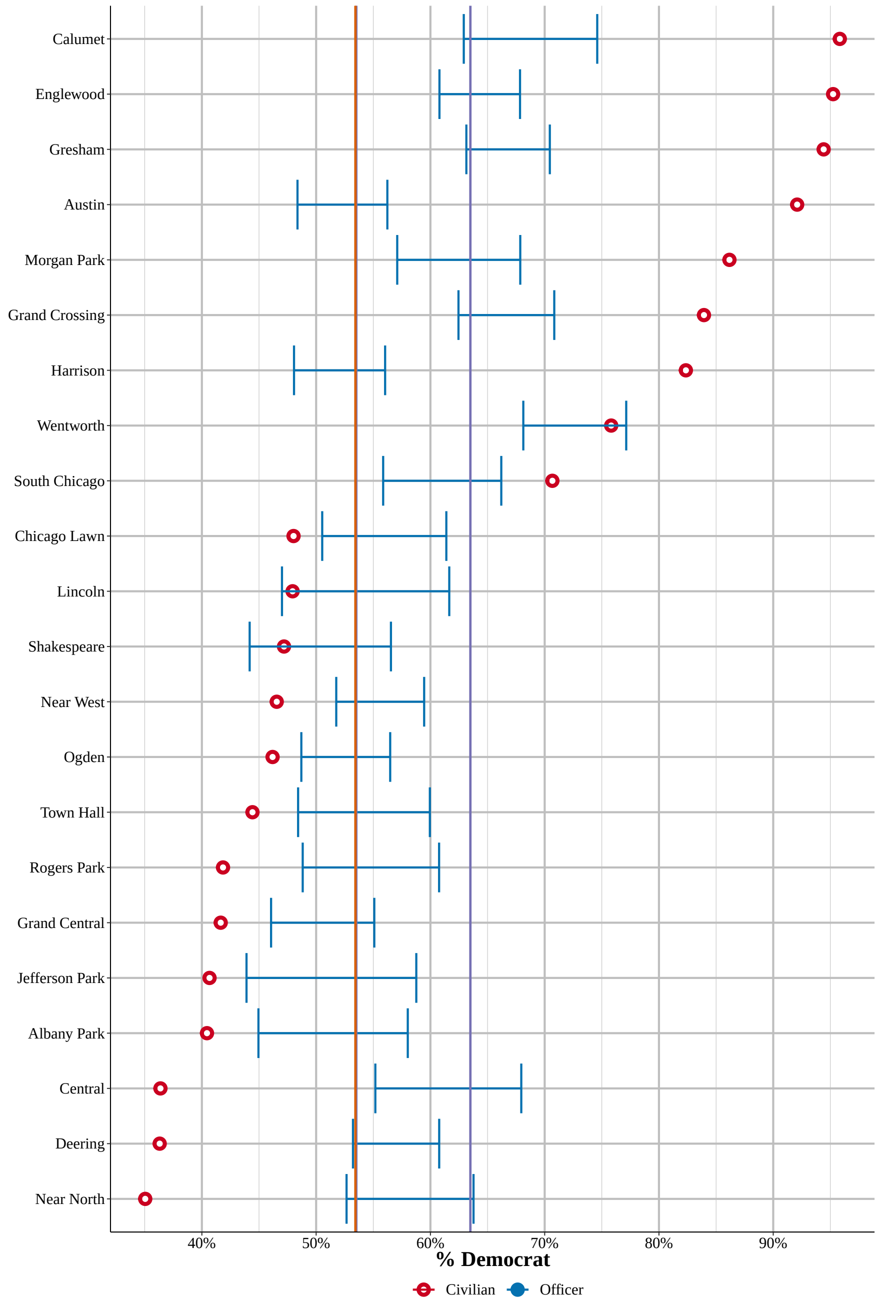

Figure B23: **Average Shares of Democratic Chicago Officers and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical pooled officer mean if each officer was randomly drawn from their respective jurisdiction.

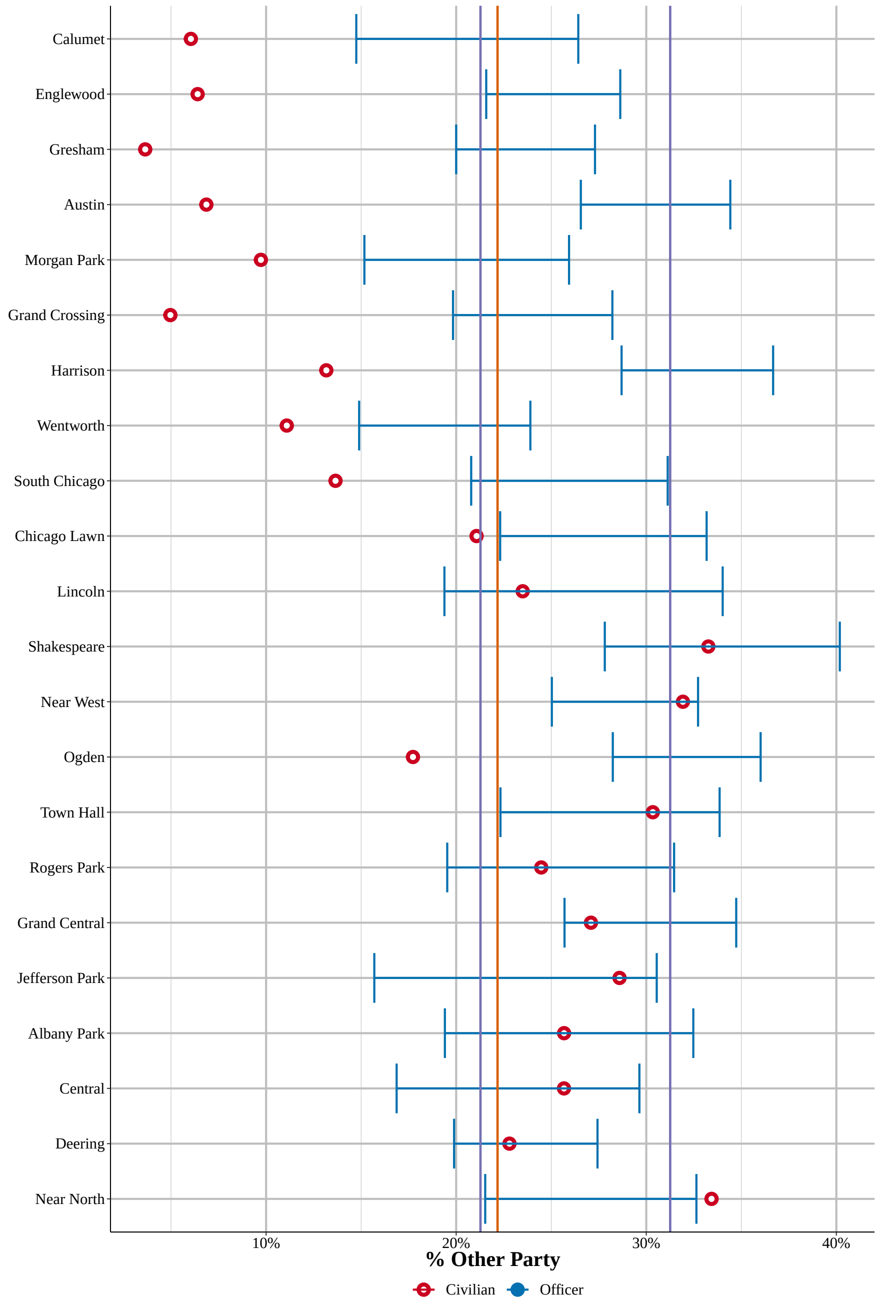

Figure B24: **Average Shares of Chicago Officers Affiliated with "Other Party" and Civilians in Officers' Assigned Districts: Sensitivity Analysis.** Blue dots are officer shares from from L2 voter file (i.e. among registered voters). Bounds show the range of possible average values accounting for officers where covariate data is missing. Red dots are civilian shares from U.S. Census. Vertical blue 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 red line is hypothetical officer mean if each officer was randomly drawn from their respective jurisdiction.