Diverse Forces? Investigating Determinants of Political Diversity in US Urban Bureaucracy

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May 8, 2024

Abstract

A rich body of research emphasizes the importance of a representative government for policymaking and public service provision. Yet, recent work on the composition of US bureaucracies reveals significant gaps in the descriptive representation of partisan and racial groups in the bureaucracy and their consequences for service delivery. What drives partisan and racial selection in professionalized bureaucracies? Focusing on selection in New York City's administration, this project addresses the question in three steps. First, I use detailed administrative data on the characteristics of city employees, including their partisanship, race, and gender, to illustrate the representational gaps between local bureaucrats and their constituents. Second, I focus on the New York Police Department (NYPD) and unpack the dynamics of partisan and racial misrepresentation. I find that Republican and White employees are more likely to be hired, promoted, appointed to senior ranks, receive more departmental awards, and have longer tenure than non-White and Democratic officers. Third, I show that the murder of George Floyd substantially increased turnover at the NYPD, especially among White and Republican officers. By delineating the complexities of selection in modern bureaucracies, this study provides new evidence about the determinants of bureaucratic representativeness and behavior.

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I thank Sara Constantino, Sanford Gordon, Kun Heo, Victor Lapuente, Julia Payson, Tara Slough, Arthur Spirling, Carolina Torreblanca, Hye Young You, and participants at APSA 2023, MPSA 2024, the NYU American Politics workshop and the NYU WINNING workshop for helpful comments and suggestions. Niklas Hähn and Paige Reddick provided excellent research assistance.

1 Introduction

A growing body of evidence shows that many US local bureaucracies, including police departments and public schools, have strong partisan and racial leanings and are often unrepresentative of the jurisdictions they serve. For example, 79% of US public school teachers are White, and White teachers often constitute the majority of a school's faculty, even in schools where most students are non-White (National Center for Education Statistics, 2020). Similarly, substantial gaps exist in the representation of US police: across a sample of 98 major US law enforcement agencies, 56% of officers are White, relative to only 38% of the population in the relevant jurisdictions. Similarly, 32% of officers are Republican vis-à-vis 14% of voting-age citizens, and only 31% of officers identify with the Democratic party relative to 43% of civilians (Ba et al., 2023).

To date, we have an incomplete understanding of what determines such a dominance of particular partisan or racial groups among rank-and-file bureaucrats. In this paper, I provide a first step towards understanding the root causes of representational disparities between the makeup of local bureaucrats and the demographics of corresponding US populations. I unpack various components of bureaucratic selection in a major US city bureaucracy. In particular, I describe how dynamics of self-selection, homophily, and institutional inertia at different stages of the selection process shape the political and racial composition of a professionalized local bureaucracy. Additionally, I examine how changes in the political environment of bureaucratic agencies affect these selection dynamics.

Understanding and disentangling the complex selection processes that dictate the representativeness of public agencies is important for multiple reasons. First, in a diverse society, a representative bureaucracy fosters government legitimacy. It showcases equitable access to power, active involvement of diverse groups in bureaucratic proceedings, and recognition of varied expertise within government (Selden, 1997; Theobald and Haider-Markel, 2008; Riccucci et al., 2014; Kringen, 2016). Second, the inclusion of diverse groups and preferences within government often meaningfully affects the quality of public goods provision and enhances the bureaucracy's ability to address the needs of marginalized communities (Bradbury and Kellough, 2011; Nicholson-Crotty et al., 2016; Bhavnani and Lee, 2018; Xu, 2021; Ba et al., 2021, 2023; Harris, 2023). Beyond demographics, partisan identities are crucial for active representation, especially given the extreme polarization of American parties and the fact that partisanship is a crucial predictor of individuals' attitudes on many policy issues. Skewed partisan representation in street-level bureaucracies can have important distributional consequences for public service provision (Lerman and Page, 2015; Forand et al., 2022; Ba et al., 2023; Donahue, 2023). Third, personnel expenditures constitute a substantial portion of city budgets nationwide. In 2021, local governments across the US employed 14 million individuals and spent more than $767 billion or 35% of their annual expenses on wages and salaries for employees (US Census Bureau, 2021a,b).[1] Thus, public employment is a key tool for distributive spending for local governments, and particularly for minority and historically disadvantaged groups, government employment serves as a symbol of status and a source of mobility (Meier, 1975). Finally, public sector employees and their unions are among the most active and powerful interest groups in American politics, especially at the local level (Anzia, 2022). Public sector unions increasingly engage in issues beyond their immediate material interests, such as matters of political identity[2], and their endorsements of local political candidates are perceived as highly partisan (Gaudette, 2024). Hence, the individuals who enter and persist in public sector unions can significantly shape the broader interests represented in politics.

Delineating the drivers of bureaucratic representativeness is challenging, since it requires detailed micro-level data on individual bureaucrats and their career trajectories over time. I draw on novel administrative data for employees across New York City (NYC) agencies and

[1] Note that this excludes expenses on retirement funds which also constitute a substantial source of expenditures.

[2] For example, the National Education Association fought book bans through their union via lawsuits and lobbying efforts. https://www.nea.org/nea-today/all-news-articles/educators-fight-book-bans-through-their-union

combine multiple relevant records, including civil service exam data, payroll information, promotion and attrition decisions, and official voter registration records. In addition to employment information, the resulting data contains measures of the partisanship, race, gender, age, place of work, and residence of individual bureaucrats. My data allows me to thoroughly trace the careers of partisan and racial groups in one of America's largest bureaucracies, covering about than 200,000 employees on the NYC payroll since 2014.

My analysis proceeds in three steps: First, I estimate municipal employees' different degrees of representativeness vis-à-vis citizens. In addition to observable traits, such as race and gender, I estimate how city employees mirror citizens of New York City in terms of their partisanship. I show stark differences in representativeness across agencies, geographic regions, and characteristics. While police, fire, and sanitation departments are consistently more Republican, White, and male relative to NYC's voting population, the Department of Social Services employs more Democrats, African Americans, and female individuals compared to the general public. Among the top five city agencies, only the Department of Correction manages to closely mirror NYC's citizens in its partisan and racial composition.

In the second step, I focus on selection within the NYPD and unpack the drivers of descriptive (mis)representation by tracing the types of individuals selecting into the bureaucracy and examining differential career trajectories and attrition rates of more than 58,000 officers. I find consistent differences in selection dynamics across individual officers by partisanship and race. My analysis suggests that while representational gaps are minimal when it comes to NYPD aspirants (exam-takers who pass the first entry exam), the gaps loom large for each subsequent selection stage: Republicans and Whites are more likely to advance to the hiring stage, are more likely to gain higher ranks in NYPD's hierarchy, are more often appointed to elite units, and receive more departmental awards than Democrats and non-Whites. Additionally, I show consistent trends of homophily and stratification: Teams headed by Democratic (black or Hispanic) leaders have lower shares of lower-ranked Republican (White) members and exhibit higher racial diversity. Finally, Democrats and non-White officers leave the force earlier, while Republican and White officers are more likely to remain on the force beyond the retirement age and are less likely to be dismissed or terminated.

In a final step, I examine how changes in the political environment of US law enforcement affect these selection dynamics. Many police departments across the US registered record high numbers of retirements and resignations by police officers following the 2020 BLM protests. Concerns arose that this "mass exodus" contributed to a rising level of crime and lower quality of police services (Nix and Wolfe, 2020; Mourtgos et al., 2022). However, without knowing the *characteristics* of departing officers—besides their mere number—it is difficult to assess the overall impact of turnover on policing services. Leveraging the substantial protest movement following the murder of George Floyd in May 2020 in an event study design, I show that Republicans and White officers were 35% and 50% more likely to leave the NYPD force immediately after George Floyd's death than Democratic and non-White employees, respectively. The results suggest that almost 900 White officers decided to step down in the six months following the protests compared to only 768 non-White members of the force.

This article makes three main contributions to scholarship on bureaucratic politics and local political economy. First, this research builds on and expands the literature on bureaucratic representation. A substantial body of work assesses the effect of the composition of bureaucracies on bureaucratic performance and policy-making. For instance, several articles highlight that bureaucrats provide better services if they are embedded in their jurisdictions, i.e., have social ties and share identity markers with citizens (White et al., 2015; Bhavnani and Lee, 2018; Ba et al., 2021; Xu, 2021). In contrast, I shed light on the *origins* of bureaucratic representation. By describing the dynamics that give rise to under- or overrepresentation in the bureaucracy, this study contributes to our understanding of what determines bureaucratic governance.

Second, this article speaks to the growing body of work on bureaucratic partisanship and selection. Both in the US (Bertelli and Lewis, 2012; Doherty et al., 2018, 2019; Bolton et al., 2020; Spenkuch et al., 2023) and other electoral democracies (Xu, 2018; Colonnelli et al., 2020; Fiva et al., 2021; Akhtari et al., 2022; Toral, 2022), the appointment of partisan bureaucrats is often linked to political turnover and politicians' ability to influence bureaucratic staffing. This explanation does not necessarily apply to bureaucratic selection in US cities, including in NYC. Its formalized civil service system with strict hiring and promotion rules ensures bureaucrats maintain a high level of independence from political control. Additionally, with the majority of elected officials in NYC consistently being Democrats, traditional explanations for partisan selection become less relevant. By shifting the focus to the broader determinants of bureaucratic selection, I provide alternative explanations for political diversity, particularly in highly professionalized civil service systems where political influence on hiring is minimal.

Third, while there is a growing interest in the dynamics of responsiveness and representation in US local governments, the primary focus of scholars has been the traits of elected officials, including city council members or county representatives (de Benedictis-Kessner and Warshaw, 2016; Einstein and Kogan, 2016; Sances, 2021). In contrast, I speak to the growing interest in the composition of local *bureaucracies* (Miller and Segal, 2018; Ba et al., 2021, 2023; Donahue, 2023) and focus on the role of bureaucrats' characteristics and their relationships with institutional processes and the political environment to understand the dynamics of political representation. Especially on the local level, where bureaucrat-citizen interactions are frequent and often the only face-to-face contact that citizens have with the state, it is critical to understand the root causes of representational gaps between bureaucracies and their jurisdictions.

2 Insights and Gaps in Representative Bureaucracy Research

A large literature spanning political science, public administration, and economics emphasizes the importance of having a bureaucracy that reflects the composition of the population it serves. This literature rests on several key premises: bureaucrats wield significant power and discretion in shaping service provision and policy-making (Meier, 1975); bureaucracies often favor more privileged segments of society, who have the necessary resources to mobilize politically and ensure favorable outcomes from the state (Riccucci and Ryzin, 2017; Meier, 2018); and centralized political control over bureaucracies is often too weak to ensure bureaucratic responsiveness to the diverse interests within democratic societies (Meier, 2018). The overarching claim is that achieving passive representation—where the bureaucracy mirrors relevant demographic attributes and social identities of the population it serves—can help address this lack in bureaucratic responsiveness and improve public service provision, particularly for marginalized groups (Kingsley, 1944; Meier, 1975). Bureaucratic agents who share the demographics of the general population (passive representation) are more likely to behave in ways that benefit citizens with those same traits due to shared values and identities (active representation) (Meier, 1975). A more closely matched representation of constituencies is also expected to improve citizens' trust in bureaucracy and government more broadly (symbolic representation) (Riccucci et al., 2014).

A substantial body of research confirms the underrepresentation of demographic minorities among US federal, state, and local bureaucracies (Meier, 1975; Riccucci and Saidel, 1997; Ba et al., 2023). Additionally, while important aspects of the theory remain underdeveloped and some empirical findings remain inconclusive (Shjarback et al., 2017; Meier, 2018; Garner et al., 2020), this research largely corroborates the positive effects of a representative bureaucracy, both at the individual and agency level (see Bishu and Kennedy (2020) for a review and Ding et al. (2021) for a meta analysis). These benefits are especially pronounced for street-level bureaucrats, including public school teachers (Nicholson-Crotty et al., 2016), judges and correction officers (Bradbury and Kellough, 2011; Harris, 2023), as well as police forces (Riccucci et al., 2014; Miller and Segal, 2018; Ba et al., 2021), where effective oversight of bureaucratic discretion is difficult and bureaucrat-citizen interactions are frequent. For example, Ba et al. (2021) show that Black, Hispanic and female officers in Chicago use force less often on the same shift and patrol assignment, especially against Black civilians and in majority-Black areas. Similarly, leveraging employment discrimination litigation across US police organizations since 1973, Harvey and Mattia (2022) find that increases in shares of Black officer substantially reduced racial disparities in crime victimization and Miller and Segal (2018) show that female representation in US policing increased reporting rates of domestic violence and decreased rates of intimate partner homicide and violent crimes against women.[3]

Despite the exponential growth and abundance of evidence in the literature on representative bureaucracy, substantial gaps persist. First, little work dissects the selection processes that determine bureaucratic representativeness.[4] Because most studies on passive representation only provide a snapshot in time and lack the necessary data to examine the full "pipeline" of bureaucratic selection, we know little about which stages—attraction to the profession, hiring, or promotion and retention—contribute to the representational gaps.

Second, research on representative bureaucracy often overlooks the differences in representational gaps both between and within agencies. The majority of studies examine a single agency and fail to theoretically and empirically distinguish between various levels of the bureaucracy.[5] Yet, hierarchy is a fundamental feature of every bureaucracy, and some evidence suggests that beneficial outcomes not only depend on *whether* bureaucracies are representative, but also on the *specific level* at which this representation occurs (Keiser et al., 2002). Therefore, it is essential to understand who occupies different levels of the bureaucracy and the selection processes that may lead to stratification within an agency.

Third, related research generally focuses on representation in terms of observable traits,

[3]This body of work does not imply that simply increasing passive representation among police will necessarily reduce racial disparities in policing outcomes. As research on the *perceptions* of representativeness and the importance of local contexts for policing shows (Brunson and Gau, 2015; Benton, 2020; Socia et al., 2021), the link between the representativeness and performance of police departments is complex, and more work is needed to determine how macro-level socioeconomic and institutional factors interact with the effect of officer identity.

[4]The exception are isolated studies on the effect of affirmative action on bureaucratic selection (e.g., McCrary (2007); Garner et al. (2020)) and recent experimental evidence on the effectiveness of different recruitment messages (Linos, 2017).

[5]Bishu and Kennedy (2020) estimate that only 9% of all recently published articles consider multiple levels of bureaucracy.

most prominently race and gender. Yet, recent work also highlights that the partisan identities of street-level bureaucrats have instrumental implications for how they do their jobs. For example, when incarceration is politically salient, Democratic correction officers are more likely to support rehabilitative models and less likely to favor punitive models of incarceration than their Republican counterparts (Lerman and Page, 2015). Similarly, Democratic police officers make fewer traffic stops and arrests, use force less often, and exhibit smaller racial disparities than Republican officers (Ba et al., 2023; Donahue, 2023). These partisan differences in officers' behavior are substantial and rival behavioral gaps across racial groups of officers.[6] Despite these findings, empirical studies on the *determinants* of bureaucratic partisanship in the US have mostly been restricted to the federal level (Doherty et al., 2018; Bolton et al., 2020; Spenkuch et al., 2023).

Taken together, several open questions remain: How does bureaucratic representativeness evolve and do leaks spring along every stage of the bureaucratic selection pipeline? How do representational gaps balance across agencies and correlate with agency missions? Does the degree of representation vary across different levels of an agency's hierarchy? And how do selection processes differ based on bureaucrats' intersectional characteristics, particularly race and partisanship? This article begins to explore these questions.

3 Attraction-Selection-Attrition Mechanisms in Bureaucracies

I characterize the representativeness of bureaucracies as a result of various selection processes. I propose that disparities—intentional or unintentional—in self-selection, hiring, promotion, and attrition practices in public bureaucracies are complementary in producing a mismatch between individual bureaucrats and the populations they serve. Using law enforcement as a case, I examine the complex selection dynamics that determine the overall representativeness of US local bureaucracies in terms of race, partisanship, and gender.

[6] Using quasi-random shift assignments of Chicago police officers, Ba et al. (2023) find that deploying a Democratic instead of a Republican officer reduces the volume of stops, arrests, and use of force by 14%, 12% and 24% per 100 shifts citywide, respectively.

The Attraction-Selection-Attrition (ASA) model, put forward by Schneider (1987) and common in the study of organizational behavior, provides a useful theoretical framework for this purpose. This model proposes that organizations—and their behaviors—are defined by the collective characteristics of people within them and that person-organization (P-O) fit is the central determinant of selection dynamics. It predicts that organizations tend towards homogeneity concerning the personality characteristics of their members due to a three-stage selection process. First, individuals are attracted to organizations based on their modal personality. Individuals decide whether to self-select into an organization from an implicit estimate of the congruence between their personality characteristics and the organization's goals (and processes, structures, and culture as manifestations of these goals). These organizations then select the most compatible applicant to the extent that they can influence the hiring process. Finally, because a lack of congruence is aversive, "misfits" tend to leave the organization. The logic is that fit yields commitment and satisfaction, which foster retention, and, by implication, those who do not fit leave (Schneider et al., 1995). The result is increasing homogeneity of members in an organization over time. In line with the general ASA framework, mission compatibility between public sector organizations and bureaucrats is found to be an essential factor for attracting, motivating, and retaining civil servants (Wilson, 1989; Besley and Ghatak, 2005; Prendergast, 2007; Dal Bó et al., 2013; Forand et al., 2022; Spenkuch et al., 2023). In the following, I delineate how the ASA mechanisms structure the racial and partisan composition of local bureaucracies. Since my empirical analysis of the selection dynamics focuses on US law enforcement, I pay particular attention to how ASA applies to recruitment, hiring, promotion, and attrition in police agencies.

3.1 Attraction

If individuals perceive their values to match those of the bureaucratic agency, they are more likely to self-select into the bureaucracy.[7] This might be because they derive intrinsic value from the specific public sector output they produce as bureaucrats (Besley and Ghatak, 2005; Prendergast, 2007) or because their partisanship and policy preferences align with those of the government agency (Forand et al., 2022). When gleaning their mission compatibility, applicants often rely on cues from an agency's public image and political environment, their networks, and their identification with the profession (Donohue, 2021). For instance, as policing has historically been an all-White male-dominated occupation, potential recruits among minority groups may choose not to become police officers due to perceptions that the profession is hostile toward them (Kringen and Kringen, 2014; Kringen, 2016) or due to a lack of role models and relatives employed in policing (Foley et al., 2008).

Similarly, issues of policing are highly politicized and polarized along partisan lines in the US. Republicans are substantially more likely to trust police, less likely to perceive police killings as a problem, and more likely to oppose protests and other efforts to reduce police violence in minority communities (Pew, 2016; Ba et al., 2023; Donahue, 2023). Moreover, the Republican Party increasingly leverages these pro-police sentiments in their electoral campaigns (Grosjean et al., 2023) and connections between police organizations and the Republican Party have recently intensified (Fineout, 2022; Donahue, 2023). Thus, from the pool of potential recruits, Republican and White citizens may be more likely to participate in the police recruitment process than Democratic and non-White individuals.

[7] Note that I do not conceptualize mission fit simply as high public service motivation (PSM) (i.e., the "predisposition to respond to motives grounded primarily or uniquely in public institutions or organizations" (Perry and Wise, 1990, p.368)). In contrast, following related work (Besley and Ghatak, 2005; Linos, 2017; Forand et al., 2022; Spenkuch et al., 2023), I assume that the congruence between the preferences and characteristics of bureaucrats and the specific goals of the relevant government agency determines mission fit.

3.2 Selection

While intended to prioritize merit, the specificities of selection procedures in meritocratic bureaucracies can further reinforce these disparities in candidate selection. Many civil service examinations include barriers in the screening process that may be particularly relevant for minority applicants, including degree requirements and background investigations. For instance, some evidence indicates that African American applicants are more likely to be disqualified during background screenings in the police hiring process, suggesting that checks for criminal histories and financial records have a disparate impact on minority candidates (Kringen and Kringen, 2014; Kringen, 2016). While affirmative action policies of bureaucratic agencies may offset these tendencies, their effectiveness for improving minority representation remains weak (Garner et al., 2020).

Alternatively, voluntary attrition during the selection process may skew the pool of potential hires. As the hiring and training process can take several months, candidates can further update their perceptions of how they fit with the respective bureaucratic agency and its mission. In the case of policing, this implies that Democratic and non-White applicants tend to self-select out of the hiring process. Indeed, based on interviews with small samples of police recruits, some studies suggest that African American police applicants view the hiring process more negatively, believe the organization is less attractive, identify less with the profession, and are more likely to withdraw from the process than White applicants (Ryan et al., 2000; Ployhart et al., 2002; Kringen and Kringen, 2014).

3.3 Promotion and Attrition

The third step in the ASA cycle predicts that bureaucrats with low fit to their agency are more inclined to exit due to lower levels of commitment and satisfaction. Promotional opportunities are an essential determinant of job satisfaction and perceived fit in later stages of bureaucrats' careers (Hilal and Litsey, 2020). For law enforcement agencies, for instance, research suggests that officers whose intentions to be promoted are thwarted become more cynical and are more likely to withdraw from the agency (Scarborough et al., 1999), and minorities and women are particularly dissatisfied with the promotions processes in their agencies (Guajardo, 2014). Part of these differences may be explained by lower promotional aspirations among officer groups whose attributes constitute a minority in the force. Democratic and non-White bureaucrats might self-select out of the promotion process for reasons related to police culture and tokenism. The need to prove themselves in a Republican and White-dominated profession, the possible backlash against perceived preferential treatment, and a lack of role models in senior positions, could impede the ambitions of Democratic and non-White officers to seek promotion (Huff and Todak, 2023). Additionally, while departments and individual supervisors have little influence on official promotions to higher ranks, they can hinder the opportunities for horizontal and discretionary career steps of minority employees, such as assignments to specialty units. These dynamics might lead Democratic and non-White officers to retire earlier than Republican and White members of the force.

4 Data and Measurement

I now discuss my strategy for measuring descriptive representation in US city bureaucracies and empirically evaluating the relevance of the attraction-selection-attrition mechanisms in explaining it. I combine detailed administrative data on employees of New York City that allow me to trace bureaucrats' careers in government. NYC is undoubtedly unique in many ways, including its demographic composition and local political environment. Yet, it also provides a valuable case for studying selection dynamics in meritocratic bureaucracies. First, the availability of granular data on the city's bureaucrats allows for a close examination of bureaucratic selection and representativeness across and within agencies. More importantly, NYC is the largest and one of the most professionalized city governments in the US. Its formalized civil service system with strict rules for hiring and promotions ensures a high independence of bureaucrats from political influence and control. Additionally, the vast majority of elected politicians in NYC have consistently been Democrats. This lack of electoral turnover in the ruling party renders the prevailing explanation for bureaucratic partisanship (i.e., political cycles) less relevant. Instead, uncovering the career trajectories of different types of NYC's street-level bureaucrats teaches us about a more endogenous development of bureaucratic partisanship and representation.

I start with a roster of roughly 200,000 unique employees across the five major agencies of NYC in terms of their staff size, including the Police Department, the Fire Department, the Department of Correction, the Department of Social Services, and the Department of Sanitation.[8] This data comes from the NYC annual payroll between 2014 and 2021 and covers employees with appointment dates between 1970 and 2021.[9] To identify the various demographic attributes of these employees, I merge the employment records with the 2021 L2 voter file based on employees' last names, first names, and middle initials. I restrict possible matches to registered voters in the city's five boroughs or one of the neighboring counties of New York State since NYC agencies require their employees to reside within these areas.[10] Following related work (Ba et al., 2023), I employ the probabilistic record linkage algorithm by Enamorado et al. (2019) and retain all matches with a posterior match probability of at least 0.7.

To study the specific drivers of selection among NYPD officers, I then add information on the career trajectories of about 58,000 uniformed police employees, including appointments, promotions, and retirements, from official records published in the City Record newspaper since 2014.[11] For a cross-section of 33,000 active officers (as of October 2021), I am further able to add information on their exact assignment, their arrest history, as well as their

[8]The Department of Education is currently excluded from the analysis due to data availability constraints.

[9]https://data.cityofnewyork.us/City-Government/Citywide-Payroll-Data-Fiscal-Year-/k397-673e; I identify unique employees based on the last name, first name, middle initial, and appointment date.

[10]Technically, NYC also allows employees to reside in Putnam and Orange County. Yet, because these counties are further away from NYC boundaries and relatively small, I exclude these to reduce the risk of false positive matches.

[11]https://www.nyc.gov/site/dcas/about/cityrecord-editions.page

departmental awards from the official NYPD profiles.[12] Finally, I obtain data on roughly 96,000 entry-level and 5,700 promotion exams for the NYPD between 2014 and 2021, which I match to the L2 voter file and the NYPD officers on the payroll. This allows me to assess the attributes of both hired and non-hired NYPD aspirants.[13] I link these administrative data probabilistically based on individuals' full names and other employment details, where possible, in all these merging procedures. Appendix A describes these different matching procedures in more detail. As Figure A1 shows, I can correctly match most employees and records with a very high probability—the median posterior probability of a match is above 0.95 across all matching procedures.

To measure the partisanship and race of individuals in my data, I rely on the information in the L2 voter files. For partisanship, I focus on the three main categories included in L2: Democrat, Republican, and Non-Partisan. Together, these comprise 96% of the 7,940,000 voter registrations in NYC and its surrounding counties. Note that the L2 information on partisanship in New York—unlike for other US states—is based on official registration records and does not require imputations. However, I must rely on L2's proprietary imputation algorithm to measure bureaucrats' and citizens' race. To code racial categories of registered voters, L2 combines the given name, surname, and demographics of a voter's census block for their inference. To assess the validity of the L2 race categories, I follow Ba et al. (2023) and bound my estimates against official counts of race groups reported by the NYPD to the 2020 Law Enforcement Management and Administrative Statistics (LEMAS) survey in Appendix Appendix A.5.[14]

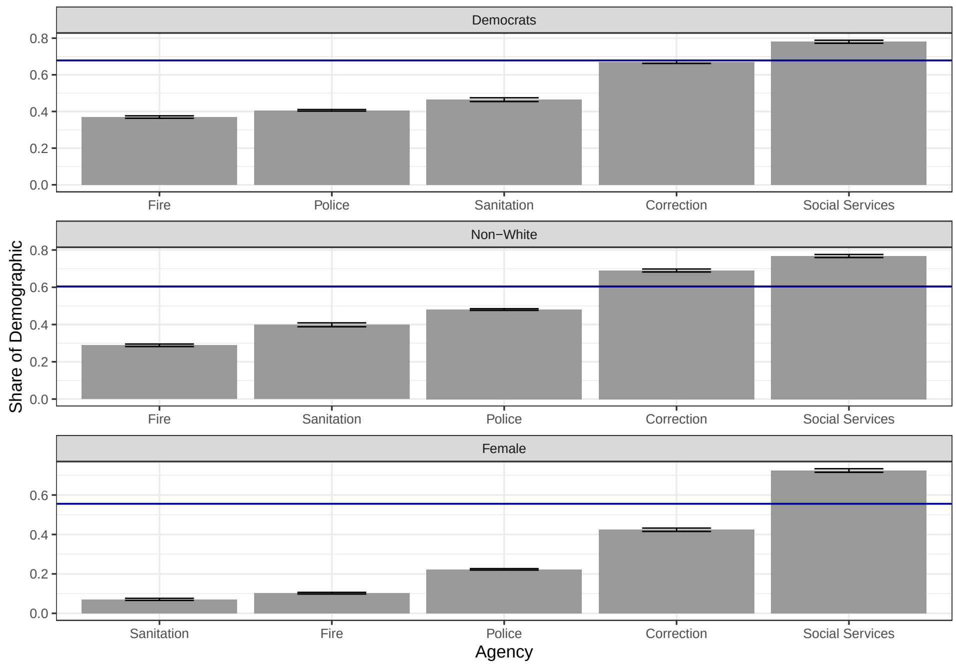
[12] https://nypdonline.org/link/2

[13] Note that the exam data does not provide information on *all* applicants, but instead contains individuals who successfully passed the exam (i.e., those with a score of 70/100 or above).

[14] In future iterations, I intend to include sensitivity analyses and bounds to address potential measurement errors in the racial categories in my statistical inferences.

5 Representativeness of NYC's Bureaucracy

Figure 1: Share of Demographics, Agencies vs. Registered Voters in NYC

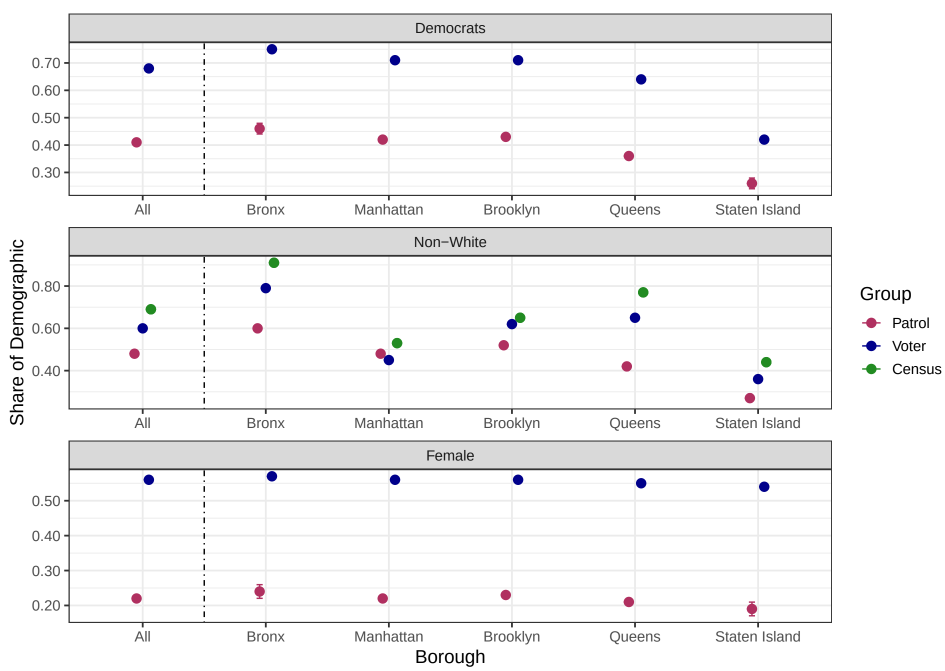


The blue line represents respective share of demographic among NYC voters. Agency employees only include uniformed/public facing employees plus leadership (i.e., I exclude administrative and other agency staff). Agency personnel includes individuals living in NYC's five boroughs and neighboring boroughs, while NYC citizens are restricted to NYC's five boroughs. Agency estimates are weighted by the posterior probability of matches between agency payrolls and the voter file.

I now compare the demographic composition of street-level bureaucrats and civilians in their jurisdictions along partisanship, race, and gender. Figure 1 first displays results across NYC agencies. Most agencies diverge from their jurisdictions regarding these attributes, albeit in different directions. Relative to the NYC voting population, the police, fire, and sanitation departments have substantially smaller shares of Democratic, non-White, and female members. For instance, while almost 70% of registered voters in NYC are Democrats and 60% are non-White, this only applies to 38% and 29% of front-line workers at the fire department, respectively. Interestingly, the two law enforcement agencies considered here (i.e., the police and correction departments) differ in their representativeness. The NYPD substantially underrepresents Democrats by 30 percentage points and non-Whites by ten percentage points. The Department of Correction, in contrast, closely matches NYC's voters in terms of partisanship and even *overrepresents* non-Whites. Similarly, the Department of Social Services skews more Democratic, non-White, and female than civilians in its jurisdictions.

These pooled results of representativeness mask some interesting trends across neighborhoods and time. Turning to descriptive representation at the NYPD in more detail, Figure 2 shows that gaps between the racial composition of citizens and NYPD officers are particularly stark in majority-Black communities, including the Bronx and Queens. At the same time, Democrats are underrepresented, and Republicans are overrepresented across all NYC boroughs, even in areas where Democrats are a minority among civilians. Yet, considering the trends in the partisan and racial composition of NYPD employees since 2014, Figure A5 indicates that the share of Republicans and White officers declined slightly, thus closing the representational gaps vis-à-vis their constituencies somewhat.

Figure 2: Share of Demographics, Police vs. Registered Voters in NYC



Uniformed police employees and traffic enforcement agents are assigned to boroughs based on their work location in their final year on the payroll. Agency estimates are weighted by the posterior probability of matches between agency payrolls and the voter file.

6 Dynamics of Selection

Based on this general overview of the representativeness of NYC's government, I now focus on selection within NYPD and unpack the dynamics of descriptive (mis)representation by tracing the types of individuals selecting in and out and the career trajectories of different types of officers. The aim is to disentangle the complex processes of self-selection, recruitment, promotion, and officer attrition that could drive the staffing of the country's largest law enforcement agency. To reiterate, I focus on the selection dynamics among race and partisan groups, but acknowledge that these are bundled categories and the descriptive analyses that follow by no means allow for a causal interpretation of the selection dynamics as a function of these demographics.[15] Particularly, while the regression analyses account for broader institutional-level confounding factors through various fixed effects (e.g., cohort, year and exam-score fixed effects), my data forces me to remain largely agnostic about micro-level differences across partisan and racial groups that may constitute the mechanisms for the disparities I document (e.g., differences in public sector motivation, personal networks, previous experiences).

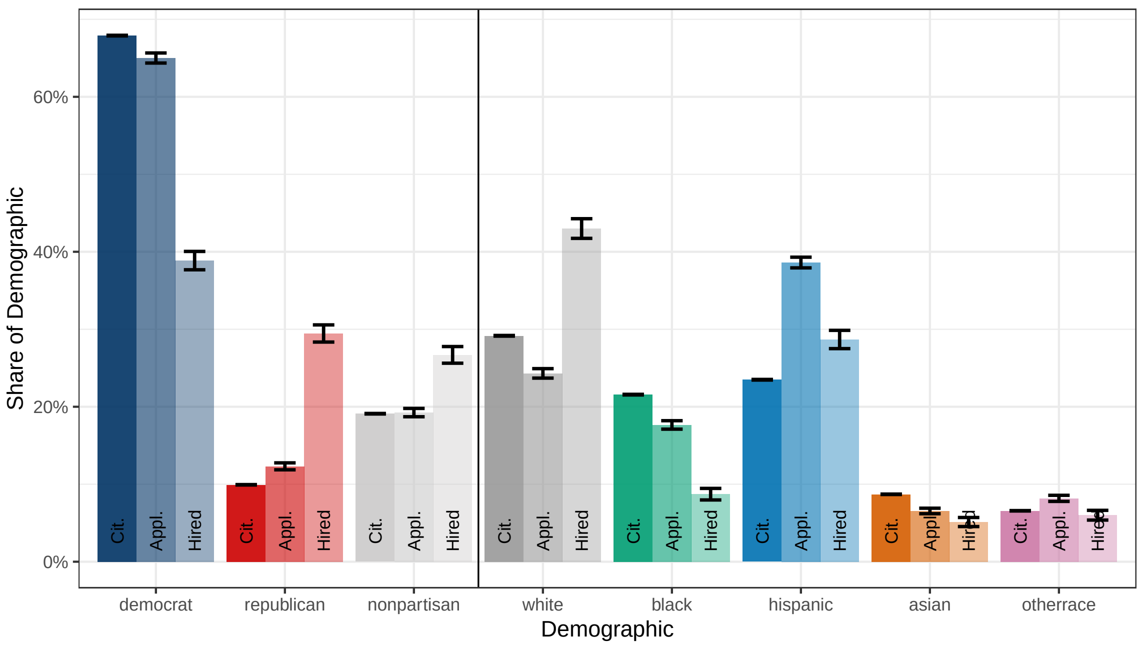
6.1 Attraction and Selection

To become a police officer at NYPD, applicants need to be between 21 and 35 years old, have earned 60 college credits with a minimum GPA of 2.0 or 2 years of military service, must live within NYC or one of the neighboring boroughs, and need to pass a check for "character and satisfactory background", which screens for arrest records, convictions, and discharge of employment. The hiring process entails a multi-stage process. Candidates who satisfy the basic selection criteria first take a written exam offered by the Department of Citywide Administrative Services which covers 9 cognitive abilities. Only candidates with a minimum score of 70% are placed upon an eligible civil service list for appointment,

[15] Unsurprisingly, Figure A4 shows that race, partisanship, and gender are strongly, but not perfectly correlated among NYPD officers in my sample.

with better performing candidates being placed further up on the list. Once a list number is reached, candidates advance to a medical exam, written and oral psychological exams, the background character investigation, a physical test, and a drug and alcohol screening. These additional examinations are all administered by NYPD directly. After successful completion of this process, candidates are then registered for the 6-month police academy, which constitutes the last prerequisite for their hiring.

Figure 3: Share of Demographics - Citizens, Police Exam Takers, Hired Exam Takers



The three bars among each partisan and racial group represent (from left to right) (1) share among NYC voters, (2) share among police exam takers, and (3) share among hired exam takers. Voters and exam takers are matched on age.

To follow the process of recruitment at the NYPD empirically, Figure 3 shows the share of party and racial categories among three different groups: NYC voters (matched to NYPD aspirants on age), all candidates who passed the NYPD entrance exam, and those applicants who were successfully hired and appointed by the NYPD. Considering partisanship first, it is clear that the pool of applicants already slightly underrepresents Democrats among its jurisdiction (68% vs. 64%) and overrepresents Republicans (12% vs. 9%). Yet, this representational gap is substantially larger between *hired* exam takers and NYC's voters: Democrats make up only 38% of hired candidates, and Republicans account for 29% of successful applicants. Similar trends are observed for race, where the share of Whites almost doubles between the application and the hiring stages.[16] These higher hiring probabilities for Republican and White applicants remain after accounting for exam difficulty and exam performance.[17] As Table 1 shows, among candidates of the same exam and similar scores, Republicans and White candidates are five percentage points and two percentage points more likely to be appointed than Democratic and Black applicants, respectively.[18]

What could explain these differences in selection into the force *after* applicants have already passed the exam? The recruitment process at the NYPD can be lengthy and uncertain. The average time it takes a candidate to be hired is one year, after which applicants must complete six months of police academy training. Republican and White applicants may be more committed to the police profession and less likely to reconsider other career options throughout this process. While the data does not allow for a direct test of this conjecture[19], Table 2 indicates that Democratic and non-White candidates are more likely to take another civil service exam within a year, suggesting that relative to Republicans and White applicants, they may see policing as just one viable appointment within the NYC bureaucracy. Additionally, Figure 4 suggests that income-based constraints might play a role in the pre-hiring attrition. I obtain information on each exam taker's income based on L2's estimated household income and per capita income matched by census tract from the 2019 American Community Survey. The figure indicates that non-hired exam takers and those taking another civil service exam are clustered among the lower end of the income

[16] One may be concerned that this result is an artifact of a low-quality match between exam takers and appointed individuals (i.e. I am only able to identify 9% of exam takers in the appointments). However, when I compare exam takers to *all* appointed officers in Figure A6, the patterns are very similar or even starker.

[17] Note that White candidates achieve slightly higher scores on the exams (see Table A4).

[18] Figure A7 further indicates that these gaps persist across exam performance.

[19] The NYPD is unwilling or unable to share data on police academy graduates (FOIL-2023-056-02128).

distribution.[20]

Table 1: Differences in Hiring By Exam Taker Characteristics

	Model 1	Model 2	Model 3	Model 4
Republican	0.05^{***}		0.05^{***}	0.05^{***}
	(0.00)		(0.00)	(0.00)
Non-Partisan	0.02^{***}		0.02^{***}	0.02^{***}
	(0.00)		(0.00)	(0.00)
Black		-0.04^{***}	-0.02^{***}	-0.02^{***}
		(0.00)	(0.00)	(0.00)
Hispanic		-0.01^{***}	0.00	0.00
		(0.00)	(0.00)	(0.00)
Asian		-0.01^{*}	0.00	0.00
		(0.01)	(0.01)	(0.01)
Other Race		-0.01^{**}	-0.00	-0.00
		(0.00)	(0.00)	(0.00)
Exam score (80-90)	0.01^{***}	0.01^{***}	0.01^{***}	
	(0.00)	(0.00)	(0.00)	
Exam score (90-100)	0.03^{***}	0.03^{***}	0.03^{***}	
	(0.00)	(0.00)	(0.00)	
Exam FE	Yes	Yes	Yes	No
Exam × Score Bin FE	No	No	No	Yes
Mean of DV	0.10	0.10	0.10	0.10
Adj. R^2	0.06	0.06	0.06	0.06
Num. obs.	64891	62719	60003	60003

Linear probability regressions, weighted by the posterior probability of a match between exam data and voter file. HC1 standard errors are in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

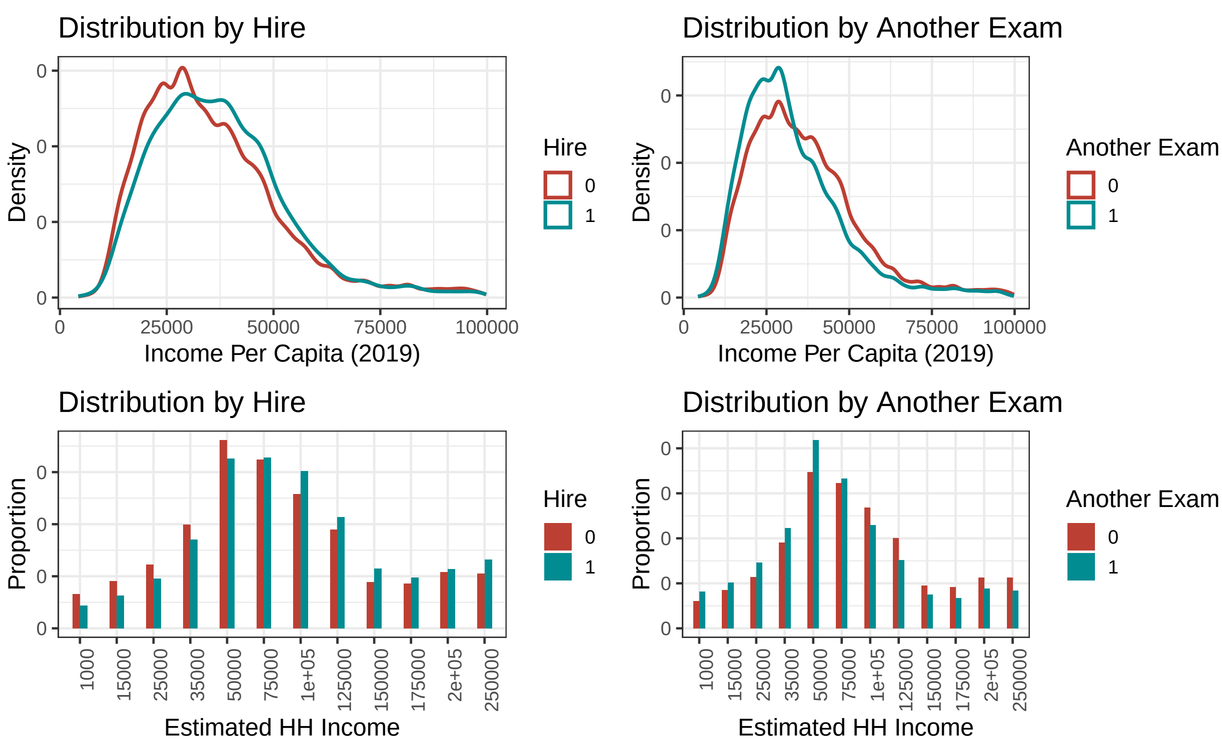
[20] Table A3 further suggests that these tendencies are stronger among non-White and Democratic exam takers, and largely hold when accounting for exam characteristics.

Table 2: Difference in Probability of Taking Another Civil Service Exam Within One Year

	Model 1	Model 2
Republican	-0.02^{***}	-0.02^{***}
	(0.00)	(0.00)
Non-Partisan	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)
Black	0.07^{***}	0.06^{***}
	(0.00)	(0.00)
Hispanic	0.02^{***}	0.02^{***}
	(0.00)	(0.00)
Asian	0.05^{***}	0.05^{***}
	(0.01)	(0.01)
Other Race	0.06^{***}	0.06^{***}
	(0.01)	(0.01)
Examscore (80-90)		-0.00
		(0.00)
Examscore (90-100)		0.00
		(0.00)
Exam FE	No	Yes
Mean of DV	0.12	0.12
Adj. R^2	0.01	0.03
Num. obs.	60003	60003

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Figure 4: Income Distributions by Exam Taker Type

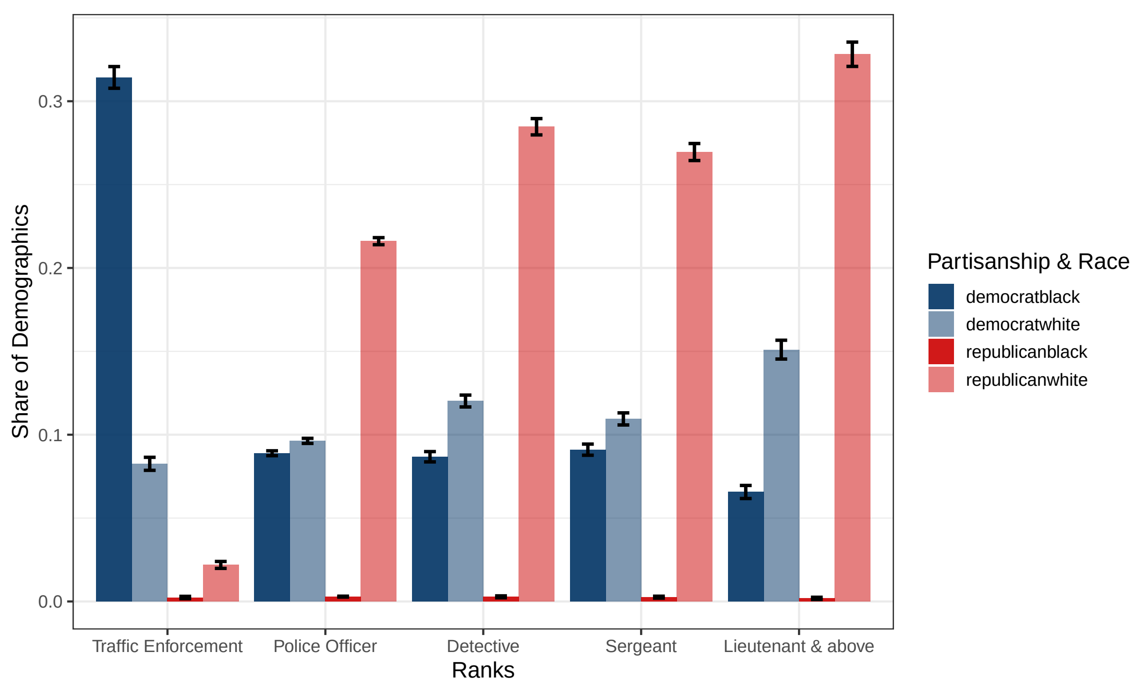


Note: The top panels use income per capita from the 2019 American Community Survey (matched by census tract), and the bottom panels use L2's estimated household income.

6.2 Career Progression

How do assignment and promotion procedures in law enforcement further exacerbate these partisan and racial disparities in selection? Using data on all uniformed employees and traffic enforcement agents on the NYPD payroll (2014-2021), Figure 5 indicates that Democrats, particularly Black Democrats, are clustered among the lower ranks. For instance, among traffic enforcement agents 33% are Black Democrats, whereas only 6% of Lieutenants or above are Black and Democratic. For White Republicans, in contrast, these figures amount to 2% and 35%, respectively.

Figure 5: Share of Demographics by Police Rank



Yet, these distributions only provide a snapshot of the rank distribution and do not account for the fact that older cohorts of officers, who could have higher shares of Republican and White officers, may have achieved higher ranks simply due to their longer tenure. To account for this, Table 3 depicts differences in promotion probabilities across partisanship and race within the same cohorts. Models (1)-(3) only include official promotions that require a promotion exam (i.e., sergeant and above), and Models (4)-(6) further include discretionary

Table 3: Differences in Promotions by Officer Characteristics

	Official Promotions			Title Changes		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Republican	0.01^{*}		0.00	0.03^{***}		0.02^{***}
	(0.00)		(0.00)	(0.00)		(0.00)
Non-Partisan	0.01		0.00	0.01^{**}		0.01
	(0.00)		(0.00)	(0.00)		(0.00)
Black		-0.01^{*}	-0.01		-0.04^{***}	-0.03^{***}
		(0.00)	(0.00)		(0.01)	(0.01)
Hispanic		-0.01^{***}	-0.01^{**}		-0.02^{***}	-0.02^{***}
		(0.00)	(0.00)		(0.00)	(0.00)
Asian		0.04^{***}	0.04^{***}		-0.00	0.00
		(0.01)	(0.01)		(0.01)	(0.01)
Other Race		0.03^{***}	0.04^{***}		-0.00	0.00
		(0.01)	(0.01)		(0.01)	(0.01)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	0.09	0.09	0.09	0.17	0.17	0.17
Adj. R^2	0.07	0.07	0.08	0.13	0.13	0.13
Num. obs.	49558	48521	45990	49558	48521	45990

Linear probability regressions, weighted by the posterior probability of a payroll and voter file match. Level of observation: Uniformed employee. Outcome: Dummy for whether the employee received a promotion/title change between 2014 and 2021. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

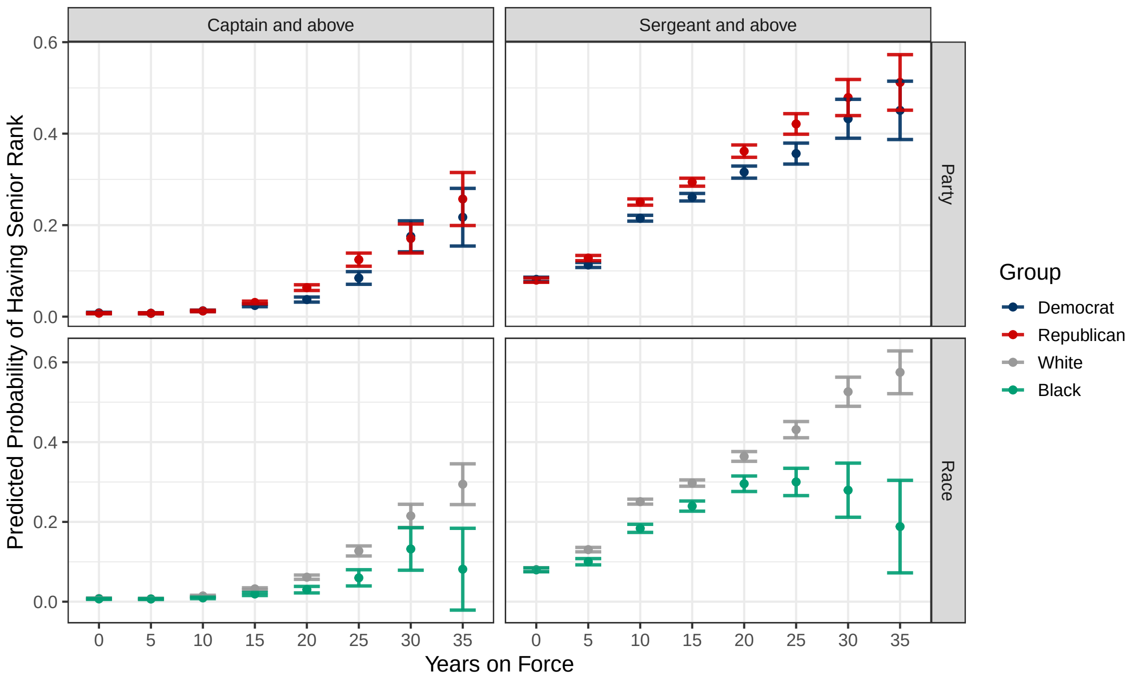
promotions (e.g., between detective grades). The estimates suggest that Republicans and Whites are one percentage point more likely to get promoted than Democratic, Black, and Hispanic officers, respectively. With an overall promotion rate of only 9% in the sample, these estimates imply substantively meaningful differences. As Table A5 shows, these differences are not explained by gaps in promotional aspirations: Republican and White officers are not more likely to take a promotion exam throughout their tenure than Democrats and non-Whites.[21] However, Table A6 indicates that scores on the promotion exams are a strong predictor of receiving a promotion, and once we account for exam performance the promotion gaps subside, suggesting that Republicans and Whites do better on promotion exams.

Notably, the partisan and racial gaps in career progressions are even larger when incor-

[21]The exception is Asian officers, who are more likely to take promotion exams and receive promotions.

porating discretionary promotions and grade changes. Supplementary analyses in Tables A7 and A8 indicate that Republican and White officers are also more likely to receive departmental awards and to be assigned to prestigious elite units, including anti-terrorism and special forces. Additionally, teams headed by non-White (Democratic) leaders have lower shares of lower-ranked White (Republican) members and exhibit higher racial diversity overall (see Tables A9 and A10).[22]

Figure 6: Seniority Gap by Years of Experience



Depicted are predicted probabilities of having a senior rank, with 95% HC1 confidence intervals. All underlying regression models (LPM) include officer cohort fixed effects.

In Figure 6, I further assess whether this partisan and racial seniority gap persists across officers' tenure. Interestingly, the Black-White gap endures and widens over time, whereas Democrats seem to catch up to the ranks of Republicans after 30 years on the force. One may wonder whether this is due to attrition by Black officers with better outside prospects. Yet, Figure A8 suggests that there is no widening gap between Black and White officers across tenure in terms of observables that might be weakly correlated with quality (i.e., the number

[22]These analyses use a cross-section of active officers (as of October 2021) for whom more detailed information on assignments and awards is available.

of arrests, awards, and disciplinary records). Taken together, this suggests that Republican, and particularly White, officers benefit from steeper progress along the career ladder in law enforcement.

6.3 Attrition

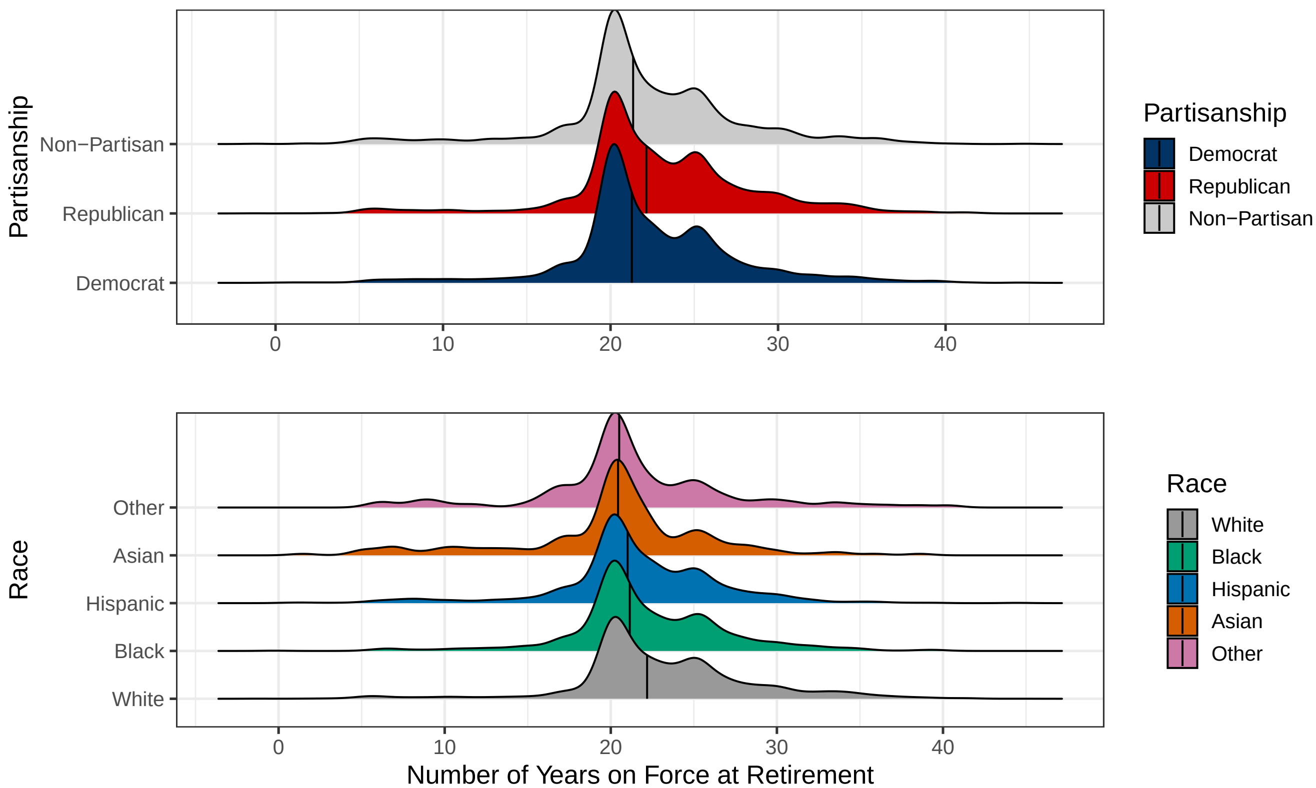
How do these differences in career trajectories across types of officers translate into their attrition from the force? Figure 7 depicts the distribution of years on the force at the time officers retire. Evidently, many officers retire around 20 and 25 years of service, when they become eligible for different retirement packages at NYPD. Yet, Republicans and White employees stay on the force somewhat longer, often working beyond the retirement age of 20 years. For instance, the median retiring Republican or White officer worked for 22.1 years, compared to 21.3 years for Democratic officers and 21 years for non-White officers. As Table A11 shows, these results hold when accounting for officers' age at appointment.[23] Further, Figure A9 illustrates that this differential attrition leads to a dominance of Republicans and Whites among longer tenured members on the force.

In addition to the timing, the reasons NYPD officers exit the force also seem to differ across partisanship and race. Across all types of officers, retirements and resignations account for the grand majority of exits (see Figure 8). However, involuntary exits (i.e., dismissals and terminations) account for significantly higher shares of exits among Democratic, Black, and Hispanic officers than for Republicans and Whites. Specifically, 2% of exiting Democrats, 3.3% of Blacks, and 2.4% of Hispanics leave involuntarily, whereas only 1.3% of Republicans and 0.9% of White officers leave due to dismissals or termination.[24]

[23] This is particularly relevant since Republican and White officers on the payroll are on average 1.6 and 1.2 years younger at initial appointment.

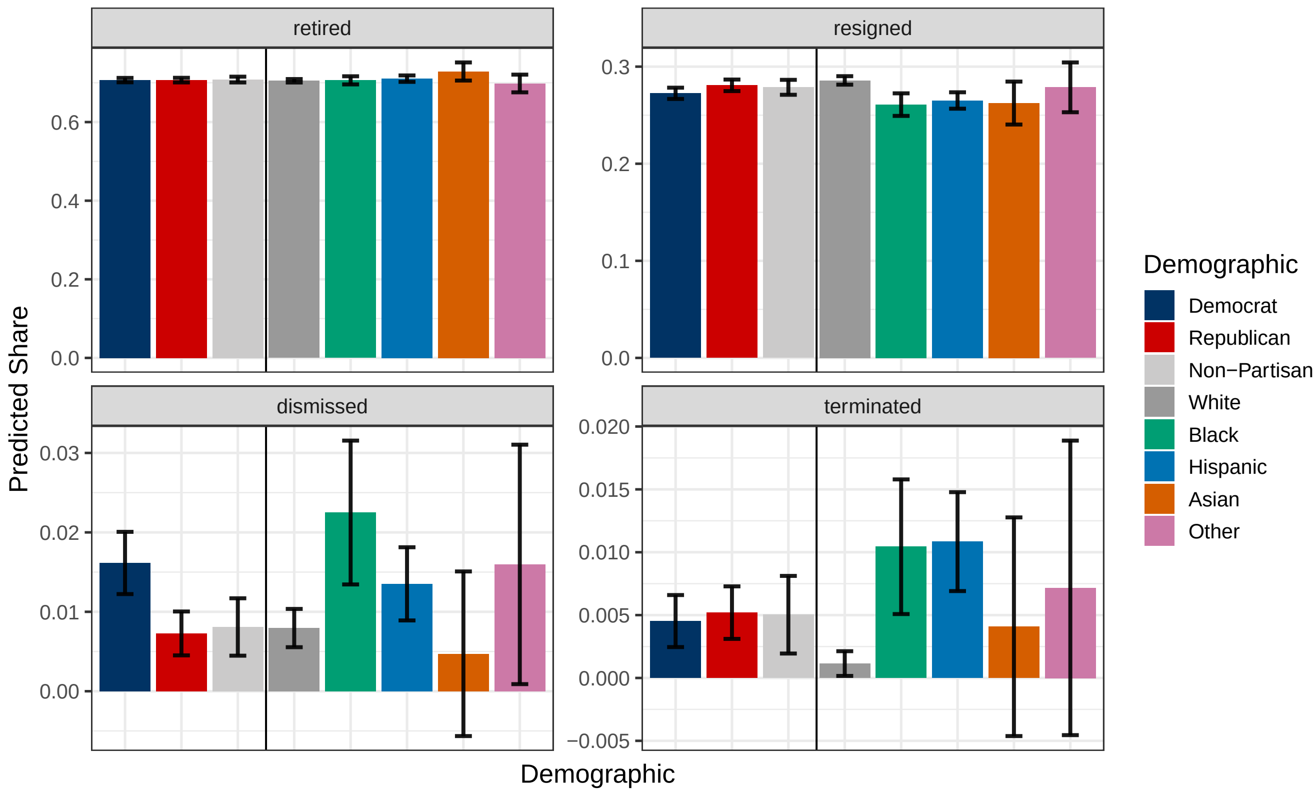
[24] Figures A10 and A11 further indicate that these higher involuntary exit probabilities for Democrats and non-Whites predominantly affect early-career officers.

Figure 7: Distribution of Years on Force at Retirement



Black lines indicate median years on the force at retirement.

Figure 8: Predicted Probability of Exit Type



The estimates are obtained from regressions of exit type (conditional on exit) on group demographic, cohort FE and fiscal year FE. The covariates are fixed at their observed values for predictions.

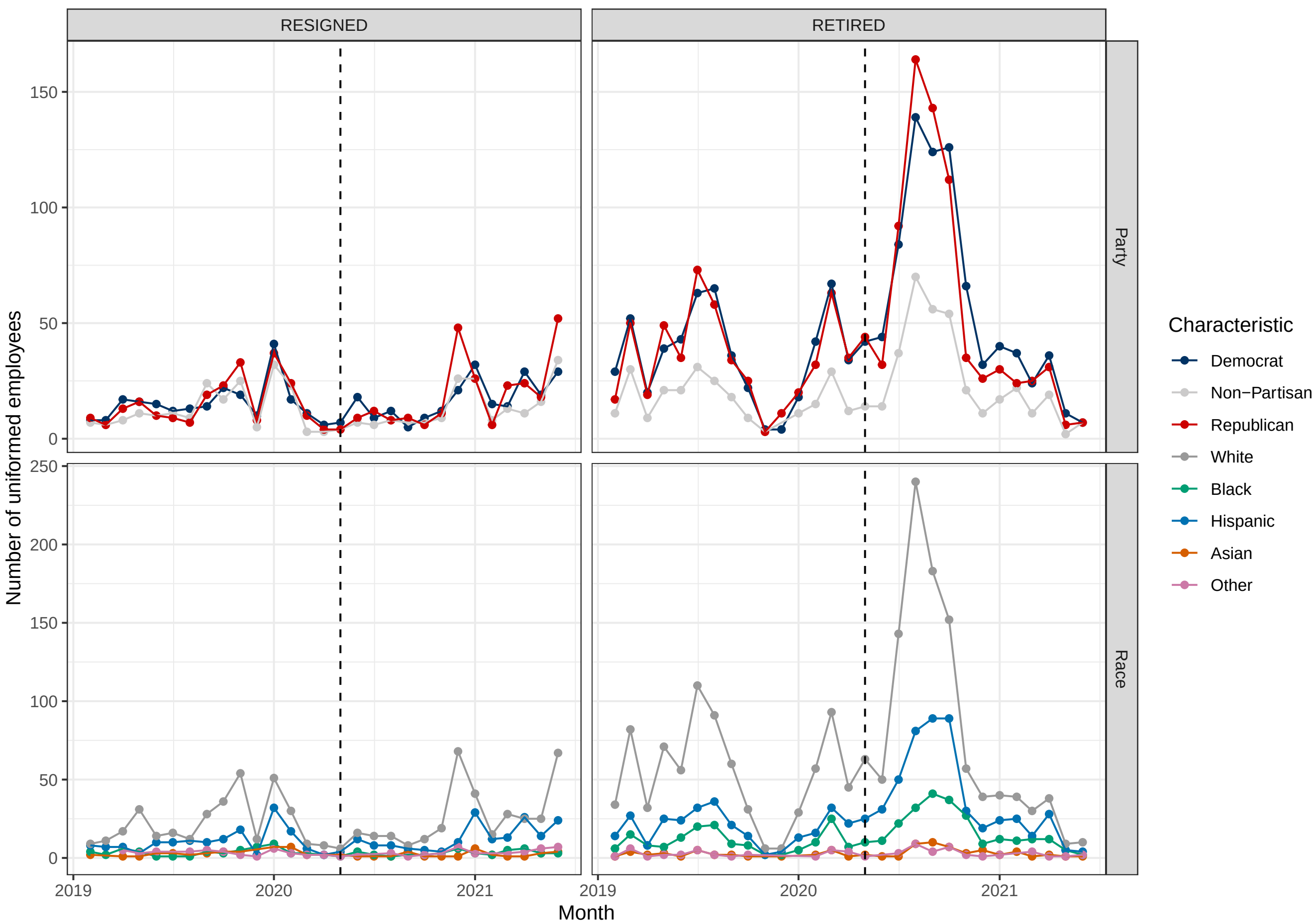
7 Police Accountability and Selection

The analysis so far has shown that disparities in officer recruitment, career progression, and turnover shape NYPD's partisan and racial composition. In this section, I assess how changes in the political environment of the police affect these selection dynamics. Many US police departments reported sharp increases in retirements and resignations following the massive public protests and police scrutiny in 2020. A survey of almost 200 agencies indicated that retirements increased by 45% and resignations rose by 18% on average between April 2020 and April 2021 compared to the previous 12 months (Police Executive Research Forum, 2021). Retiring officers often cited the lack of support from policymakers and the public, together with low pay, as the main reasons for leaving their departments (MacFarquhar, 2021).

This "mass exodus" sparked concerns that the high turnover rates would lead to decreased quality of service and rising crime rates (Mourtgos et al., 2022). Prior research links fewer officers per capita to higher numbers of violent and property crimes (Levitt, 1997; Chalfin and McCrary, 2018; Piza and Chillar, 2021; Chalfin et al., 2022). Some estimates suggest that an additional ten officers abate approximately one homicide, with particularly strong declines in homicides for Black victims (Chalfin et al., 2022). These findings prompted the speculation that officers' rapid departure from their agencies has disproportionately negative consequences for minority communities (Nix and Wolfe, 2020; Mourtgos et al., 2022). Yet, to fully gauge the impact of officer turnover on policing and citizen welfare, it is essential to examine the *type* of departing officers besides the overall number of exits. Since the race and partisanship of officers are important determinants of police behavior (Ba et al., 2021, 2023), the characteristics of officers who leave in response to public protests likely affect the overall costs of police turnover.

To assess the impact of large-scale protests and calls for police reform on the composition of US police, I study the attrition by different groups of NYPD officers following the murder of George Floyd in May 2020. Figure 9 describes the total number of monthly exits by officer traits over time.[25] Retirements spiked between July and September 2020, reaching a maximum of 434 in August 2020. While this trend applies to all groups of officers, the increase seems particularly pronounced for Republican and especially White employees.

Figure 9: Total Number of Retirements and Resignations by Employee Groups



To assess these attrition dynamics across partisanship and race more systematically, I build an officer-month panel data set for all active officers on the payroll in the months directly preceding and following George Floyd's death. This yields a panel of 38,001 officers and higher-ranked employees, of whom 2,887 left within six months before and after George

[25]While not the focus of this analysis, Figure A12 and Figure A13 show the corresponding numbers for appointments and promotions. Evidently, given the budget constraints following the George Floyd protests, there were virtually no appointments and promotions in the immediate months after George Floyd's murder.

Floyd's killing. I then estimate a model akin to an event study design:

$$\begin{aligned}\text{exit}_{it} = \alpha &+ \sum_{k\in[-6,6]\setminus\{0\}} \text{GeorgeFloyd}_{tk}\delta_k + \sum_{k\in[-6,6]\setminus\{0\}} (\text{group}_i \times \text{GeorgeFloyd}_{tk})\beta_{ik} \\ &+ \gamma_i + \delta\text{Age}_{it} + \varepsilon_{it} \qquad (1)\end{aligned}$$

where exit_{it} is a binary indicator for whether an employee i exits the NYPD force in month t, group_i is a categorical indicator for employee i's partisanship or race and GeorgeFloyd_{tk} measures the distance to May 2020. In other words, $\text{GeorgeFloyd}_{tk} = 1$ if George Floyd had passed away in month $t + k$. γ_i are fixed effects for employees' cohort, rank, and work location, and ε_{it} indicates robust standard errors. The inclusion of cohort fixed effects effectively turns this analysis into a survival analysis. The main coefficients of interest, β_{ik}, measure the month-specific differential propensity of partisan and racial officer groups to exit.

Figure 10 depicts the estimated interaction coefficients β_{ik}. The results suggest that compared to Democratic and non-White officers, Republicans, and especially Whites, were more likely to retire in the months immediately after George Floyd's death and the resulting protest movement. In August 2020, for example, Republicans were 0.3 percentage points more likely to exit than Democrats ($p = 0.06$), and White officers were 0.7 percentage points more likely to leave than non-Whites ($p < 0.001$). Importantly, although these estimates are small, they are substantively meaningful: Since the monthly propensity to exit the NYPD is small among all active uniformed employees, these differences imply a 35% increase in exit probability for Republicans relative to Democrats and a 50% increase for Whites relative to non-White officers.[26]

What is the overall effect of George Floyd's murder on the differential exit of officers? When re-estimating Equation (1) with a binary indicator for months before and after George

[26] To illustrate this, Figures A14 and A15 depict the marginal effects of GeorgeFloyd_{tk} (i.e., the predicted increase in exit probability compared to May 2020) across partisanship and race.

Floyd's death, I find that the probability of exiting increased by 0.53 percentage points for non-White officers immediately after George Floyd's murder (see Table A12). For Whites, however, it increased by an additional 0.23 percentage points or 43% more. Simple back-of-the-envelope calculations suggest that 895 White officers left in the six months after the George Floyd protests, compared to 330 officers who left before the demonstrations. For non-Whites, these figures only amount to 768 and 386.[27] For the Republican-Democratic gap in exits, Table A12 suggests that the aggregated effect of George Floyd's death is also positive but small and indistinguishable from zero ($p = 0.62$).[28] It is worth noting that the partisan and racial differences in attrition persist after accounting for differences in age or the date of appointment, i.e., the increased exit of White officers is not an artifact of their general ability and incentives to retire after George Floyd's murder.

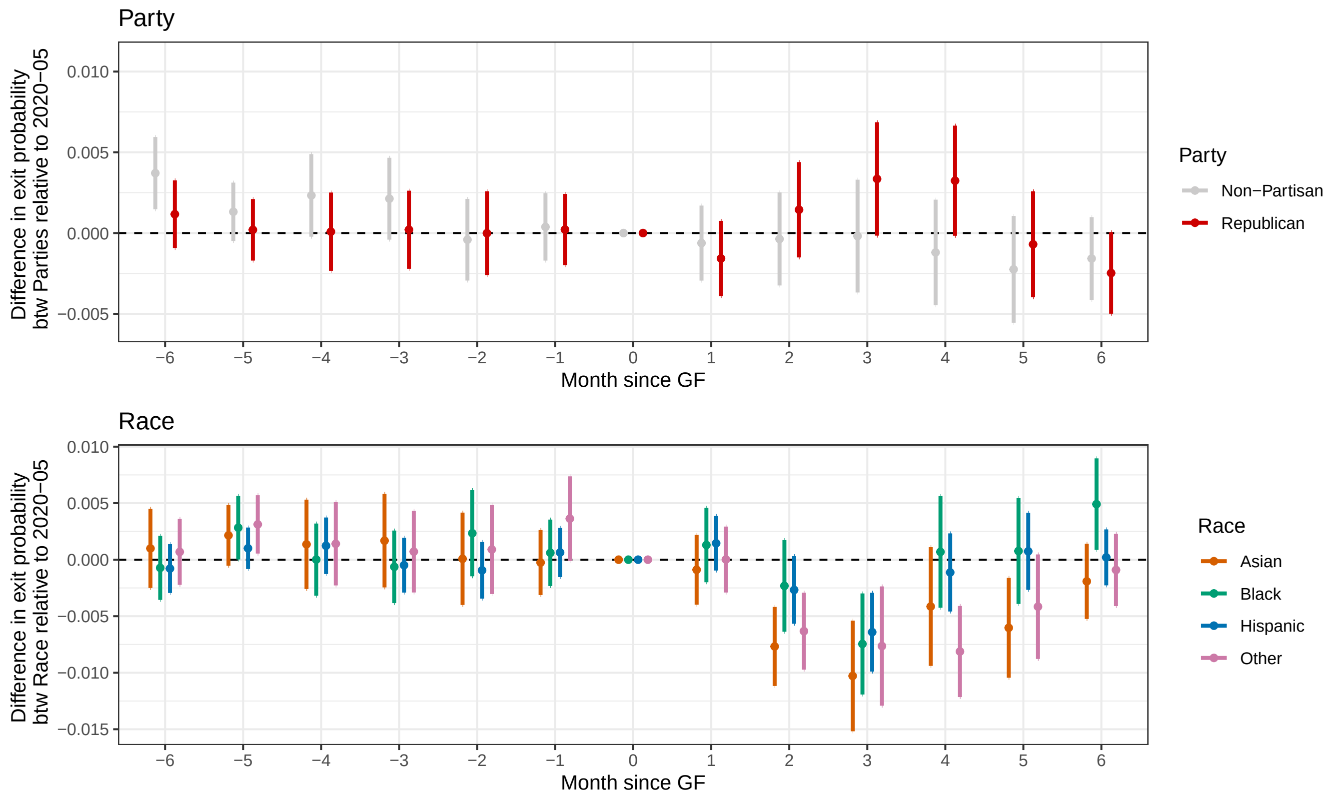
Did these effects on attrition translate into broader shifts in the overall composition of the force? Unsurprisingly, given the large number of uniformed employees at the NYPD, the answer is no. Figure A20 shows the stickyness of the overall demographic composition of uniformed employees despite the differential trends in attrition.

One may be concerned that these differential exit trends only capture a delayed effect of the COVID-19 pandemic on officers' willingness to remain on the force. To alleviate these concerns, I estimate Equation (1) for front-line workers at the NYC fire department (FDNY). Given that FDNY bureaucrats resemble NYPD officers in many dimensions—including unionization rates, salary and their exposure to the pandemic on the job—but were less affected by the 2020 police protests and changing political climate, they serve as a valid placebo analysis. Figures A18 and A19 indeed show that there is no substantial increase in turnover among fire fighters following the George Floyd protests and, more importantly, no differential exit trends across party or racial groups of bureaucrats. This further bolsters

[27] These figures are based on the predicted probabilities of exit across race and period (before George Floyd, White: 0.0031; after George Floyd, White: 0.0107; before George Floyd, non-White: 0.0035; after George Floyd, non-White: 0.0088) together with the total number of White and non-White officers by period.

[28] Figures A16 and A17 further indicate that officers leaving in the six months after George Floyd's death were also older, more senior, and had higher records of misconduct than in previous periods.

Figure 10: Difference in Exit Probability between Parties and Race Groups



Estimated interaction coefficients (β_{ik}) from Equation (1) with robust 95% confidence intervals. Democrats (top panel) and Whites (bottom panel) are the baseline category.

the claim that the increase in departures among NYPD officers, and particularly Whites, resulted from the increased public scrutiny, calls for police reform, and changes in officer morale.

8 Conclusion

The race and partisanship of street-level bureaucrats are central to issues of representative bureaucracy and are crucial determinants of public service provision (Ba et al., 2021, 2023; Donahue, 2023). This article argues that the complex selection dynamics as well as the political environment of modern civil service systems determine the political representativeness of city bureaucracies. Whereas previous studies focus on patronage and political cycles to explain the partisan and racial composition of bureaucracies, this article highlights how dynamics of self-selection, recruitment, promotion, and attrition of bureaucrats influence who becomes and remains a bureaucrat. I document representational gaps between bureaucrats and citizens and disentangle the complex selection dynamics using novel administrative data on public employment in NYC's bureaucracy.

I illustrate various representational gaps between local bureaucrats and citizens, including differences in representativeness across agencies and geographic regions. Focusing on selection within the NYPD, I also unpack the dynamics of descriptive (mis)representation by tracing the types of individuals selecting into the bureaucracy and examining differential career trajectories and attrition rates of more than 58,000 officers. I find consistent differences in selection dynamics across individual officers by partisanship and race, with higher probabilities of hiring, promotions, appointments to elite units, departmental awards, and longer tenures among White and Republican employees relative to non-White and Democratic officers. Finally, I show how prominent cases of police violence affect selection in local law enforcement. Leveraging the substantial protest movement following the May 2020 murder of George Floyd in an event study design, I find that Republicans and White officers were 35% and 50% more likely to leave the NYPD force immediately after George Floyd's death than Democratic and non-White employees, respectively.

These findings have important implications for how we think about bureaucratic representativeness. First, by clarifying the mechanisms that determine bureaucratic representation, we can better reconcile inconclusive findings in the literature on representative bureaucracy and understand the limited effectiveness of affirmative action measures in enhancing the quality and equity of public service provision. For example, the recent death of Tyre Nichols at the hand of five Black police officers in Memphis suggested that demographic diversity in policing does not provide a panacea against police brutality. My research directly addresses this debate by examining disparities in the careers of different types of officers. To succeed in a predominantly white and Republican environment, minority officers may feel compelled to mimic their peers to succeed. If opportunities for promotion and favorable assignments were more evenly distributed, minority officers might feel less pressure to signal their alignment with prevailing norms and behavior. Consequently, while initiatives such as affirmative action may diversify the composition of police forces, meaningful change requires addressing institutional disparities in career progression, promotions, and attrition among officers of different backgrounds. In essence, to fully theorize about the effects of demographic shifts in police forces, we need to incorporate the mechanisms through which the demographic composition arises.[29]

Second, the findings reinforce recent calls to study bureaucratic representation as a multi-dimensional concept that explicitly incorporates partisanship (Ba et al., 2023). In a politically polarized society where partisanship has become a central identity marker, this conceptualization provides a richer framework to understand who receives what from the government and why.

Finally, the results help to reassess some conventional wisdom about selection at US law enforcement agencies. At the recruitment stage, for instance, a common perception suggests that the lack of minority hires is due to lower attraction to the profession for non-White candidates. However, this article indicates that the underrepresentation of minority and Democratic appointments arises at the hiring stage (i.e., *after* potential recruits have already taken the written entrance exam). Similarly, amid the 2020 protest movements, concerns arose that the underrepresentation of minorities among police forces would worsen, as non-White officers were increasingly caught between their job and their identity and thus incentivized to leave (Barnett, 2020). In contrast, this article finds that the George Floyd protests motivated primarily White and older officers to exit. This dynamic suggests an unexplored mechanism through which large-scale protests might achieve more police accountability without explicit police reforms.

Yet, important issues and open questions remain. Although the large administrative data

[29] An explicit micro-foundation of related selection mechanisms proved fruitful for the study of political selection (Ashworth et al., 2024) and provides an important frontier in the study of bureaucratic representativeness.

from NYC allows for a rich picture of partisan and racial selection, the analysis is restricted to only one primary US jurisdiction. It remains to be seen how the results presented here generalize to other city governments, particularly other law enforcement agencies. Additionally, the nature of this article is inherently descriptive and only offers a first step toward uncovering determinants of representativeness in city bureaucracies. More specifically, it cannot uncover the exact mechanisms that led to the documented disparities in bureaucrats' partisanship and race. For instance, the fact that Republican and White officers are more likely to receive promotions and desirable assignments could be explained by individual-level factors, such as job satisfaction and motivation to advance in the profession, or institutional-level aspects, including support from superiors and the agency more broadly. Future research may seek to use other data sources and methods, such as surveys of street-level bureaucrats and experimental designs, to further explore the mechanisms at play.

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Appendix: Supporting Information for *Diverse Forces*

A Merging Procedures and Quality

In this section, I describe the different merging procedures and the quality of the resulting matches. As described in the main text, I start with a roster of the five largest agencies in NYC (currently excluding the Department of Education due to data availability). I identify individual employees by unique combinations of last name, first name, middle initial and appointment date. I then use a probabilistic record linkage algorithm to match demographic information for all employees from the L2 voter file (Enamorado et al., 2019), retaining all matches with a posterior match probability of at least 0.7. For first and last names, I allow for partial string distance matches using the Jaro-Winkler distance methods, while for the middle initial I enforce an exact match. Since I need to rely on name information only for these matches, one might be concerned that this introduces a large amount of duplicates in the list of unique employees. However, note that the combination of first name, last name, and middle initial already uniquely identifies 95% of all bureaucrats. Table A1 shows that I am able to identify more than 80% of bureaucrats across all agencies, and Figure A1 indicates that the median posterior probability for these matches is more than 0.95. Additionally, Table A1 shows that the true match rate is estimated to be at least 69% across the agencies, and with low false discovery rates (FDR) and high false negative rates (FNR) the algorithm clearly errs on the side of not identifying a bureaucrat in the voter file rather than matching the wrong voter to a bureaucrat. More importantly, the FDR is relatively similar across race and party groups, albeit somewhat lower for Republicans, Whites and male bureaucrats across the agencies.[1] It's important to note that I weight by the posterior probability of matches in all analyses to quantify the uncertainty inherent in my merge procedures, and to calibrate and account for the amount of false positives and false negatives across demographic groups in my data.

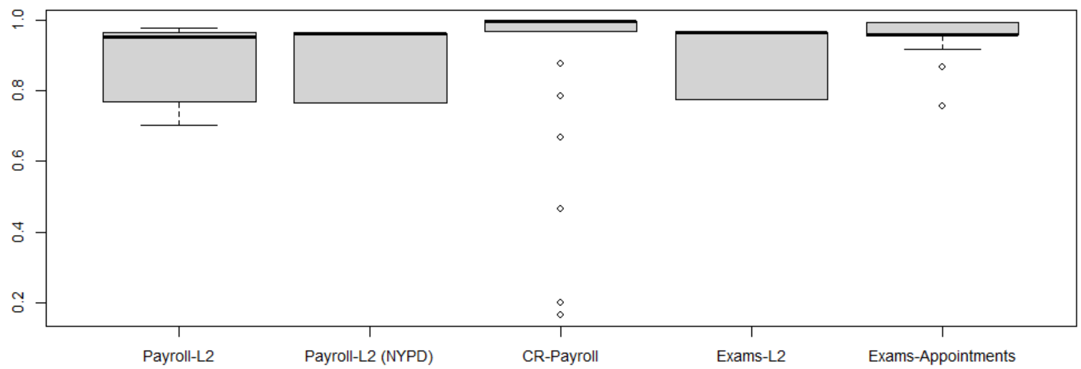
[1] Unfortunately, the FNR is computationally impossible to calculate by race or partisanship, since this would require retaining matches for *all* pairs across the two data sets, i.e. $N_{bureaucrats} \times N_{voters} \geq 168,577,197,264$.

Table A1: Merging of NYC Payroll (2014-2021) to 2021 L2 Voter File (N=7,940,144)

	NYPD (N=91,975)	Sanitation (N=32,468)	FDNY (N=28,016)	Social Services (N=22,386)	Corrections (N=21,231)
Number of matches	80,661 (88%)	26,618 (82%)	26,172 (93%)	18,909 (85%)	18,345 (87%)
True match rate[a]	78%	73%	87%	69%	74%
False negative rate (FNR)[b]	94%	95%	96%	92%	93%
False discovery rate (FDR)[c]	11%	11%	7%	18%	15%
FDR by groups					
Non-Partisan	11%	11%	7%	20%	15%
Democrat	12%	12%	8%	17%	14%
Republican	9%	11%	6%	21%	15%
White	9%	10%	6%	18%	14%
Hispanic	13%	13%	9%	20%	17%
Black	11%	11%	8%	16%	13%
Other Race	14%	14%	10%	23%	16%
Asian	15%	16%	11%	22%	18%
Female	12%	12%	9%	18%	14%
Male	10%	11%	7%	18%	15%

[a] Share of matches weighted by their posterior probability of a match; [b] Probability of wrongfully declaring a non-match given the threshold; [c] Probability of wrongfully declaring a match given the threshold

Figure A1: Boxplots of Posterior Probabilities of Correct Matches across Matching Procedures



For my analysis of the selection dynamics at the NYPD, I collected various additional data sets. Particularly, I obtained information on (1) career milestones, including appointments, promotions, and retirements from official records published in the daily City Record newspaper since 2014[2]; (2) unit assignment, awards, and arrest records for a cross-section of about 33,000 active officers (as of October 2021) from NYPD's official officer profiles[3]; (3) civil service exams, both for entry and promotions.[4] I then match these different data sets to the roster of NYPD bureaucrats. The following sections describe these various matches in more detail. Table A2 illustrates the number of successful matches across data sets, and Figure A2 illustrates the high posterior probability of a match across the procedures together with slight differences across demographic groups.

A.1 Merge City Records with NYPD Payroll

I link the 65,856 City newspaper records on appointments, promotions, demotions, retirements, resignations, dismissals, and terminations to the roster of NYPD bureaucrats in the following way: To maximize overlap, I restrict the city records to those with effective date between January 1, 2014, and July 1, 2021. I then match on first name, last name, and middle initial, and retain matches with a minimum posterior of 0.7. I do not deduplicate matches returned by the algorithm. Instead, I deal with city records that match to multiple payroll names in the following way:

[2] https://www.nyc.gov/site/dcas/about/cityrecord-editions.page
[3] https://nypdonline.org/link/2
[4] I carefully combined both active and terminated civil service lists as of July 2022 from https://opendata.cityofnewyork.us/.

- In cases where there is one maximum posterior, we keep the maximum posterior match (equivalent what fastLink enforces as default)

- For cases where there is no unique maximum posterior probability, I use additional information in the data.

- For *appointments*, I identify exact matches using the appointment date provided in both data sets. If there is more than one exact match, I use the maximum posterior probability for these duplicates again and if these maxima are not unique, I retain the payroll entry with the earliest appointment. If there are no exact matches using the appointment date, I retain those with the smallest difference between the appointment date in the payroll and the effective date in the city records. If there is more than one such time distance match, I use the maximum posterior match probability for these duplicates again and if these maximum posteriors are not unique, I retain the payroll entry with the earliest appointment.

- For *attrition*, I again follow the default in fastLink and use the maximum posterior to find the best match in cases of multiple matches based on name. If there are more than one such maximum posterior match, I use the smallest difference between the fiscal year at the date of attrition and the last fiscal year recorded in the payroll. If this still does not give a unique match, I use the employee with the earliest appointment date, i.e. the person who has been on the force the longest before retirement.

- For *promotions*, I use information on changes in job titles on the payroll to adjudicate between multiple maximum-posterior matches. I first retain the maximum posterior among all promotion matches. If there is more than one possible match, I use the year of promotion that matches the promotion in the city records. If this is not the case, I use the minimum difference in the year of the title change on the payroll and the year of promotion in the city records. For the remaining duplicates, I use the employee who was appointed first. For the remaining 4 duplicates, I finally use the first observation in the data.

A.2 Merge NYPD Payroll to NYPD Online Officer Profiles

I used another iterative process to match the roster of active officers from NYPD online to my payroll roster. I first merge these records based on exact matches using the appointment date, the first name, the last name, and the middle initial. All payroll records I fail to match exactly, I then also match based on a fuzzy name match and extensive manual checks by research assistants.

A.3 Merge Entry Exams to Appointments and L2 Voter File

To match entry-level exams to the roster of NYPD personnel, I collect the information on 96,883 NYC civil service exams for police officer and traffic enforcement agents. Following a probabilistic record linkage based on the first name, last name and middle initial, I first retain all matches with a minimum posterior probability of 0.5. I then rely on the following procedure to deduplicate matches of the same exam: First, I restrict matches by enforcing that the position title of the exam (police officer or traffic enforcement agent) corresponds to the title of the employee's appointment. I further deduplicate matches by requiring that the date of the exam needs to be before the date of appointment. I further filter duplicates by retaining the maximum posterior probability match by exam. For the remaining duplicates, I use the minimum distance between the appointment date and the exam date. In the analysis, I also account for the fact that some hired NYPD employees took the exam more than once before getting hired. I again rely on the maximum posterior match and the exam date relative to the appointment date to identify the successful exam for these individuals. Finally, I also match the entry exams to the L2 voter file, following exactly the same procedure as for the payroll-L2 merging described above.

A.4 Merge Promotion Exams to Awarded Promotions and L2 Voter File

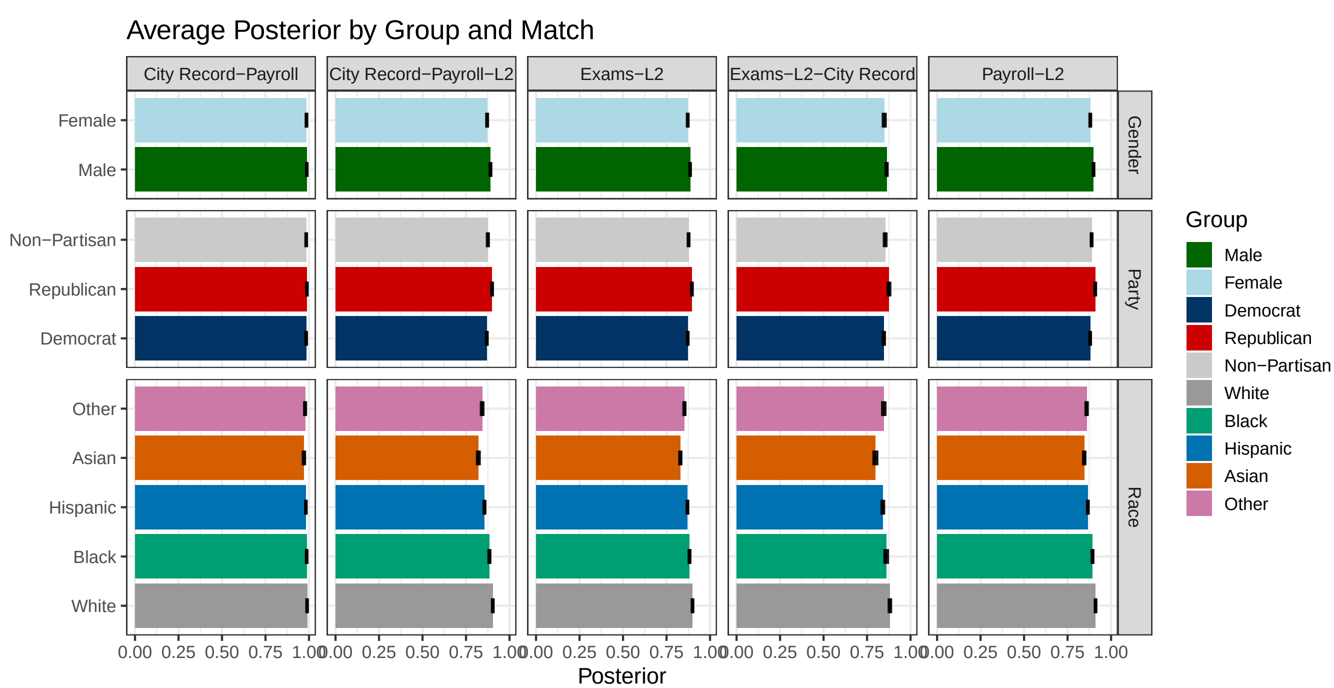
Individuals who seek promotions to the ranks of Sergeant, Lieutenant, and Captain need to successfully pass additional civil service exams at the NYPD. I match promotion exams to the promotions recorded in the city records probabilistically based on employee's first name, last name and middle initial. After retaining matches with a minimum posterior match probability of 0.5, I again ensure that exam titles correspond to the titles of the matched promotion records. Similar to the entry exams, I also require that the date of the promotion exam is before the date of the promotion, and use the minimum time difference between the exam date and the promotion date for the remaining duplicates. I then also match the promotion exams to the L2 voter file, following exactly the same procedure as for the payroll-L2 merging described above.

Table A2: Merging of NYPD Data Sets

	L2 Voter File, 2020 (N=7,940,144)	City Records, 2014-2021 (N=65,856)	Active Officer Profiles (N=33,072)	Other Civil Service Exams (N=195,308)
NYPD Payroll*, FY2014-2021 (N=91,975)	80,661 (88%, .)	65,184 (., 99%)	32,632 (., 99%)	
Officer/TEA Entry Exams, 2012-2021 (N=96,883)	80,584 (83%, .)	10,347 (11%, 60%[a])		14,950 (15%,.)
Promotion Exams, 2012-2021 (N=5,725)	5,226 (91%,.)	3,501 (61%,.)		

Percentages of matched observations in parentheses (row percentages, colum percentages); * includes both uniformed and civilian personnel; [a] among appointments only (N=17,153)

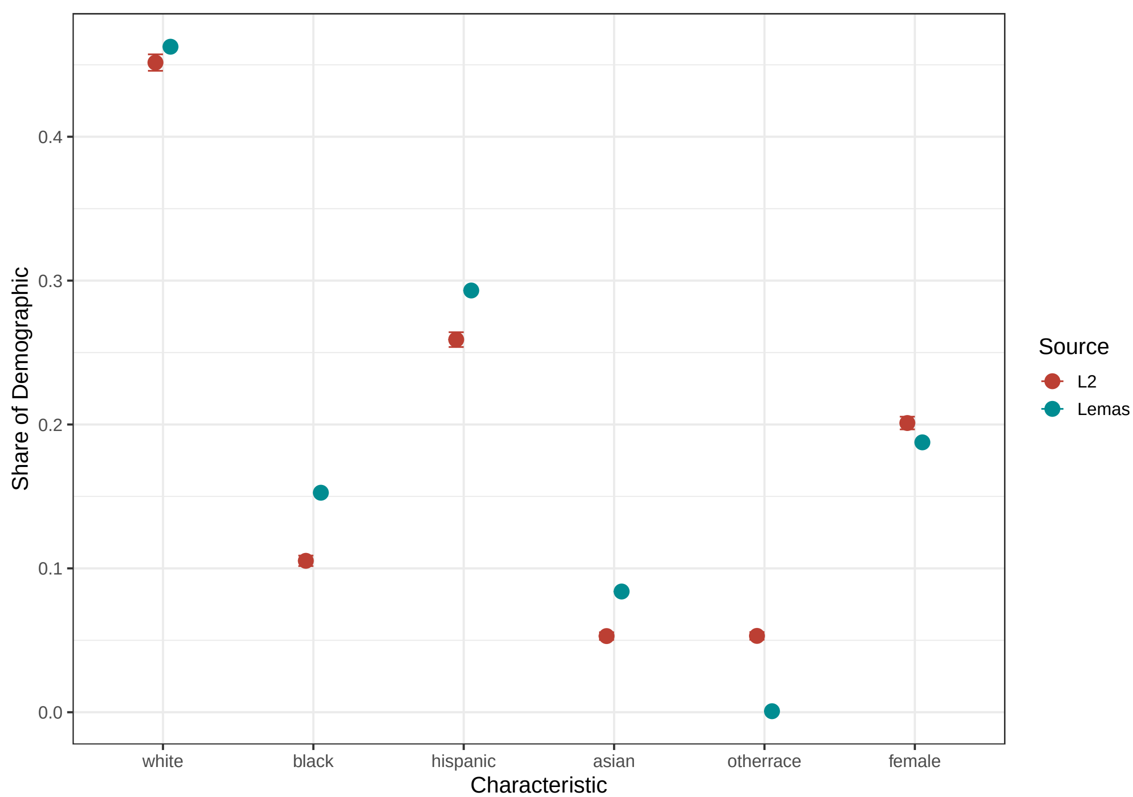
Figure A2: Average Posterior Probabilities of Correct Matches By Groups across Matching Procedures



A.5 Measurement Error in L2 Race/Ethnicity

The LEMAS survey asks police agencies to report the number of sworn full time employees across different demographic groups (particularly, race and gender). I draw on the answers of the NYPD in the 2020 LEMAS survey to assess the validity of the L2 information on race and gender. Figure A3 depicts the proportion of officers in each racial/ethnic category and by gender as measured by L2 vs. LEMAS. To ensure optimal overlap in the populations used in both data sets, I restrict the payroll to only sworn personnel and weight estimates by the posterior probability of a match. As the figure shows, L2 slightly underrepresents the proportion of White officers, and more so, the share of other minorities. This discrepancy largely stems from the overrepresentation of the "other/unknown" category, which makes up 5% in the L2 data, but essentially 0% in the LEMAS data. The L2 data also slightly overrepresents female officers compared to the LEMAS data.

Figure A3: Comparison of 2020 LEMAS and L2 Measures of Officer Race



B Tables

Table A3: Income Differences by Exam Taker Characteristics

	L2 Household Income			Census 2019 Per Capita Income		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Hire	2280^{**}	277	3097^{**}	-454^{*}	-773^{*}	-42
	(726)	(1331)	(1106)	(206)	(354)	(325)
Black	-39418^{***}	-39868^{***}	-39394^{***}	-17753^{***}	-17832^{***}	-17748^{***}
	(919)	(967)	(920)	(255)	(267)	(255)
Hispanic	-42199^{***}	-42563^{***}	-42196^{***}	-15791^{***}	-15845^{***}	-15793^{***}
	(1378)	(1387)	(1378)	(248)	(263)	(248)
Asian	-13576^{***}	-13695^{***}	-13582^{***}	-9778^{***}	-9737^{***}	-9779^{***}
	(1427)	(1580)	(1427)	(274)	(296)	(274)
Other Race	-26737^{***}	-26827^{***}	-26744^{***}	-12964^{***}	-13007^{***}	-12969^{***}
	(1173)	(1356)	(1171)	(257)	(294)	(256)
Republican	17216^{***}	17255^{***}	17561^{***}	1463^{***}	1470^{***}	1542^{***}
	(759)	(758)	(817)	(195)	(195)	(190)
Non-Partisan	6424^{***}	6432^{***}	6442^{***}	350	352	422^{*}
	(584)	(584)	(648)	(183)	(183)	(210)
Hire × Black		5974^{**}			1103^{**}	
		(2026)			(406)	
Hire × Hispanic		3635^{*}			544	
		(1771)			(357)	
Hire × Asian		1081			-378	
		(3176)			(1076)	
Hire × Other Race		853			397	
		(3348)			(937)	
Hire × Republican			-2821			-748
			(1640)			(641)
Hire × Non-Partisan			-319			-807
			(1485)			(545)
Exam Score (80-90)	2082^{*}	2074^{*}	2088^{*}	713^{***}	710^{***}	714^{***}
	(875)	(874)	(875)	(201)	(202)	(201)
Exam Score (90-100)	3480^{***}	3470^{***}	3487^{***}	1148^{***}	1146^{***}	1149^{***}
	(877)	(872)	(877)	(311)	(311)	(311)
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	89308	89308	89308	37167	37167	37167
Num. obs.	70222	70222	70222	71369	71369	71369
Adj. R^2	0.14	0.14	0.14	0.16	0.16	0.16

Regressions weighted by posterior probability of a match between exam data and voter file. Dependent variable: Estimated HH income (L2, columns 1-3) and Census per capita income (2019 American Community Survey, columns 4-6). Standard errors clustered by exam in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A4: Differences in Exam Scores across Demographics

	Model 1	Model 2	Model 3	Model 4
Republican	0.00	-0.04	-0.07	0.44^{***}
	(0.08)	(0.08)	(0.08)	(0.08)
Non-Partisan	0.04	-0.03	-0.03	0.24^{***}
	(0.07)	(0.07)	(0.06)	(0.06)
Black	-1.21^{***}	-1.27^{***}	-1.23^{***}	-2.26^{***}
	(0.08)	(0.08)	(0.08)	(0.08)
Hispanic	-0.74^{***}	-0.83^{***}	-0.79^{***}	-1.89^{***}
	(0.07)	(0.07)	(0.07)	(0.07)
Asian	-0.03	-0.11	-0.04	-1.43^{***}
	(0.12)	(0.12)	(0.12)	(0.12)
Other Race	-2.21^{***}	-2.14^{***}	-2.08^{***}	-3.35^{***}
	(0.11)	(0.11)	(0.11)	(0.10)
Veteran Credit		6.32^{***}	6.35^{***}	6.43^{***}
		(0.13)	(0.13)	(0.13)
Parent/Sibling Legacy Credit			9.77^{***}	9.90^{***}
			(0.37)	(0.35)
Residency Credit				4.39^{***}
				(0.06)
Exam FE	Yes	Yes	Yes	Yes
Mean of DV	88.47	88.47	88.47	88.47
Adj. R^2	0.12	0.15	0.16	0.21
Num. obs.	71684	71684	71684	71684

Regressions weighted by posterior probability of a match between exam data and voter file. Dependent variable: Exam score in entry-level exam. Veteran credits are awarded for veterans and disabled veterans. Parent and sibling legacy credits are additional credits on the exam score to candidates who lost a parent/sibling as a result of 911. Residency credits are given on exams to candidates who maintain a continuous period of residency in NYC. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A5: Difference in Probability of Taking a Promotion Exam (2014-2021)

	Model 1	Model 2	Model 3
Republican	-0.00		0.00
	(0.00)		(0.00)
Non-Partisan	0.00		-0.00
	(0.00)		(0.00)
Black		-0.00	-0.00
		(0.00)	(0.00)
Hispanic		0.00	0.00
		(0.00)	(0.00)
Asian		0.05^{***}	0.05^{***}
		(0.01)	(0.01)
Other Race		0.04^{***}	0.04^{***}
		(0.01)	(0.01)
Cohort FE	Yes	Yes	Yes
Mean of DV	0.09	0.09	0.09
Adj. R^2	0.12	0.12	0.12
Num. obs.	49558	48521	45990

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A6: Difference in Probability of Receiving Promotion After Promotion Exam (2014-2021)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Republican	0.02	0.01			0.01	0.01
	(0.01)	(0.01)			(0.01)	(0.01)
Non-Partisan	0.04^{*}	0.01			0.01	0.01
	(0.02)	(0.01)			(0.01)	(0.01)
Black			-0.05^{*}	-0.00	0.00	0.00
			(0.02)	(0.02)	(0.02)	(0.02)
Hispanic			-0.02	0.01	0.01	0.01
			(0.02)	(0.01)	(0.01)	(0.01)
Asian			-0.03	-0.03	-0.03	-0.03
			(0.03)	(0.02)	(0.02)	(0.02)
Other Race			0.03	0.01	0.01	0.01
			(0.03)	(0.02)	(0.02)	(0.02)
Examscore (80-90)		0.56^{***}		0.56^{***}	0.56^{***}	
		(0.01)		(0.01)	(0.01)	
Examscore (90-100)		0.72^{***}		0.72^{***}	0.72^{***}	
		(0.02)		(0.02)	(0.02)	
Exam FE	Yes	Yes	Yes	Yes	Yes	Yes
Exam × Score Bin FE	No	No	No	No	No	Yes
Mean of DV	0.62	0.62	0.61	0.61	0.61	0.61
Adj. R^2	0.14	0.51	0.14	0.51	0.51	0.51
Num. obs.	4963	4963	4790	4790	4549	4549

Linear probability regressions, weighted by the posterior probability of a match between promotion exams and voter file. Level of observation: Promotion exam taker. Outcome: Dummy for whether the exam taker actually received a promotion between 2014 and 2021. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A7: Differences in (Log) Number of Awards by Officer Characteristics

	Model 1	Model 2	Model 3
Republican	0.20^{***}		0.13^{***}
	(0.01)		(0.01)
Non-Partisan	0.08^{***}		0.04^{**}
	(0.01)		(0.01)
Black		-0.27^{***}	-0.21^{***}
		(0.02)	(0.02)
Hispanic		-0.16^{***}	-0.12^{***}
		(0.01)	(0.01)
Asian		-0.26^{***}	-0.24^{***}
		(0.02)	(0.02)
Other Race		-0.14^{***}	-0.12^{***}
		(0.02)	(0.02)
Cohort FE	Yes	Yes	Yes
Mean of DV	0.92	0.91	0.91
Adj. R^2	0.21	0.21	0.22
Num. obs.	28422	27609	26222

Regressions weighted by posterior probability of a match between payroll and voter file. The information on awards received is only available for active officers (here as of October 2021). Level of observation: Employee. Outcome: Log number of departmental awards since their appointment date at NYPD. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A8: Differences in Command Assignments for Active Officers (as of 10/20/2021)

	All Elite	Terrorism	Drugs	Special Forces
Republican	0.03^{***}	0.00	0.00	0.02^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Non-Partisan	0.02^{***}	0.00	0.00	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
Black	-0.03^{***}	-0.01^{**}	-0.00	-0.01^{**}
	(0.01)	(0.00)	(0.00)	(0.00)
Hispanic	-0.01	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Asian	-0.03^{***}	-0.00	-0.01^{***}	-0.01^{**}
	(0.01)	(0.01)	(0.00)	(0.00)
Other Race	-0.02^{**}	-0.00	-0.00	-0.02^{***}
	(0.01)	(0.01)	(0.00)	(0.00)
Cohort FE	Yes	Yes	Yes	Yes
Mean of DV	0.10	0.04	0.02	0.04
Adj. R^2	0.05	0.02	0.01	0.02
Num. obs.	26222	26222	26222	26222

Regressions weighted by posterior probability of a match between payroll data and voter file. The command information is only available for active officers (here as of October 2021). Level of observation: Employee. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A9: Correlation of Team Leadership and Team Composition

	Share of Party			Share of Race				
	Republican	Democrat	Non-Partisan	Hispanic	White	Asian	Black	Other
Republican leader	0.05^{*}	-0.04^{*}	-0.01	-0.03	0.02	-0.01	0.01	0.01
	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)
Non-Partisan leader	-0.02	-0.03	0.05^{**}	-0.01	0.01	-0.01	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)
Asian leader	0.04	-0.06	0.02	-0.02	-0.07	0.08^{***}	-0.02	0.04^{*}
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.01)	(0.02)	(0.02)
Black leader	-0.02	0.04	-0.02	-0.01	-0.13^{***}	0.03^{*}	0.08^{***}	0.03^{**}
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.01)
Hispanic leader	-0.03	0.02	0.00	0.06^{**}	-0.09^{***}	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Other Race leader	-0.03	0.05	-0.02	0.02	-0.10	0.02	-0.01	0.07^{***}
	(0.05)	(0.05)	(0.03)	(0.04)	(0.05)	(0.02)	(0.03)	(0.02)
Mean DV	0.38	0.39	0.23	0.27	0.52	0.05	0.11	0.05
R^2	0.05	0.03	0.03	0.06	0.11	0.10	0.05	0.05
Adj. R^2	0.03	0.01	0.01	0.04	0.09	0.08	0.03	0.03
Num. obs.	644	644	644	644	644	644	644	644

Cross-sectional OLS; The information on team assignment is only available for active officers (here as of October 2021). Level of observation: Team. Outcome: Share of relevant demographic per team. Regressions also control for 5 bins of team size, precinct team dummy, special operations team dummy and the highest rank of the leader. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A10: Correlation of Team Diversity and Team Leadership

	Gini Coefficient	
	Party	Race
Republican	0.03	0.03
	(0.02)	(0.02)
Non-Partisan	-0.01	0.03
	(0.02)	(0.02)
Asian	-0.03	-0.11^{***}
	(0.04)	(0.03)
Black	0.06^{*}	-0.05^{*}
	(0.03)	(0.02)
Hispanic	0.03	-0.01
	(0.02)	(0.02)
Other Race	0.01	-0.10^{**}
	(0.05)	(0.03)
Adj. R^2	0.13	0.22
Num. obs.	644	644

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Regressions also control for 5 bins of team size, precinct team dummy, special operations team dummy and the highest rank of the leader. Level of observation: Team. Dependent variable: Gini index.

Table A11: Differences in Years on Force at Retirement, by Characteristics and Rank

	Model 1	Model 2	Model 3
Republican	0.52^{***}		-0.04
	(0.13)		(0.15)
White		1.48^{***}	1.50^{***}
		(0.13)	(0.14)
Age at appointment	-0.12^{***}	-0.11^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.01)
Mean of DV	22.36	22.35	22.35
Adj. R^2	0.05	0.07	0.07
Num. obs.	6624	6613	6613

OLS, weighted by probability of matches between payroll and voter file and payroll and retirement records. Level of observation: Retiree. Outcome: Time since appointment date at retirement. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

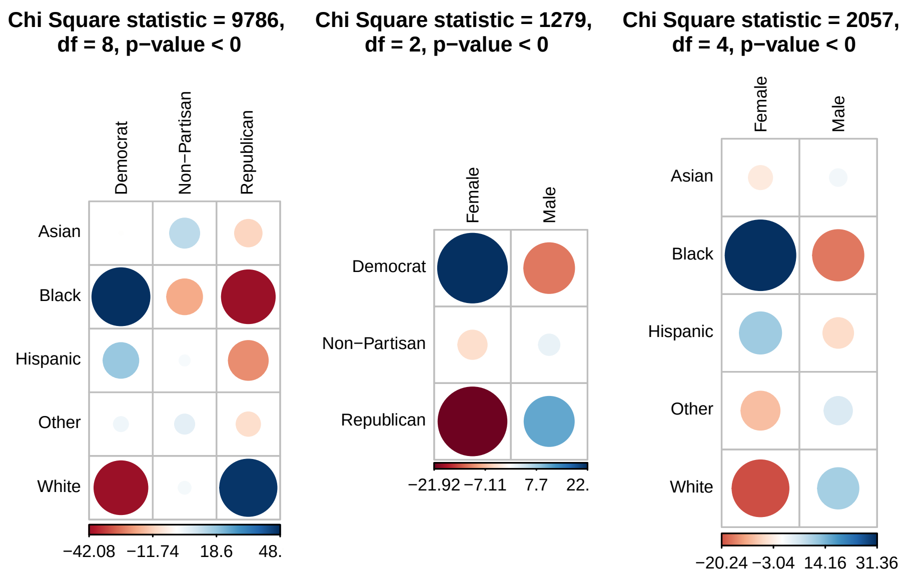
Table A12: Effect of George Floyd on Differential Exits

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
George Floyd	0.0055^{***}	0.0066^{***}	0.0066^{***}	0.0044^{***}	0.0053^{***}	0.0053^{***}
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Republican	0.0004	0.0005	0.0005			
	(0.0003)	(0.0003)	(0.0003)			
George Floyd × Republican	0.0002	0.0003	0.0003			
	(0.0006)	(0.0006)	(0.0006)			
White				0.0012^{***}	-0.0004	-0.0004
				(0.0003)	(0.0003)	(0.0003)
George Floyd × White				0.0020^{***}	0.0023^{***}	0.0023^{***}
				(0.0005)	(0.0005)	(0.0005)
Fixed effects	No	Yes	Yes	No	Yes	Yes
Age control	No	No	Yes	No	No	Yes
Mean of DV	0.0060	0.0060	0.0060	0.0060	0.0060	0.0060
Adj. R^2	0.0012	0.0212	0.0212	0.0014	0.0210	0.0211
Num. obs.	301477	299928	299600	388169	386154	385572

OLS, weighted by posterior probability of a match between payroll and voter file. Outcome: Official exit (retirement, resignation, termination or dismissal). Level of observation: Employee-month. HC1 standard errors in parentheses. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

C Figures

Figure A4: Pearson Residuals from Chi Square tests of Independence between Officer Demographics



The dots indicate the size and direction of the Pearson residuals (i.e. standardized residuals from Chi-square tests). Cells with highest absolute standardized residuals contribute the most to the total Chi-square score.

Figure A5: Share of Demographics at NYPD

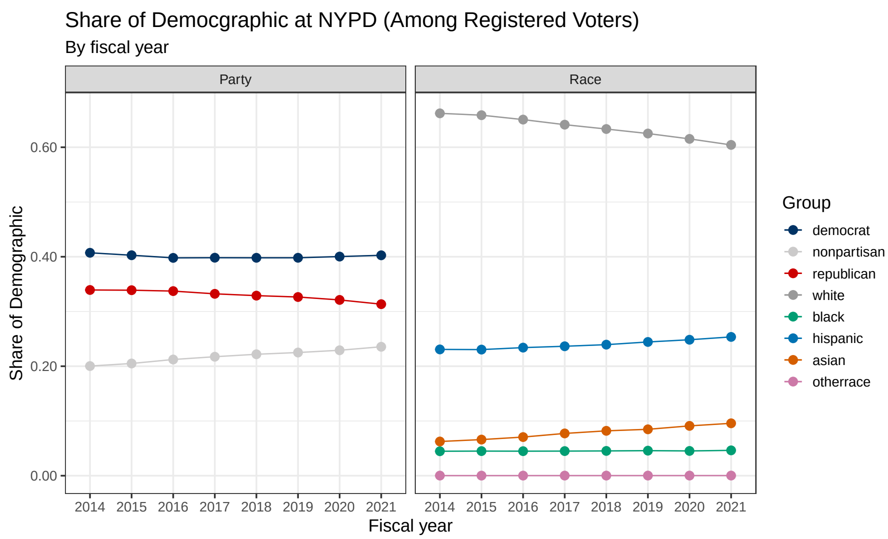
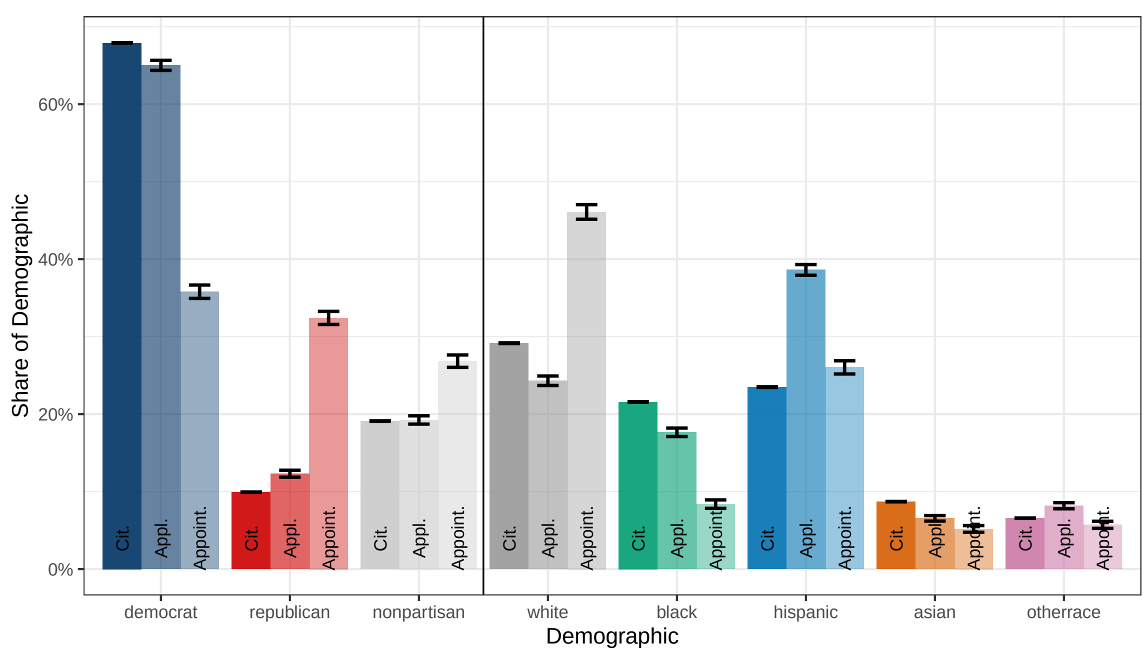


Figure A6: Share of Demographics - Citizens, Police Exam Takers, Appointments



The three bars among each partisan and racial group represent (from left to right) (1) share among NYC voters, (2) share among police exam takers, and (3) share among all appointed officers. Voters and exam takers are matched on age.

Figure A7: Hiring Differences Across Exam Scores

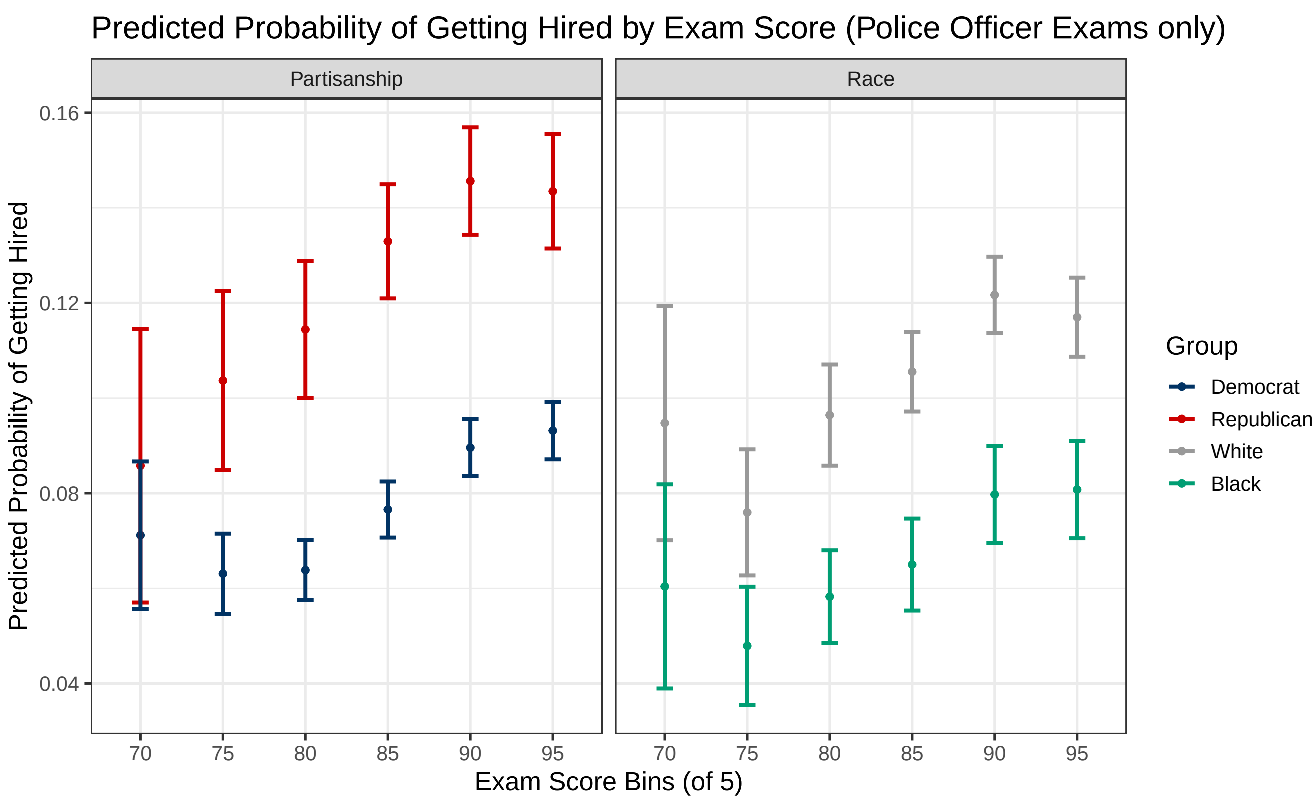


Figure A8: Difference in Behavior on the Job by Demographic and Tenure

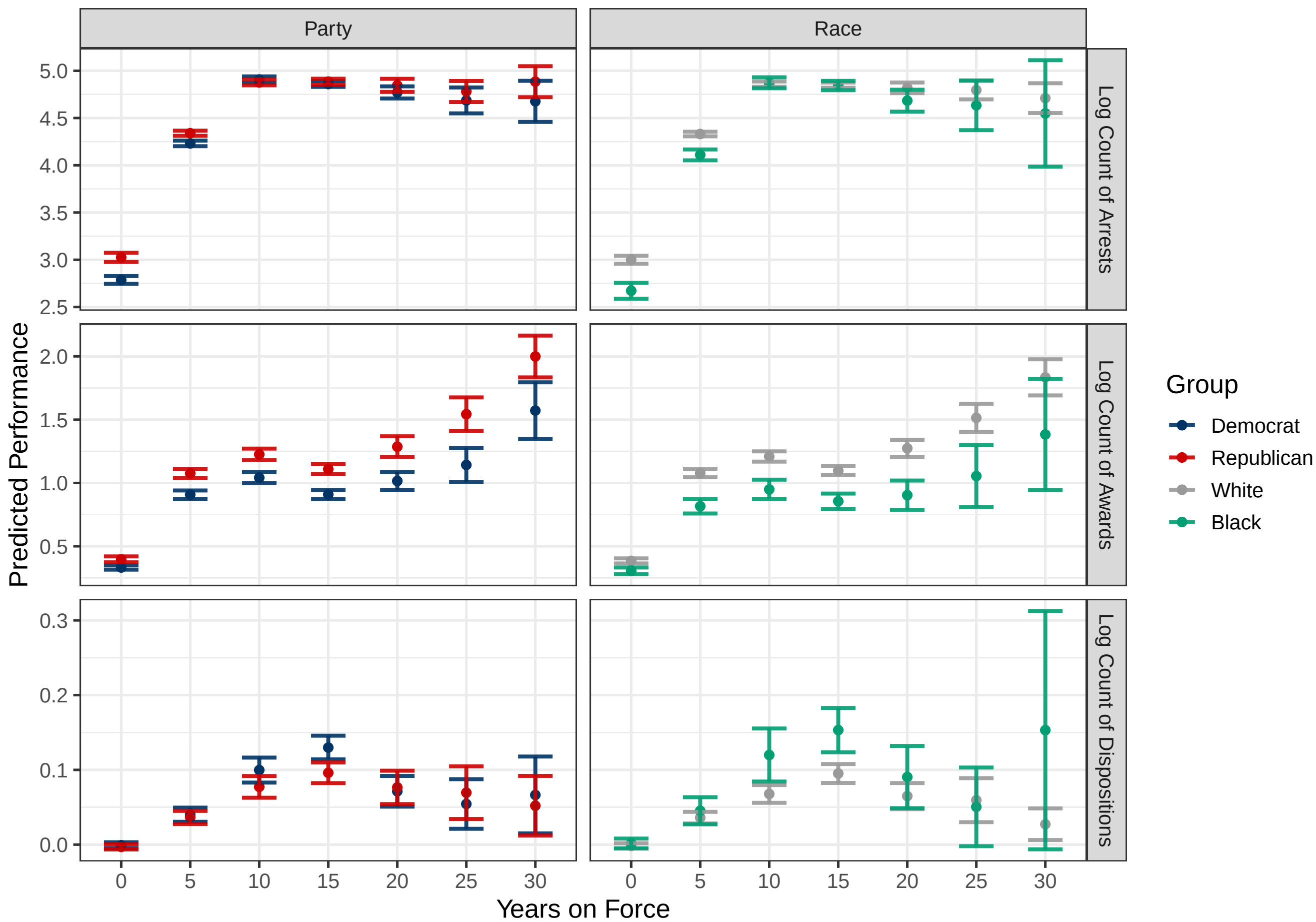
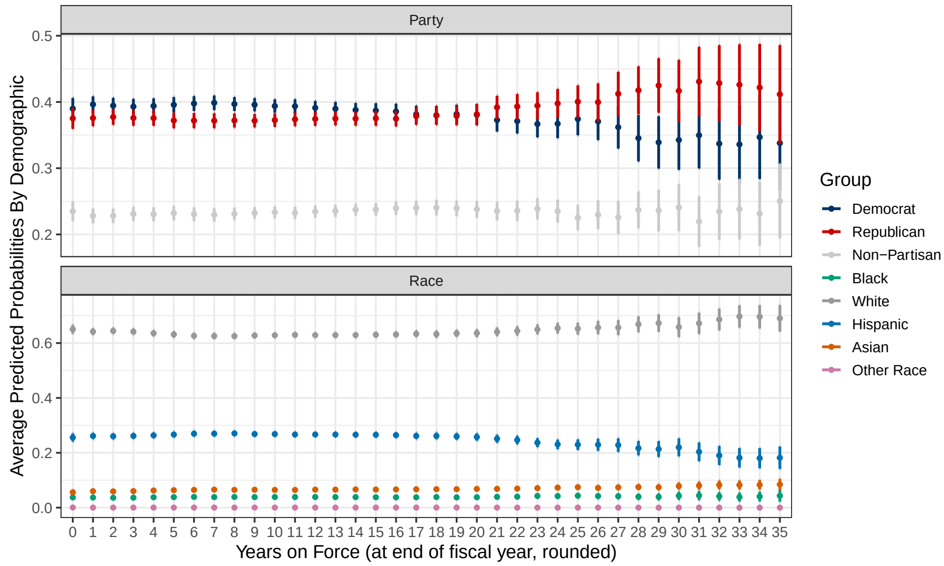


Figure A9: Predicted Probability of Demographic By Experience



The estimates are predicted probabilities based on regressions of group indicators on experience, cohort FE and fiscal year FE. This accounts for the fact that certain cohorts are skewed in terms of partisanship and race because of their composition at the time of appointment rather than differential attrition. The covariates are fixed at their observed values for the predictions.

Figure A10

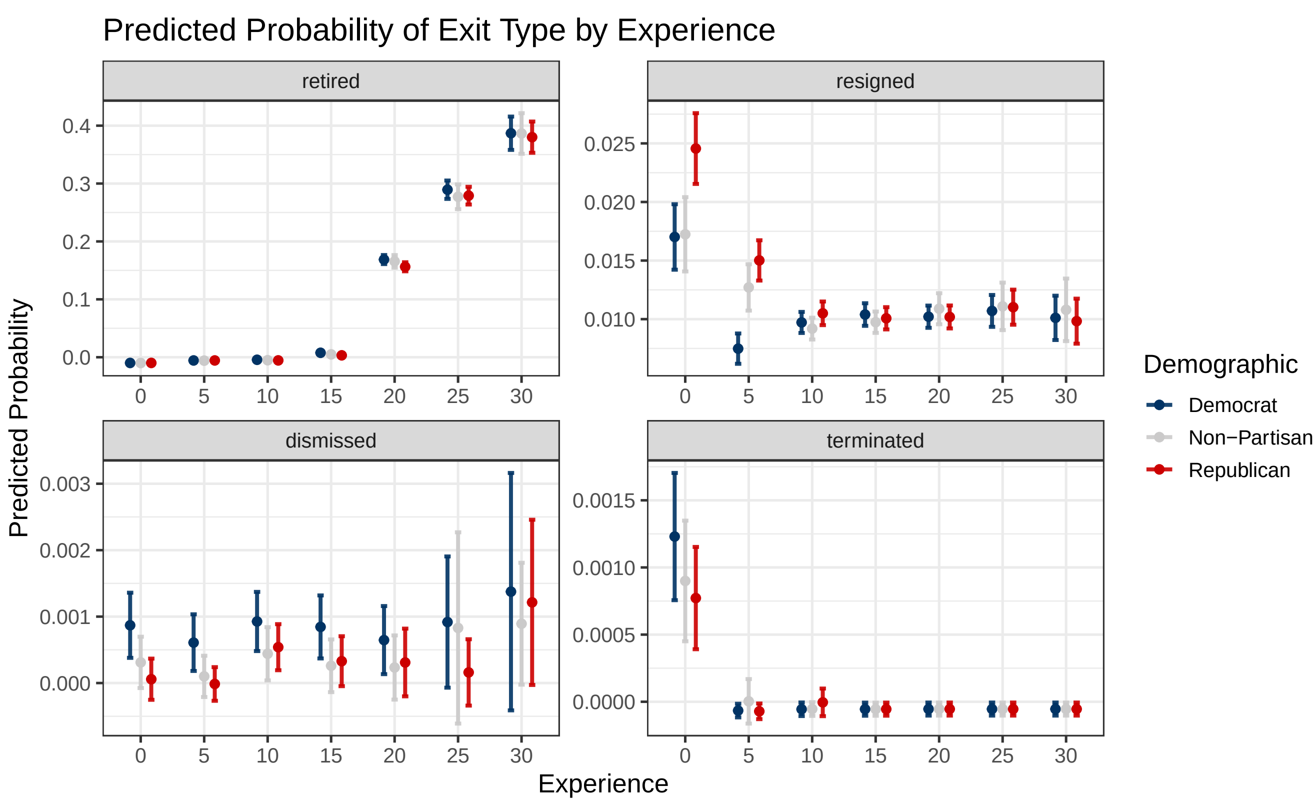
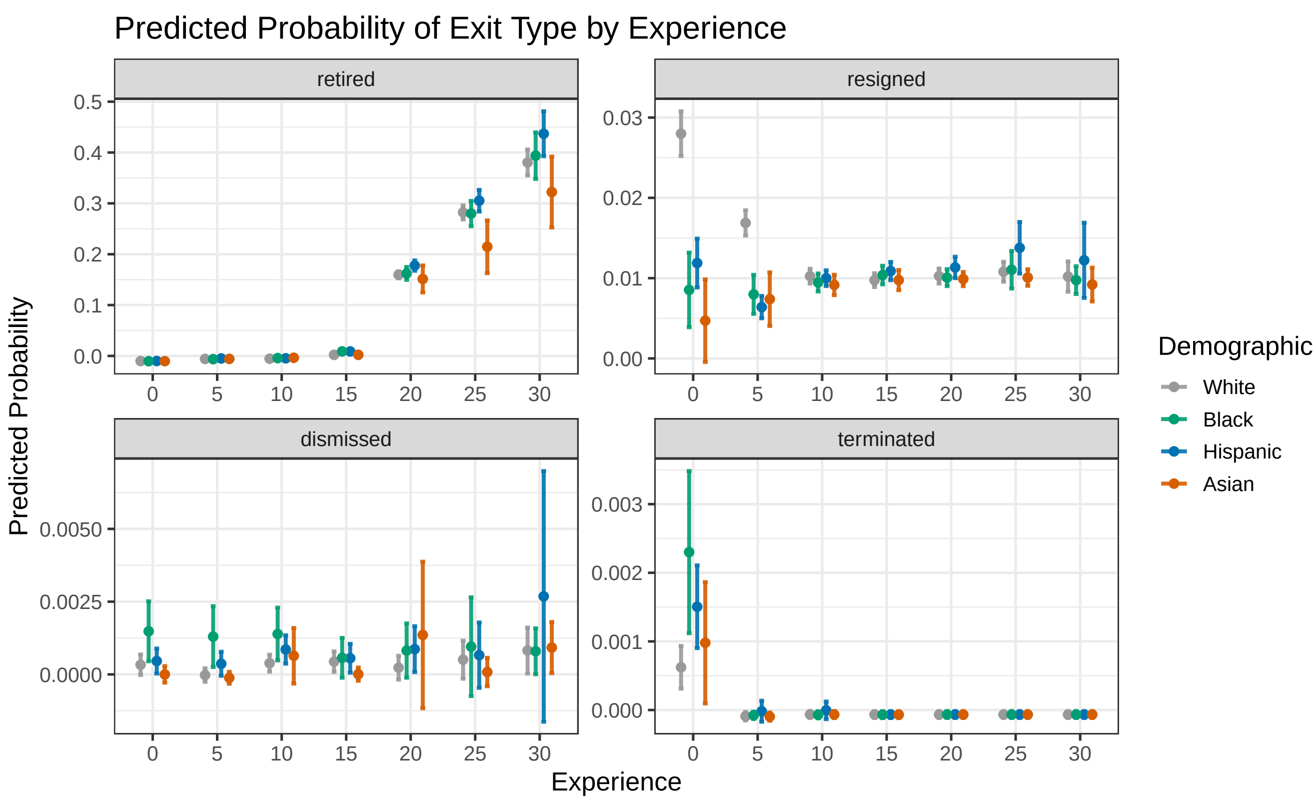


Figure A11



Predicted Probability of Exit Type by Experience
retired
resigned
dismissed
terminated
Predicted Probability
Experience
Demographic
White
Black
Hispanic
Asian

Figure A12: Total Number of Appointments by Employee Groups

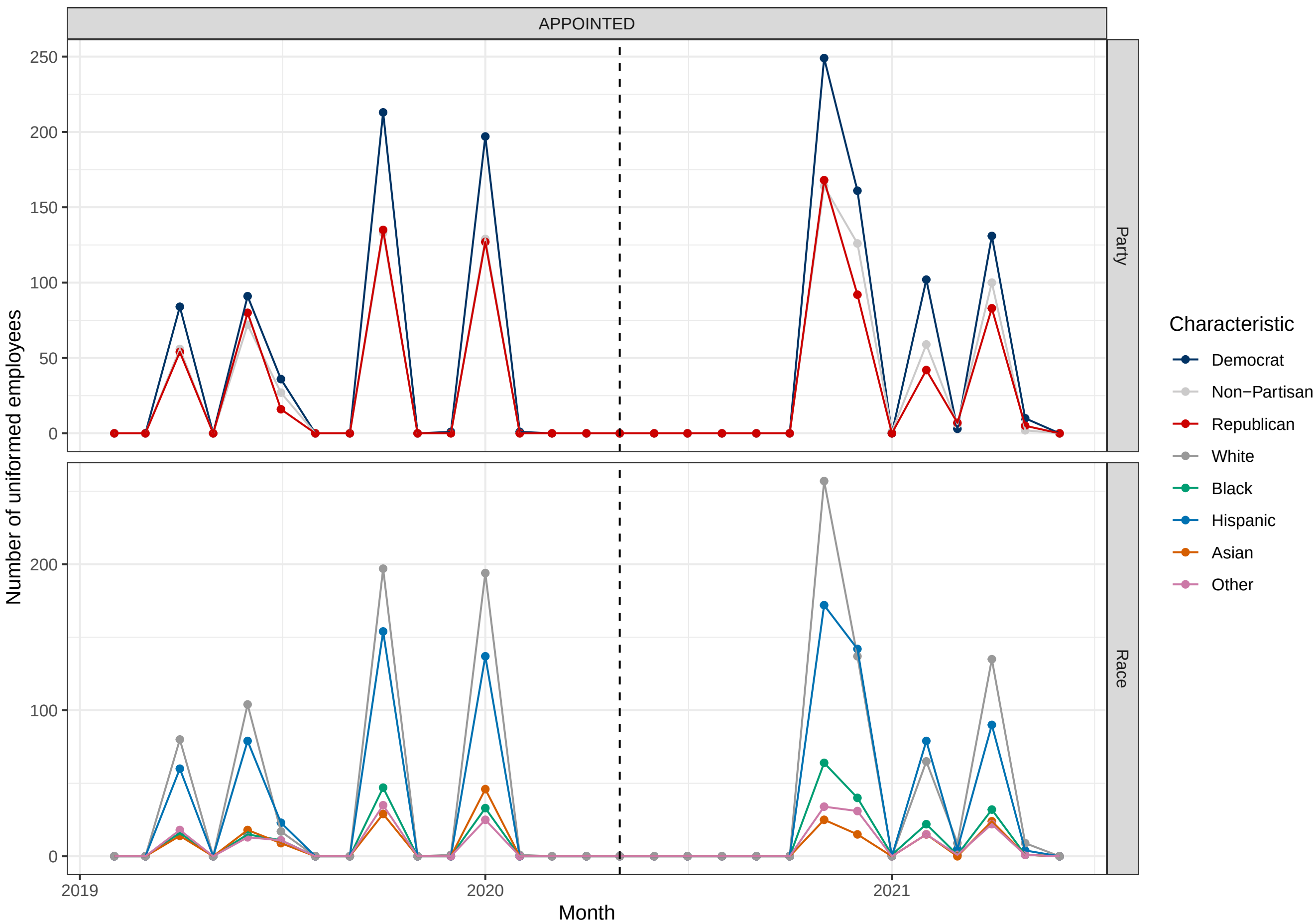


Figure A13: Total Number of Promotions by Employee Groups

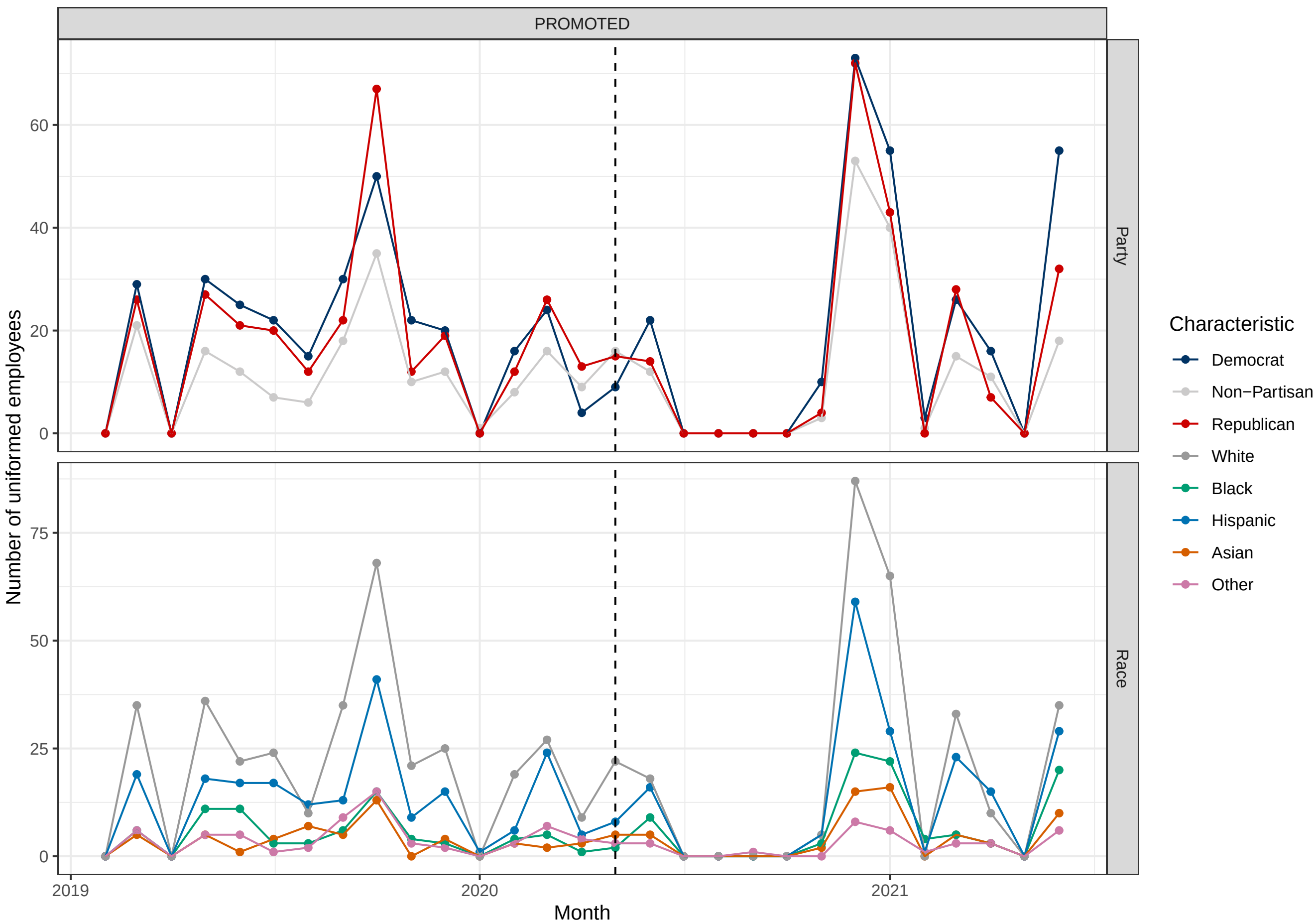


Figure A14: Marginal Effect of GeorgeFloyd$_{tk}$ on Probability of Exit, by Party

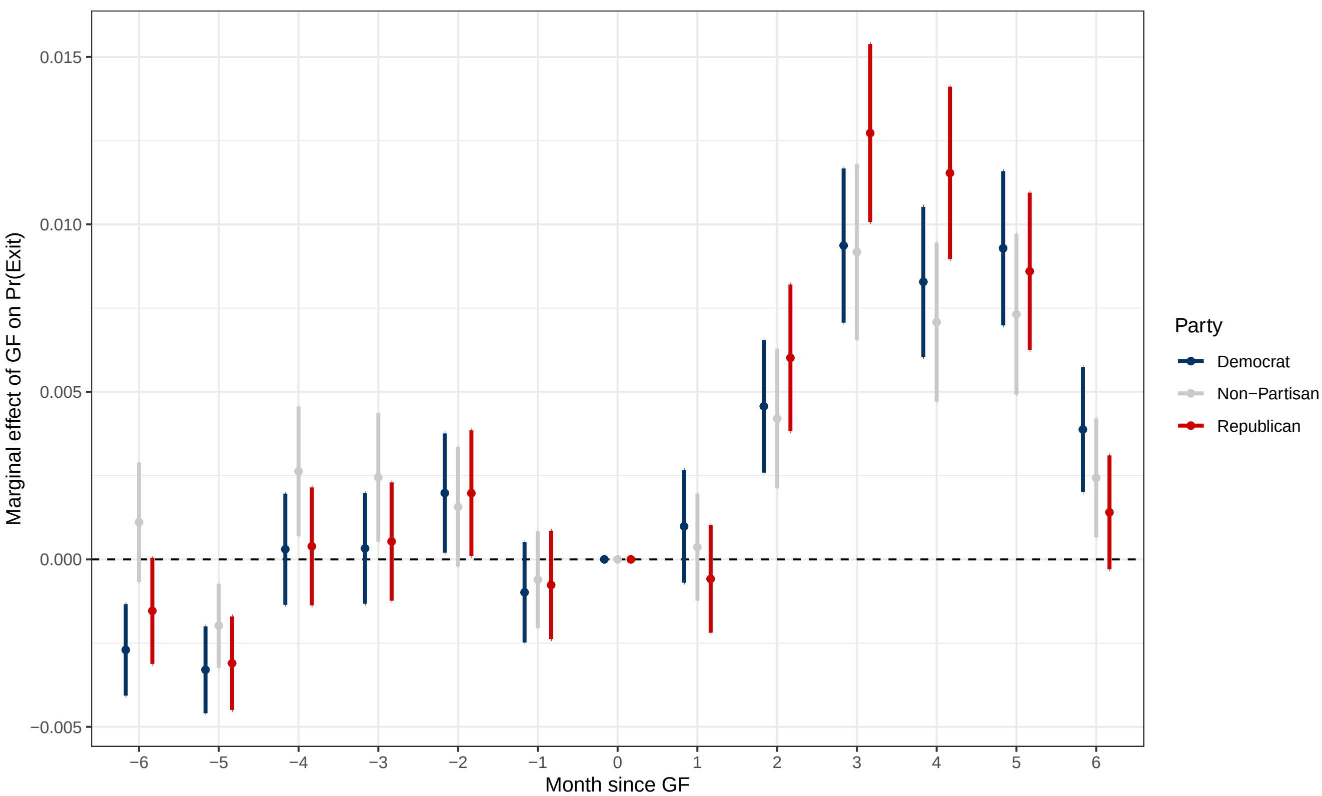


Figure A15: Marginal Effect of GeorgeFloyd$_{tk}$ on Probability of Exit, by Race

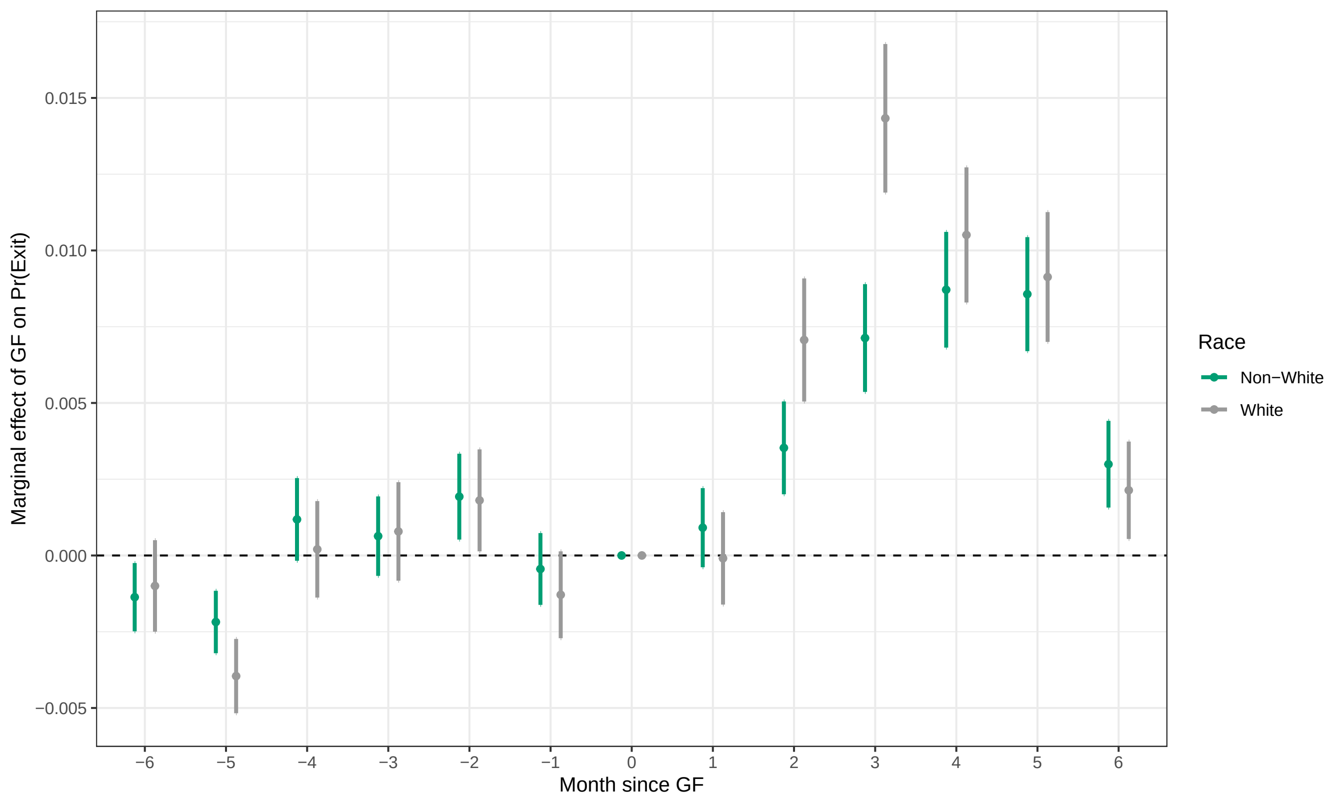


Figure A16: Description of Exiting Officers in 6-months Windows (June-November)

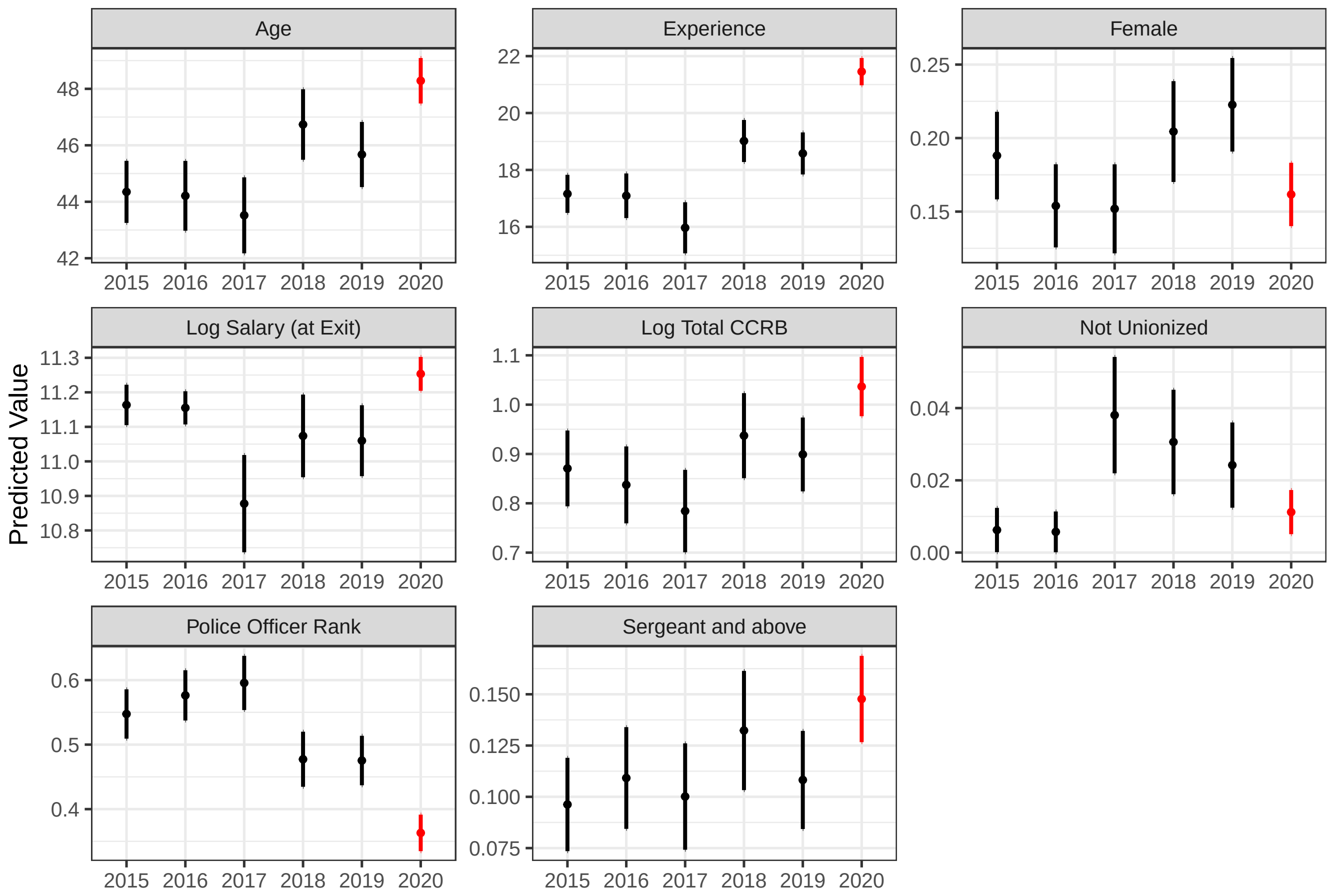


Figure A17: Power of Covariates to Predict Exit across Periods, Importance Scores of Random Forest Algorithm

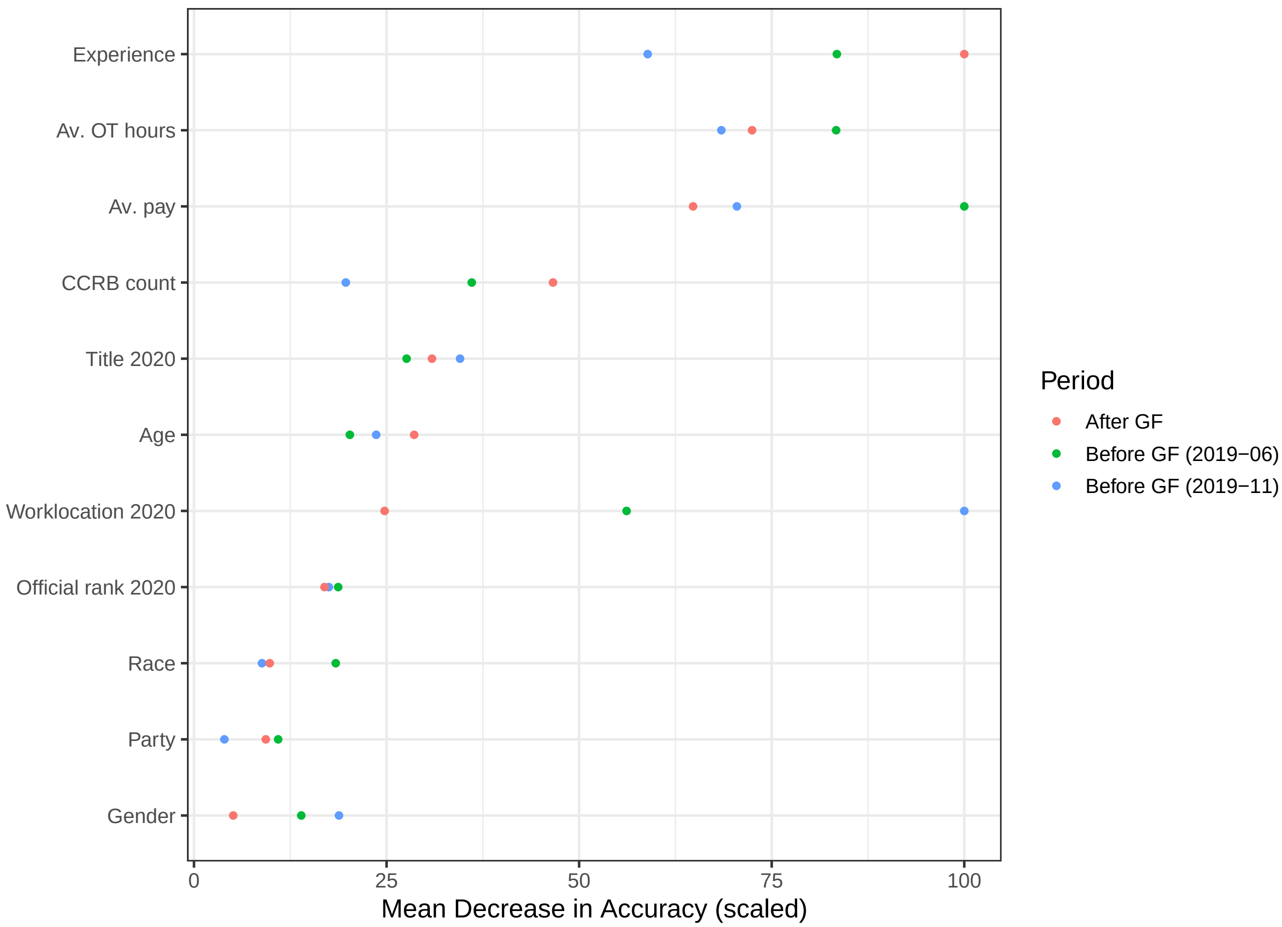


Figure A18: Placebo: Total Number of Retirements and Resignations for FDNY

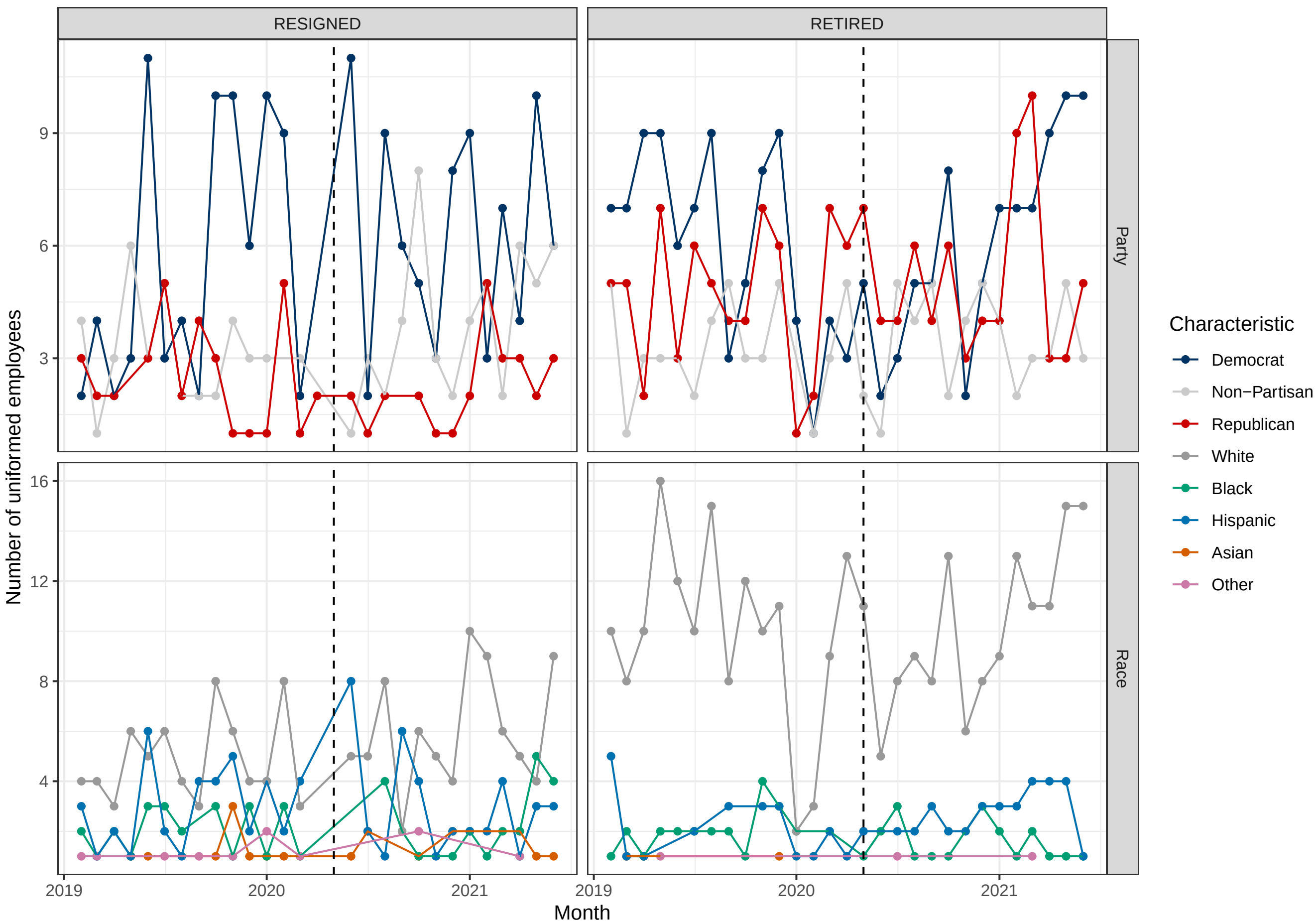
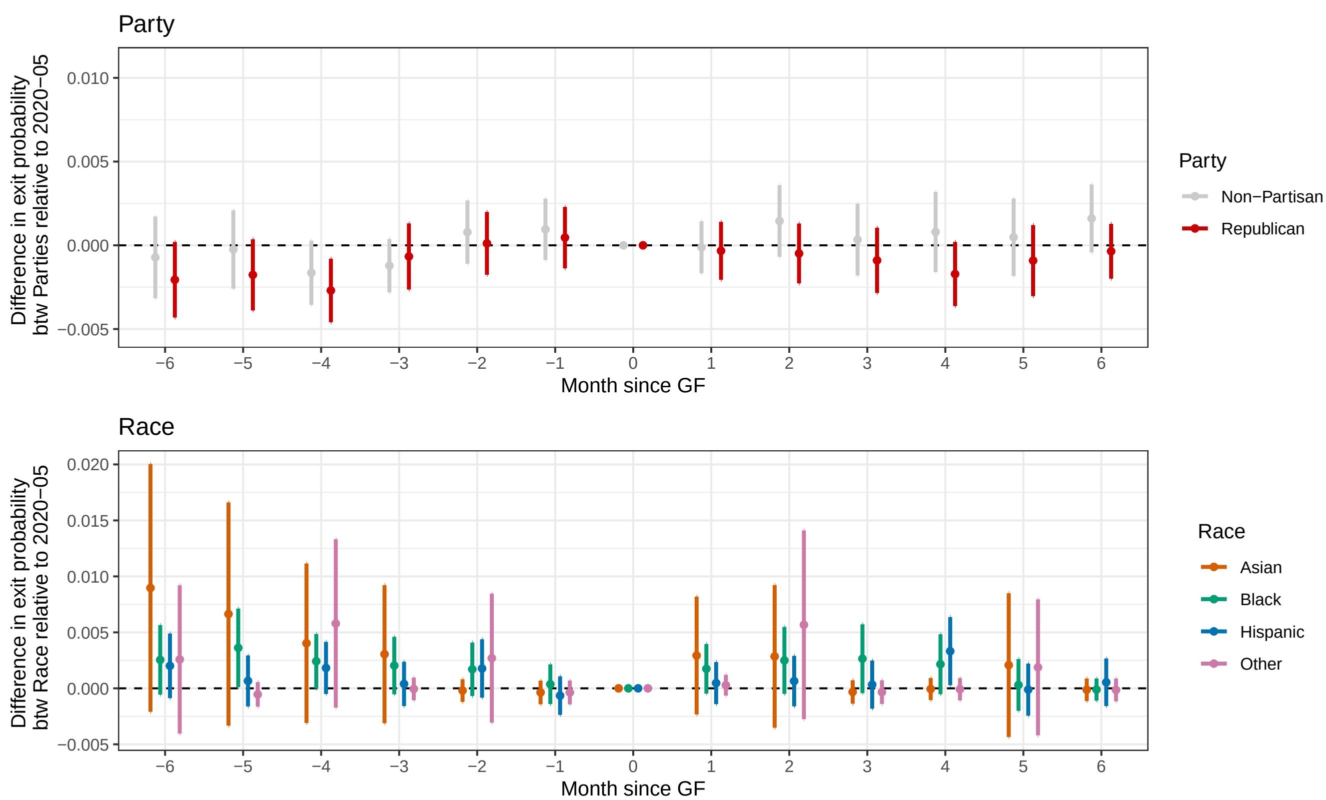
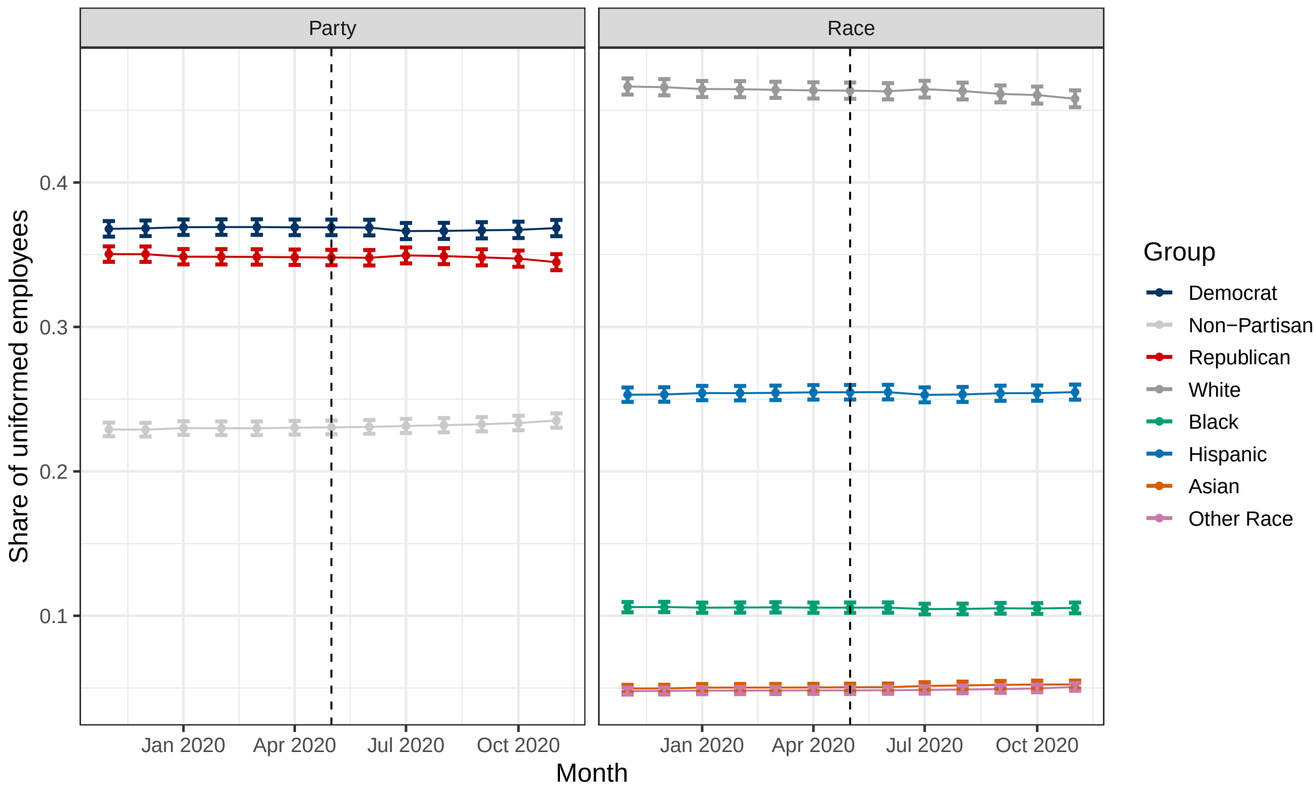


Figure A19: Placebo: Difference in Exit Probability between Parties and Race Groups at FDNY



Estimated interaction coefficients (β_{ik}) from Equation (1) with robust 95% confidence intervals. Democrats (top panel) and Whites (bottom panel) are the baseline category.

Figure A20: Average Composition of NYPD Before and After George Floyd



Average share of demographic groups, weighted by posterior probability of a match with L2 voter file with 95% confidence intervals.