WHERE RACIAL AND ETHNIC DISPARITIES IN POLICING COME FROM: THE SPATIAL CONCENTRATION OF ARRESTS ACROSS SIX CITIES

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ABTRACT

We examine the extent to which citywide racial and ethnic disparities in arrests are driven by a subset of places within cities. Data are drawn from six US cities—New York City, Los Angeles, Chicago, Washington D.C., Tucson, and Colorado Springs—from 2014 to 2019. Results indicate that arrests in all cities are strongly concentrated within a few block groups, for all race and ethnicities. The higher rates of arrests for blacks and (in some cities) Hispanics compared to whites and other racial groups means that a few places in every city are responsible for driving citywide racial and ethnic disparities in arrests. These arrest hotspots demonstrate very high year-to-year stability. There is a strong relationship between crime and arrest hotspots, making crime hotspots key drivers of citywide racial and ethnic disparities in arrests. Our results imply that an intense focus on reducing arrests in hotspots may yield outsized reductions in population-level racial and ethnic disparities. Place-based and group-based interventions at these locations may help reduce racial disparities in arrests and enhance public safety.

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Understanding racial and ethnic disparities in arrests is a pivotal topic given widespread societal concern over inequalities in policing and the criminal justice system. Arrests are a consequential form of police contact, serving as the gateway to the criminal justice process. The experience of being arrested may be harmful even if it does not lead to criminal court actions. Arrest patterns across America are characterized by large and persistent racial and ethnic disparities (Federal Bureau of Investigation, 2020). Across decades of changes in crime and various police reforms, racial and ethnic disparities in arrests have persisted. An improved understanding of the sources of disparities in arrests may provide clues into policies that help reduce them.

An extensive body of research has established that citywide crime is highly concentrated within a few micro-places. Across various contexts, 50% of crime occurs in about 5% of a city's street segments, what has been termed the law of crime concentration (Weisburd, 2015). Scholars have often commented on possible connections between hotspots of crime and racial disparities in policing (Braga & Weisburd, 2010; Briggs & Keimig, 2017; Wheeler, 2019), but research on the criminology of place has to date focused almost exclusively on the spatial concentration of crime and not arrest patterns or how their concentration explains population-level racial disparities.[1]

There are, however, several reasons to expect that extending the criminology of place to confront the spatial concentration of police enforcement and racial disparities therein may yield important insights. For one, research on the concentration of crime shows that a city's crime rate can be largely driven by a small set of places. This is not only of theoretical interest, as focusing on targeted solutions for those few places can yield effective crime reduction practices (Braga et al., 1999, 2014; Braga & Weisburd, 2010). This suggests value in examining whether similar insights may follow from applying this lens to racial disparities in arrests. But the connections run deeper; most obviously, police responding to the spatial concentration of crime can be expected to produce some degree of concentration of arrests. Given the persistence of racial residential segregation and concentrated disadvantage (Massey & Denton, 1993; Wilson, 1987, 1996), ultimately making certain racial minority groups more likely to be living in higher crime places (Sampson et al., 2018; Sampson & Wilson, 1995), it stands to reason that arrests in response to crime hotspots would produce racial disparities. Beyond crime, there are other reasons that police may concentrate their enforcement in small parts of the city, such as commercial corridors or downtown business districts, and these areas too may be especially responsible for producing racial disparities in arrests.

To be sure, an extensive literature confronts the nexus of race, place, and policing (Braga et al., 2019). Quantitative work in this tradition typically examines the conditional association between predictors, such as racial composition, and the level of some police behaviors at relatively large geographic scales, such as neighborhoods (e.g., Fagan et al., 2010, 2016; Smith, 1986; Terrill & Reisig, 2003). While valuable and complementary to our focus, such work has not directly modelled the extent to which citywide racial disparities reflect the concentration of arrests in specific places. More generally, relatively little quantitative work in this tradition has focused on arrests as the outcome of interest, despite its status as one of the most common yet consequential forms of police contact. A likely reason for this, and for the dearth of analyses on the spatial concentration of arrests, is that until recently geocoded arrest data have not been readily available to researchers. Today, as cities have started making geocoded arrest data available, more extensive analyses are now possible.

In this article, we thus extend research on race, place, and policing by examining the extent to which a few places within cities are responsible for producing citywide racial and ethnic disparities in arrests. To do so, we draw on data from six geographically divergent US cities—New York City, Los Angeles, Chicago, Washington D.C., Tucson, and Colorado Springs—over the years 2014-2019. With datasets for these six cities, we establish how concentrated arrests are by place, how the concentration of arrests varies by racial and ethnic group, the extent to which a few places drive citywide racial and ethnic disparities, the temporal stability of arrest hotspots, and the extent to which these arrest patterns overlap with the more established phenomenon of crime hotspots. In so doing, we also extend the criminology of place by shifting the focus from crime to enforcement patterns and by moving beyond race neutral scholarship to put racial disparities front and center.

Our analyses reveal several consistent patterns across the cities, coupled with some city-level variability. First, in all six cities arrests are highly concentrated within a few block groups, and this is true for all racial and ethnic groups. It is common for about 5% of block groups to account for about 40% of arrests; the exact figure varies by about 10 percentage points depending on the city and racial/ethnic group. Second, when coupled with higher overall rates of arrests for blacks and (in some cities) Hispanics compared to whites and other racial groups, this spatial concentration means that a few places in every city are especially responsible for driving most citywide racial disparities in arrest. For example, in Los Angeles nearly half of the disparately high rates of black arrests originate in 5% of the city's places and almost all of it comes from a quarter of the city. Third, the places with the most arrests exhibit very high levels of year-to-year stability, in all cities and for all racial and ethnic groups. Fourth, there is a close association between crime hotspots and arrest hotspots, an association which persists largely unaltered when conditioning on several plausible confounding factors. Finally, the spatial crime-arrest association means that a few high crime places generate a good deal of citywide racial disparities in arrests. For instance, it is common for about 30% of black-white disparities in arrests rates to stem from the arrests that happen in the top 5% highest crime block groups.

Together, our results indicate that citywide racial and ethnic disparities in arrests are primarily generated in relatively few places within cities, and that these are often though not exclusively crime hotspots. These descriptive patterns carry theoretical implications, as theories of race and policing must be able to account for them if they are to substantively explain what drives racial disparities in police enforcement. Ultimately, our analyses yield more questions than answers about which places generate racial disparities in arrests and why, including what exactly it means for crime and arrest hotspots to be associated. Answers to these questions are not only of academic interest but also carry practical value. Our findings imply that changes to policing arrest practices in most places in a city will have little consequence for addressing overall levels of racial and ethnic disparities. This suggests real limits of the effectiveness of popular policing reforms in reducing disparities, such as implicit bias training or body-worn cameras. Conversely, our findings mean that policies and practices that lower arrest rates in a handful of places could produce large reductions in citywide racial disparities. Given the limited geographic scale of such interventions, they may be effective and feasible. Yet, the effectiveness of different interventions—for example, whether place-based or group-based—fundamentally depends on why arrests are as concentrated as they are. After presenting our results, these theoretical and policy implications are discussed in detail.

Extending the Criminology of Place Towards Race and Policing

Since the 1980s a growing body of research has focused on the concentration of crime by place (Sherman et al., 1989; Weisburd, 2015; Weisburd et al., 2012). In city after city studied, research has revealed that crime tends to concentrate in a few places (Weisburd, 2015). Typically, about 5% of street segments or small geographies account for 50% of crime, though there is variability around this, including variability from examining different spatial resolutions and types of crimes (Andresen et al., 2017; Bernasco & Steenbeek, 2017; O'Brien, 2019). Further, the locations of these hotspots of crime exhibit a high degree of stability over time (Weisburd et al., 2004). These findings form the core of the criminology of place, characterized by an emphasis on the criminogenic nature of micro-places, or areas smaller than neighborhoods (Sherman et al., 1989; Weisburd et al., 2012).

The observed concentration of crime within cities suggests important insights for theories of crime and policy responses. From a policy standpoint, the hyper-concentration of crime suggests that precisely targeted interventions to the places with the most crime may yield outsized crime reduction benefits. It is no coincidence that the criminology of place literature emerged in tandem with hotspot policing, or the use of elevated, often proactive, police presence in crime hotspots (cf. Sherman et al., 1989; Sherman & Weisburd, 1995). Beyond its practical applicability, the concentration of crime also provides a deeper understanding of the theoretical mechanisms that lead some places to have chronically higher rates of crime than others. (Weisburd, 2015; Wilcox & Cullen, 2018).

To date, however, the criminology of place has largely neglected enforcement patterns. There are some exceptions; for instance, Weisburd et al. (2014) show that about 80% of NYPD stops on street segments during 2009-2010 occurred in just 5% of New York City's street segments. In other cases, scholars have invoked the spatial concentration of enforcement without providing analogous estimates (Briggs & Keimig, 2017; Chillar, 2021; Wheeler, 2019; Wheeler et al., 2018). The descriptive question of how concentrated arrests are by place within cities has largely been unaddressed. To the extent that the police's response to crime is proportional to its concentration, the spatial concentration of arrests will closely resemble the concentration of crime. The police responses generating such concentration could stem from responding to calls for service, but also deliberately place-based strategies such as hotspots policing. The extra-allocation of police to high crime areas is particularly evident in cities like New York that adopted the "new policing model" of linking officer assignments to crime analytics (MacDonald et al., 2016). It needn't be only crime that police respond to; responding to any sort or combination of spatially concentrated social problems would suffice to similarly concentrate arrests. Importantly, micro-places with high levels of law enforcement activity may generate an outsized share of the racial disparities in arrests. While the criminology of place has mostly concerned itself with overall patterns of spatial concentration of crime, extending this tradition to confront race-specific patterns in police enforcement stands to reveal the concentrated sources of racial disparities in arrests.

Segregation and Concentrated Disadvantages: The Roots of Concentrated Disparities

Crime hotspots are often located in highly disadvantaged, segregated communities of racial and ethnic minorities (Braga & Weisburd, 2010; Wheeler, 2019). Given that various forms of social problems tend to cluster (Sampson, 2012), this is likely true of other types of hotspots as well. The resultant coupling of spatially concentrated arrests with almost exclusively racial/ethnic minority populations means that what appears to be a citywide phenomenon—differences in rates of arrest by race or ethnicity—could stem disproportionately from relatively few micro-places within the city.

There are historical and structural reasons for the spatial overlap between certain racial/ethnic groups and concentrated poverty and other disadvantages within US cities. In the case of African Americans, this reflects the legacy and persistence of segregation, which concentrates disadvantages, thereby perpetuating various social problems (Massey & Denton, 1993; Wilson, 1987, 1996). African Americans are on average more likely than whites and other groups to live in neighborhoods with high spatial concentrations of poverty, unemployment, joblessness, family disruption, and geographic isolation. Such structural differences between predominately black and white neighborhoods, including the way in which they impact social processes such as informal social control and certain cultural adaptations, explain differences in crime rates between them (Krivo et al., 2009; Sampson et al., 2018; Sampson & Wilson, 1995).

The problems generated by these processes of urban inequality extend beyond crime, as do the problems to which the police respond. In contrast to arrests for gun violence, enforcement patterns may have less connection to public safety when they involve arrests for drug possession, municipal violations of public order, and other nonviolent offenses (Harcourt & Ludwig, 2007; Stuart, 2016). Regardless of the legitimacy of the "problems" police are responding to, if they are spatially concentrated, they will likely be in places disproportionately populated by poor African Americans. By implication, citywide black arrest rates may be mostly generated in a few places.

Complicating this picture somewhat, central business districts with low black residential populations often have especially high rates of property crime and certain forms of disorder. Spatially concentrated arrests may thus extend beyond racially segregated residential neighborhoods to downtown cores where the ambient population is racially diverse. Yet, it is likely the case that the legacy and persistence of segregation and concentrated disadvantage still shapes arrest patterns in these areas, insofar as they influence the rates of offending by race in downtown cores as well as the way that police perceive people of different races as they use these spaces (Gelman et al., 2007). We do not set out to test these various mechanisms, but raise these issues to make it clear that the concentration of arrests for African Americans may extend beyond segregated spaces because of the same historical legacy and social processes of disadvantage.

The category Hispanic encompasses an exceptionally wide array of nationalities and socioeconomic backgrounds, among other differences, making it hard to provide a meaningful summary of the “Hispanic experience” in America (Massey & Denton, 1987; Portes & Rumbaut, 2006; South et al., 2005). For instance, while many populations of Dominicans and Puerto Ricans in mainland America live in areas characterized by high levels of concentrated disadvantage, many Mexican communities in the United States are cohesive, immigrant-filled ethnic enclaves with a substantial middle-class. Also, many Hispanic people do not live in segregated areas, though their segregation levels vary by period, place, and country of origin (Logan et al., 2002, 2004; Massey & Denton, 1987). The specific ethnic composition of Hispanic populations varies substantially across US regions and cities. As a result, whether Hispanics face disparately high arrest rates relative to whites and other non-Black minority populations, and the extent to which there are spots that generate high rates of Hispanic arrests, likely depends on the context of the city being examined.

Prior Scholarship on Race, Place, and Policing

Prior research has documented substantial neighborhood variability in police behaviors—including arrests, stops, searches and frisks, the use of force, and misconduct—and examined the neighborhood-level correlates (e.g., Fagan et al., 2010, 2016; Kane, 2002; Lautenschlager &

Omori, 2019; Levchak, 2017; MacDonald & Braga, 2019; Smith, 1986; Terrill & Reisig, 2003). Many of these studies find a relationship between neighborhood racial composition and levels of police enforcement or deployment. Such studies often invoke racial threat theory (Blalock, 1967), which maintains that heavy-handed policing is used disparately on minority populations because of their perceived threat to the dominant social order. Other research has found levels of poverty and disadvantage (Fagan & Davies, 2000; Kirk, 2008; Sampson, 1986) and crime (Petrocelli et al., 2003; Roh & Robinson, 2009) to be associated with levels of policing, among other factors (e.g., Beck, 2020; Fagan et al., 2012; Laniyonu, 2018). Together, this body of research indicates that policing varies across neighborhoods, that this variation is socially patterned, including by neighborhood-level processes, and that place is essential in assessing racial disparities in policing.

This article builds on prior work in several ways. First, we add to the criminology of place by focusing on the extent to which racial disparities in arrests are also hyper-concentrated by place. Second, while existing quantitative studies on race, place, and policing typically test for conditional associations between neighborhood-level policing and covariates such as racial composition (e.g., Fagan et al., 2010), we focus instead on the extent to which spatially concentrated arrests drive citywide racial disparities in arrest rates. This empirical approach involves not only a smaller spatial resolution than is typical, but also a shift in focus towards answering the question of how responsible a subset of places are in producing population-level racial and ethnic disparities in arrests, a topic that is distinct yet complementary to prior research on race, place, and policing.

Relatedly, our focus on estimating the contribution of places to citywide racial and ethnic disparities in arrests contrasts with the more typical approach of attempting to identify racially discriminatory policing by parsing out the extent to which disparities do not reflect legally justified reasons for arrests (for reviews see Kochel et al., 2011; National Academy of Sciences, 2018; Neil & Winship, 2019; Ridgeway & MacDonald, 2010). While such research is valuable, our stance is that even racial disparities in policing that are legally justifiable would be better off lowered when possible. Legally justified racial disparities in arrests do not negate the importance of reducing population-level disparities. A focus on places that generate a disproportionate share of arrests can help identify ways in which population-level racial disparities can be reduced, regardless of their legality.

Methods

Data

Our analysis centers on data from six US cities during the years 2014 to 2019. These cities—New York City, Los Angeles, Chicago, Washington D.C., Tucson, and Colorado Springs—were chosen because they reflect a diverse array of cities in the US and have publicly available geocoded arrest and crime data. The cities range from medium sized to very large (New York, LA, and Chicago are the three largest US cities) and span multiple geographic regions. In addition, they vary in other notable ways, such as in population density and their racial and ethnic composition, including many different types of Hispanic populations. Thus, while our sample does not give a representative estimate of the concentration of arrests across all American cities, it does allow for an examination of whether recurrent patterns exist across cities that have different physical, demographic, sociopolitical, and economic contexts.

For each city, geocoded arrest and crime data were drawn from the city's open data portals. These data were aggregated to the block-group level using 2010 Census shapefiles, and additional block-group level covariates were taken from the 2015-2019 American Community Survey (ACS) block-group level estimates. Both the shapefiles and ACS data were obtained from Social Explorer. We focus on block groups because this is the smallest geographic level of population enumeration for the ACS, and to account for the fact that not every city reports the exact spot where arrests/crimes occur (e.g., NYPD data geocodes arrests to the nearest intersection or middle of the nearest street segment).

The same variables are used and analyzed in the same way for all six cities. The key outcome of interest is the *number of arrests* in each block group, which is measured separately for three racial/ethnic groupings: black, Hispanic, and white/other. These groupings are used given the predominant concern with racial disparities in arrests against black and Hispanic individuals. While non-Hispanic whites make up the majority of the third grouping in every city, the "other" category (in most cities this is mostly Asians) have similar, often slightly lower, arrest rates. All arrests reported by each city are included in this analysis. Arrests are measured monthly, yearly, and across the entire 6-year study period in various analyses, depending on what is most appropriate to answer specific research questions.

The amount of *crime* in each block group is measured as the number of crime incidents reported to the respective police departments. While reported crime is a subset of actual crimes, it is the crime that the police are aware of and thus capable of responding to.[2] In some models we include additional covariates. These include *month* and *year* fixed effects to account for temporal trends common to all areas of a city. We also include an index of *concentrated disadvantage,* constructed with principal components analysis (PCA). Specifically, the first component of a PCA is extracted from a combination of unemployment rates, female-headed household rates, family poverty rates, vacancy rates, and the fraction of adults without college degrees. In every city the first component accounted for a good deal of variation (ranging from 42 to 61%). Block group's *land area* is measured in case larger areas experience more enforcement as a function of their geographic size. Similarly, the block group's *total population* is measured in case more populated areas experience more enforcement. Demographic information on the *youth population*, *black population*, and *Hispanic population* of each tract is also measured as those may impact enforcement levels.

Block groups with missing ACS data are omitted from analysis.[3] The omitted block groups do not account for many of each city's arrests (ranging from 0 to 2.5%). Because the first section of analyses does not require ACS data, in a supplementary check we carried out those analyses using all block groups; this did not noticeably alter results.[4]

Importantly, the definitions and data collection processes for the arrest and crime data are not identical across the six cities. For example, Washington, D.C. data does not contain the arrests of juveniles and only contains index crimes. Also, for Colorado Springs arrest data is only available from 2016 to 2019. There are likely other small differences stemming from varying data management systems and practices across cities. As such, we caution against comparing the specific levels of arrests across cities. Though, care was taken to clean the data to include only valid incidents in every city, allowing for an assessment of whether the same general patterns of the spatial concentration of arrests by race and ethnicity exists across cities.

[Table 1 about here]

Table 1 shows summary statistics for each city and racial/ethnic group on the average monthly count of arrests per block group, their share of the population, and the arrest rate per population of residents. While the number of arrests per block group-month varies considerably, this partially reflects the differing shares of the population of the various racial and ethnic groups. As the arrest rate column indicates, however, relative to their population there are disparities in arrests of African Americans. In New York City, for example, the black arrest rate is the highest among all groups, and at 0.46 per person is nearly 6 times higher than the arrest rate of whites/others (0.08). This disparity is not exceptionally large compared to other cities; the equivalent figure is 11 times higher in Chicago and over 3.5 times higher in Colorado Spring, the city where black arrest rates are proportionately most similar to those of whites/others. The degree of disparities in Hispanic arrests is considerably more variable, though always lower than disparities in black arrest rates. For instance, in Colorado Springs, Hispanic individuals are arrested at the same rate as whites/others, whereas in Washington D.C. and New York City—the cities with the highest Hispanic arrest rates relative to whites/others—their arrest rates are about three times higher. There are thus clear disparities in the arrest rates of African Americans and in some cities Hispanic individuals. These citywide statistics, however, do not convey the extent to which racial and ethnic arrest disparities are concentrated by place.

Analytic Strategy and Models

The first section of analysis sets out to quantify the concentration of arrests by race across the six cities by examining Lorenz curves and Gini coefficients (Steenbeek & Weisburd, 2016).

The second section of analysis adds in covariates to examine the place-based correlates of arrest concentration by race. Specifically, negative binomial models are used to estimate the number of monthly arrests in each block group for each of the three racial groups separately. Model 1 examines the association between block-group level crime and arrests and takes the form:

$$Arrests_{it}^{cr} \sim NegBin(\lambda_{it}^{cr}), \tag{1}$$

$$\lambda_{it}^{cr} = \exp(\beta_1^{cr} + \beta_2^{cr} CrimeQ2_{it}^{cr} \dots \beta_{20}^{cr} CrimeQ20_{it}^{cr})$$

where *r* indicates racial/ethnic grouping and *c* indicates city; the model is fit separately for each racial/ethnic group in each city, yielding 18 models in total. A negative binomial stochastic component is used due to the count outcome and because likelihood ratio tests indicated a superior fit compared to analogous Poisson models.[5] For each racial group in each city, the number of arrests in block group *i* during month *t* is thus modelled as a function of a stochastic component and a structural component which includes an intercept and 19 of the 20 quantiles of crime (the lowest quantile is omitted to be the reference group), where crime quantile is also measured monthly. We use 20 crime quantiles to allow a flexible functional form of the crime-arrest relationship.[6]

In Model 2, we examine the association of crime with arrest while adjusting for a series of additional covariates:

$$Arrests_{it}^{cr} \sim NegBin(\lambda_{it}^{cr}), \qquad (2)$$

$$\lambda_{it}^{cr} = \exp\,(\beta_1^{cr} + \beta_2^{cr} CrimeQ2_{it}^{cr} \dots \beta_{20}^{cr} CrimeQ20_{it}^{cr} +$$

$$\pi^{cr} \cdot \mathrm{X}_i^c + \eta_t^{cr} + \delta_y^{cr})$$

where the terms which appear in Equation 1 have the same meaning, and in addition π indicates a vector of coefficients which corresponds to X (concentrated disadvantage, land area, total population, youth population, black population, and Hispanic population), a vector of the control variables for each block group *i* for each city *c,* η indicates month fixed effects, and δ indicates year fixed effects. We utilize the information contained within this model to estimate the contribution of specific crime quantiles to citywide racial disparities in arrest.

For all negative binomial models, cluster-robust standard errors are calculated with a parametric bootstrap, clustered at the block-group level to account for unmeasured spatial dependence over time. In Model 2, we obtain expected values of monthly arrests as a function of crime by holding the other covariates at their observed levels and calculating predicted values for each neighborhood at a given quantile of crime, then averaging those predictions (Hanmer & Kalkan, 2013).

Results

The Concentration of Arrests by Race and Place

We first examine the extent to which arrests are concentrated within a few places, by racial/ethnic group and city. Figure 1 presents the cumulative fraction of arrests (the y-axis) that occur within a given fraction of a city's block groups (the x-axis). Each panel corresponds to a city and each colored line to a racial/ethnic grouping. Strikingly, for every grouping in all six cities, a small fraction of places account for most arrests. For example, in New York City the top 5% highest arrest block groups account for 47.8% of black arrests, 45.9% of Hispanic arrests, and 47.6% of white/other arrests.[7] In Chicago, those figures are, respectively, 35.5%, 32.4%, and 35.8%. While there is variability across cities and race in terms of the extent of arrest concentration (ranging from a low of 26.5% for whites/others in Tucson to a high of 52.2% for blacks in Los Angeles), what stands out most is the recurring pattern of substantial arrest concentration in a few places.

[Figure 1 about here]

Figure 1 also contains Gini coefficients for every racial/ethnic group for each city. Gini coefficients range between 0 (uniform distribution of arrests across block groups) and 1 (all arrests happen in one place). Gini coefficients are closely related to Figure 1; they are equivalent to the fraction of the area above the 45-degree that is below each curve. While there is variability by race and across cities, arrests are substantially concentrated. In the online Appendix, simulations are presented of the expected concentration and Gini coefficients if arrests were distributed randomly throughout the city (Bernasco & Steenbeek, 2017; Chalfin, Kaplan, et al., 2021; Mohler et al., 2019). The observed quantities presented in Figure 1 are vastly more concentrated than these simulated values.

[Figure 2 about here]

While it is clear from Figure 1 that the concentration of arrests does not vary much by race, it is important to recognize that this concentration metric is a relative measure that is agnostic to differences in the levels of arrests by race. Figure 2 accounts for levels of arrests by showing the cumulative race-specific rate of arrests accounted by a given fraction of blocks. The rightmost value of each curve is the observed arrest rate for a given racial/ethnic group in that city, and to the left the curves indicate what the arrest rate would be if only counting arrests that happened in a given fraction of the block groups. So, for example, the arrest rates for blacks, Hispanics, and white/others in Los Angeles over the period 2014-2019 was 0.481 per person, 0.149, and 0.086 respectively. At x-values of 0.25, the lines show what the arrest rates are when only counting those arrests that happened in the highest 25% arrest places: 0.414 for blacks, 0.109 for Hispanics, and 0.069 for whites/others.

Again, we see that in all cities the arrest rates for blacks tend to be much higher than the other groups, and in some cities the Hispanic arrest rate is higher than that of whites/others. Figure 2 reveals the consistent pattern that a small fraction of block groups drives a large share of city-level racial and ethnic disparities in arrests. Steep slopes, as exist for black arrests (the red lines) and in some cities Hispanic arrests (the green lines), indicate places where a small fraction of places drives up that group's arrest rate. Flat lines represent places with few arrests; that all the lines quickly flatten out therefore means that most racial and ethnic disparities in arrests come from only a small part of each city.

In Los Angeles, for example, most of black arrest rates are driven by the top 25% of block groups, as it is for the other groups though they have relatively low arrest rates. This means that citywide arrest rates are driven by a subset of block groups, and that what happens in the other 75% of the city does not matter much for racial disparities in arrest rates. Approximately 87% of the citywide black-white/other gap in arrest rates in Los Angeles (0.481-0.086=0.395) is accounted for by the top 25% highest-arrest places (0.414-0.069=0.345). Similarly, the top 5% of arrest places accounts for much of the black-white/other gap in arrest rates (0.25-0.04=0.19), meaning nearly half of overall disparities in black arrest rates comes from this small part of the city (0.19/0.395 ≈ 48%).

[Figure 3 about here]

The analyses described above calculate arrest concentration by combining data from six years. This aggregation could mask important year-to-year variation in arrest rates by places. Figure 3 shows how the average quantile of block groups that were in the top 5% (i.e., 20th quantile) of block groups by arrests in 2014 changed through to 2019 (for Colorado Springs, from 2016 to 2019). For most cities and racial groups, the top 5% of arrest block groups remain in, at, or above the top 10% every year. For example, in the New York City the top 5% arrest block groups in 2014 never drops below the top 10% (19th quantile), on average, for any race or ethnic group between 2015 and 2019. Thus, not only are racial and ethnic disparities in arrests powerfully driven by a few locations, these block groups are largely the same places year after year.

The Relationship between Arrest and Crime Hotspots

Figure 4 displays the relationship between reported crimes and arrests at the block group level. Specifically, it shows the proportion of block groups in the top (20^{th}) arrest quantiles that are also in the top (20^{th}) crime quantile. The denominator is 5% of the number of block groups in a city and the numerator is the number of block groups that are in the top 5% of the distributions of both crime and race-specific arrests. Figure 4 reveals variability across cities, but that there is in general a high degree of overlap between crime and arrest hotspots, for all racial groups.[8] In many cases, over half the leading arrest hotspots are also leading crime hotspots.

[Figure 4 about here]

Figure 5 presents the results from Model 1 that estimates the association between monthly crimes and arrests, by city and racial/ethnic group (tabular regression output is reported in the Table A1 of the online Appendix). In every city, a nonlinear pattern emerges such that many lower crime quantiles—indeed most of the city's block groups—experience relatively few arrests whereas higher crime areas experience sharply elevated arrest levels. For example, in the bottom 50% of block groups in terms of crime in Chicago (i.e., crime quantile 10 and lower) monthly arrest rates are near zero for every racial and ethnic group. This remains largely true for Hispanics and white/others in the top 50% highest crime block groups, the biggest exception being for the top quantile where their arrest rates are closer to 1. In contrast, the black arrest rate increases nonlinearly in the top half of the crime distribution, such that the expected arrest rate for blacks in the highest crime block groups is nearly 8 per month. Looking at the other panels, though, the racial/ethnic group whose expected arrests increases most with crime varies by city.

[Figure 5 about here]

Figure 5 reveals an association between arrest and crime at the block group level, but two things obfuscate the extent to which higher crime block groups contribute to racial disparities in arrests. The first is that these estimates may reflect differences in other area-related factors like concentrated disadvantage, land area, or population. The second is that because the estimates are not corrected for citywide racial composition, the relative height of the different racial/ethnic curves within a given city cannot be compared to understand the role of crime in shaping arrest disparities. For example, Tucson does not have many black residents, so it is not too surprising that blacks are arrested the least in block groups of any crime level. To provide a more direct answer to the question of how much a few high crime locations shape citywide racial disparities, we build on the model above in two ways.

[Figure 6 about here]

Figure 6 shows the results estimating the relationship between arrests and crime after including an additional set of control variables outlined in Model 2 (tabular regression output is reported in Table A2 of the online Appendix). Strikingly, the estimates are largely unchanged compared to Figure 5, the analogues of these plots without the added control variables. Thus, the descriptive relationship between arrest rates and crime does not simply reflect their correlation with other important factors—such as demographics, socioeconomics, temporal, and land size covariates—that could influence both.

[Figure 7 about here]

Figure 7 incorporates additional information to show the extent to which citywide racial disparities in arrests are driven by block groups at a given level of crime. Specifically, the leftmost point for each line in each panel of Figure 7 corresponds to the estimated rate of arrests for a given racial/ethnic group in each city. This number is obtained by dividing the estimated number of arrests—the sum of predicted values from Model 2—by that racial/ethnic group's population in that city. Each point represents what happens to the race and ethnic-specific arrest rates citywide when removing the arrests that happened in quantiles of lower crime locations. For example, the y-values where the x-axis equals 1 indicate what the arrest rates would be if arrests in the lowest 5% of block groups in terms of crime were not counted. The x-axis is cumulative such that 2 on the x-axis does not count the bottom 10% of block groups in terms of crime, and so on until no arrests are counted at a value of 20 on the x-axis.

Despite some variability across cities, a general pattern emerges in that the lines start off less steep before dropping off precipitously. This indicates that arrest rates are not much affected by those arrests that happen in the lower crime parts of cities and are strongly impacted by the arrests that happen in the small sections of cities with the highest crime levels. Since white/other, and in most but not all cases Hispanic, arrest rates are so low to begin with, this generally means their lines gradually fall from a low level to a lower level. For blacks—who consistently face elevated rates of arrests in each city—this pattern means that their arrest rates are strongly driven by those arrests that happen in the highest crime locations. Consider Colorado Springs as an example; ignoring the arrests that happened in the bottom 50% of block groups in terms of crime does not greatly change arrest rates, as the Hispanic and white/other lines indicate, and even for blacks the arrest rate would fall by 0.04 (i.e., 0.34-0.3). On the other hand, as indicated by the sharp drop off in the red line at the right of the plot, ignoring the top 5% highest crime block groups drops the black arrest rate by a further 0.12. There is some city-level variability; for example, Washington D.C. stands out in that the arrests of blacks that happen in lower crime places influence the overall black arrest rate to a larger degree, as indicated by the relatively straight red line. Still, the influence of the top 5% highest crime block groups on black arrest rates in that city is comparable in size to the influence of the bottom 40%.

[Table 2 about here]

Table 2 shows the share of citywide disparities accounted for by block groups of a specific crime quantile. As an example, the black arrest rate in New York City during the study period was 0.51, but if it were not for the arrests that happened in the top 5% of block groups by crime the black arrest rate would have been 0.30, or 41.2% lower.[9] The percentage decline for whites/others and Hispanics would have been similar, albeit in absolute terms a smaller reduction. As a result, the citywide difference between black and white/other arrest rates shrinks from 0.4 to 0.23 when removing the top 5% of crime spots, a 42.5% decline. While this is the largest such drop of the six cities, the value for Los Angeles is 40%, the smallest two reductions (Washington D.C. and Tucson) are about 20% and in Chicago and Colorado Springs one-third or more of the disparity is removed. Table 2 also includes results of removing the top 10% and 20% of block groups by crime. To be sure, racial and ethnic disparities in arrests exist beyond such places, but they are relatively small in an absolute sense, reflecting the extent to which it is high crime areas driving spatially concentrated arrests and in turn citywide disparities in arrests.

Discussion

In this article, we set out to examine the extent to which the spatial concentration of arrests drives citywide racial and ethnic disparities. To do so, we drew on data from 2014-2019 for six cities: New York City, Los Angeles, Chicago, Washington D.C., Tucson, and Colorado Springs. A series of analyses revealed several recurrent patterns across all six cities, despite some city-level variability.[10] Arrests are concentrated within a few block groups, often with 5% of block groups accounting for roughly 40% of the arrests of any racial and ethnic group. In turn, this spatial concentration means that relatively few block groups in every city are especially responsible for driving most of the citywide racial disparities in arrests. These arrest hotspots exhibit high levels of year-on-year stability, in all cities and for all racial and ethnic groups. Further, there is a close association between crime hotspots and arrest hotspots, even in models that adjusted for demographic, socioeconomic, and other key features of places. A few high crime places generate a good deal of citywide racial disparities. Depending on the city, about 20 to 40% of black-white disparities in arrests rates is the result of what happens in the top 5% of highest crime block groups.

Theoretical Implications and Future Research Directions

Broadly, our results demonstrate the value of expanding the criminology of place from a focus on crime to examining police enforcement patterns and how spatial concentration shapes racial disparities in arrests. While there is widespread recognition that police activities are often more aggressive in disadvantaged minority neighborhoods (Fagan et al., 2010, 2016; Lautenschlager & Omori, 2019), the extent to which citywide racial disparities in arrests are generated in a few places has not previously been reported. This recurrent, strong, descriptive finding—that the concentration of arrests by place drives population-level racial disparities in arrests— is a fact that theories of police behavior and discretion must account for if they are to provide substantively strong explanations of why racial disparities exist.

While this study does not seek to provide causal explanations for why racial disparities in arrests are so highly influenced by a subset of any city, it is worth noting the difficulty that many predominant theoretical frameworks face in accounting for our findings. For example, the fact that adjusting for racial composition of residential populations in each block group did not alter our estimates hints that even if racial threat theory is correct, it may not be a particularly important driver of arrest disparities. Likewise, it is hard to reconcile the stable concentration of arrests with theories focused on errant “bad apple” officers or more universal processes such as implicit bias (Chalfin & Kaplan, 2021; Russell-Brown, 2018). To be clear, our findings do not mean any of these theories are wrong, but they are incomplete and unlikely to be a main driver of population-level racial disparities in arrests. Arguably, this situation stems from the focus of scholarship to date on identifying particularly egregious patterns of racial discrimination in police actions at the expense of modelling the substantive importance of various factors in producing disparities. Addressing this disconnect may require expansions or revisions to existing theories and novel research designs that move beyond the common approach of focusing on statistical significance (especially of race coefficients) in regression models towards an examination of the substantive drivers of racial disparities in arrests.

Ultimately, our results yield more questions than answers. One is whether our findings extend to other police behaviors. Although we found a strong arrest-crime association at the block group level, it was an imperfect relationship and leaves unanswered what else is going on at these places of arrest concentration. Additionally, even though arrest hotspots are often crime hotspots, this study does not address whether police resources and enforcement actions are lawful or commensurate with citizens demands. Certainly, the police have different options in how they choose to respond to concentrated crime. For example, the concentration of arrests could be driven by the police reacting to more calls to service (e.g., from 911), proactive strategies such as hotspot policing, or some mixture of both. Relatedly, it’s unclear the extent to which the people being arrested are those that committed the crimes driving the police response;

or if higher crime areas that have a greater police presence results in officers detecting more low-level offenses for which they choose to make arrests (Black & Reiss, 1970).

There are four important ways to further unpack the spatial crime-arrest association. First, the place-based association between arrests and crime does not necessarily mean it is purely a place-based process, as it could reflect the aggregation of police targeting certain people or groups found in those places. Therefore, it is important to understand the extent to which spatially concentrated arrests reflect subgroups being arrested in these places, such as chronic offenders or street gangs. Prior research shows that police contact is highly skewed towards such subgroups, and within certain subunits of police organizations such as the gang unit (Fagan et al., 2016; Wolfgang et al., 1972). Second, our analyses examined all arrests and crimes, but the extent to which arrest types and crime types do or do not correspond within places would be informative. For instance, high rates of drug possession arrests in high violence areas could indicate arrests that result from pretextual reasons (Geller & Fagan, 2010). Third, our focus on block groups, while pragmatic, raises the question of whether our patterns would hold up at smaller micro-places such as street segments. The criminology of place has conclusively shown that there is value in studying finer resolutions (Weisburd et al., 2012). Hypothetically, if "problem" addresses (O'Brien & Winship, 2017) drove much of the block group level concentration this would provide greater insight as to what processes our findings represent. While we have shown arrests to be quite concentrated, 5% of block groups encompasses a larger portion of the city than is typical in studies on the criminology of place; it is worthwhile to assess these patterns at smaller scales where population level enumeration is not possible. Finally, a more systematic study of variation across departments or over time is of interest insofar as it could reveal features of police departments that produce exceptionally large disparities in certain places. These are not insignificant questions: because the sources of racial disparities are so concentrated, the answers are important for understanding racial disparities in arrests and by extension inequality in the criminal justice system.

Implications for Policy and Practice

Our findings offer several insights for policy and practice. For one, changes to arrest patterns in most parts of a city will have little impact on citywide racial and ethnic disparities in arrests. To recall, what happened in 75% of Los Angeles hardly influenced citywide disparities in arrest rates between blacks and whites/other racial groups. This is not to say that policing reforms across much of a city are worthless, but that special efforts to reduce racial disparities in arrests should target those subsets of a city that are the main drivers of these disparities.

Importantly, the findings from this study suggest that an intense focus on reducing arrest hotspots may yield outsized reductions in population-level racial disparities. In Los Angeles, we found that about half of citywide disparities in the arrest rates of African Americans came from just 5% of block groups. Targeted interventions in these arrest hotspots may be especially feasible and effective, and they are not mutually exclusive with other, departmentwide reform efforts. The police, and other relevant policymakers, thus ought to prioritize identifying arrest hotspots within their jurisdictions and thinking of how they could stem the flow of arrests from them. Of course, major social programs to break segregation or its links to concentrated disadvantage would go a long way. This is hardly a novel observation, the issue being that it is often largely out of reach in America, especially to city-level political organizations. Yet, there are different approaches that could hypothetically make a difference, that fall within the scope and capacities of police departments and local politics. The effectiveness of these various approaches, some of which we detail below, depends on what exactly is causing arrests at these hotspots.

Place-based interventions are one type of approach to address hotspots of arrests, of which there are police and non-police components. It is important that police reflect on whether all arrests are necessary in places where their arrests are most concentrated. While segregation and concentrated disadvantage serves to spatially concentrate various social problems (Massey & Denton, 1993; Sampson, 2012; Wilson, 1987), thereby acting as distal sources of racial disparities, they do not on their own determine how often arrests are used in response to crime and other social problems, or who is arrested for what in those places. If people in arrest hotspots are being arrested on mostly trivial charges, one potential reform is to simply move away from high-arrest strategies, such as street sweeps and zero-tolerance dragnet approaches. By contrast, proactive police stops and arrests that are based on actual suspicion of criminal behavior instead of lose heuristics of suspicion help reduce crime and minimize racial disparities in who is stopped by the police (MacDonald et al., 2016). Treating everyone in an area with suspicion will yield little public safety benefit and exacerbate racial disparities in police contact.

The police should consider alternative approaches to maintain and improve public safety in arrest hotspots. For example, a problem-oriented policing approach (Braga & Bond, 2008; Goldstein, 1979, 1990) would advocate for a police response that identifies the sources of crime in places and a diversity of responses that do not rely on the use of police arrest powers.[11] In this way, the police may reduce crime and other problems by addressing their key drivers, rather than simply react to them in a seemingly endless cycle of disparity-generating arrests.

Place-based anticrime initiatives are not the domain of police alone, and the police should not work in isolation from other public agencies (Goldstein, 1979, 1990). Evidence from experiments suggests that when police and other municipal agencies work with community members to reduce problem places that generate the disproportionate share of serious crime on blocks—such as a problematic bar or poorly managed apartment building—crime drops without the collateral consequences of additional arrests (Braga & Weisburd, 2010). Situational crime prevention strategies that focus on changing the structural aspects of places that generate crime could reduce serious crime in areas without displacing it nearby (Braga & Bond, 2008; Branas et al., 2018; Chalfin, Hansen, et al., 2021; MacDonald et al., 2021). Changing streetlights, cleaning up vacant lots, and remediating abandoned housing are all examples of place-based interventions that can be scaled up to high crime areas to benefit many people living in these spaces (MacDonald et al., 2019). Directing more public safety resources to improving the small percentages of places that generate most arrests could substantially reduce population-level racial disparities in arrests.[12]

To the extent to which the concentration of arrests in certain places reflects the aggregation of lower-level processes, such as gangs, homelessness, addiction, or mental health problems, then group-based approaches may especially help reduce racial disparities.[13] Many of the people that police arrest frequently are likely known to them and in many cases the police are making accurate assessments about that person's engagement with the problem or crime to which they are responding. For police, there is great value in thinking about non-arrest responses and other interventions that may help break the revolving door of arrests. Partnerships with other agencies to address what is driving higher arrest populations in particular places may be particularly beneficial. A problem-oriented policing model that focuses on a diversity of approaches and moves beyond the "standard model of policing" of using arrests as the principle response to crime in places may be particularly beneficial (Weisburd & Eck, 2004). What is important to remember with these potential responses is that focused attention on the places where arrests most concentrate stands to improve population level racial disparities the most.

These various responses contain two different pathways to reducing racial disparities in arrests. The first is by reducing the degree of crime in arrest hotspots, police could also reduce disparities in arrests for these offenses. The second is that given problems occur and spatially concentrate, non-arrest responses could be prioritized more. Several of the interventions above work simultaneously through both pathways. Of course, reducing racial disparities in arrests is not the only desirable criminal justice outcome and requires careful consideration with the goals of maintaining public safety (Manski & Nagin, 2017). Yet, many of the proposed responses could create an alignment of benefits: reduced racial disparities in arrests coupled with improved public safety.

Conclusion

Without figuring out ways to reduce arrests in the places where they are most concentrated, racial disparities in arrests will persist. Since racial disparities in arrests are the key source of racial disparities in the wider criminal justice system (A. J. Beck & Blumstein, 2018), inequality in the criminal justice system will also persist without a focus on how to reduce the spatially concentrated, high arrest rates of certain racial and ethnic groups. Understanding why arrests are so concentrated in a few places thus carries great academic and practical value for those seeking to make sense of and redress racial inequalities in the criminal justice system. We have provided a roadmap by which such an understanding might be advanced. But a key insight is already clear: by giving special attention to reducing arrests in a few key places, large improvements to racial disparities may be within reach.

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Notes

[1] In this article we use racial disparities as shorthand for racial and ethnic disparities, while being specific about which racial or ethnic groups are being compared when appropriate.

[2] Some offenses may only be recorded if the police set out to enforce laws against them, as is often the case with drug crimes. We repeated our analyses limiting offenses to FBI index crimes (excluding arson and sexual assault), felonies for which there is a direct victim. This yielded similar findings to the main analysis and all substantive conclusions are left intact (see the online Appendix for results).

[3] They are uncommon: 98 of 6,291 block groups in New York City (1.6%); 19 of 2,825 in Los Angeles (0.7%); 13 of 2,331 in Chicago (0.6%); 2 of 450 in Washington, D.C. (0.4%); 15 of 422 in Tucson (3.6%); and 1 of Colorado Spring's 296 block groups (0.3%) are missing data. Further, missing data indicates that a block group is a place like jail, large park, or airport.

[4] In the main analysis, we count block groups as part of the city even if they are only partially within city limits, counting only the crimes and arrests that happen within city limits for those block groups. In supplementary analyses, we only included block groups that were at least 90% within city limits; doing so does not meaningfully change the results.

[5] The Poisson versions of these models revealed very similar coefficients for the focal crime covariates.

[6] See the online Appendix for an analogue of Figure 7—the figure that contains the key results for the crime-focused analyses—that avoids parametric distributional or functional form assumptions but yields the same findings as this quantile-based approach.

[7] Within each city, block groups are separately ordered to calculate the line for each racial/ethnic group. As such, it is not necessarily the same small set of block groups explaining the large

fraction of arrests across races. In practice, there is substantial though imperfect overlap in the highest arrest block groups across race.

[8] The overlap would likely be even larger if race-specific measures of crime were used. For example, many of the highest crime spots in Chicago are in parts of South Chicago that have few Hispanic people in them, which limits the possible overlap between Chicago's top crime spots and the spots that drive Hispanic arrests.

[9] These values, as with all estimates shown in Figure 7, are based on the crime-arrest association obtained from Model 2, which is the model with added control variables.

[10] A notable difference across cities was whether Hispanic disparities in arrest rates relative to whites/others even existed. We did not examine why, but—*prima facie*—cities where such disparities were small or non-existent tended to be those where the Hispanic population has many immigrants, particularly from Mexico.

[11] As Eck (2006:119) notes, problem-oriented policing contains a "normative principle' that "police are supposed to reduce problems rather than simply respond to incidents and apply the relevant criminal law."

[12] Sherman (2007:299) has similarly noted that the biggest benefit for interventions to reduce crime and show efficacy of in experimental trials would be those that focus on the "power few" or "the small percentage of places, victims, offenders, police officers or other units in any distribution of crime or injustice which produces the greatest amount of harm."

[13] The place-based versus person/group-based distinction is somewhat artificial, made for expository reasons, and in any case is not mutually exclusive.

Table 1: Summary Statistics for Six Cities

	Arrests per Block Group-Month			
	Mean	S.D.	% of Population	Arrest Rate
New York City				
Black	1.88	6.03	21.80	0.46
Hispanic	1.33	4.18	29.08	0.24
White/Other	0.72	2.58	49.12	0.08
Los Angeles				
Black	0.94	4.21	8.98	0.48
Hispanic	1.55	3.76	47.67	0.15
White/Other	0.81	2.99	43.35	0.09
Chicago				
Black	1.10	2.67	28.19	0.22
Hispanic	0.24	0.72	28.80	0.05
White/Other	0.14	0.53	43.01	0.02
Washington D.C.				
Black	4.62	7.03	45.67	0.47
Hispanic	0.33	0.94	11.00	0.14
White/Other	0.44	1.68	43.33	0.05
Tucson				
Black	0.68	1.77	3.96	0.85
Hispanic	2.25	4.31	42.67	0.26
White/Other	2.25	4.05	53.37	0.21
Colorado Springs				

Table 1: Summary Statistics for Six Cities

	Arrests per Block Group-Month			
	Mean	S.D.	% of Population	Arrest Rate
Black	0.89	2.76	6.03	0.39
Hispanic	0.73	2.00	17.36	0.11
White/Other	3.23	8.89	76.61	0.11

Note: Arrest rate refers to the number of arrests per resident of that race/ethnicity over the entire study period.

Table 2: Observed versus Simulated Arrest Rates by Race/Ethnicity and City

	City					
Race/Ethnicity	NYC	LA	Chicago	DC	Tucson	CS
Arrest Rates: Observed						
Black	0.51	0.50	0.18	0.46	1.02	0.34
Hispanic	0.27	0.14	0.06	0.14	0.25	0.08
White/Other	0.11	0.10	0.03	0.04	0.21	0.10
Arrest Rates: Top 5% Crime Block Groups Removed						
Black	0.30	0.31	0.12	0.37	0.80	0.22
Hispanic	0.17	0.11	0.05	0.11	0.19	0.05
White/Other	0.07	0.07	0.02	0.03	0.16	0.07
Arrest Rates: Top 10% Crime Block Groups Removed						
Black	0.24	0.25	0.09	0.32	0.66	0.17
Hispanic	0.14	0.09	0.04	0.10	0.16	0.04
White/Other	0.06	0.06	0.02	0.03	0.14	0.05
Arrest Rates: Top 20% Crime Block Groups Removed						
Black	0.15	0.17	0.06	0.25	0.46	0.11
Hispanic	0.09	0.07	0.03	0.08	0.11	0.03

Table 2: Observed versus Simulated Arrest Rates by Race/Ethnicity and City

	City					
Race/Ethnicity	NYC	LA	Chicago	DC	Tucson	CS
White/Other	0.04	0.04	0.01	0.02	0.10	0.03

Figure 1: The Concentration of Arrests by Race Across Six Cities

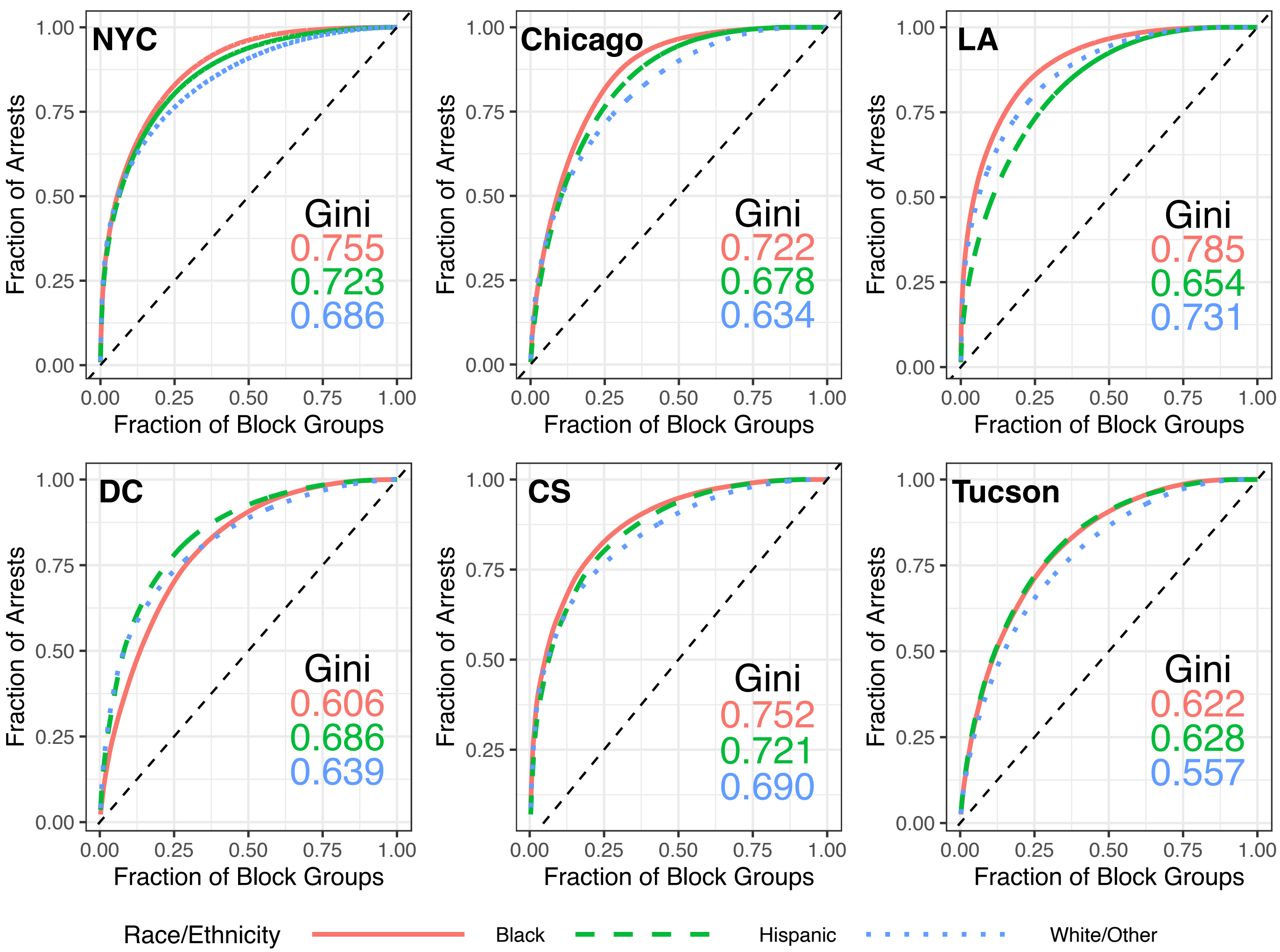


Figure 2: Citywide Racial Disparities in Arrests are Driven by a Few Places

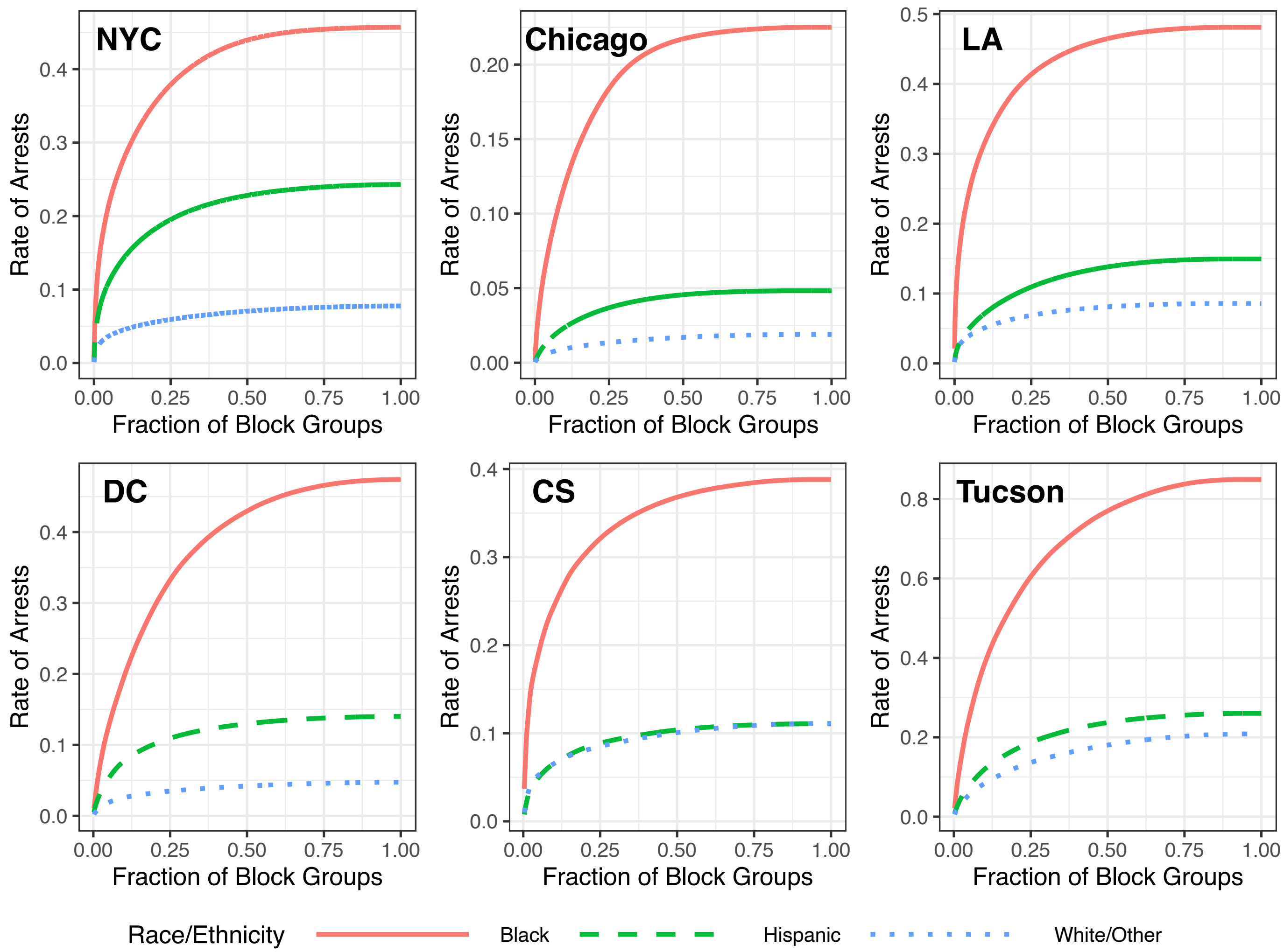


Figure 3: The Stability of the Top (20th) Arrest Quantile over Time

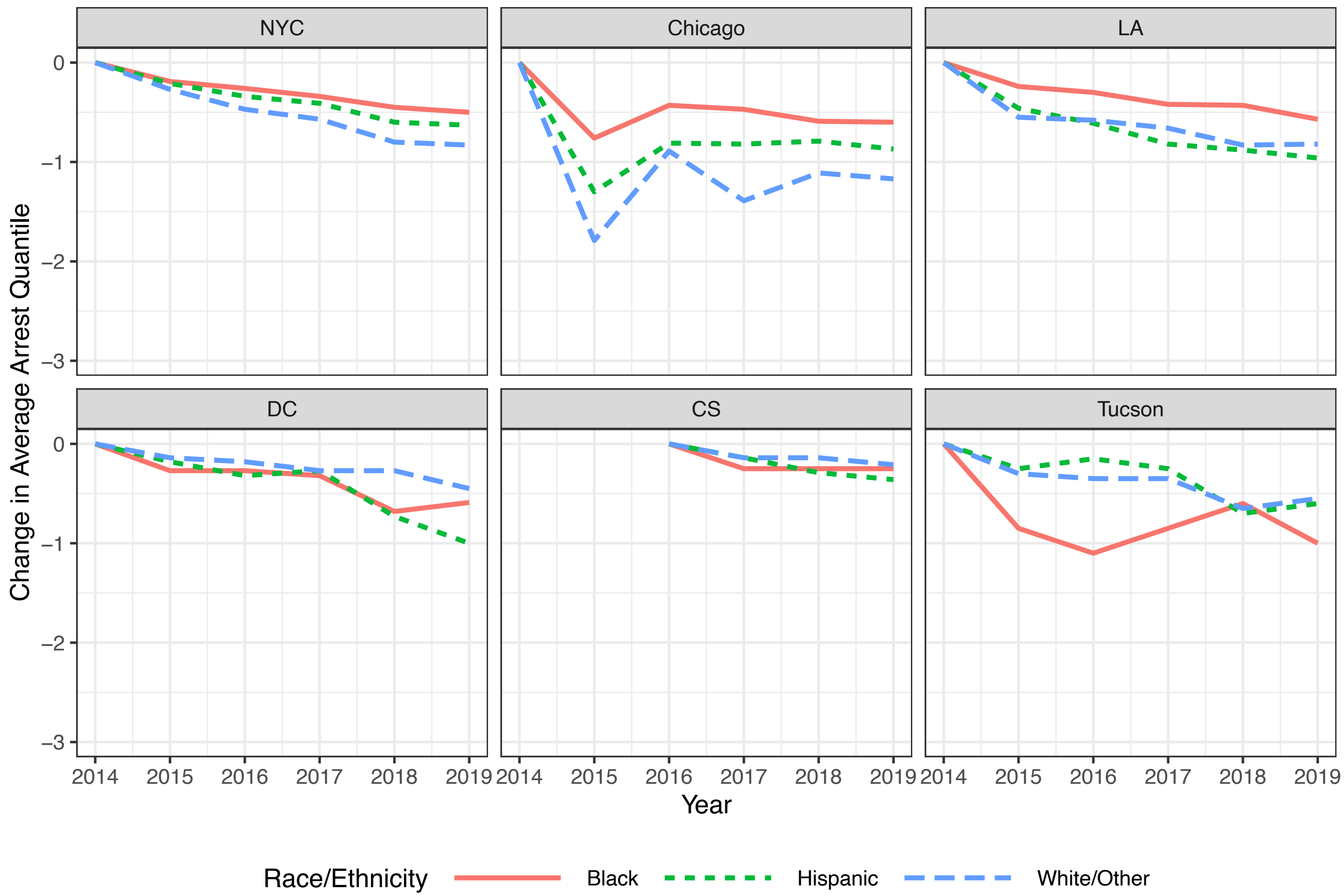


Figure 4: The Overlap in the Top Arrest and Crime Quantiles by Race

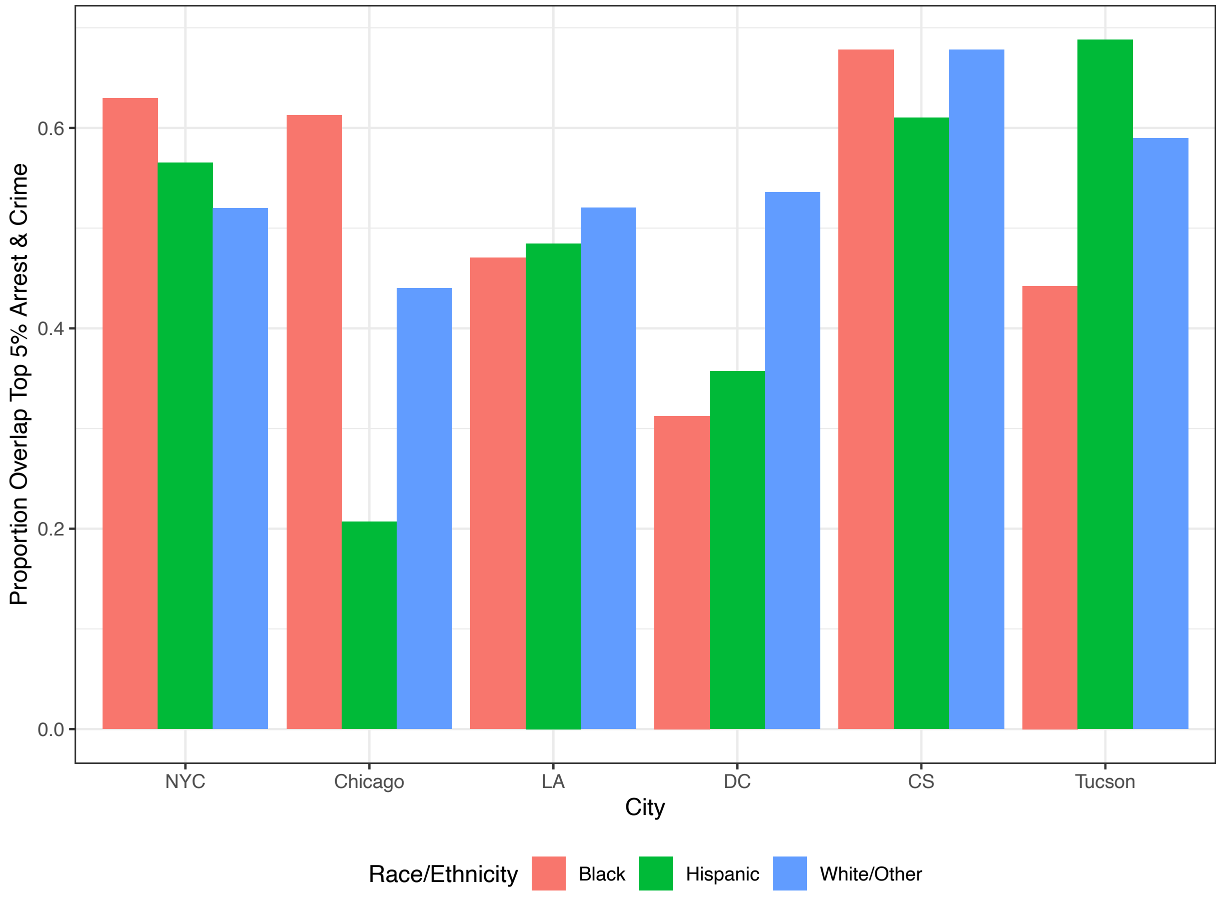


Figure 5: Unconditional Estimates of Expected Monthly Arrest Count by Race and Crime

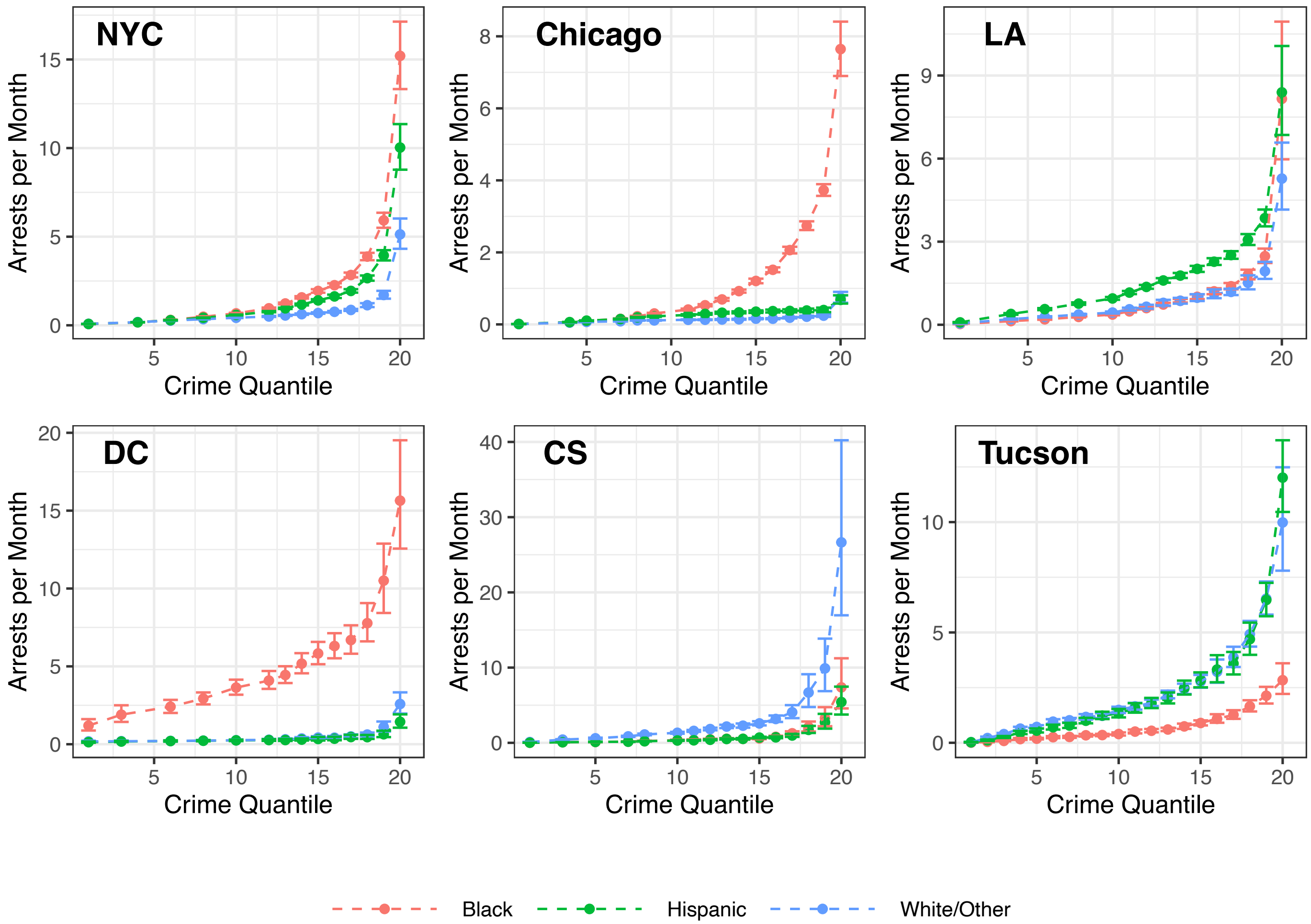


Figure 6: Conditional Estimates of Expected Monthly Arrest Count by Race and Crime

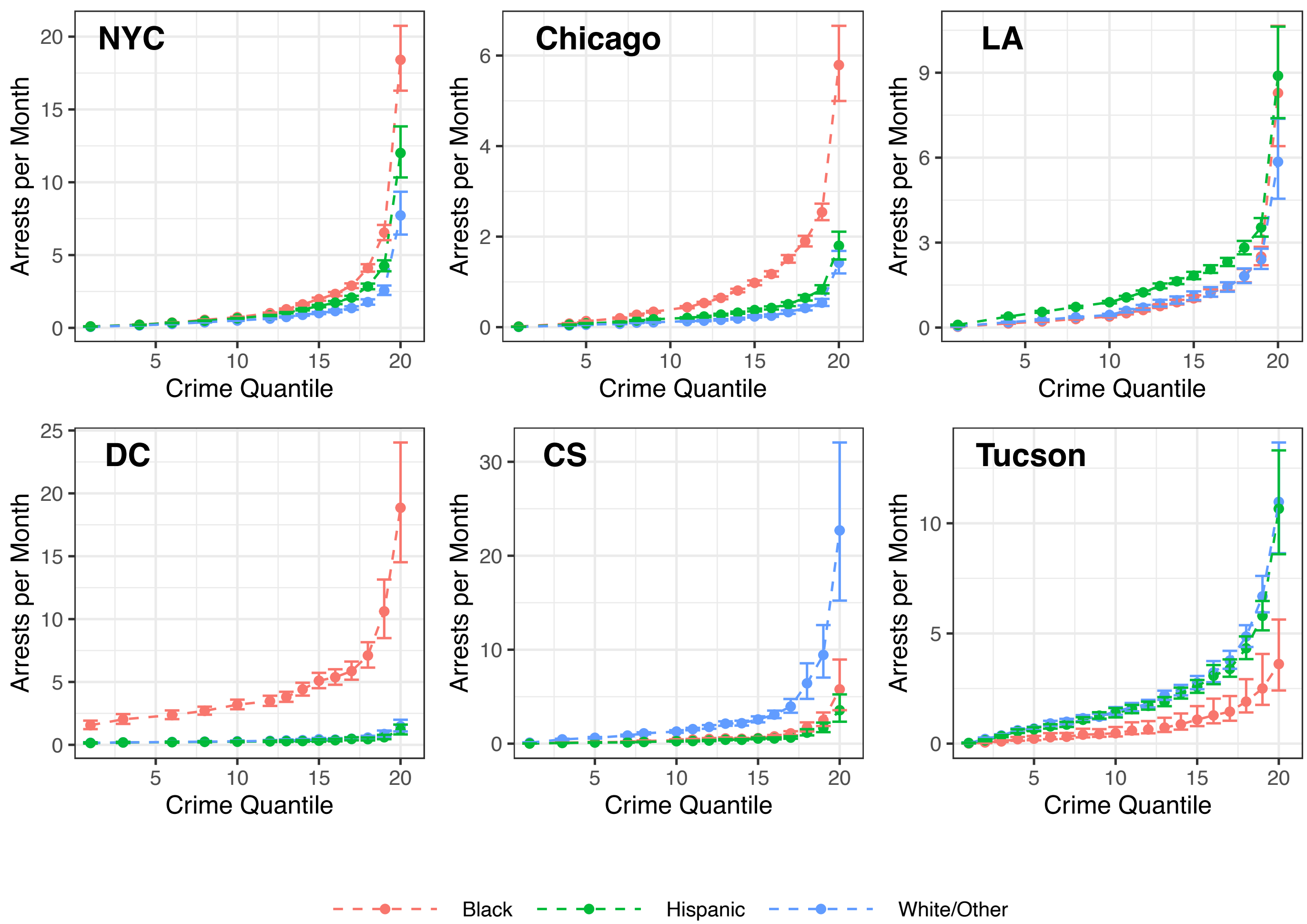
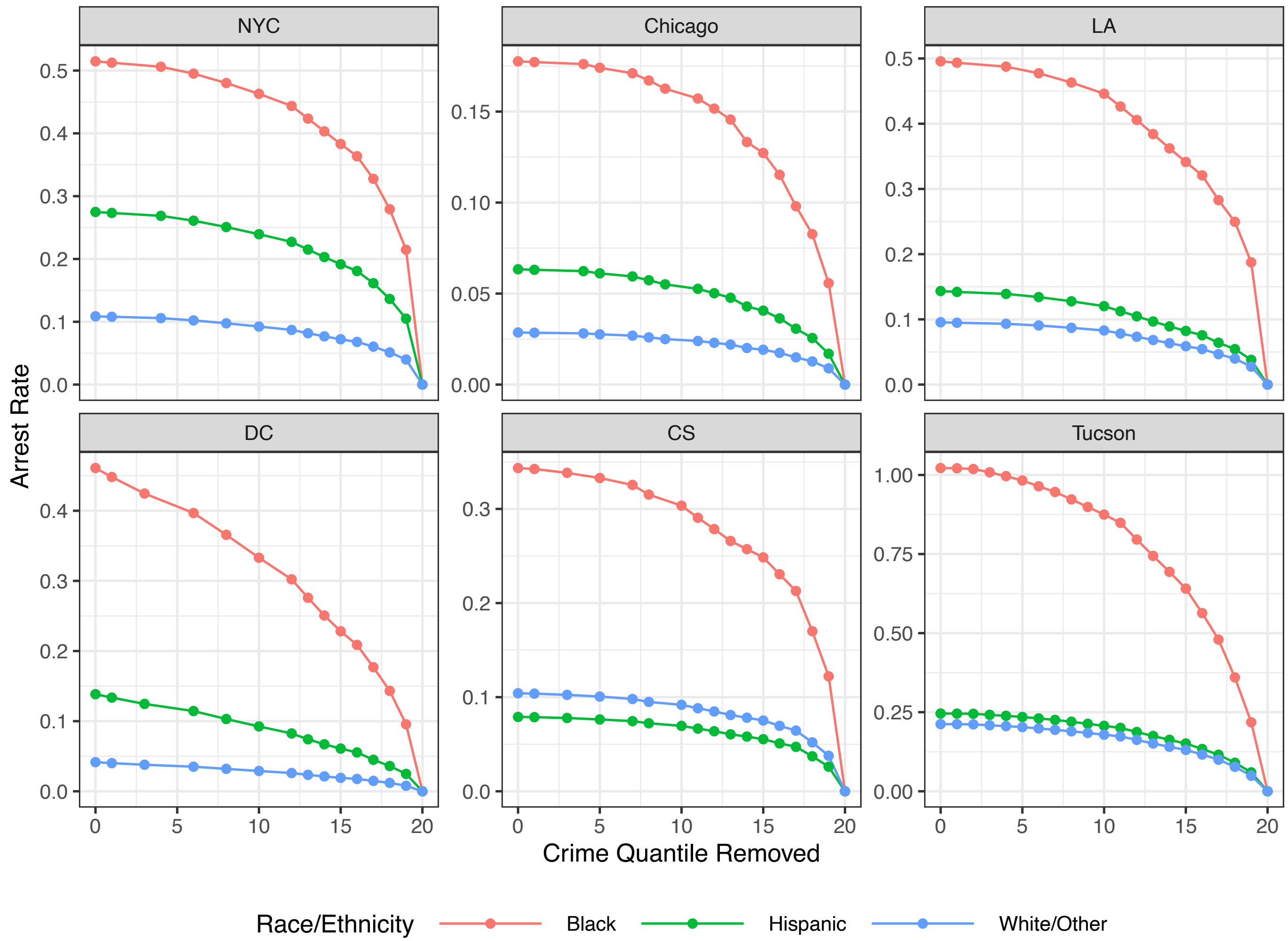


Figure 7: How Arrest Rate Changes when Removing Arrests in bottom X Crime Quantiles



Online Appendix

to

"Where Racial and Ethnic Disparities in Policing Come From: The Spatial Concentration of Arrests Across Six Cities"

I. Restricting Offenses to Index Crimes

Some crimes, such as certain drug, disorder, and traffic offenses, are unlikely to be recorded unless they are enforced by police, or at least will be strongly influenced by levels of enforcement. As such, their overlap with arrests may not be surprising insofar as the arrest incident generates the crime report. This concern is mitigated with index crimes, relatively serious crimes in which there is a direct victim, and which are typically recorded because of citizen reports to the police. As such, we repeated Model 2 but used index crime (except arson and sexual assault) as opposed to all recorded offenses.

[Figure A1 about here]

Figure A1 is analogous to Figure 6, and indeed shows a very similar pattern whereby it is the highest crime neighborhoods which have especially high arrest rates. In general, the crime-arrest relationship appears to be slightly more linear than in Figure 6, though in every case the relationship is still quite nonlinear.

[Figure A2 about here]

As a result, Figure A2, the analogue of Figure 7 but using index crimes, shows a similar pattern to the main results as well. That the curves are slightly straighter than in the main analyses indicates that index crime hotspots are slightly less responsible for driving racial disparities in arrests compared to when measuring all offenses, but again, the key finding is that the highest crime neighborhoods are those in which a disproportionate share of racial disparities are generated.

II. Nonparametric Analogue of Figure 7

Figure 7 contains the key findings for how areas of concentrated crime impact racial and ethnic disparities in arrest rates. Because it uses information drawn from Model 2, it contains that model's parametric assumptions: a negative binomial stochastic component, the use of quantiles to model crime levels, and the inclusion of a series of controls with linear terms. The worry is that these assumptions may unduly influence conclusions. To check this, we used an analogous approach that avoided these assumptions by doing the following: for each city, sort the neighborhoods by crime, then examine how the arrest rates (and disparities therein) change as arrests are progressively ignored, starting with the lowest crime block groups-months (we use block group-months, rather than block groups, to be consistent with the specification of Model 2). As with Figure 7, this reveals the extent to which arrest rates are influenced by a subset of particularly high crime neighborhoods. But it does so without quantiles, parametric distributions, or even control variables. We view this as an alternative, rather than a superior way, of examining the same question. As comparing Figures A3 to 7 makes clear, however, both approaches lead to the same conclusion: high crime areas are especially responsible for driving racial disparities in arrest rates.

[Figure A3 about here]

III. Comparing the Observed to Simulated Random Arrest Concentrations

As is the case when examining the spatial concentration of crime, an important consideration is the extent of concentration expected by chance, and how this compares to observed concentration. Even if incidents are randomly distributed throughout the city, the expected distribution may be very concentrated within a few places rather than uniformly distributed. This is particularly the case when the number of incidents is small relative to the number of places examined (Chalfin, Kaplan, et al., 2021). A larger number of places typically means a smaller spatial resolution, in that the city is cut up into finer pieces.

Our goal is thus to compare the observed results to what they would look like if there were no spatial clustering of arrests beyond that which arises randomly. To do so we simulated "null" distributions with the following procedure: for each racial group in each city, each block group was randomly assigned a certain number of arrests by drawing from a Poisson distribution with a mean (λ) equal to the observed number of arrests divided by the number of block groups. We repeated this procedure 1000 times and took the mean values of those 1000 simulations to average out the simulation variation, which was quite small. This procedure is similar in spirit to that advanced by Chalfin et al. (2021), who randomly assign incidents to places with replacement; indeed, additional simulations (not presented) revealed that both methods get the same answer in expectation.

[Figure A4 about here]

To simplify the presentation of results, we focus on two important values: Gini coefficients and the fraction of arrests that happened in the highest-arrest areas (those in the top 5% of the arrest distribution). Figure A4 presents these results for each city and racial group. The observed Gini coefficients are far larger than the simulated values, meaning that the degree of arrest concentration we observe far exceeds what would be expected if arrests were distributed randomly. Similarly, the top 5% highest-arrest areas in our data account for about 40% of arrests, give or take roughly 10%. In contrast, the expected number of arrests accounted for by these blocks is slightly above 5%. That the simulated value is close to 5% reflects that there are many arrests relative to the number of places examined. Clearly, our results diverge sharply from what would have been observed if arrests were randomly distributed across space.

Table A1: Model 1 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Intercept	-2.615 (0.041)	-2.523 (0.031)	-2.576 (0.035)	-3.609 (0.076)	-3.045 (0.077)	-2.463 (0.074)	-4.623 (0.091)	-4.573 (0.08)	-4.509 (0.083)	0.166 (0.153)	-1.724 (0.122)	-2.053 (0.162)	-5.406 (0.575)	-3.758 (0.328)	-3.739 (0.301)	-4.165 (0.274)	-2.373 (0.172)	-4.256 (0.249)
Crime2													2.23 (0.445)	2.21 (0.298)	1.54 (0.297)			
Crime3										0.467 (0.066)	0.07 (0.096)	0.293 (0.104)	2.926 (0.551)	2.821 (0.321)	2.39 (0.301)	1.659 (0.308)	1.519 (0.18)	1.619 (0.267)
Crime4	0.837 (0.034)	0.799 (0.03)	0.8 (0.033)	1.581 (0.075)	1.453 (0.073)	1.521 (0.066)	1.746 (0.097)	1.572 (0.087)	1.749 (0.087)				3.61 (0.576)	3.311 (0.332)	2.963 (0.307)			
Crime5							2.315 (0.095)	1.905 (0.087)	2.244 (0.086)				3.72 (0.585)	3.42 (0.336)	3.138 (0.314)	1.988 (0.293)	1.862 (0.182)	2.157 (0.257)
Crime6	1.41 (0.035)	1.191 (0.032)	1.331 (0.034)	1.975 (0.074)	1.786 (0.072)	1.89 (0.063)				0.71 (0.1)	0.156 (0.119)	0.463 (0.127)	4.027 (0.584)	3.713 (0.332)	3.384 (0.313)			
Crime7							2.747 (0.095)	2.132 (0.086)	2.601 (0.082)				4.069 (0.582)	3.774 (0.332)	3.488 (0.312)	2.318 (0.29)	2.214 (0.178)	2.323 (0.262)
Crime8	1.888 (0.039)	1.464 (0.036)	1.719 (0.037)	2.341 (0.076)	2.046 (0.078)	2.191 (0.071)	3.133 (0.095)	2.379 (0.085)	2.875 (0.084)	0.907 (0.13)	0.248 (0.135)	0.551 (0.151)	4.323 (0.583)	3.913 (0.333)	3.733 (0.308)	2.748 (0.275)	2.478 (0.179)	2.672 (0.257)
Crime9							3.431 (0.095)	2.372 (0.087)	3.013 (0.087)				4.352 (0.582)	3.958 (0.332)	3.943 (0.309)			

Table A1: Model 1 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Crime10	2.221	1.666	2.036	2.61	2.224	2.41				1.12	0.352	0.649	4.477	4.154	4.02	3.112	2.659	3.086
	(0.041)	(0.035)	(0.037)	(0.08)	(0.082)	(0.072)				(0.146)	(0.146)	(0.151)	(0.583)	(0.332)	(0.309)	(0.288)	(0.18)	(0.262)
Crime11				2.88	2.462	2.612	3.736	2.517	3.174				4.725	4.257	4.183	3.218	2.832	3.151
				(0.081)	(0.088)	(0.074)	(0.095)	(0.088)	(0.087)				(0.582)	(0.332)	(0.308)	(0.289)	(0.178)	(0.262)
Crime12	2.573	1.826	2.312	3.099	2.615	2.775	3.991	2.527	3.275	1.237	0.468	0.724	4.793	4.349	4.316	3.398	2.976	3.354
	(0.043)	(0.04)	(0.039)	(0.082)	(0.093)	(0.076)	(0.095)	(0.09)	(0.089)	(0.153)	(0.144)	(0.175)	(0.58)	(0.331)	(0.308)	(0.291)	(0.179)	(0.262)
Crime13	2.823	1.936	2.531	3.294	2.809	2.932	4.257	2.575	3.382	1.323	0.559	0.728	4.896	4.538	4.439	3.529	3.143	3.583
	(0.043)	(0.036)	(0.039)	(0.084)	(0.102)	(0.077)	(0.095)	(0.091)	(0.091)	(0.154)	(0.144)	(0.194)	(0.579)	(0.33)	(0.308)	(0.285)	(0.178)	(0.261)
Crime14	3.069	2.057	2.734	3.462	2.899	3.036	4.544	2.619	3.414	1.474	0.717	0.827	5.105	4.648	4.644	3.504	3.194	3.609
	(0.045)	(0.043)	(0.041)	(0.084)	(0.097)	(0.077)	(0.094)	(0.091)	(0.092)	(0.162)	(0.163)	(0.194)	(0.582)	(0.331)	(0.308)	(0.289)	(0.184)	(0.267)
Crime15	3.275	2.152	2.916	3.615	3.019	3.164	4.811	2.729	3.469	1.595	0.867	0.942	5.294	4.777	4.777	3.617	3.322	3.888
	(0.048)	(0.042)	(0.042)	(0.087)	(0.099)	(0.078)	(0.095)	(0.097)	(0.096)	(0.164)	(0.154)	(0.231)	(0.579)	(0.332)	(0.307)	(0.288)	(0.18)	(0.261)
Crime16	3.43	2.25	3.064	3.793	3.15	3.286	5.039	2.725	3.512	1.674	0.848	0.997	5.481	4.923	4.932	3.934	3.524	3.936
	(0.047)	(0.045)	(0.046)	(0.088)	(0.106)	(0.078)	(0.094)	(0.094)	(0.098)	(0.164)	(0.17)	(0.219)	(0.583)	(0.338)	(0.316)	(0.287)	(0.185)	(0.266)
Crime17	3.657	2.379	3.238	3.937	3.216	3.385	5.347	2.893	3.525	1.734	1.024	1.262	5.638	5.111	5.013	4.395	3.769	4.219
	(0.047)	(0.045)	(0.044)	(0.086)	(0.091)	(0.078)	(0.094)	(0.096)	(0.101)	(0.167)	(0.171)	(0.216)	(0.581)	(0.333)	(0.311)	(0.289)	(0.202)	(0.271)
Crime18	3.969	2.649	3.554	4.198	3.459	3.584	5.63	3.027	3.557	1.883	1.244	1.252	5.904	5.35	5.28	4.891	4.257	4.788
	(0.049)	(0.058)	(0.045)	(0.09)	(0.115)	(0.08)	(0.094)	(0.103)	(0.106)	(0.173)	(0.161)	(0.216)	(0.581)	(0.333)	(0.312)	(0.317)	(0.239)	(0.286)

Table A1: Model 1 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Crime19	4.393 (0.056)	3.06 (0.071)	3.947 (0.052)	4.514 (0.093)	3.703 (0.112)	3.81 (0.083)	5.938 (0.094)	3.154 (0.109)	3.587 (0.116)	2.183 (0.187)	1.815 (0.193)	1.592 (0.23)	6.158 (0.583)	5.633 (0.333)	5.602 (0.307)	5.334 (0.334)	4.644 (0.251)	5.238 (0.313)
Crime20	5.335 (0.075)	4.16 (0.088)	4.88 (0.077)	5.698 (0.174)	4.704 (0.141)	4.585 (0.123)	6.656 (0.104)	4.266 (0.129)	4.124 (0.118)	2.576 (0.188)	2.661 (0.182)	2.407 (0.22)	6.445 (0.589)	6.052 (0.348)	6.223 (0.309)	6.134 (0.36)	5.637 (0.279)	5.93 (0.307)

Note: Coefficients are on logarithmic scale. Cluster-robust standard errors in parentheses. Crime# represents quantiles. Rows missing coefficients are those in which 20 perfect crime quantiles could not be formed, often due to many block groups having no or almost no crime.

Table A2: Model 2 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Intercept	-2.441	-1.703	-2.43	-3.164	-1.554	-2.333	-4.158	-3.78	-4.692	-0.434	-0.73	-2.721	-4.81	-3.206	-4.268	-3.979	-1.953	-4.467
	(0.072)	(0.062)	(0.071)	(0.157)	(0.154)	(0.115)	(0.107)	(0.112)	(0.116)	(0.165)	(0.192)	(0.227)	(0.574)	(0.344)	(0.318)	(0.373)	(0.244)	(0.329)
Crime2													2.118	2.147	1.717			
													(0.446)	(0.314)	(0.309)			
Crime3										0.266	0.194	0.282	2.766	2.731	2.546	1.655	1.513	1.64
										(0.063)	(0.102)	(0.115)	(0.555)	(0.336)	(0.311)	(0.316)	(0.184)	(0.274)
Crime4	0.778	0.842	0.789	1.678	1.446	1.429	1.729	1.616	1.654				3.428	3.216	3.051			
	(0.034)	(0.03)	(0.035)	(0.091)	(0.077)	(0.068)	(0.097)	(0.088)	(0.095)				(0.584)	(0.348)	(0.312)			
Crime5							2.261	2.021	2.093				3.544	3.338	3.197	1.955	1.821	2.165
							(0.095)	(0.088)	(0.093)				(0.596)	(0.352)	(0.316)	(0.301)	(0.184)	(0.264)
Crime6	1.287	1.316	1.283	2.059	1.809	1.777				0.422	0.357	0.391	3.816	3.631	3.382			
	(0.035)	(0.033)	(0.036)	(0.089)	(0.076)	(0.065)				(0.074)	(0.124)	(0.136)	(0.594)	(0.348)	(0.315)			
Crime7							2.646	2.321	2.399				3.876	3.707	3.483	2.222	2.151	2.282
							(0.095)	(0.087)	(0.09)				(0.594)	(0.35)	(0.316)	(0.297)	(0.18)	(0.267)
Crime8	1.7	1.671	1.64	2.397	2.108	2.053	2.975	2.636	2.67	0.555	0.474	0.519	4.151	3.861	3.71	2.603	2.39	2.577
	(0.038)	(0.039)	(0.04)	(0.091)	(0.082)	(0.074)	(0.096)	(0.087)	(0.093)	(0.089)	(0.139)	(0.164)	(0.595)	(0.351)	(0.312)	(0.287)	(0.183)	(0.263)
Crime9							3.191	2.712	2.833				4.194	3.915	3.867			
							(0.096)	(0.088)	(0.093)				(0.594)	(0.35)	(0.313)			

Table A2: Model 2 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Crime10	1.992	1.949	1.928	2.656	2.311	2.26				0.723	0.582	0.567	4.29	4.104	3.945	2.915	2.551	2.948
	(0.04)	(0.04)	(0.041)	(0.094)	(0.086)	(0.074)				(0.098)	(0.146)	(0.166)	(0.594)	(0.349)	(0.313)	(0.3)	(0.184)	(0.269)
Crime11				2.915	2.59	2.434	3.451	2.915	2.998				4.522	4.216	4.072	3.016	2.736	3.014
				(0.096)	(0.093)	(0.078)	(0.098)	(0.09)	(0.094)				(0.593)	(0.35)	(0.314)	(0.3)	(0.183)	(0.269)
Crime12	2.307	2.18	2.186	3.119	2.769	2.59	3.642	2.998	3.133	0.805	0.696	0.66	4.598	4.305	4.165	3.171	2.873	3.185
	(0.043)	(0.047)	(0.043)	(0.097)	(0.098)	(0.079)	(0.098)	(0.091)	(0.095)	(0.104)	(0.144)	(0.187)	(0.59)	(0.349)	(0.311)	(0.303)	(0.184)	(0.271)
Crime13	2.543	2.345	2.39	3.321	2.953	2.755	3.835	3.116	3.298	0.899	0.799	0.718	4.726	4.502	4.268	3.278	3.054	3.415
	(0.045)	(0.046)	(0.043)	(0.099)	(0.105)	(0.083)	(0.099)	(0.093)	(0.096)	(0.108)	(0.147)	(0.2)	(0.589)	(0.348)	(0.312)	(0.297)	(0.186)	(0.268)
Crime14	2.777	2.523	2.58	3.488	3.079	2.863	4.059	3.273	3.439	1.044	0.848	0.75	4.909	4.602	4.451	3.208	3.075	3.402
	(0.047)	(0.055)	(0.046)	(0.1)	(0.103)	(0.084)	(0.1)	(0.092)	(0.098)	(0.116)	(0.159)	(0.203)	(0.59)	(0.348)	(0.312)	(0.299)	(0.188)	(0.275)
Crime15	2.976	2.65	2.753	3.631	3.221	2.978	4.25	3.499	3.608	1.191	1.039	0.85	5.126	4.733	4.575	3.344	3.244	3.682
	(0.051)	(0.056)	(0.048)	(0.102)	(0.107)	(0.086)	(0.101)	(0.097)	(0.1)	(0.118)	(0.155)	(0.225)	(0.59)	(0.349)	(0.312)	(0.3)	(0.187)	(0.267)
Crime16	3.144	2.776	2.899	3.795	3.337	3.095	4.432	3.567	3.723	1.245	0.966	0.951	5.291	4.891	4.751	3.601	3.426	3.689
	(0.051)	(0.059)	(0.052)	(0.104)	(0.107)	(0.085)	(0.101)	(0.095)	(0.1)	(0.123)	(0.168)	(0.218)	(0.588)	(0.349)	(0.313)	(0.298)	(0.19)	(0.272)
Crime17	3.361	2.942	3.082	3.963	3.471	3.21	4.682	3.839	3.903	1.33	1.116	1.185	5.412	5.045	4.849	3.954	3.673	3.852
	(0.051)	(0.062)	(0.051)	(0.102)	(0.101)	(0.085)	(0.103)	(0.096)	(0.101)	(0.128)	(0.168)	(0.212)	(0.589)	(0.347)	(0.312)	(0.3)	(0.205)	(0.276)
Crime18	3.712	3.205	3.394	4.198	3.713	3.41	4.913	4.079	4.147	1.521	1.291	1.164	5.685	5.299	5.093	4.405	4.152	4.443
	(0.055)	(0.071)	(0.056)	(0.11)	(0.112)	(0.09)	(0.104)	(0.103)	(0.103)	(0.135)	(0.169)	(0.207)	(0.589)	(0.348)	(0.312)	(0.317)	(0.241)	(0.291)

Table A2: Model 2 Regression Output

	NYC			LA			Chicago			DC			Tucson			CS		
Variable	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other	Black	Hispanic	White/Other
Crime19	4.176 (0.06)	3.576 (0.081)	3.797 (0.063)	4.518 (0.11)	3.993 (0.112)	3.633 (0.092)	5.204 (0.107)	4.326 (0.106)	4.396 (0.109)	1.917 (0.164)	1.687 (0.192)	1.452 (0.208)	5.955 (0.592)	5.613 (0.352)	5.387 (0.315)	4.774 (0.319)	4.537 (0.242)	4.79 (0.299)
crime20	5.211 (0.079)	4.679 (0.102)	4.833 (0.084)	5.706 (0.161)	4.881 (0.141)	4.545 (0.122)	6.027 (0.127)	5.291 (0.121)	5.167 (0.128)	2.492 (0.183)	2.236 (0.191)	2.123 (0.206)	6.333 (0.596)	6.106 (0.368)	5.999 (0.331)	5.595 (0.353)	5.411 (0.256)	5.542 (0.314)
Land Area	-0.311 (0.135)	0.689 (0.102)	-0.148 (0.102)	-0.359 (0.138)	-0.036 (0.027)	-0.004 (0.015)	0.042 (0.038)	0.023 (0.059)	-0.021 (0.031)	-0.01 (0.243)	0.845 (0.193)	-0.072 (0.305)	-0.011 (0.015)	0 (0.004)	-0.002 (0.005)	-0.005 (0.004)	0.004 (0.005)	0.001 (0.004)
Total Pop.	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Disadvantage	-0.004 (0.014)	0.035 (0.013)	0.016 (0.014)	0.116 (0.029)	-0.015 (0.048)	0.1 (0.027)	0.053 (0.014)	0.036 (0.025)	0.088 (0.022)	0.224 (0.032)	0.215 (0.036)	0.005 (0.062)	0.097 (0.028)	0.075 (0.019)	0.097 (0.022)	0.1 (0.04)	0.063 (0.031)	0.064 (0.038)
Youth Pop.	-0.551 (0.249)	-0.199 (0.244)	-0.546 (0.253)	-2.343 (0.418)	-2.976 (0.486)	-2.572 (0.312)	-0.579 (0.201)	0.678 (0.276)	-0.205 (0.262)	-2.765 (0.608)	-4.673 (0.541)	-4.204 (0.764)	-0.153 (1.026)	-0.034 (0.918)	-1.625 (1.005)	-1.42 (0.916)	-1.617 (0.674)	-1.059 (0.801)
Black Pop.	1.82 (0.06)	-2.423 (0.196)	-0.768 (0.106)	2.546 (0.145)	-3.073 (0.331)	-1.383 (0.165)	0.978 (0.079)	-2.741 (0.119)	-1.75 (0.119)	1.586 (0.191)	-1.404 (0.217)	0.761 (0.327)	2.217 (0.688)	0.669 (0.601)	1.339 (0.673)	2.378 (0.815)	0.002 (0.963)	1.954 (0.912)
Hispanic Pop.	0.173 (0.093)	-1.704 (0.1)	1.736 (0.083)	0.447 (0.134)	-1.001 (0.167)	1.604 (0.103)	-0.361 (0.098)	-1.014 (0.093)	2.01 (0.088)	0.017 (0.398)	0.013 (0.399)	6.012 (0.425)	-0.913 (0.291)	-1.089 (0.25)	1.895 (0.235)	1.955 (0.661)	0.463 (0.763)	2.055 (0.638)

Note: Coefficients are on logarithmic scale. Cluster-robust standard errors in parentheses. Crime# represents quantiles. Rows missing coefficients are those in which 20 perfect crime quantiles could not be formed, often due to many block groups having no or almost no crime. This model also contains month and year fixed effects (coefficients not shown).

Figure A1: Conditional Estimates of Expected Monthly Arrest Count by Race and Index Crime

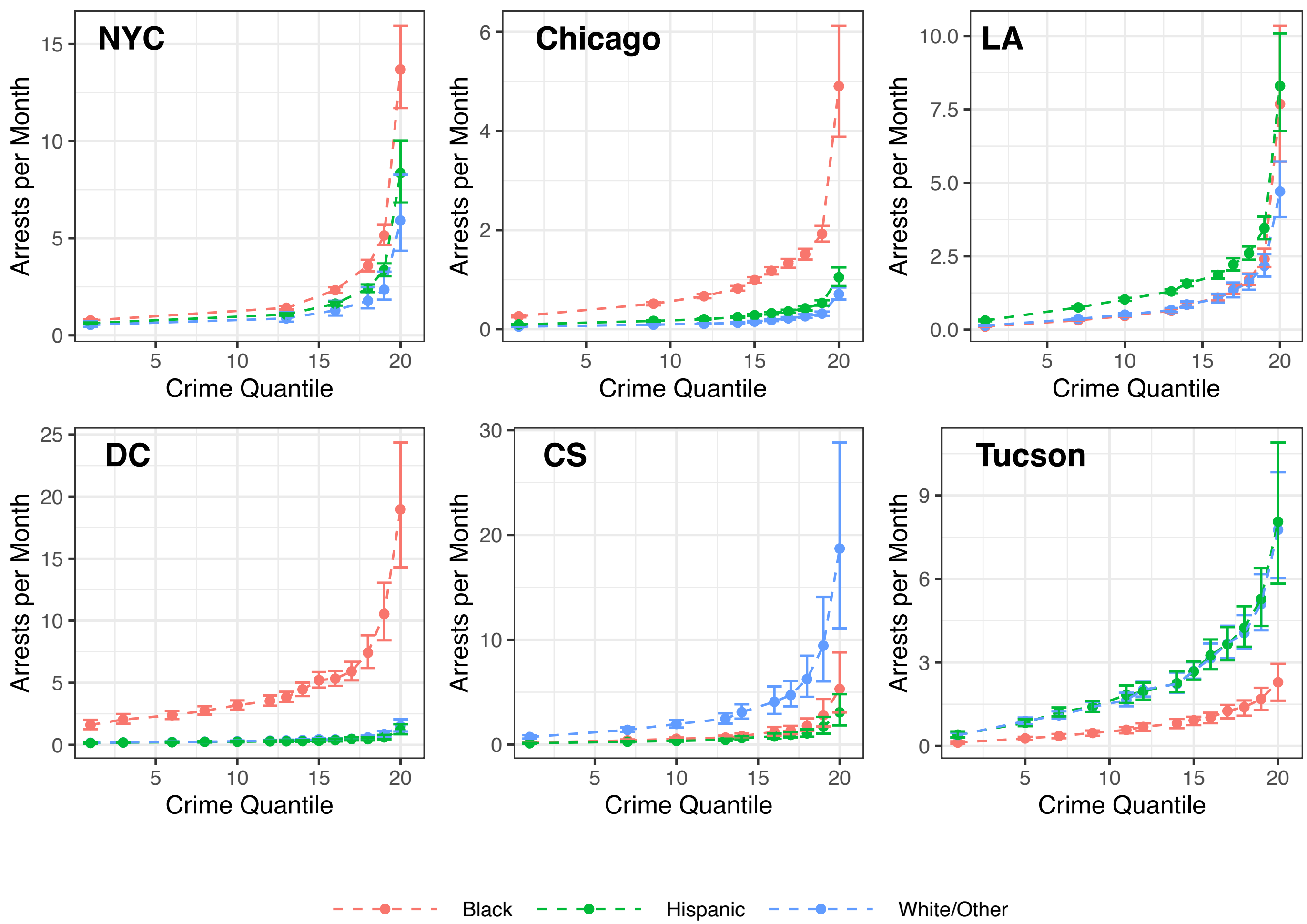


Figure A2: How Arrest Rate Changes when Removing Arrests in bottom X Index Crime Quantiles

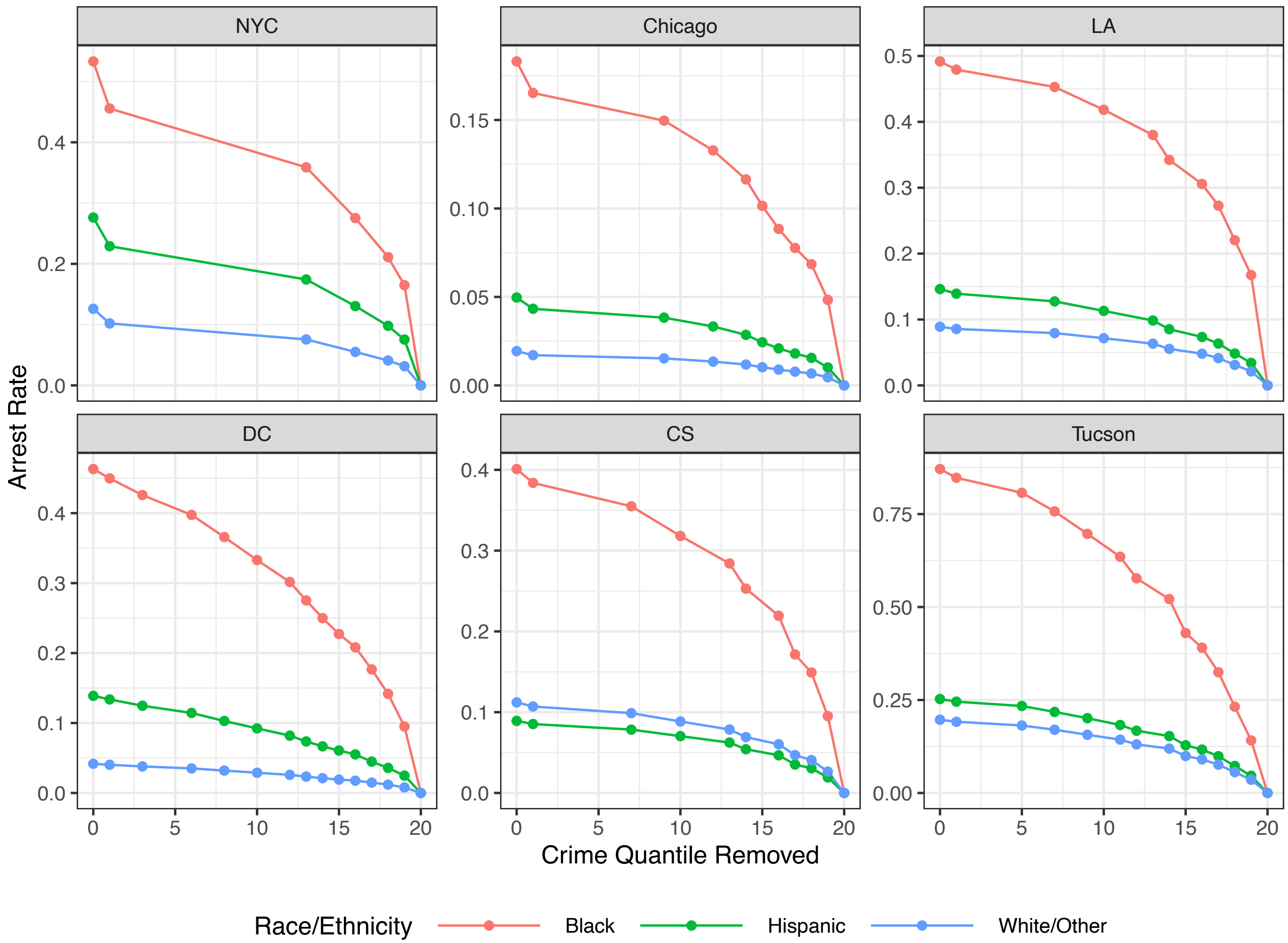


Figure A3: How Arrest Rate Changes when Removing Arrests in Lowest Crime Places

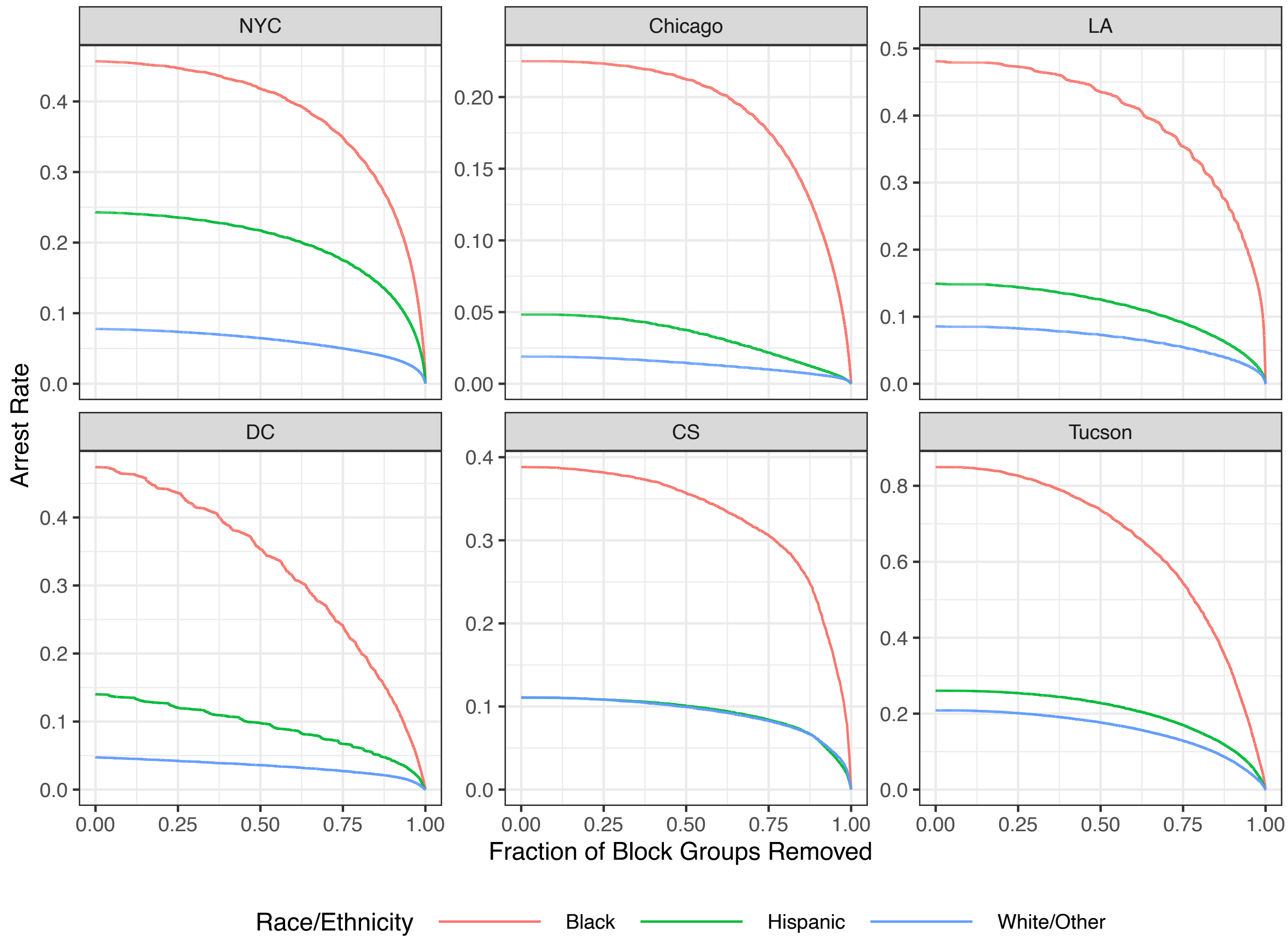


Figure A4: Observed Quantities versus Simulated Null Values