From the Block to the Beat: How Violence in Officers' Neighborhoods Influences Racially Biased Policing[1]

Samuel Thomas Donahue
Harvard University

Gerard Torrats-Espinosa
Columbia University

Research on the relationship between police discrimination and place has focused on a single context: the workplace. Yet, theories of exclusion and group identity suggest that where people live shapes their perceptions and actions. This article bridges this gap by investigating how homicides near officers' homes influence their behavior on duty. We link administrative records from the Chicago Police Department with voter registration data to create a novel dataset capturing officers' demographic backgrounds, policing activity, and residential contexts. Our quasi-experimental design exploits the exogenous timing of homicides near officers' homes relative to their work schedules. We find that White officers use force against Black pedestrians more frequently in the week following a homicide in their neighborhood. By demonstrating how violence near officers' homes influences legally sanctioned violence in other neighborhoods, our study reveals a pathway through which violence diffuses across the city and between social groups.

INTRODUCTION

Does the residential context of police officers influence their workplace behavior? In cities like Chicago, Los Angeles, and New York, the presence of

[1] Both authors contributed equally and are listed alphabetically. We thank Peter Bearman, Adam Reich, Kiron Roy, Mario Small, Bruce Western, George Wood, Patrick

 https://doi.org/10.1086/734296

highly segregated police enclaves is common knowledge. In New York City, for example, many White NYPD officers live in Breezy Point, a gated, cooperative community at the western end of the Rockaway peninsula (Kilgannon 2020). In Los Angeles, many LAPD officers reside in Simi Valley, an area that gained national attention for hosting the trial of the officers involved in the beating of Rodney King—an event whose acquittals sparked the 1992 Los Angeles Riots (Mikulan 2002). And in Chicago, a significant proportion of the city's White police officers reside in Mount Greenwood, a neighborhood on the southwestern edge of the city (Briscoe 2016).

Theories of place and community suggest that residential contexts are unique in their social importance (Gieryn 2000). People ascribe symbolic meanings to the places they live, and these places can shape their personal identity and sense of belonging (Sampson 2012). In the now-classic monograph, *Great American City*, Robert Sampson (2012, p. 54) illustrates how neighborhoods serve as "markers for one's station in life and are frequently invoked for this purpose." Others have shown that the conditions in one's neighborhood profoundly impact important social and economic outcomes (see Sampson, Morenoff, and Gannon-Rowley et al. [2002] and Sharkey and Faber [2014] for reviews).

Given its importance, it is perhaps unsurprising that residential context plays a crucial role in theories of racial discrimination (Blumer 1958; Blalock 1967). White residents have been shown to interpret the presence of minority groups as a sign of neighborhood disorder and criminal activity (Quillian and Pager 2001; Sampson and Raudenbush 2004) and tend to be more politically active when living near large minority populations (Enos 2016). To that effect, researchers have long documented White residents' efforts to maintain control over the racial demographics of their neighborhoods, from opposition to busing in the 1960s (Bobo 1983) to decisions about relocation (Emerson, Yancey, and Chai 2001).

Despite evidence that residential context can shape discriminatory attitudes (Blalock 1967; Bobo and Zubrinsky 1996; Oliver and Mendelberg 2000; Louie and DeAngelis 2024) and behaviors (Sampson et al. 2002; Enos 2016), research on racial bias in policing has largely overlooked the role

Youngblood, and four *AJS* reviewers for their valuable feedback. We also thank Matt Chapman at Lucy Parsons Lab. This project was supported by a Russell Sage Foundation Trustee Grant. Direct correspondence to either author: Samuel Thomas Donahue, Department of Sociology, Harvard University, William James Hall, Sixth Floor, 33 Kirkland Street, Cambridge, Massachusetts 02138. Email: sd3184@columbia.edu; or Gerard Torrats-Espinosa, Department of Sociology, Columbia University, Knox Hall, 606 West 122nd Street, New York, New York 10027. Email: gerard.torrats@columbia.edu.

of officers' residential context. Instead, this research has focused on how characteristics of the workplace (Smith 1986; Novak and Chamlin 2012; Renauer 2012; Smith and Holmes 2014; Shoub et al. 2020; Omori, Lautenschlager, and Stoler 2022) or macrospatial processes at the municipal and county level (Stolzenberg, D'Alessio, and Eitle 2004; Kent and Jacobs 2005; Stults and Baumer 2007; Carmichael and Kent 2014; Kent and Carmichael 2014; Legewie and Fagan 2016) correlate with officer behavior.

In this article, we attend to this gap by investigating whether violence near the homes of Chicago Police Department (CPD) officers impacts their workplace behavior. Using linked administrative data on officers' residential addresses, daily assignments, and records of contact with civilians, we estimate the causal effect of homicides that occur near officers' homes on the probability that those officers stop, arrest, or use force against Black, White, and Hispanic pedestrians.

Our findings reveal that when a homicide occurs near a White officer's home, the probability that the officer uses force against Black pedestrians increases sevenfold for the following week. This effect is not observed for Black or Hispanic officers or during encounters with White or Hispanic civilians. Additionally, this increase in discrimination is specifically associated with homicides in which the suspect is Black or perceived as Black. By considering how the meanings attributed to and attachments formed with the places (Gieryn 2000) can amplify feelings of racial threat, these findings contribute to a large literature on discrimination and group position (Blumer 1958; Blalock 1967; Quillian 1996; Bobo 1999; Eitle, D'Alessio, and Stolzenberg 2002; Stults and Baumer 2007; Legewie 2016; Legewie and Fagan 2016; Abascal 2020).

Alongside contributions to a large literature on racial threat, these findings extend a growing body of research on the spatial patterning of racial discrimination (Blalock 1967; Quillian 1995; Quillian and Pager 2001; Sampson and Raudenbush 2004; Legewie and Fagan 2016; Mobasseri 2019) and is one of the first studies to address the effect of residential proximity to violence on workplace behaviors. Furthermore, by showing how events that occur near an officer's home can cascade into violence in other parts of the city, this study contributes to recent research on the geographic structure and networked nature of violence (Legewie and Schaeffer 2016; Papachristos and Bastomski 2018; Ouellet et al. 2019; Wood, Roithmayr, and Papachristos 2019; Zhao and Papachristos 2020).

RACIAL DISPARITIES IN POLICING

Violent encounters with police and racial disparities in police contact continue to draw public outrage and elicit widespread pressure for reform (Buchanan, Bui, and Patel 2020; Olzak 2021). Despite these calls, racial disparities are still found in almost every measure of police contact, from traffic stops (Lundman and Kaufman 2003; Epp, Maynard-Moody, and Haider-Markel 2014; Pierson et al. 2020; Shoub et al. 2020; Grosjean et al. 2022) to arrests (Beckett, Nyrop, and Pfingst 2006; Ba et al. 2021). Yet disparities in the use of force are among the most severe and consequential (Legewie 2016; Legewie and Fagan 2016; Ba et al. 2021; Bell 2021; Lett et al. 2021). For example, exposure to direct and vicarious police violence impairs performance in school, altering the educational trajectories of children and adolescents (Kirk and Sampson 2013; Gottlieb and Wilson 2019; Legewie and Fagan 2019; Ang 2021; Legewie and Cricco 2022), and can increase symptoms of depression and anxiety (Geller, Tyler, and Link 2014; Bor et al. 2018; DeVylder et al. 2018).

The predictors of racial discrimination in policing are extensive, and researchers have approached the issue from several angles. One line of research focuses on the demographic characteristics of officers. This work shows that male officers (Ba et al. 2021; Shoub, Stauffer, and Song 2021), Republican officers (Donahue 2023), and White officers (Anwar and Fang 2006; Ba et al. 2021) are more likely to discriminate than their female, Democratic, and non-White colleagues. Other research suggests that the ecological and institutional contexts in which police officers operate may also contribute to racially biased policing practices. This work has examined discrimination in relation to the characteristics in the beats (see Shjarback [2018] for a review), counties, and municipalities (Eitle et al. 2002; Legewie and Fagan 2016) where officers are assigned to work.

RACIAL THREAT

Research on the ecology of police discrimination tends to rely on theories of racial threat and group position (Blumer 1958; Blalock 1967). At their core, such theories describe discrimination as a group-level process wherein prejudices among the dominant group are ignited by perceived threats to their economic, demographic, or symbolic status (Blumer 1958; Blalock 1967; Bobo 1983, 1999; Bobo and Zubrinsky 1996).[2]

Without specific regard to police work, researchers have found considerable evidence that supports these theories of discrimination. For example,

[2] Theories of group threat are alternatively called racial threat, minority threat, Black crime threat, status threat, demographic threat, and political threat. Although each of these variants suggests a specific hypothesis (i.e., political threat predicts increased discrimination related to changing political dynamics), they all ascribe to a similar logic of discrimination. In this study, we do not adjudicate between these variations of group threat but rather describe the overarching framework to which they all belong.

studies have shown that the perceived population prevalence of non-White racial groups is associated with a contraction in the phenotypical boundaries around Whiteness (Abascal 2020), declining support for welfare programs (Wetts and Willer 2018), and increased support for punitive criminal justice policies (Duxbury 2021). In a particularly illuminating study, Enos (2016) found that after the sudden displacement of over 25,000 Black residents from a Chicago neighborhood, White voter turnout in that neighborhood decreased by 10 percentage points, highlighting the political influence of Black neighbors on White residents.

Yet theories of racial threat take on distinct importance when applied to policing, where discrimination has substantial social consequences (Bell 2021). At an institutional level, law enforcement has been used as a tool of racial exclusion and social control (Muller 2012). Police forces tend to be larger in more segregated cities (Kent and Carmichael 2014) and are often deployed in ways that maintain this segregation (Laniyonu 2018). Yet police officers are more than just neutral bureaucrats; they possess significant discretionary authority and, through an array of informal and formal channels, are inundated with narratives of racialized criminality and the threat of Black men (Vitale 2021; Simon 2023; Sierra-Arévalo 2024). This process of police socialization, however, does not affect all officers equally. Recent research finds that while White officers are more likely than the average White civilian to harbor racial biases and perceive Black individuals as violent, Black and Hispanic officers do not exhibit these heightened levels of racial prejudice (LeCount 2017).

Police officers also tend to operate in environments that exacerbate unease and promote violent and aggressive professional responses (Carlson 2019; Simon 2023). In his ethnographic account, Sierra-Arévalo (2024) emphasizes this point, describing how "the daily production of policing . . . revolves primarily around one thing: survival" (p. 9). Given their substantial discretionary power, exposure to narratives about racialized criminality and Black male danger, and a pervasive culture of precarity, police officers may be particularly sensitive to feelings of racial threat and—perhaps most importantly—uniquely positioned to act on them.

Consistent with these accounts, several recent studies provide strong evidence that police officers respond to perceived racialized threats to their professional identity by escalating discriminatory behavior (Legewie 2016; Grosjean et al. 2022; Zhao and Papachristos 2024). Legewie (2016), for example, shows that the rate at which New York Police Department (NYPD) officers used force against Black pedestrians increased for several days following the murder of a fellow officer by a Black suspect. Critically, Legewie (2016) finds no similar effect when NYPD officers were killed by Hispanic or White suspects. In another recent study, Zhao and Papachristos (2024) show that when a police officer is injured or killed by a Black suspect, other officers who are in the same professional networks react by discriminating against Black civilians.

Racial Threat and Neighborhood Context

These studies present strong evidence that officers respond to perceived threats with increased aggression toward Black pedestrians, often escalating interactions by using additional force. However, by focusing on threats to officers' professional identity—such as the injury or killing of peers (Legewie 2016; Zhao and Papachristos 2024)—existing research overlooks how similar responses might arise from other areas of officers' social and personal lives. Just as officers may react aggressively to violence against colleagues, violence that occurs in their residential environment may also provoke feelings of threat. When a Black suspect is involved in a homicide near a White officer's home, for example, it may "raise fundamental questions about relations and awaken a sense of racial identification" (Blumer 1958, p. 6).

Although we are not the first to consider the possibility that policing practices are shaped by proximate racialized violence, previous studies have produced inconsistent findings that appear to be contingent on the nature of geography analyzed. Several studies, for example, reveal a strong connection between the county- and municipal-level prevalence of violent crime committed by Black suspects against White civilians and the incidence of discriminatory policing practices (Eitle et al. 2002; Stults and Baumer 2007; Legewie and Fagan 2016). Controlling for other characteristics, including rates of Black-on-Black crime, this research shows that police departments have more officers (Kent and Jacobs 2005; Stults and Baumer 2007; Carmichael and Kent 2014) and racial disparities in arrests and police killings are larger in counties and cities where Black-on-White crime is more prevalent (Eitle et al. 2002; Legewie and Fagan 2016; Grosjean et al. 2022). Using crowdsourced data on police killings from across the nation, Legewie and Fagan (2016), for example, find that the rate of Black-on-White homicides in cities predicts the number of Black people killed by police. Eitle et al. (2002) similarly show that net of other characteristics, the county-level prevalence of Black-on-White crime predicts the rate of Black arrests. Although descriptive, researchers tend to suggest that these findings are consistent with theories of group threat and that the "perception of crime threat increases the popular and political demand for social control" (Legewie and Fagan 2016, p. 6), including use of force against and arrest of Black civilians.

Other research focused on the conditions in the beats and neighborhoods in which officers work is more qualified (Novak and Chamlin 2012; Renauer 2012; Rojek, Rosenfeld, and Decker 2012; Shjarback 2018). Novak and Chamlin (2012) and Rojek et al. (2012), for example, find that officers are more likely to cite and search Black people in beats characterized by a higher proportion of White people and are more likely to cite and search White people in beats characterized by a higher proportion of Black people. At the same time, however, research on racial disparities in use of force complicates these "race out of place" findings. Studies consistently find that the incidence of use of force against Black pedestrians is higher in areas with greater proportions of Black residents (Omori et al. 2022). However, this effect is often colinear with the prevalence of violent crime (Shjarback 2018) and is itself mitigated by high levels of segregation (Smith and Holmes 2014; Klinger et al. 2016).

Research on the ecological predictors of police discrimination often overlooks how the choice of geographical unit (i.e., school district, residential neighborhood, municipality, city, county, workplace, etc.) and its social meaning may shape empirical expectations or the suitability of theoretical frameworks such as racial threat. We argue that this lack of specification has made findings at various geographic levels appear incompatible and has had the unintended consequence of obscuring the connection between place-based attachments and perceptions of threat. Perhaps, most importantly, however, by focusing narrowly on the workplace or broadly on counties, researchers have overlooked the ways in which the residential context of officers may be an important avenue through which a sense of group position and feelings of racial threat are produced.

The Importance of Residential Context

Although it is often overlooked in research on policing, a large literature in political science and sociology explores the degree to which empirical and theoretical expectations may be shaped by the choice of geography or the operationalization of place (Gieryn 2000; Oliver and Mendelberg 2000; Welch et al. 2001; Baybeck 2006; Sharkey and Faber 2014). Baybeck (2006, p. 395), for example, stresses the complex, nested nature of municipalities, arguing that there is "no 'one' context" but rather "the neighborhood, the school district, the city, and the county, to name but a few," and Oliver and Mendelberg (2000, p. 577) argue that "identifying a context's boundaries is essential for understanding its potential effect." In a recent review of the literature on neighborhood effects, Sharkey and Faber (2014) similarly advocate for a theoretically grounded operationalization of place.

Theories of place also complicate the reliance on census geographies. These theories argue that places are associated with abstract and contextually dependent meanings that may be related to but are functionally separate from demographic, topographic, or material features (Milligan 1998; Scannell and Gifford 2010). The ways people form emotional connections and draw personal meaning from their surroundings is well explained by Gieryn, who identifies the symbolic typologies people use to differentiate between places: "ours or theirs; safe or dangerous; public or private; unfamiliar or known; rich or poor; black or white; beautiful or ugly; new or old; accessible or not" (Gieryn 2000). Others have shown that residents find safety, respite, and comfort in their communities (Suttles 1968; Merry 1981; Altman and Low 1992).

Given its symbolic importance, it is no surprise that research on discrimination and place suggests that residential contexts tend to structure perceptions of racialized urban disorder (Sampson and Raudenbush 1999, 2004), racial threat, and feelings of racial prejudice (Bobo and Hutchings 1996; Chiricos, McEntire, and Gertz 2001; Quillian and Pager 2001; Goyette, Farrie, and Freely 2012; Enos 2016). Observational, quasi-experimental, and experimental studies have shown that the physical and social geography of residential areas, including the spatial separation between groups within residential contexts (Enos 2014, 2017), can contribute to the development and intensification of perceptions of disorder, which can, in turn, lead to prejudices and discriminatory behaviors. For example, Sampson and Raudenbush (2004) find that perceptions of disorder in Chicago neighborhoods are more strongly associated with the racial and ethnic composition of the neighborhood than readily observed signs of disorder. Similarly, Quillian and Pager (2001) show that even after controlling for actual levels of neighborhood crime, the perception of crime among White residents is associated with the proportion of young Black men living in the neighborhood.

Although there has been limited research on the relationship between neighborhood violence and discriminatory behaviors, there are reasons to believe that living close to violence may trigger feelings of threat. From one perspective, violence occurring near one's home may be perceived as a violation of an important physical and symbolic boundary—the separation between the "racialized disorder" of the outside world and the order of one's residential space (Altman and Low 1992). In an interview study on the ways that police chiefs frame gun violence, Carlson (2019) shows that chiefs tend to emphasize the symbolic and spatial containment of such activity. One chief, for example, describes being "concerned with making sure that the gang violence does not spill over. As we say, we like to keep our enemies on the other side of the gate" (Carlson 2019, p. 409).

Without addressing racial threat or policing specifically, an emerging literature offers evidence that exposure to nearby violence does indeed impact important outcomes and behaviors. Although this research has primarily focused on the effect of proximate violence on adolescents (see Sharkey and Faber [2014] for a review), recent work suggests that exposure to violence can also increase discriminatory behavior, including in the workplace. Mobasseri (2019), for example, finds that exposure to nearby violent crime reduces the likelihood that Black job applicants receive a callback.

Despite evidence that residential context is imbued with meaning that may be important in shaping feelings of group position and racial threat, research on police behavior attends almost exclusively to workplace context. And while evidence suggests that officers draw from workplace context when making decisions about whom to stop and when to use force, it is not clear why one should expect workplace context to shape the ways that officers understand their relative group position. For example, the characteristics of officers' neighborhoods are likely distinct from the characteristics of their workplaces. In some cases, officers may even be exposed to conditions at work that are disconnected from or in conflict with the conditions they are exposed to at home. As a result of citywide changes in racial segregation, for instance, an officer may observe an increasing minority population in their assigned beat but a shrinking minority population in their neighborhood.

Although not focused exclusively on workplace conditions, research that examines large geographic areas, such as counties, states, or municipalities, faces its own set of challenges. While these broad units of analysis may capture conditions that influence the political will and subsequent policy or electoral outcomes (Campbell, Wong, and Citrin 2006; Zingher and Steen Thomas 2014; Duxbury 2021), they can also obscure the dynamics that link demographic factors to individual officer behavior. Aside from the allocation of resources and policy variations influenced by public political pressure, it remains unclear how officers' feelings of threat would be linked to such broad and abstract measures of violence. While it is plausible that an officer would be aware of a homicide occurring within the municipality where they work or reside—and react accordingly—it seems improbable that they would be aware of a homicide on the opposite side of the county.

The use of large geographic units, therefore, may obscure the nuanced spatial dynamics of homicides. For instance, previous studies that document a positive association between Black-on-White killings (but not Black-on-Black killings) and the use of deadly force and arrest rates cannot account for the fact that Black-on-White crimes may disproportionately occur in close proximity to White people's homes. This could drive increased discrimination independent of the symbolic nature of the crime. In fact, there is some indirect evidence that supports this notion. The effect of Black-on-White killings is less pronounced in counties with high levels of racial segregation (Eitle et al. 2002), which are presumably areas with less spillover violence.

Given the symbolic importance of residential context and its link to perceptions of racial threat, we expect that incidents of extreme violence will heighten feelings of group insecurity, leading to increased discrimination. Prior research shows that perceptions of threat are driven by Black crime (Legewie 2016). Consequently, we expect that officers will exhibit more discriminatory responses when suspects are Black, while responses will remain largely unchanged for White or Hispanic suspects. Finally, because White officers are especially sensitive to narratives of Black criminality (LeCount 2017) and typically occupy the top of the racial hierarchy, we expect them to be most susceptible to perceptions of racial threat.

DATA

Police Administrative Data

This study relies on four sources of administrative data from the CPD: (1) an officer demographic file, which contains demographic characteristics of officers (race, sex, age, and years of service) and unique identifiers (full name, year of birth, and badge number); (2) a schedule and assignment file, which includes the assignment of officers to beats and shifts for each day that they worked; (3) an event file, which includes all arrests, stops, and use-of-force incidents in which CPD officers participated; and (4) point-specific crime data, which include the location, time, and demographics of victims and suspects for all homicides and nonfatal shootings that occurred in Chicago during the study period. The data cover January 1, 2012, to December 31, 2020.

The use-of-force data are drawn from the Tactical Response Report (TRR) forms. Officers complete these compulsory forms following an encounter involving force. A separate record is generated for each incident and every officer involved. These records contain information on the timing of the event, its location, the officers involved, and the race of the pedestrians involved. If more than one type of force or weapon is used, it is recorded in the TRR form. In the event that a firearm is discharged, the form includes details about the kind of firearm and the number of rounds discharged.[3] Additionally, each record contains information on whether the incident resulted in the injury of the involved pedestrian and whether the pedestrian engaged in "active" or "passive" resistance. Arrest and stop data include pedestrian demographic information, identifiers of officers involved, and the reason for the arrest or stop (e.g., drug offense, traffic stop, possession of a firearm, and so on).

The assignment and scheduling data provide information on officers' daily shifts and geographic beat assignments.[4] These data allow us to observe shifts

[3] Because of sample limitations, our main analysis does not distinguish between different types of force used. However, we provide additional analyses in the online appendix, where we decompose the results by examining the effects separately for incidents involving force where the officer reported that the pedestrian was injured and incidents where the officer reported that the pedestrian was not injured.

[4] CPD officers request shifts (day, swing, night) based on seniority and unit needs, which also applies to furlough days (additional leave beyond regular days off). Patrol assignments are determined through a combination of shift allocation and consultations with unit commanders. Officers are assigned in advance to "day-off groups" based on an annual operations calendar. For officers on standard 8.5-hour shifts, a typical cycle consists of six consecutive workdays followed by two days off, with an extra day off if these coincide with a

in which officers worked but did not engage in police stops, arrests, or force. The ability to observe these uneventful shifts helps prevent issues of improper benchmarking and selection on the dependent variable that have confounded previous research (see Knox, Lowe, and Mummolo [2020] for a critique of studies that used incomplete administrative data to draw inferences on police behavior).

We link these data using unique identifiers, creating a data structure where each row represents an officer-day observation that includes the date, a variable that indicates whether the officer was scheduled to work, the officer's demographics (race, age, and gender), the beat and shift to which the officer was assigned, the number of arrests, stops, and use-of-force incidents that the officer participated in on that day, and a set of variables that indicates whether a homicide occurred within a given distance from the officer's home within the three weeks prior. We disaggregate each officer-civilian interaction by race, distinguishing how many of these incidents involved Black, Hispanic, or White pedestrians.[5]

We limit our analysis sample to CPD officers who are assigned to patrols in geographic beats, which include police officers, sergeants, and lieutenants.[6] By restricting our sample in this way, we ensure that each officer in our analysis has the potential to interact with pedestrians while on duty. Additionally, because of their small numbers, we exclude officers who identify as Native Americans, Asian Americans, or Pacific Islanders.

Officers' Addresses

We retrieved officers' residential addresses by matching each officer to their voter registration records.[7] This matching process used four identifying

weekend. Because the schedule doesn't follow a weekly pattern, an officer's shifts do not consistently fall on the same weekdays over time. Officers are assigned to shifts (first, second, or third) based on seniority and operational needs.

[5] Whereas use-of-force incidents record the specific behavior of each involved officer, stop and arrest records do not. Instead, these records simply list the officers involved. Because of this, we cannot distinguish who initiated the stop, if it was even initiated by a single officer. As such, we consider all officers equal participants in the arrest or stop incident. Our decision to treat each officer as an equal participant is based on conversations with CPD officers who informed the authors that the order in which officers are listed in administrative records is unrelated to their role in the incident and is rather a function of who will appear in court, if such an appearance is necessary.

[6] The variable "beat" in the CPD data represents patrol tasks. Most of these patrol tasks include patrolling geographic beats by police officers (on foot or by car), but they also include administrative tasks and desk duties. We assess the behavior of officers assigned to geographic beats only. We exclude officers who are not assigned to geographic beats, such as detectives and field training officers.

[7] Historical Illinois voter records were purchased from L2, a distributor of individual-level voter registration records.

elements: first name, middle initial, last name, and date of birth. To ensure temporal accuracy, we used historical snapshots of Cook County voter files corresponding to each year in our study period, allowing us to associate officers with their addresses at the time they were scheduled to work. For instance, we matched 2012 officer data with 2012 voting records, 2013 officer data with 2013 voting records, and so forth. This year-by-year matching approach captured changes in officers' residences over time.

Of the 11,215 Black, Hispanic, and White police officers on active duty and assigned to patrol functions between 2012 and 2020, we are able to match 8,946 (79.8%) to the Illinois voter registration file. The unmatched officers are either not registered to vote or disregarded CPD's residency requirement policy and registered to vote outside of Chicago. Ultimately, the sample of matched officers used in our analysis includes 2,194 Black officers, 2,641 Hispanic officers, and 4,111 White officers. This yields a panel data set with 3,586,221 officer-day observations where we observe the number of stops, arrests, and use-of-force events in which each officer was involved.

Table 1 describes the demographic characteristics and workplace behaviors of the officers in our analytic sample.[8] Of the matched Black officers, 66.16% are male, with an average age of 42.44 years as of 2015. Among Hispanic officers, 76.15% are male, and their average age is 36.13 years. A higher percentage of White officers are male (80.50%), with an average age of 39.79 years. A smaller proportion of White officers hold the rank of police officer, but they are more likely than Hispanic or Black officers to hold the rank of sergeant or lieutenant.

Table 1 also provides details about the relationship between where officers live and work. Approximately 23.27% of Black officers, 25.62% of Hispanic officers, and 30.85% of White officers reside within their regularly assigned police district. When we narrow the geographic window from districts to assigned police beats, we find that 9.24% of Black officers, 9.68% of Hispanic officers, and 12.60% of White officers live inside the beat that they are most likely to patrol.[9]

Finally, table 1 describes our outcomes: the probability that officers arrest, stop, and use force against civilians of different racial groups during a given shift. White officers have the highest overall probability of using force during a shift, at 0.35%. Hispanic officers have a 0.29% probability

[8] Table A1 in the online appendix reproduces table 1 for the officers we could not match to voter records (365 Black officers, 711 Hispanic officers, and 1,193 White officers). Table A1 reveals that there are no systematic differences in the demographic characteristics or behavior of unmatched and matched officers.

[9] Officers may be assigned to different patrol beats and districts over the course of a year. To assess whether officers live in the same beats and districts that they patrol, we identify the modal beat and district in a given year and determine whether the officer's place of residence falls inside the beat and district boundaries.

TABLE 1
Officer Characteristics: CPD, 2012–20

	Black (N = 2,194)	Hispanic (N = 2,641)	White (N = 4,111)
Demographics:			
Male, %	66.16	76.15	80.50
	(47.32)	(42.62)	(39.63)
Female, %	33.84	23.85	19.50
	(47.32)	(42.62)	(39.63)
Age in 2015	42.44	36.13	39.79
	(10.38)	(9.72)	(9.69)
Rank, %:			
Police officer	96.39	96.06	91.81
	(18.65)	(19.46)	(27.43)
Sergeant	3.53	3.88	7.85
	(18.47)	(19.32)	(26.90)
Lieutenant	.07	.06	.34
	(2.71)	(2.42)	(5.86)
Place of residence and work, %:			
Lives in the district	23.27	25.62	30.85
	(42.26)	(43.66)	(46.19)
Lives in the beat	9.24	9.68	12.60
	(28.97)	(29.57)	(33.19)
Probability of using force during a shift, %:			
All civilians	.22	.29	.35
	(.86)	(.70)	(1.10)
Black civilians	.19	.21	.25
	(.83)	(.59)	(.97)
White civilians	.01	.03	.04
	(.11)	(.17)	(.26)
Hispanic civilians	.01	.05	.05
	(.08)	(.32)	(.43)
Probability of making a stop during a shift, %:			
All civilians	26.88	34.00	39.76
	(31.93)	(40.42)	(46.37)
Black civilians	22.88	20.01	24.36
	(28.99)	(30.87)	(37.64)
White civilians	1.81	4.22	6.34
	(4.80)	(9.22)	(12.40)
Hispanic civilians	1.95	9.35	8.60
	(5.71)	(16.23)	(17.12)
Probability of making an arrest during a shift, %:			
All civilians	13.87	19.25	17.82
	(12.31)	(13.98)	(15.62)
Black civilians	11.99	12.48	11.59
	(11.70)	(12.03)	(13.46)
White civilians	.70	1.80	2.22
	(1.42)	(3.03)	(4.67)
Hispanic civilians	1.13	4.86	3.87
	(3.27)	(6.50)	(6.20)

Note.—The data include 8,946 CPD members with the ranks of police officer, sergeant, and lieutenant assigned to geographic beats at any point during the years 2012–20 (2,194 Black, 2,641 Hispanic, and 4,111 White). We exclude police officers assigned to administrative duties and for whom the address could be inferred from the voter registration file. We present standard deviations in the parentheses.

of using force, and Black officers have a 0.22% probability. Similarly, White officers have the highest overall probability of making a stop during a shift. When we disaggregate by the race of the civilians involved, we observe some heterogeneity. Regardless of the officer's race, there is a significantly higher probability that an officer stops, arrests, or uses force against a Black pedestrian compared to a White or Hispanic pedestrian.[10]

Neighborhood Crime and Demographic Data

To assess the characteristics of officers' neighborhoods, we link officers' home addresses to block group-level demographic data drawn from the American Community Survey (ACS) 5-year estimates.[11] Additionally, we link block group-level crime rates obtained from Chicago's Citizen Law Enforcement Analysis and Reporting (CLEAR) system, which records all reported instances of crime in Chicago, including the type of crime, the date of the crime, and the location of the crime.

In the quasi-experimental analysis, which we describe in detail below, we rely on data from the publicly available Violence Reduction—Victims of Homicides and Non-Fatal Shootings dataset. These data include individual-level information on every fatal and nonfatal shooting between 2012 and 2020 and provide details such as latitude, longitude, incident date, CPD case number, and the victim's race. We determine the race of the suspect by linking the victimization data to CPD arrest records using the CPD case number, which is included in both datasets. Among other information, the CPD arrest records include the race of the arrested individual and the date of the arrest. This linkage allows us to identify the race of both the victim and the perpetrator of each homicide and shooting for which an arrest was made. Yet, because CPD's clearance rates are low and because the race of the suspect is drawn from arrest records, information on the suspect's race is not always available. As shown in table 2 and extensively documented in the literature (Cook and Mancik 2024), the vast majority of homicides and shootings do not result in an arrest.

Table 2 describes the characteristics of homicides in Chicago between 2012 and 2020, along with a cross-tabulation of the race of the victim and

[10] It is important to note that these probabilities do not account for officers' unequal distribution across beats and shifts and should not be used to draw any inferences about racial gaps in officer-civilian interactions. As documented in the literature (Ba et al. 2021), Black officers are more likely to be assigned to beats where the likelihood of coming into contact with Black civilians is higher, which will increase the probability that they stop, arrest, or use force against those civilians. Our models will account for that unequal distribution of patrol assignments.

[11] We use block group data from the ACS in the year corresponding with officers first appearance in the data (e.g., for an officer who first appears in the CPD data in 2014, we use 2010–14 ACS data). See notes to table 3 for more details.

TABLE 2
Race of Victims and Perpetrators: Homicides in Chicago, 2012–20

	Suspect's Race (%)					
Victim's Race	Black	Hispanic	White	Other	No Arrest	Total
Black	672 (16.3)	14 (.3)	6 (.1)	0 (0)	3,429 (83.2)	4,121 (100)
Hispanic	36 (4.5)	94 (11.7)	11 (1.4)	0 (0)	664 (82.5)	805 (100)
White	24 (10.0)	23 (9.6)	16 (6.7)	2 (.8)	174 (72.8)	239 (100)
Other	9 (15.3)	3 (5.1)	0 (0)	0 (0)	47 (79.7)	59 (100)
Total	741 (14.2)	134 (2.6)	33 (.6)	2 (0)	4,314 (82.6)	5,224 (100)

the race of the perpetrator. In the column labeled “No arrest,” we show the rate of unsolved homicides.

The clearance rate in Chicago is approximately 18% but varies slightly by the race of the victim. For example, when the victim is White, the clearance rate is higher, at around 27%. Table 2 also shows a pattern of racial homophily between the victim and suspect when an arrest is made. For example, when the victim is Black, 97% of those arrested are also Black, and when the victim is Hispanic, 67% of the arrests are of Hispanics. The exception is for homicides where the victim is White, in which case Black individuals are most commonly arrested.

DESCRIPTIVE RESULTS: THE RESIDENTIAL CONTEXT OF POLICE OFFICERS

Our first set of results documents the spatial distribution of officers and outlines the typical conditions in the neighborhoods where officers live. Figure 1 presents spatial density plots of officer residences, with warmer colors indicating higher concentrations. Subfigures A, B, and C show the density of Black, Hispanic, and White officers, respectively. These density plots are overlaid on a map of census tract boundaries shaded by the proportion of Black residents, with darker hues representing a higher proportion and lighter hues indicating a smaller proportion of Black residents.[12]

Figure 1 reveals the presence of racialized police enclaves. White CPD officers reside primarily in the northwest and southwest regions of the city, with a high concentration in Norwood Park, Edison Park, Mount Greenwood, and Beverly—neighborhoods known for their large populations of people with Irish and Italian ethnicity (Zorbaugh 1983). Black officers tend to reside in the southern parts of the city in predominantly Black neighborhoods, such as Chatham, Roseland, and Auburn Gresham. Hispanic officers have a more widespread presence, overlapping with White officers in some

[12] Similar density plots overlaid on maps showing the proportion of White and Hispanic residents are provided in figs. A6 and A7 in the appendix.

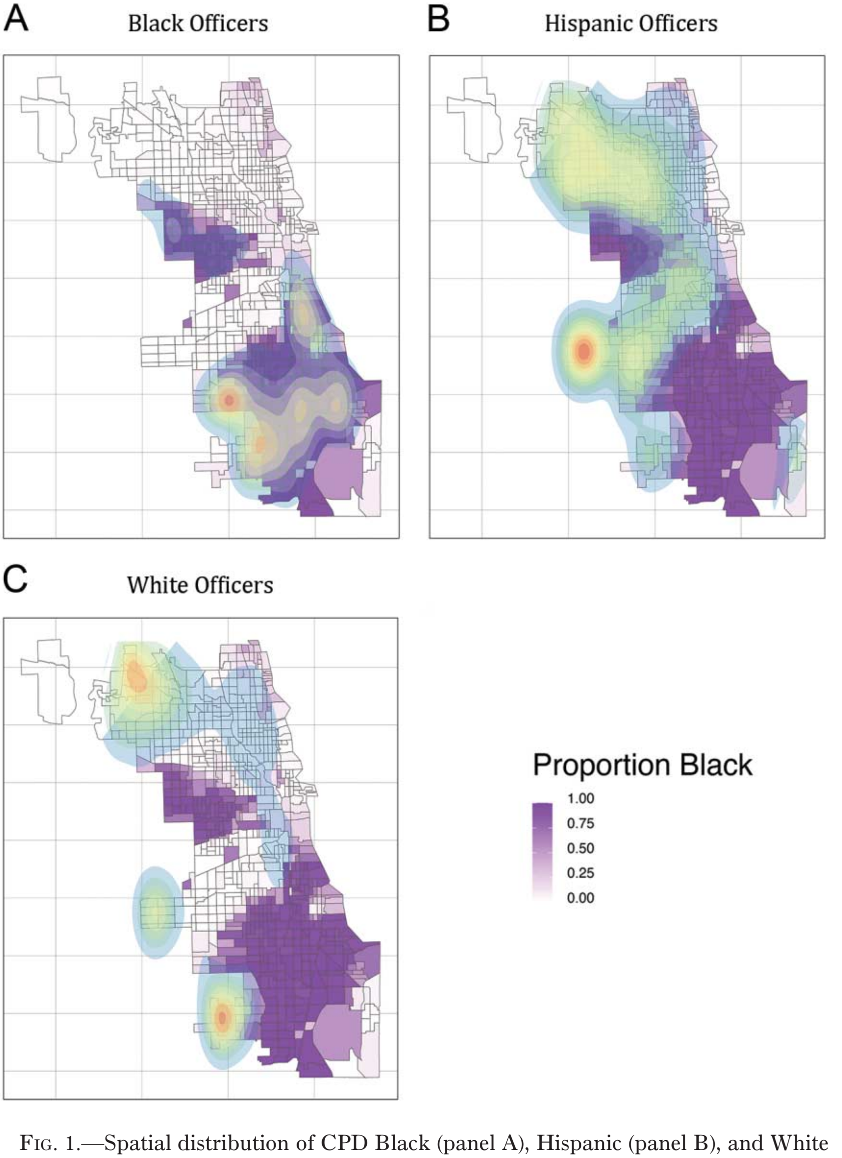

FIG. 1.—Spatial distribution of CPD Black (panel A), Hispanic (panel B), and White (panel C) officer residences over census tract–level proportions of Black residents, Chicago, 2012–20. The data include 8,946 CPD members with the ranks of police officer, sergeant, and lieutenant assigned to geographic beats at any point during the years 2012–20 (2,194 Black, 2,641 Hispanic, and 4,111 White). We exclude police officers assigned to administrative duties and for whom the address could not be inferred from the voter registration file. The maps reflect the boundaries of census tracts using 2010 delineations. The spatial density of officer residence has been computed using Gaussian kernels.

cases and in others, concentrating in predominantly Hispanic neighborhoods like Little Village and Pilsen. The racial patterning of officer residences mirrors the broader racial and ethnic segregation that characterizes Chicago's residential landscape.

To more precisely examine the neighborhood characteristics of CPD officers and explore how neighborhood conditions differ by officer race, we calculate exposure measures. Drawing from previous research (Ellen Steil, and De la Roca 2016), we calculate a weighted average for each neighborhood characteristic, with weights based on the number of officers from a specific racial group living in each block group. By accounting for the uneven distribution of officers across neighborhoods, this approach effectively creates a summary statistic for the "typical" officer's neighborhood. For each neighborhood characteristic (e.g., the percentage of non-Hispanic Black residents), we estimate the exposure for the typical officer of racial/ethnic group r as follows: $E^r = \Sigma_{j=1}^{J}\left(C_j * \frac{r_j}{R}\right)$, where E^r is the exposure measure to neighborhood characteristic C for officer of racial/ethnic group r, C_j is the neighborhood attribute (such as the percentage of non-Hispanic Black residents) in block group j, r_j is the number of officers of a given race/ethnicity in block group j, and R is the number of total officers of racial/ethnic group r in the city.

Using data from the ACS, we estimate the exposure measure for the following neighborhood demographic characteristics: percentage non-Hispanic White, percentage non-Hispanic Black, percentage non-Hispanic Asian, percentage Hispanic, percentage with less than a high school degree, percentage with a college degree or more, unemployment rate, median household income, percentage receiving public income assistance, and percentage of families below the poverty line. We also describe the incidence of violent crime in the block group, measured as the yearly average number of homicides and violent crimes (assaults, homicides, and robberies)[13] occurring from 2012 to 2020. We create exposure measures for the typical Black, Hispanic, and White officer. Finally, to assess how the neighborhood characteristics of CPD officers compare to those of the typical residents in Chicago, we compute the same exposure measures for the typical Black, Hispanic, and White Chicagoan.

Table 3 shows that the typical Black officer lives in a block group where the homicide rate is 26.3 per 100,000 residents. This is almost eight times larger than the homicide rate in the block groups where the typical White CPD officer lives (3.4 homicides per 100,000 residents) and nearly four times the homicide rate in the neighborhoods where the typical Hispanic officer lives (7.6 homicides per 100,000 residents). The disparities in exposure to crime between White and Black officers are remarkably similar to the relative differences in exposure to crime when we consider all Chicagoans. For

[13] Rape is not included in the Chicago crime data.

TABLE 3
NEIGHBORHOOD CHARACTERISTICS OF A TYPICAL CPD OFFICER AND A TYPICAL CHICAGOAN BY RACE/ETHNICITY: CHICAGO, 2012–20

	Black Officer	Hispanic Officer	White Officer	Black Chicagoan	Hispanic Chicagoan	White Chicagoan
Violent crimes per 100,000	1,668.0	614.9	401.1	2161.0	775.3	556.8
Homicides per 100,000	26.3	7.6	3.4	38.6	11.5	4.4
Population density	13.7	17.6	14.6	17.2	23.2	28.3
% White	12.6	40.3	65.9	8.4	23.0	61.2
% Black	73.2	6.9	5.5	79.4	9.0	7.8
% Asian	2.4	4.7	4.9	2.0	4.1	8.0
% Hispanic	10.0	46.4	21.7	8.7	62.5	20.6
% Less than high school	13.3	20.3	9.9	17.6	28.9	9.7
% College or more	27.9	27.8	38.9	21.5	22.3	53.5
% Unemployed	10.2	6.0	4.4	11.5	7.1	4.5
% Median household income	58.7	71.4	92.0	44.0	59.2	90.3
% With public income assistance	4.5	2.8	1.9	6.5	3.8	2.1
% Families below poverty line	19.0	12.6	6.4	27.0	18.9	8.6

NOTE.—Each value is a block group-level exposure computed for the corresponding group. We compute officers' crime exposures using crime rates from the first year that officers appear in the CPD data. For officers' exposure to other neighborhood characteristics, we use block group data from the ACS from the year corresponding to when officers first appear in the data (e.g., for an officer who first appears in the CPD data in 2014, we use 2010–14 ACS data). To compute exposures for the nonofficer population, we use average crime rates across years 2012–20 and use ACS data averaged across 5-year estimates from years 2006–10, 2011–15, and 2016–20.

instance, the typical Black Chicago resident lives in a block group where the murder rate is 38.6, which is almost nine times the crime rate in the block group where the typical White Chicagoan lives and 4.4 times the crime rate in the block group where the typical Hispanic Chicagoan lives. These patterns of unequal exposure to violence persist when we examine exposure to other violent crimes like aggravated assaults and robberies.

Table 3 also reveals substantial racial and economic differences in the neighborhoods where White, Black, and Hispanic CPD officers live. While the typical Black officer lives in a block group where 12.6% of the population is White, 73.2% is Black, 2.4% is Asian, and 10% is Hispanic, the typical White officer lives in a block group where 65.9% of the population is White, 5.5% is Black, 4.9% is Asian, and 21.7% is Hispanic. The racial composition of the neighborhood where the typical Hispanic officer lives is 40.3% White, 6.9% Black, 4.7% Asian, and 46.4% Hispanic. As with differences in exposure to violence, the spatial segregation of CPD officers mirrors the patterns of racialized spatial sorting of the typical Chicago resident.

ESTIMATING THE CAUSAL EFFECT OF NEIGHBORHOOD VIOLENCE ON OFFICER BEHAVIOR

Next we turn to our main analysis, which estimates the causal effect of homicides that occur near officers' homes on their subsequent propensity to stop, arrest, and use force. To do this, we use a quasi-experimental design that takes advantage of the exogenous variation induced by the timing of homicides near officers' residences relative to their predetermined work schedules. While the incidence and location of homicides are not random, their relative timing is exogenous to officers' work schedules and assignments, which are set in advance. This independence induces random variation in the relative recency of a nearby homicide. Using this random variation in exposure to homicides, we set up a difference-in-differences model that compares the on-the-job behaviors of exposed and unexposed officers who work in the same beat and shift and on the same day of the week and month.[14]

Before introducing the formal difference-in-differences equation, we offer a visual representation of our research design. In the left panel of figure 2, we show the logic of the treatment condition: The red star represents a homicide, the small black dot represents the home of an exposed officer, and the small white dot represents the home of an unexposed officer. Rather than using census geographies like blocks, block groups, or tracts to measure exposure to homicides, we draw a series of concentric rings expanding out from the officer's home in radial increments of one-eighth of a mile. We show these exposure measures in the map detail, where the blue shaded area measures officers who are between zero and one-eighth of a mile from the homicide, the red circular rings measure officers who are between one-eighth and one-fourth of a mile from a homicide, and so forth. This approach avoids the rigid boundaries of census geographies and allows us to assess whether the impact of homicides varies with distance.[15]

Following Ba et al. (2021), we control for workplace conditions by comparing exposed officers to unexposed officers whose work assignment is

[14] Similar designs have been used to assess the effect of residentially proximate homicides on children's cognitive performance (Sharkey 2010; Sharkey et al. 2012) and mental health (Cuartas and Leventhal 2020).

[15] To test the effect of distance, our models include four dummy variables corresponding to the mutually exclusive exposure rings shown in fig. 2. The first dummy variable is 1 for officers living within one-eighth of a mile from the homicide and 0 otherwise. The second dummy is 1 for those living between one-eighth and one-fourth of a mile from the homicide and 0 otherwise. The third dummy is 1 for those living between one-fourth and three-eighths of a mile from the homicide and 0 otherwise. The fourth dummy is 1 for those living between three-eighths and one-half a mile from the homicide and 0 otherwise. Officers who did not experience a homicide or experienced one beyond one-half of a mile from their home serve as the control group for officers living in the four exposure circular rings. The coefficients on these dummies test for differences in behavior between the control group and officers in each exposure ring. We introduce formal notation for this modeling approach in eq. (2).

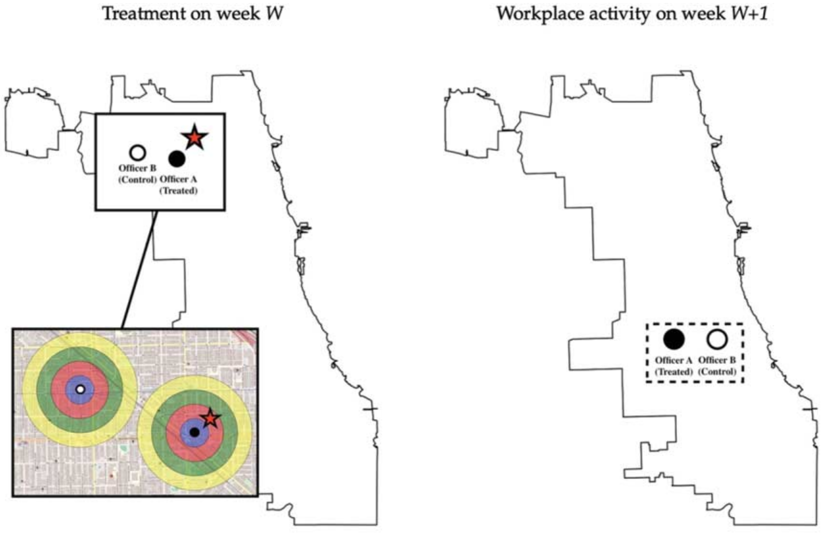

FIG. 2.—Research design. Effect of homicide exposure in the neighborhood of residence on workplace behavior. Officers A and B live in different areas of the city, but they both work in the same beat during the same shift. A homicide occurs within a quarter mile of where Officer A lives. No homicide happens within half a mile of where Officer B lives. During shifts in the following week, Officers A and B are assigned to the same beat and shift and thus face the same conditions on the ground, with an equal probability of interacting with civilians of different racial groups. Holding constant those conditions on the ground, we assess how the probability of a use-of-force incident differs across these two officers during the three weeks after Officer A was exposed to a homicide.

defined by the same unique combination of month of the year, M (January 2012 to December 2020); day of the week, D (Monday to Sunday); beat, B; and shift, S (first, second, or third watch). In comparing treated and untreated officers within unique $MDSB$ combinations, we assume that these officers experience the same on-the-ground conditions and therefore behave in similar ways, absent exposure to a homicide.[16]

[16] One important consideration of our empirical strategy is the number of unique combinations of month of the year, day of the week, shift, and beat, that is, $MDSB$, that contribute to the estimation. Eq. (1) estimates the within-$MDSB$ differences in officer behavior across treated and untreated officers, and as in any fixed-effects setup, only the observations that are in fixed-effects groups where there is variation in the explanatory variable contribute to the estimation. This means that officers in $MDSB$s that have no variation in exposure to a homicide (i.e., all or none of the officers in the $MDSB$ combination were exposed) do not contribute to the estimation. Of the 477,745 unique $MDSB$ combinations that are defined by month of the year, day of the week, shift, and beat, only 10,721 include both treated and untreated officers. Those 10,721 unique $MDSB$s include 3,794 unique officers. Since we fit models by officer race and ethnicity, it is also important to assess how many $MDSB$s and officers contribute to those models. The models that include Black officers have 7,848 unique $MDSB$s, and 1,157 officers contribute to the

We visualize this procedure in the right panel of figure 2, where we show that although Officer A was exposed to a homicide at time W and Officer B was not, they work during the same shift, on the same day of the week, in the same month, and in the same beat (represented by the dotted box). Therefore, despite being differentially treated, the officers work in nearly identical conditions.[17] From this comparison, we arrive at our estimand: the difference in the probability that treated officers engage in stops, arrests, and use-of-force incidents in the weeks that follow a homicide compared to untreated officers.

It is important to highlight that our causal design rests on the assumption that officers become aware of homicides in their residential areas shortly after they occur. Although our data do not directly indicate whether or not an officer became aware of a residentially proximate homicide, qualitative accounts provide strong evidence that officers are routinely exposed to information about local violent crime (Sierra-Arévalo 2024). In a recent ethnography of contemporary policing, Sierra-Arévalo (2024), for example, shows that officers are inundated with information about violent crime, despite the fact that such incidents constitute a small fraction (less than 1%) of the calls they ultimately respond to. Sierra-Arévalo describes the intersecting and overlapping channels—both formal and informal—that keep officers abreast of local violence; during roll call, lieutenants narrate the gruesome details of the previous shifts' violent crimes (Sierra-Arévalo 2024, p. 131); printed handouts called "hot sheets" offer detailed information about violent crimes including location, date, time, and description of the involved suspect; and officer safety bulletins flash on television screens throughout precincts with information about both local and nonlocal threats to officer safety.

Modeling Strategy

Despite the binary nature of our outcome, we model our data using a series of linear probability models (LPMs). Our results, however, are robust to an array of nonlinear specifications, the output of which we include in the online appendix. While LPMs have known limitations, such as heteroskedasticity and predictions outside the [0,1] range, logistic regression models with many fixed effects pose their set of issues. One important issue is the incidental

estimation; the models that include White officers have 5,924 unique *MDSB*s, and 1,744 officers contribute to the estimation; and the models that include Hispanic officers have 4,745 unique *MDSB*s, and 893 officers contribute to the estimation.

[17] We test the assumption that treated and untreated officers are comparable by examining differences in the weeks leading up to the treatment (this is equivalent to testing the common trends assumption in a traditional difference-in-differences framework). We simultaneously estimate the impact of exposure to a homicide in the three weeks prior to exposure and in the three weeks after exposure in a panel event study with lags and leads.

parameter problem (Neyman and Scott 1948), which often leads to artificially small standard errors. Although conditional maximum-likelihood logit models with jackknife bias corrections can partially mitigate this issue (Fernández-Val and Weidner 2016), these adjusted models remain imperfect (Katz 2001).

It is also important to note that even when logistic models with fixed effects are converted to marginal effects, their interpretation can still be peculiar, differing in important ways from similarly specified LPMs. For instance, logistic regression with fixed effects excludes groups that include no variation in both the independent and dependent variables, leading to estimates that only reflect the impact of a proximate event (e.g., a homicide) on use of force in areas and periods where force is occasionally used. In officer fixed-effects models, this means the estimated effect is limited to officers who sometimes use force. One of the advantages of LPMs, and one of the reasons we include them in this study, is that the coefficients are directly interpretable as marginal changes in the probability of the outcome (Hellevik 2009).

Despite these limitations, we conducted additional robustness checks using a set of nonlinear models, including unconditional fixed-effects logit, conditional fixed-effects logit, and rare-events fixed-effects logit. The rare-events logit is particularly useful for handling infrequent incidents, producing unbiased estimates with lower variance (King and Zeng 2001). Full regression outputs for these models, along with the LPM results, are presented in the appendix (tables A3–A5; all appendices are online). Our results remain robust across all of these specifications.

Time and Distance Models

Our analysis considers an array of intersecting variables: the race of the officer, the race of the victim of the homicide, the race of the suspect, distance from the homicide, and time from the homicide. While we address each of these variables in turn, we begin by testing the core assumption of our causal identification strategy: that the treated and untreated officers behaved similarly prior to the homicide. This time-based analysis also allows us to establish the length of the effect, providing a temporal window that we apply to subsequent models.

To simplify this first specification, we limit the exposure distance to homicides that occur within one-eighth of a mile of an officer's residence. This distance measure covers an area about the size of four square blocks, with the officer's residence at the center. This hyperlocal radius represents the immediate neighborhood context where residents are most likely to have intimate knowledge of local dynamics and social connections. By concentrating on this distance, we aim to capture the area where a homicide would have the most immediate and significant impact for local residents.

The estimating equation and formal notation for the time model are as follows:

$$Y_{imdsb} = \alpha + \gamma_{mdsb} + \sum_{j=3}^{J}\beta_j \text{Lead } j_{imdsb} + \sum_{k=3}^{K}\delta_k \text{Lag } k_{imdsb} + \epsilon_{imdsb}. \quad (1)$$

In equation (1), Y_{imdsb} is a binary indicator for whether officer i, who is assigned to beat b, in shift s, in month-year m, in the day of the week d, participated in a use-of-force event, an arrest, or a stop (with separate models estimated for each outcome). We scale the dependent variable from 0 to 100 so that coefficients can be interpreted as changes in percentage points. The vector γ_{mdsb} is a set of fixed effects that define all unique combinations of month of the year, day of the week, shift, and beat (*MDSB*); $\Sigma_{j=3}^{J}\text{Lead } j_{imdsb}$ is a set of three binary indicators for the three weeks that followed the occurrence of a homicide in the neighborhood where officer i lives; and $\Sigma_{j=3}^{J}\beta_j$ is the set of estimated coefficients in each of the lead indicators. Similarly, $\Sigma_{k=3}^{K}\text{Lag}k_{imdsb}$ is a set of three binary indicators for the three weeks that preceded the occurrence of a homicide in the neighborhood where officer i lives, and $\Sigma_{k=3}^{K}\delta_k$ is the set of estimated coefficients in each of the lag indicators. Across all models, we cluster standard errors by police district.[18]

If an officer was exposed to a homicide in the seven days before the date of their work assignment, the lag indicator corresponding with that week will take on a value of 1. Similarly, if the homicide happened eight to 14 days before their assignment, the lag indicator corresponding with that week will take on a value of 1. The same applies if the homicide took place 15–21 days prior to their assignment. The lead indicators follow the reverse logic: If a homicide occurred in the seven days after the officer is assigned to work, the lead indicator for that week will take on a value of 1, and so on.

The three lag and three lead indicators take as a reference group officers who were not exposed to a homicide in those three weeks. This includes officers who were never exposed to a homicide as well as officers who were exposed to a homicide outside of the window defined by the lag and lead indicators. To explore differences by the race of the officer and the race of the pedestrian, we estimate separate models for Black, Hispanic, and White officers and for interactions with Black, Hispanic, and White pedestrians.

If exposure to a homicide makes officers more likely to make contact with pedestrians for the weeks that follow, the coefficients on the lag indicators ($\Sigma_{k=3}^{J}\delta_k$) will be positive. The magnitudes of the three lag coefficients reveal whether the impact of such exposure increases or decreases over time. Similarly, the coefficients on the lead indicators ($\Sigma_{j=3}^{J}\beta_j$) reveal any anticipatory effects in

[18] Among all possible clustering strategies (by officer, by beat, by *MDSB*, or by district), clustering at the level of police districts yields the most conservative (i.e., larger) set of standard errors.

the weeks leading to the proximate homicide. Under the assumption that the timing of homicides is exogenous to the work assignment of officers (holding constant their beat, shift, month, and day of the week), we expect to find no anticipatory changes in behavior in the weeks before a homicide takes place.

Next, we measure the effect of distance from a homicide on the probability of using force, stopping, or arresting, holding constant the temporal window. The distance model assesses the impact of homicides that occur in four exposure circular rings illustrated in figure 2. The estimating equation and formal notation for the distance model are as follows:

$$Y_{imdsb} = \alpha + \gamma_{mdsb} + \sum_{j=4}^{J} \beta_j \text{Dist } j_{imdsb} + \epsilon_{imdsb}. \tag{2}$$

In equation (2), Y_{imdsb} and γ_{imdsb} have the same interpretation as they do in equation (1), and $\Sigma_{j=4}^{J}\text{Dist } j_{imdsb}$ is a set of four binary indicators that capture whether a homicide occurred within the four concentric areas around the officers' homes. These areas are defined by incremental and mutually exclusive radii of one-eighth of a mile: from zero to one-eighth of a mile from the officer's residence, from one-eighth to one-fourth of a mile, from one-eighth to three-eighths of a mile, and from three-eighths to one-half of a mile. The expression $\Sigma_{j=3}^{J}\beta_j$ is the set of estimated coefficients in each of the distance indicators. Essentially, equation (2) compares the behavior of officers who experienced a homicide within these specified distance thresholds to those who either were not exposed to a homicide near their home or for whom the exposure distance was beyond one-half of a mile. A circle of one-eighth of a mile covers an area of 0.05 square miles, and a circle of one-half of a mile covers an area of 0.79 square miles.[19]

Victim and Suspect Model

In our last model, we examine the heterogeneous effects of different types of homicides. Specifically, we assess how officers respond to homicides in their neighborhoods when the victim is Black, Hispanic, or White and when suspect is Black, White, or Hispanic or remains unidentified. To simplify this model, we fix our geographic and temporal window based on the results of the previous models. The estimating equation and formal notation for the victim-suspect model are as follows:

$$Y_{imdsb} = \alpha + \gamma_{mdsb} + \sum_{j=12}^{J} \beta_j \text{Vict-Susp} j_{imdsb} + \epsilon_{imdsb}. \tag{3}$$

[19] On average, Chicago census blocks have an area of 0.005 square miles, block groups have an average area of 0.09 square miles, and tracts have an average area of 0.3 square miles.

In equation (3), Y_{imdsb} and γ_{imdsb} have the same interpretation as in equation (1), and $\Sigma_{j=12}^{J}$Vict-Suspj_{imdsb} is a set of 12 binary indicators that capture all possible combinations of race of the victim (Black, Hispanic, and White) and race of the suspect (Black, Hispanic, White, and no arrest made). In these models, officers in the control group are officers who were either not exposed to any homicide or exposed to a homicide that is outside the temporal and distance windows identified as relevant in models 1 and 2.[20]

Robustness Checks: Officer Fixed-Effects Model

To assess the robustness of our identification strategy, we run all time, distance, and victim-suspect models with officer fixed effects. These models replace the γ_{mdsb} fixed effects for a set of individual officer fixed effects and separate fixed effects for month and day of the week. Effectively, these models compare each officer to themselves in days before and after exposure while accounting for the seasonality of crime and work assignment. Officer fixed models, reported in figures A11 to A13 in the appendix, yield the same results as the models from equations (1), (2), and (3) above.

Treatment Variable

Table 4 shows the number of officer shifts where the working officer had been exposed to a homicide within a half mile of their residence in the previous three weeks. From 2012 to 2020, Black officers worked 32,192 shifts following exposure to a homicide in the last 21 days, White officers worked 9,711 shifts under the same conditions, and Hispanic officers worked 16,947 shifts. Overall, we observe 43,597 shifts where an officer had been exposed to a nearby homicide within the preceding 21 days. Consistent with the racial differences in exposure to crime documented in table 3, we find significantly fewer shifts worked by White and Hispanic officers after exposure to a homicide near their home.

RESULTS

We begin by testing our core assumption: that treated and untreated officers behave comparably when working in the same beat, on the same shift, in the same month, and during the same day of the week. To test this assumption, we model the behavior of treated and untreated officers in the three weeks before the treated officers were exposed to a homicide. As mentioned in the methods section, this test is analogous to testing the parallel trends assumption

Thus, our distance models assess how homicides occur within an area that is larger than a city block but smaller than a block group and an area that is twice the size of a census tract.

[20] When combined with the race of the suspect, homicides where the victim was Asian or of another racial/ethnic group are very rare. We omit those events from our data.

TABLE 4
Shifts Worked Where the Officer Was Exposed to a Homicide in the Three Weeks Prior

	Black Officer Shifts	Hispanic Officer Shifts	White Officer Shifts
Black victim:			
Black suspect	4,746	798	1,014
Hispanic suspect	93	238	25
White suspect	70	11	62
No arrest made	25,410	4,396	3,299
Hispanic victim:			
Black suspect	48	361	185
Hispanic suspect	160	1,207	471
White suspect	21	272	23
No arrest made	1,011	7,527	2,562
White victim:			
Black suspect	93	182	59
Hispanic suspect	17	294	202
White suspect	72	160	272
No arrest made	451	1,501	1,537

Note.—Homicide within one-half mile of residence, CPD, 2012–20. The data include 8,946 CPD members with the ranks of police officer, sergeant, and lieutenant assigned to geographic beats at any point during the years 2012–20 (2,194 Black, 2,641 Hispanic, and 4,111 White). We exclude police officers assigned to administrative duties and for whom the address could be inferred from the voter registration file.

in a traditional difference-in-differences design and helps us determine whether there are any preexisting differences between treated and untreated officers that might confound our results. For readability, we only report coefficients for the week prior. However, we show the full output where we model three anticipatory weeks in the appendix.

In addition to plotting anticipatory effects, we model the three weeks following a homicide. This allows us to examine the length and decay of the effect. For simplicity, we limit our exposure distance to one-eighth of a mile, where we believe the effect will be strongest. Additionally, we do not differentiate between homicides by the victims' or suspects' race. In later analyses, we attend to heterogeneity by distance and victim-suspect race pairings.

In figures 3 and 4 the y-axis shows the effect of a proximate homicide on the probability that an officer engages in an arrest or stop or uses force during subsequent shifts. The x-axis represents time, displaying the treatment effect during shifts worked in the three weeks after a nearby homicide occurred as well as the week leading up to the homicide. To test for differences by the race of the officer, we model the effect separately for White, Hispanic, and Black officers. We display the effect for White officers in blue, Hispanic officers in green, and Black officers in orange. We subset the figure by the race of the pedestrian in the columns and the type of contact in the rows.

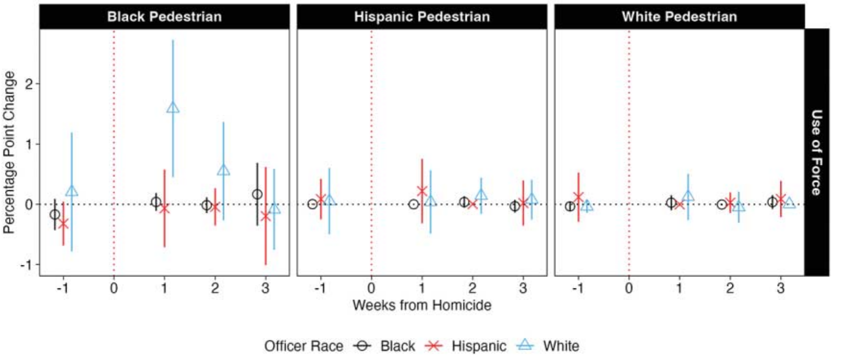

FIG. 3.—Effect of homicides near the home of an officer on the subsequent percentage probability of a use-of-force incident, CPD, 2012–20, by time. The data include CPD members holding the ranks of police officer, sergeant, or lieutenant who are assigned to geographic beats, excluding those with administrative duties. The analysis is further limited to officers whose addresses were directly identified from the voter registration file, totaling 2,194 Black officers, 2,641 Hispanic officers, and 4,111 White officers. The data cover the years 2012–20. Outcomes are binary but rescaled to 0 and 100 so that regression coefficients can be read as changes in percentage points. All models include year, beat, shift, month, and day-of-the-week fixed effects. Standard errors are clustered by police district and are robust to heteroskedasticity. Error bars around estimated coefficients represent 99% confidence intervals.

Figures 3 and 4 confirm that treated and untreated officers working in the same areas, on the same shifts, and on the same days behave in identical ways in the week prior to the treatment. The lack of anticipatory effects is robust when we model three weeks prior to treatment (see app. fig. A1). This supports the premise that observed differences in the probability of police activity after a homicide can be attributed to the treatment itself rather than preexisting differences between the groups.

Consistent with our expectations, figure 3 shows that White officers are significantly more likely to use force against Black civilians for the weeks that follow a homicide within one-eighth of a mile of the home. In the first week after exposure, White officers are around 1.6 percentage points more likely than unexposed officers to use force against Black pedestrians during their shifts. In the second week, we see a decay in the coefficient to around 0.52 percentage points and an increase in the p value ($p = .07$), and in the third week, we see the effect disappear entirely.

Although a 1.6 percentage point increase in the probability of using force against a Black civilian during a shift may seem small, it represents a substantively large increase. Considering that the baseline probability that a White officer using force against a Black civilian during any given shift is approximately 0.26%, a treatment effect of 1.6 percentage points translates into a sevenfold increase.

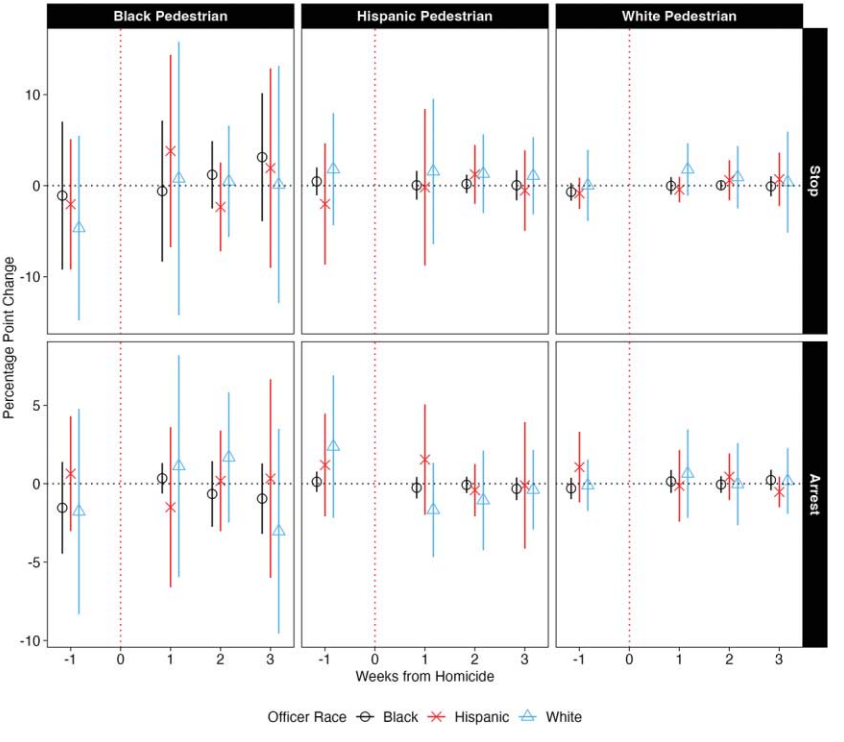

FIG. 4.—Effect of homicides near the home of an officer on the subsequent percentage probability of an arrest or stop, CPD, 2012–20, by time. See figure 3 for description of the data.

Also consistent with theories of racial threat (Blumer 1958; Blalock 1967), figure 3 shows that the increase in the likelihood of using force against Black civilians following a homicide near an officer's residence is limited to White officers. We do not observe any evidence that Hispanic or Black officers who were exposed to a nearby homicide are more likely than their unexposed counterparts to use force against pedestrians. Among White officers, the effect is also particular to incidents involving Black pedestrians. We see no similar impact on the likelihood of use-of-force incidents involving White or Hispanic pedestrians.

Contrary to expectations, figure 4 shows that a nearby homicide has no effect on the probability that officers arrest or stop Black pedestrians. To test the robustness of these null findings, we decompose arrests into several categories, including arrests for property crimes, violent crimes, traffic violations, and drug offenses (see app. table A8). Across all of these subsamples, we find no effect. We discuss the implications of these null findings in the discussion section.

Given these results, we simplify subsequent analyses so that they measure changes in the probability of using force for the week following a proximate homicide and concentrate on interactions between White officers and Black pedestrians. It is worth noting, however, that regardless of the model specification, we see no effect for Hispanic or Black officers or incidents involving White or Hispanic civilians. The complete set of results can be found in appendix figures A1, A2, A18, and A19.

In the previous analysis, we examined officers who lived within one-eighth of a mile of a homicide, allowing the time after exposure to vary. In the next set of analyses, we focus on the week following a homicide, where the effect is strongest, and allow the distance an officer lives from the homicide to vary.

Figure 5 shows that the closer a White officer lives to a homicide, the more likely they are to engage in force against Black pedestrians during their shifts for the following week. Consistent with figure 3, figure 5 shows that when a homicide occurs within one-eighth a mile of a White officer's home, there is a 1.6 percentage point increase in the probability that they use force against Black civilians for the following week. Additionally, among White officers who live between one-eighth and one-fourth of a mile from a homicide, we see a 0.56 percentage point increase in the probability of using force against Black civilians the following week. We observe no difference between unexposed officers and officers for whom a homicide occurred between one-fourth and one-half a mile from their homes.

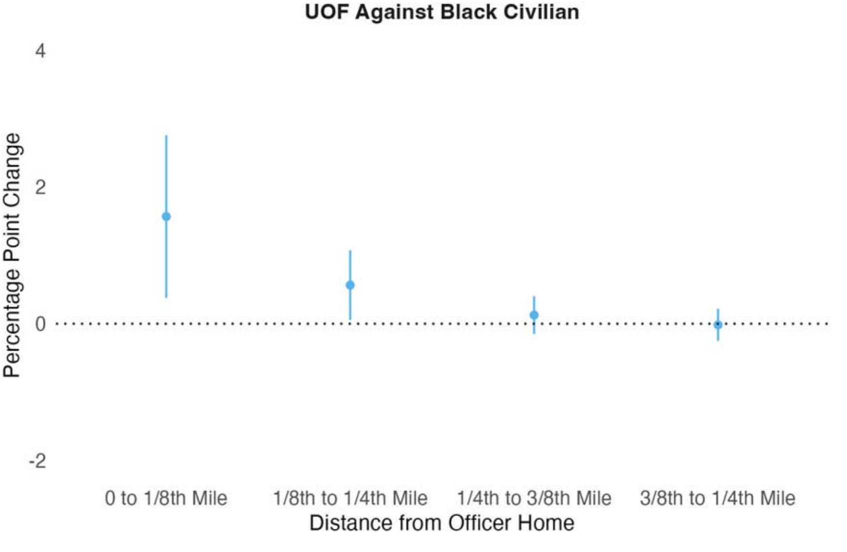

FIG. 5.—Effect of homicides near the home of an officer on the subsequent percentage probability of a use-of-force incident, CPD, 2012–20, by distance. See figure 3 for description of the data.

There are several reasons why the geographic distance from a homicide might influence officers' perceptions of racial threat. First, officers who live farther from the homicide may be less likely to know about it. Second, even if officers are aware of a homicide, the fact that it occurred farther from their home could make it less salient and less likely to induce feelings of racial threat. While we cannot determine the precise mechanism of the decay, both of these factors should lead to a diminishing impact of a homicide on officer behavior as the geographic distance from the incident increases.

Taken together, these findings show that homicides near White officers' homes increase their likelihood of using force against Black civilians. However, homicides vary across a number of important and potentially relevant characteristics. Indeed, theories of racial threat suggest that certain types of homicides should be perceived as more threatening and more disruptive to entrenched racial hierarchies than others. But existing literature presents mixed findings: some studies link Black-on-White homicides to increased discriminatory policing (Eitle et al. 2002; Legewie and Fagan 2016), while others suggest the race of the victim doesn't matter when the victim is a police officer (Legewie 2016; Zhao and Papachristos 2024).

To assess these theories, we decompose our treatment in figure 6 by parsing the homicides by the race of the victims and suspects. Some homicide

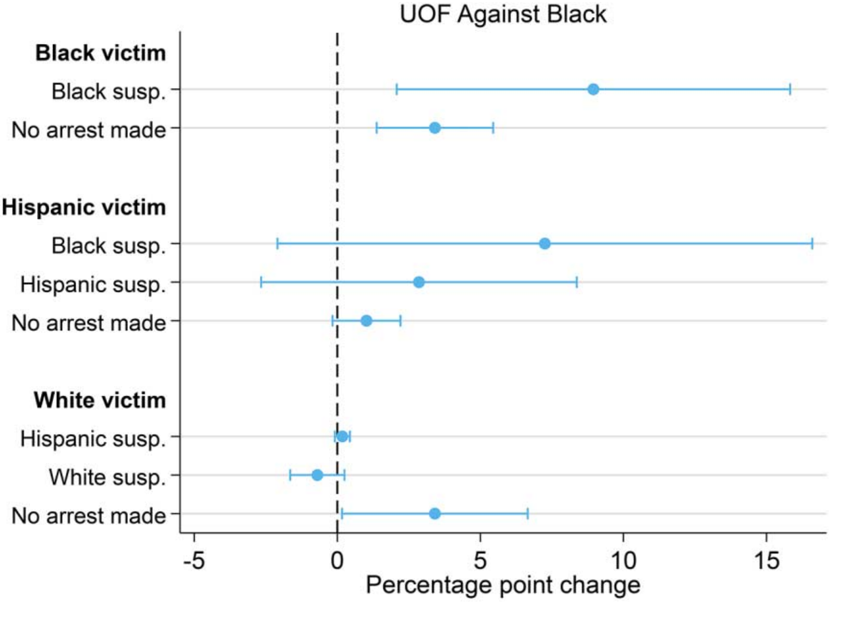

FIG. 6.—Effect of a homicide near the home of a White officer on the subsequent probability of use of force against Black civilians, CPD, 2012–20, by race of victim and perpetrator. See figure 3 for description of the data.

combinations—such as Black victims with Hispanic or White suspects, Hispanic victims with White suspects, or White victims with Black suspects—occur too infrequently near White officers' homes to generate statistically meaningful variation within the *MDSB* or officer fixed-effects specification. Therefore, the effect of these kinds of homicides on officer behavior cannot be identified.

Figure 6 shows that three types of homicides drive the increased likelihood that White officers use force against Black pedestrians: (1) homicides where the victim is Black and no arrest is made, (2) homicides where the victim is Black and the arrested suspect is also Black, and (3) homicides where the victim is White and no arrest is made. We find no evidence of such patterns when the use of force is directed at Hispanic and White civilians, as shown in appendix figures A18 and A19.

Although we cannot assess the race of the suspect when no arrest is made, research on gang violence indicates that police often blur the distinction between the perpetrator and the victim (Carlson 2019). As shown in table 2, only 17.4% ($n = 910$) of the homicides in Chicago between 2012 and 2020 were cleared. Of the cleared homicides, 81.4% ($n = 741$) involved a Black suspect. We believe it is likely that police officers assume the race of homicide suspects based on these patterns of cleared homicides and tend to infer that the perpetrators are Black when victims are White or Black.

The fact that the impact of exposure to homicide is only visible when White officers interact with Black pedestrians strongly suggests that this exposure activates racial bias rather than an instrumental professional response. If the proximity to a homicide increased the likelihood of using force against Black pedestrians due to arrests related to these nearby homicides, we would expect the effect among all officers and in relation to all homicides, regardless of the officer's race, pedestrian's race, suspect's race, or victim's race. Moreover, if it were an instrumental professional response, we would not expect to see an effect for homicides where no arrest was made. However, the data show a strong effect in these cases.

Nevertheless, we consider the possibility that the increased use of force by White officers against Black pedestrians reflects an attempt to make an arrest connected to the homicide to which the officer was exposed. First, we test the effect of a homicide on the rate at which White officers make arrests for violent crimes and weapons offenses (see fig. A8). In both cases, we find no effect. Second, we examine the effect of a homicide on officers who work and live in the same area (see fig. A9). Homicides typically occur near the residences of both the victim and the perpetrator (Block 1977; Reiss and Roth 1993). If the observed effect were due to officers arresting a suspect related to a homicide near their home, we would expect the effect to be concentrated among officers who work and live in the same neighborhoods. Our results show that this is not the case.

Additional Sensitivity Checks

To test the robustness of our findings, we remodel our data in several ways. First, we drop the *MDSB* fixed effects and introduce an officer fixed effect. Rather than compare a treated officer to an untreated officer working under similar work conditions, this model specification estimates the within-officer change associated with exposure to a homicide. The results, which we display in appendix figures A12 and A13, are nearly identical to our primary models.

Next, we subset our data in various ways, testing whether the effect is driven by a subset of events or a subset of officers. We estimate separate models for two seasonal periods: April to September and October to March, helping us assess effect heterogeneity between the summer and winter months. Additionally, we run separate models for weekdays and weekends. Results from these models are included in appendix figures A14, A16, and A17.

These sample splits are informed by prior research that documents seasonality in officer vacation bidding and crime, which may confound our inferences. For example, given that officer seniority plays a role in how officers bid for shift and patrol assignments, failing to account for day-of-the-week or time-of-the-year seasonality could mask effect heterogeneity. If senior officers are less likely to work on the weekends, the association between homicide exposure and the use of force could be concentrated among junior officers. Similarly, if senior officers are more likely to be off during the summer months, when homicides are more frequent, failing to account for the seasonality of crime across the year would also mask effect heterogeneity. Yet, our main findings hold across these different sample splits.[21]

Finally, we analyze the heterogeneous effects across different types of use-of-force incidents. Specifically, we differentiate the use of force based on the type of resistance reported by the officer, whether the officer reported a civilian injury, and whether the use of force involved more than one officer. Differentiating our data by the type of pedestrian resistance recorded by the officer provides insights into how officers escalate their responses based on perceived threats in their residential environment. Similarly, examining whether the use of force results in civilian injuries allows us to assess the severity and consequences of these incidents. Lastly, considering whether multiple officers were involved in the use of force reveals dynamics of group

[21] Importantly, splitting the sample into smaller subsamples and assessing the sensitivity of our estimates helps us address concerns about the potential artifact of statistical significance due to multiple hypotheses testing. By dividing the data into meaningful subsamples and consistently observing the effect across these groups, we can demonstrate that our findings are not merely a result of random variation. Such an approach tests the robustness of the results under different conditions and contexts, reducing the probability that our significant findings are an artifact of the testing process itself.

behavior and collective decision-making in response to perceived threats. The output of these analyses can be found in figures A3, A4, and A5 in the appendix. We find that the effect is robust across all of these sample splits, although there is a diminished effect in incidents where the officer reported a civilian injury.

DISCUSSION

The durability of racial disparities in police use of force continues to be a site of significant public attention (Buchanan et al. 2020; Olzak 2021) and the focus of many policy interventions (Bass 2021). Although explanations for the persistence of racialized police violence abound (Eberhardt et al. 2004; Laniyonu 2018; Ba et al. 2021; Shoub et al. 2021), recent work tends to emphasize the importance of officers' reactions to the perception of threats, showing that discriminatory policing is more prevalent after events that officers perceive as affronts to their racial and professional identity (Legewie 2016; Grosjean et al. 2022; Donahue 2023; Zhao and Papachristos 2024) and in counties where symbolic threats to White hegemony are most apparent (Eitle et al. 2002; Ross 2015; Legewie and Fagan 2016). In the present article, we extend this work by arguing that the residential context of police officers is an understudied but important setting in which perceptions of group position are structured and is, therefore, key to understanding patterns of racially discriminatory policing.

We show that when a homicide takes place within one-eighth of a mile of a White officer's residence, that officer is seven times more likely to employ physical force against Black individuals during their shifts in the subsequent week. Unlike previous studies, which suggest that Black-on-White crime is particularly impactful (Eitle et al. 2002; Legewie and Fagan 2016), our findings indicate that this effect is triggered by homicides where the victim is either Black or White and the suspect is Black or presumed to be Black.

These findings contribute to the literature on the connections between place, racial threat, group position, and discrimination. We extend previous research by emphasizing the significance of residential context, arguing that place is more than just a "bundle of analytical variables" (Gieryn 2000, p. 466), and arguing that for police officers, workplaces and residential areas hold different meanings and that theories of racial threat should be applied accordingly. Drawing from Hubert Blumer's classic text on racial group position, we contend that homicides involving a Black suspect near White officers' residences are perceived as a sign of social disorder, which touch "deep sentiments, that seems to raise fundamental questions about relations, and that awakens strong feelings of identification with one's racial group" (Blumer 1958, p. 6), increasing feelings of threat and the likelihood of subsequent anti-Black discrimination.

It is notable that we observe an effect only in the propensity to use force, with no similar effect on the likelihood of arresting or stopping Black pedestrians. This suggests that officers are not more likely to discriminate at the initial point of contact but are more likely to behave aggressively and escalate once contact is made. We show that these null findings are robust by introducing officer fixed effects and examining arrests related to a variety of offenses. Although this contradicts our expectations, previous research provides some theoretical support. For example, ethnographic accounts of policing tend to emphasize the defensive and fear-based acculturation of officers, where officers are trained to identify attacks before they occur by searching for signs of potential violence in the nuanced facial expressions and body movements of the individuals they encounter (Sierra-Arévalo 2024). Furthermore, research in social psychology suggests that stereotypes about Black criminality are often linked to fears for physical safety (Quillian and Pager 2010). To that effect, increased feelings of racial threat may lead White officers to feel more endangered and precarious around Black pedestrians they have stopped, prompting them to escalate interactions but not initiate additional stops. This perspective aligns with several recent studies that indicate that escalation itself is a distinct site of racially disparate treatment associated with feelings of threat (Kramer and Remster 2018; Hoekstra and Sloan 2022). To the degree that we observe increased discrimination in escalation but not initiation, this study provides evidence that racial threat, as theorized, operates differently across various aspects of police work. Future research should consider to what degree different mechanisms induce different types of discriminatory police action.

In addition to documenting the causal effect of a residentially proximate homicide, this article is the first to report the spatial distribution of officers' residences. We find a pattern of racial segregation among CPD officers consistent with city-level patterns of residential segregation. White police officers tend to live in historically Irish and Italian enclaves, while Hispanic and Black officers live in Hispanic and Black neighborhoods. Although Black and Hispanic officers live in areas that experience less crime and are characterized by less poverty relative to the average Black or Hispanic Chicagoan, these officers still live in neighborhoods that are poorer and considerably more violent than the average White Chicagoan. These spatial patterns are consistent with previous evidence that shows that Black middle-class households live in neighborhoods that are, on average, more socioeconomically disadvantaged than the neighborhoods where White lower-class households live (Sharkey 2014). Future research should explore the mechanisms of residential sorting among police officers and the downstream consequences of officer segregation on retention, mental health, performance, and behavior.

The present study is limited in several ways. Although we are able to match a sizable proportion of the total police officers to the voter file, our sample is nevertheless limited to these officers, and we are, therefore, unable to make claims about unmatched officers. We attempt to address concerns that the sample of matched officers is unrepresentative by comparing the matched and unmatched samples across various characteristics. We find that officers in our matched sample are similar to officers in our unmatched sample.

Additionally, because officers rarely move and residential characteristics are fairly stable, this study is unable to make inferences about the causal effect of more static residential characteristics like neighborhood-level socioeconomic conditions on officer behavior. For example, we cannot test whether White officers become more prejudiced as their neighborhood of residence becomes less White, an obvious hypothesis of the racial threat framework. Future research should attempt to address this gap.

Another limitation involves the potential for spillover treatment effects or violations of the stable unit treatment value assumption (SUTVA). For instance, if two officers are patrolling together and only one of them has recently been exposed to a nearby homicide, there is a chance that peer effects might indirectly cause the untreated officer to become influenced by this exposure. For example, if the treated officer discusses the homicide at the beginning of their shift, the untreated officer may "absorb" some of the biases, leading them to behave more aggressively. If this exposure is fully transferred to the untreated officer, our models would yield null results. Alternatively, if only a partial transfer occurs, causing the untreated officer to adopt a portion of these aggressive tendencies, our models would still generate a positive estimate—although smaller in magnitude than the true causal effect.

Although it is difficult to quantify the magnitude of such contamination, we believe that any violation of SUTVA would result in an underestimation of the true effect. We address this concern in two ways. First, we remodel our outcome using an officer fixed effect. This specification compares the same officer to themselves before and after exposure to a homicide. These models yield point estimates and confidence intervals that are virtually identical to those in the beat, shift, day, month (BSDM) fixed-effects models (see fig. A13). We also address the possibility of SUTVA violations by estimating models that involve single-officer use-of-force incidents, as shown in figure A5. While models do not yield statistically significant results, likely due to the reduction in the sample size, the point estimate remains consistent with our broader findings, suggesting that any SUTVA violations have only a minimal impact on our causal estimation.

Few studies have explored how residential environments affect workplace behavior. Our research demonstrates that police officers' actions are influenced by violence near their homes. It is possible that other professionals' workplace conduct is similarly affected by their neighborhood conditions. Future research should examine other fields, such as medicine, real estate, and education, where employees have considerable discretion and play a key role in producing racially disparate outcomes.

An important and growing literature in sociology highlights the geographically and socially structured nature of urban violence (Legewie and Schaeffer 2016; Papachristos and Bastomski 2018; Ouellet et al. 2019; Wood et al. 2019; Zhao and Papachristos 2020). This work shows that violent behavior can be transmitted among gang members (Papachristos 2009) or among police (Ouellet et al. 2019) but rarely addresses the possibility that violence, which occurs between neighborhood denizens, may be transmitted to police officers and transformed into legally sanctioned violence on the other side of the city. By demonstrating the effect of violence near the homes of police officers on legally authorized violence in other neighborhoods, this study suggests another avenue through which violence may percolate from one part of the city into another (Levy et al. 2020) and from one social group to another.

DATA AVAILABILITY

The code to replicate the analyses from this article can be found in Donahue and Torrats-Espinosa (2025) in the Harvard Dataverse, https://doi.org/10.7910/DVN/TY1BBR.

REFERENCES

Abascal, Maria. 2020. “Contraction as a Response to Group Threat: Demographic Decline and Whites’ Classification of People Who Are Ambiguously White.” *American Sociological Review* 85 (2): 298–322.

Altman, Irwin, and Setha M. Low, eds. 1992. *Place Attachment*. Springer US.

Ang, Desmond. 2021. “The Effects of Police Violence on Inner-City Students.” *Quarterly Journal of Economics* 136 (1): 115–68.

Anwar, Shamena, and Hanming Fang. 2006. “An Alternative Test of Racial Prejudice in Motor Vehicle Searches: Theory and Evidence.” *American Economic Review* 96 (1): 127–51.

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

Bass, Karen. 2021. H.R.1280, 117th Congress (2021–2022): George Floyd Justice in Policing Act of 2021. March. Archive Location: 2021-02-24.

Baybeck, Brady. 2006. “Sorting Out the Competing Effects of Racial Context.” *Journal of Politics* 68 (2): 386–96.

Beckett, Katherine, Kris Nyrop, and Lori Pfingst. 2006. “Race, Drugs, and Policing: Understanding Disparities in Drug Delivery Arrests.” *Criminology* 44 (1): 105–37.

Bell, Monica C. 2021. “Next-Generation Policing Research: Three Propositions.” *Journal of Economic Perspectives* 35 (4): 29–48.

Blalock, Hubert. M. 1967. *Toward a Theory of Minority-Group Relations*. Wiley.

Block, Richard. 1977. *Violent Crime: Environment, Interaction, and Death*. Lexington Books.

Blumer, Herbert. 1958. “Race Prejudice as a Sense of Group Position.” *Pacific Sociological Review* 1:3–7.
Bobo, Lawrence. 1983. “Whites’ Opposition to Busing: Symbolic Racism or Realistic Group Conflict?” *Journal of Personality and Social Psychology* 45 (6): 1196.
Bobo, Lawrence D. 1999. “Prejudice as Group Position: Microfoundations of a Sociological Approach to Racism and Race Relations.” *Journal of Social Issues* 55 (3): 445–72.
Bobo, Lawrence, and Vincent L. Hutchings. 1996. “Perceptions of Racial Group Competition: Extending Blumer’s Theory of Group Position to a Multiracial Social Context.” *American Sociological Review* 61 (6): 951.
Bobo, Lawrence, and Camille L. Zubrinsky. 1996. “Attitudes on Residential Integration: Perceived Status Differences, Mere In-Group Preference, or Racial Prejudice?” *Social Forces* 74 (3): 883.
Bor, Jacob, Atheendar S. Venkataramani, David R. Williams, and Alexander C. Tsai. 2018. “Police Killings and Their Spillover Effects on the Mental Health of Black Americans: A Population-Based, Quasi-Experimental Study.” *The Lancet* 392 (10144): 302–10.
Briscoe, Tony. 2016. “Authorities Probe Chaotic Scene That Led to Fatal Police Shooting.” *Chicago Tribune*. https://digitaledition.chicagotribune.com/tribune/article_popover.aspx?guid=9ac4a37d-b52a-4688-8f5c-097aa2df4f73.
Buchanan, Larry, Quoctrung Bui, and Jugal K. Patel. 2020. “Black Lives Matter May Be the Largest Movement in U.S. History.” *New York Times*, July 3.
Campbell, Andrea Louise, Cara Wong, and Jack Citrin. 2006. “‘Racial Threat,’ Partisan Climate, and Direct Democracy: Contextual Effects in Three California Initiatives.” *Political Behavior* 28 (2): 129–50.
Carlson, Jennifer. 2019. “Police Warriors and Police Guardians: Race, Masculinity, and the Construction of Gun Violence.” *Social Problems* 67 (3): 399–417.
Carmichael, Jason T., and Stephanie L. Kent. 2014. “The Persistent Significance of Racial and Economic Inequality on the Size of Municipal Police Forces in the United States, 1980–2010.” *Social Problems* 61 (2): 259–82.
Chiricos, Ted, Ranee McEntire, and Marc Gertz. 2001. “Perceived Racial and Ethnic Composition of Neighborhood and Perceived Risk of Crime.” *Social Problems* 48 (3): 322–40.
Cook, Philip J., and Ashley Mancik. 2024. “The Sixty-Year Trajectory of Homicide Clearance Rates: Toward a Better Understanding of the Great Decline.” *Annual Review of Criminology* 7 (1): 59–83.
Cuartas, Jorge, and Tama Leventhal. 2020. “Exposure to Community Violence and Children’s Mental Health: A Quasi-Experimental Examination.” *Social Science and Medicine* 246:112740.
DeVylder, Jordan E., Hyun-Jin. Jun, Lisa Fedina, Daniel. Coleman, Deidre Anglin, Courtney Cogburn, Bruce Link, and Richard P. Barth. 2018. “Association of Exposure to Police Violence with Prevalence of Mental Health Symptoms Among Urban Residents in the United States.” *JAMA Network Open* 1 (7): e184945.
Donahue, Samuel Thomas. 2023. “The Politics of Police.” *American Sociological Review* 88 (4): 656–80.
Donahue, Samuel Thomas, and Gerard Torrats-Espinosa. 2025. “Replication Data for: ‘From the Block to the Beat: How Violence in Officers’ Neighborhoods Influences Racially Biased Policing.’” Harvard Dataverse, https://doi.org/10.7910/DVN/TY1BBR.
Duxbury, Scott W. 2021. “Who Controls Criminal Law? Racial Threat and the Adoption of State Sentencing Law, 1975 to 2012.” *American Sociological Review* 86 (1): 123–53.
Eberhardt, Jennifer L., Phillip Atiba Goff, Valerie J. Purdie, and Paul G. Davies. 2004. “Seeing Black: Race, Crime, and Visual Processing.” *Journal of Personality and Social Psychology* 87 (6): 876–93.

Eitle, David, Stewart J. D'Alessio, and Lisa Stolzenberg. 2002. "Racial Threat and Social Control: A Test of the Political, Economic, and Threat of Black Crime Hypotheses." *Social Forces* 81 (2): 57–576.

Ellen, Ingrid Gould, Justin P. Steil, and Jorge De la Roca. 2016. "The Significance of Segregation in the 21st Century." *City and Community* 15 (1): 8–13.

Emerson, Michael O., George Yancey, and Karen J. Chai. 2001. "Does Race Matter in Residential Segregation? Exploring the Preferences of White Americans." *American Sociological Review* 66 (6): 922–35.

Enos, Ryan D. 2014. "Causal Effect of Intergroup Contact on Exclusionary Attitudes. *Proceedings of the National Academy of Sciences* 111 (10): 3699–704.

Enos, Ryan D. 2016. "What the Demolition of Public Housing Teaches Us About the Impact of Racial Threat on Political Behavior." *American Journal of Political Science* 60 (1): 123–42.

Enos, Ryan D. 2017. *The Space Between Us: Social Geography and Politics*. Cambridge University Press.

Epp, Charles R., Steven Maynard-Moody, and Donald P. Haider-Markel. 2014. *Pulled Over: How Police Stops Define Race and Citizenship*. University of Chicago Press.

Fernández-Val, Iván, and Martin Weidner. 2016. "Individual and Time Effects in Nonlinear Panel Models with Large N, T." *Journal of Econometrics* 192(1): 291–312.

Geller, Amanda, Jeffrey Fagan, Tom Tyler, and Bruce G. Link. 2014. "Aggressive Policing and the Mental Health of Young Urban Men." *American Journal of Public Health* 10 4 (12): 2321–27.

Gieryn, Thomas F. 2000. "A Space for Place in Sociology." *Annual Review of Sociology* 26 (1): 463–96.

Gottlieb, Aaron, and Robert Wilson. 2019. "The Effect of Direct and Vicarious Police Contact on the Educational Achievement of Urban Teens." *Children and Youth Services Review* 103:190–99.

Goyette, Kimberly A., Danielle Farrie, and Joshua Freely. 2012. "This School's Gone Downhill: Racial Change and Perceived School Quality Among Whites." *Social Problems* 59 (2): 155–76.

Grosjean, Pauline, Federico Masera, and Hasin Yousaf. 2022. "Inflammatory Political Campaigns and Racial Bias in Policing." *Quarterly Journal of Economics* 138 (1): 413–63.

Hellevik, Ottar. 2009. "Linear Versus Logistic Regression When the Dependent Variable Is a Dichotomy." *Quality and Quantity* 43 (1): 59–74.

Hoekstra, Mark, and Carly Will Sloan. 2022. "Does Race Matter for Police Use of Force? Evidence from 911 Calls." *American Economic Review* 112 (3): 827–60.

Katz, Ethan. 2001. "Bias in Conditional and Unconditional Fixed Effects Logit Estimation." *Political Analysis* 9 (4): 379–84.

Kent, Stephanie L., and Jason T. Carmichael. 2014. "Racial Residential Segregation and Social Control: A Panel Study of the Variation in Police Strength Across U.S Cities, 1980–2010." *American Journal of Criminal Justice* 39 (2): 228–49.

Kent, Stephanie L., and David Jacobs. 2005. "Minority Threat and Police Strength from 1980 to 2000: A Fixed-Effects Analysis of Nonlinear and Interactive Effects in Large U.S. Cities." *Criminology* 43 (3): 731–60.

Kilgannon, Corey. 2020. "A Gated Community in N.Y.C. Where Trump Flags Fly." *The New York Times*, October 20.

King, Gary, and Langche Zeng. 2001. "Logistic Regression in Rare Events Data." *Political Analysis* 9 (2): 137–63.

Kirk, David S., and Robert J. Sampson. 2013. "Juvenile Arrest and Collateral Educational Damage in the Transition to Adulthood." *Sociology of Education* 86 (1): 36–62.

Klinger, David, Richard Rosenfeld, Daniel Isom, and Michael Deckard. 2016. "Race, Crime, and the Micro-Ecology of Deadly Force." *Criminology and Public Policy* 15 (1): 193–222.

Knox, Dean, Will Lowe, and Jonathan Mummolo. 2020. "Administrative Records Mask Racially Biased Policing." *American Political Science Review* 114 (3): 619–37.

Kramer, Rory, and Brianna Remster. 2018 “Stop, Frisk, and Assault? Racial Disparities in Police Use of Force During Investigatory Stops.” *Law and Society Review* 52 (4): 960–93.
Laniyonu, Ayobami. 2018. “Coffee Shops and Street Stops: Policing Practices in Gentrifying Neighborhoods.” *Urban Affairs Review* 54 (5): 898–930.
LeCount, Ryan Jerome. 2017. “More Black Than Blue? Comparing the Racial Attitudes of Police to Citizens.” *Sociological Forum* 32 (S1): 1051–72.
Legewie, Joscha. 2016. “Racial Profiling and Use of Force in Police Stops: How Local Events Trigger Periods of Increased Discrimination.” *American Journal of Sociology* 122 (2): 379–424.
Legewie, Joscha, and Nino José Cricco. 2022. “Long-Term Exposure to Neighborhood Policing and the Racial/Ethnic Gap in High School Graduation.” *Demography* 59 (5): 1739–61.
Legewie, Joscha, and Jeffrey Fagan. 2016. “Group Threat, Police Officer Diversity and the Deadly Use of Police Force.” SSRN working paper. papers.ssrn.com/sol3/papers.cfm?abstract_id=2778692.
Legewie, Joscha, and Jeffrey Fagan. 2019. “Aggressive Policing and the Educational Performance of Minority Youth.” *American Sociological Review* 84 (2): 220–47.
Legewie, Joscha, and Merlin Schaeffer. 2016. “Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict.” *American Journal of Sociology* 122 (1): 125–61.
Lett, Elle, Emmanuella Ngozi Asabor, Theodore Corbin, Dowin Boatright. 2021. “Racial Inequity in Fatal US Police Shootings, 2015–2020.” *Journal of Epidemiology and Community Health* 75 (4): 394–97.
Levy, Brian L., Nolan E. Phillips, and Robert J. Sampson. 2020. “Triple Disadvantage: Neighborhood Networks of Everyday Urban Mobility and Violence in U.S. Cities.” *American Sociological Review* 85 (6): 925–56.
Louie, Patricia, and Reed T. DeAngelis. 2024. “Fear of a Black Neighborhood: Anti-Black Racism and the Health of White Americans.” *Social Forces* 102 (3): 817–38.
Lundman, Richard J., and Robert L. Kaufman. 2003. “Driving While Black: Effects of Race, Ethnicity, and Gender on Citizen Self-Reports of Traffic Stops and Police Actions.” *Criminology* 41 (1): 195–220.
Merry, Sally Engle. 1981. *Urban Danger: Life in a Neighborhood of Strangers*. Temple University Press.
Mikulan, Steven. 2002. Copland. *LA Weekly*. Section: News.
Milligan, Melinda J. 1998. “Interactional Past and Potential: The Social Construction of Place Attachment.” *Symbolic Interaction* 21 (1): 1–33.
Mobasseri, Sanaz. 2019. “Race, Place, and Crime: How Violent Crime Events Affect Employment Discrimination.” *American Journal of Sociology* 125 (1): 63–104.
Muller, Christopher. 2012. “Northward Migration and the Rise of Racial Disparity in American Incarceration, 1880–1950.” *American Journal of Sociology* 118 (2): 281–326.
Neyman, J., and Elizabeth L. Scott. 1948. “Consistent Estimates Based on Partially Consistent Observations.” *Econometrica* 16 (1): 1–32.
Novak, Kenneth J., and Mitchell B. Chamlin. 2012. “Racial Threat, Suspicion, and Police Behavior: The Impact of Race and Place in Traffic Enforcement.” *Crime and Delinquency* 58 (2): 275–300.
Oliver, J. Eric, and Tali Mendelberg. 2000. “Reconsidering the Environmental Determinants of White Racial Attitudes.” *American Journal of Political Science* 44 (3): 574–89.
Olzak, Susan. 2021. “Does Protest Against Police Violence Matter? Evidence from U.S. Cities, 1990 Through 2019.” *American Sociological Review* 86 (6): 1066–99.
Omori, Marisa, Rachel Lautenschlager, and Justin Stoler. 2022. “Organizational Practice and Neighborhood Context of Racial Inequality in Police Use-of-Force.” *Social Problems* 71 (3): 748–69.
Ouellet, Marie, Sadad Hashimi, Jason Gravel, and Andrew V. Papachristos. 2019. “Network Exposure and Excessive Use of Force.” *Criminology and Public Policy* 18 (3): 675–704.

Papachristos, Andrew V. 2009. “Murder by Structure: Dominance Relations and the Social Structure of Gang Homicide.” *American Journal of Sociology* 115 (1): 74–128.

Papachristos, Andrew V., and Sara Bastomski. 2018. “Connected in Crime: The Enduring Effect of Neighborhood Networks on the Spatial Patterning of Violence.” *American Journal of Sociology* 124 (2): 517–68.

Pierson, Emma, Camelia Simoiu, Jan Overgoor, Sam Corbett-Davies, Daniel Jenson, Amy Shoemaker, Vignesh Ramachandran, Phoebe Barghouty, Cheryl Phillips, Ravi Shroff, and Sharad Goel. 2020. “A Large-Scale Analysis of Racial Disparities in Police Stops Across the United States.” *Nature Human Behaviour* 4 (7): 736–45.

Quillian, Lincoln. 1995. “Prejudice as a Response to Perceived Group Threat: Population Composition and Anti-Immigrant and Racial Prejudice in Europe.” *American Sociological Review* 60 (4): 586–611.

Quillian, Lincoln. 1996. “Group Threat and Regional Change in Attitudes Toward African-Americans.” *American Journal of Sociology* 102 (3): 816–60.

Quillian, Lincoln, and Devah Pager. 2001. “Black Neighbors, Higher Crime? The Role of Racial Stereotypes in Evaluations of Neighborhood Crime.” *American Journal of Sociology* 107 (3): 717–67.

Quillian, Lincoln, and Devah Pager. 2010. “Estimating Risk: Stereotype Amplification and the Perceived Risk of Criminal Victimization.” *Social Psychology Quarterly* 73 (1): 79–104.

Reiss Jr., Albert J., and Jeffrey A. Roth. 1993. *Understanding and Preventing Violence: Volume 1*, 6th ed. National Academies Press.

Renauer, Brian C. 2012. “Neighborhood Variation in Police Stops and Searches: A Test of Consensus and Conflict Perspectives.” *Police Quarterly* 15 (3): 219–40.

Rojek, Jeff, Richard Rosenfeld, and Scott Decker. 2012. “Policing Race: The Racial Stratification of Searches in Police Traffic Stops.” *Criminology* 50 (4): 993–1024.

Ross, Cody T. 2015. “A Multi-Level Bayesian Analysis of Racial Bias in Police Shootings at the County-Level in the United States, 2011–2014.” *PLOS One* 10 (11): e0141854.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*. University of Chicago Press.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. 2002. “Assessing ‘Neighborhood Effects’: Social Processes and New Directions in Research.” *Annual Review of Sociology* 28(1): 443–78.

Sampson, Robert J., and Stephen W. Raudenbush. 1999. “Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods.” *American Journal of Sociology* 105 (3): 603–51.

Sampson, Robert J., and Stephen W. Raudenbush. 2004. “Seeing Disorder: Neighborhood Stigma and the Social Construction of ‘Broken Windows.’” *Social Psychology Quarterly* 67 (4): 319–42.

Scannell, Leila, and Robert Gifford. 2010. “Defining Place Attachment: A Tripartite Organizing Framework.” *Journal of Environmental Psychology* 30 (1): 1–10.

Sharkey, Patrick. 2010. “The Acute Effect of Local Homicides on Children’s Cognitive Performance.” *Proceedings of the National Academy of Sciences* 107 (26): 11733–38.

Sharkey, Patrick. 2014. “Spatial Segmentation and the Black Middle Class.” *American Journal of Sociology* 119 (4): 903–54.

Sharkey, Patrick, and Jacob W. Faber. 2014. “Where, When, Why, and or Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects.” *Annual Review of Sociology* 40 (1): 559–79.

Sharkey, Patrick, T., Nicole Tirado-Strayer, Andrew V. Papachristos, and C. Cybele Raver. 2012. “The Effect of Local Violence on Children’s Attention and Impulse Control.” *American Journal of Public Health* 102 (12): 2287–93.

Shjarback, John. 2018. “‘Neighborhood’ Influence on Police Use of Force: State-of-the-Art Review.” *Policing: An International Journal* 41 (6): 859–72.

Shoub, Kelsey, Derek A. Epp, Frank R. Baumgartner, Leah Christiani, and Kevin Roach. 2020. "Race, Place, and Context: The Persistence of Race Effects in Traffic Stop Outcomes in the Face of Situational, Demographic, and Political Controls." *Journal of Race, Ethnicity, and Politics* 5 (3): 481–508.

Shoub, Kelsey, Katelyn E. Stauffer, and Miyeon Song. 2021. "Do Female Officers Police Differently? Evidence from Traffic Stops." *American Journal of Political Science* 65 (3): 755–69.

Sierra-Arévalo, Michael. 2024. *The Danger Imperative: Violence, Death, and the Soul of Policing*. Columbia University Press.

Simon, Samantha J. 2023. "Training for War: Academy Socialization and Warrior Policing." *Social Problems* 70 (4): 1021–43.

Smith, Brad W., and Malcolm D. Holmes. 2014. "Police Use of Excessive Force in Minority Communities: A Test of the Minority Threat, Place, and Community Accountability Hypotheses." *Social Problems* 61 (1): 83–104.

Smith, Douglas A. 1986. "The Neighborhood Context of Police Behavior." *Crime and Justice* 8:313–41.

Stolzenberg, Lisa, Stewart J. D'Alessio, and David Eitle. 2004. "A Multilevel Test of Racial Threat Theory." *Criminology* 42 (3): 673–98.

Stults, Brian J., and Eric P. Baumer. 2007. "Racial Context and Police Force Size: Evaluating the Empirical Validity of the Minority Threat Perspective." *American Journal of Sociology* 113 (2): 507–46.

Suttles, Gerald. D. 1968. *The Social Order of the Slum: Ethnicity and Territory in the Inner City*. University of Chicago Press.

Vitale, Alex S. 2021. *The End of Policing*. Verso Books.

Welch, Susan, Lee Sigelman, Timothy Bledsoe, and Michael Combs. 2001. *Race and Place: Race Relations in an American City*. Cambridge University Press.

Wetts, Rachel, and Robb Willer. 2018. "Privilege on the Precipice: Perceived Racial Status Threats Lead White Americans to Oppose Welfare Programs." *Social Forces* 97 (2): 793–822.

Wood, George, Daria Roithmayr, and Andrew V. Papachristos. 2019. "The Network Structure of Police Misconduct." *Socius: Sociological Research for a Dynamic World* 5, 237802311987979.

Zhao, Linda, and Andrew V. Papachristos. 2020. "Network Position and Police Who Shoot." *The ANNALS of the American Academy of Political and Social Science* 687 (1): 89–112.

Zhao, Linda, and Andrew V. Papachristos. 2024. "Threats to Blue Networks: The Effect of Partner Injuries on Police Misconduct." *American Sociological Review* 89 (1): 159–95.

Zingher, Joshua N., and M. Steen Thomas. 2014. "The Spatial and Demographic Determinants of Racial Threat." *Social Science Quarterly* 95 (4): 1137–54.

Zorbaugh, Harvey Warren. 1983. *The Gold Coast and the Slum: A Sociological Study of Chicago's Near North Side*. University of Chicago Sociological Series. University of Chicago Press.