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CRIMINOLOGY

ORIGINAL ARTICLE

Homicides involving Black victims are less likely to be cleared in the United States

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Replication Data and Code
All data needed to replicate the analyses reported in the current article are openly available, along with the relevant R scripts, at the following Zenodo repository: https://zenodo.org/records/100240677 (or use the DOI: https://doi.org/10.5281/zenodo.10024067).

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Abstract

Does a victim's race explain variation in the likelihood of homicide clearance? Attempts to address this issue date back to the 1970s. Yet, despite its theoretical and policy relevance, we lack a comprehensive and clear empirical answer to this critical question. Here, I causally focus on this problem by investigating racial disparity in homicide clearance in the United States, exploiting two sources covering the 1991–2020 period: the Murder Accountability Project data set (N = 522,278) and the National Incident-Based Reporting System data set (N = 98,677). I primarily analyze these sources by employing exact matching to achieve perfect covariate balance and subsequently isolate the effect of race on the probability of clearance. For comparative purposes, I also use regression adjustment without matching obtaining complementary estimates. I demonstrate that the likelihood of clearance is 3.4 to 4.8 percent lower for homicides involving Black victims, depending on the sampling and estimation approach. In addition, I empirically show that this race effect is slightly higher for males and that racial disparity has moderately but significantly increased over time. These findings contribute to the extensive amount of evidence on discrimination affecting Black individuals in the administration of justice in

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the United States, calling for structural efforts to reduce this divide.

KEYWORDS
causal inference, homicide clearance, police, racial inequality, violence

1 | INTRODUCTION

Racial inequalities in the administration of criminal justice in the United States are a central issue in the research agenda of scholars across different domains and disciplines. In recent years, media reports have also brought public attention to a layer of racial disparity in another critical phenomenon linked to policing and criminal justice that has received less attention compared with other issues such as police violence and mass imprisonment: homicide clearance.[1] A notable example in this regard is *The Washington Post*'s 2019 investigation of 50,000 homicides that occurred in the United States from 2007 to 2017, indicating that arrests after homicide of a White victim occurred in 63 percent of the cases compared with only 48 percent for Latino and 46 percent for Black victims.

The public discussion on racial disparity complemented the more extensive debate on the overall decreasing ability of law enforcement agencies to clear homicide cases in the United States, a trend that began in the 1970s and continues to date (Council on Criminal Justice, 2021).

In the sociological and criminological debate, however, the hypothesis that different groups or categories of people are associated with different outcomes in the investigation of homicides is not recent. In 1976, Black proposed his so-called "theory of law," which later gave birth to one of the two fundamental perspectives attempting to shed light on the reasons behind variation in homicide rates. The perspective that originated from Black's theory has been labeled "discretionary" because it posits that law enforcement focuses on investigating homicide cases with varying emphasis, rigor, and efforts depending on who the victim is, determining variation in clearance likelihood.

An alternative perspective, called "nondiscretionary," having its roots in the works of Wolfgang (1958) and Gottfredson and Hindelang (1979), rejects the idea that the characteristics of the victims play a role in the outcome of homicide investigations. Instead, according to the nondiscretionary viewpoint, the explanation for such variations is associated with the context surrounding the homicide, proxied by the weapon used, the circumstances causing the event, the location, and the broader area in which the homicide happened. Complementary and alternative theoretical arguments, such as the police devaluation, victims' lifestyles, and police resources perspectives, also have emerged, enriching the complex tessellation of explanations for why some homicides are cleared and some others end up being unsolved.

This vibrant debate around the dynamics of homicide clearance has produced dozens of research articles providing heterogeneous results that give partial credit to portions of each theory. More importantly, despite the salience of the question, we lack reliable estimates mapping the racial disparities in homicide clearance to date.

[1] See, for instance, pieces and reports written by the *Wall Street Journal, NBC News, CBS News, Vox*, and *The Guardian*.

Notwithstanding a rich production of studies directly or indirectly addressing the issue of race effects in homicide clearance (Addington, 2006; Campedelli, 2022; Cardarelli & Cavanagh, 1994; Lee, 2005; Paintsil, 2022; Puckett & Lundman, 2003; Regoeczi et al., 2008; Riedel & Rinehart, 1996; Roberts & Lyons, 2011; Roberts & Smith, 2023; Vaughn, 2020), no comprehensive and credible empirical quantification of this extremely policy-relevant divide is available. Although precious in contributing to knowledge on the broader issue of homicide clearance research, previous studies have faced two critical limitations due to data availability constraints. On the one hand, they mainly focused on single cities or counties. On the other hand, they concentrated on single years or restricted time frames. These two aspects severely hindered the possibility of generalizing results beyond limited geographic boundaries or specific temporal windows. Furthermore, and equally importantly, the extant literature is characterized by research designs offering only descriptive or correlational findings.

Therefore, this study seeks to solve these issues by assessing whether, and to what extent, homicides involving Black victims are less likely to be cleared than homicides involving non-Black victims through a research design aiming at identifying the causal effect of being a Black victim on the likelihood of solving a case focusing on three decades of data accounting for hundreds of thousands of homicides.

I pursue this goal by analyzing data on victims of homicides that occurred in the United States retrieved from two distinct sources: the Murder Accountability Project (MAP) data set, using data recorded from 1991 to 2020 (Hargrove, 2019), which expands the Supplementary Homicide Reports data curated by the FBI's Uniform Crime Reporting (UCR) Program, and the National Incident-Based Reporting System (NIBRS) database, covering the same 1991–2020 period (Kaplan, 2021b). For robustness purposes, I also exploit data from the "Murder with Impunity" project curated by *The Washington Post* (2019), which gathered information on more than 52,000 homicides between 2007 and 2017 in the 50 largest American cities.

The two primary data sets ensure varying levels of representativeness and coverage, rely on different definitions of "clearance," and provide different sets of variables. Both data sets have their own limitations and strengths; hence, by scrutinizing both in parallel, I investigate the fundamental research problem of this work ensuring that the outcome of the analysis is not a consequence of the peculiar characteristics of a single data set. This comprehensive focus leads to more reliable and generalizable results, allowing us to obtain the most comprehensive and detailed analysis of the homicide clearance disparity between Black and non-Black victims in the United States.

In terms of empirical strategy, I compare the probability of clearance for Black victims versus non-Black victims in the MAP and NIBRS data, investigating the likelihood of clearance at the victim-event level in two main forms. To gather credible causal estimates, I primarily employ exact matching to obtain balance among relevant covariates to compare pairs or subgroups of homicides that are identical except for the victim's race, minimizing bias due to heterogeneity in covariate distributions. Specifically, I perform matching on a set of possible sources of distortion that have been highlighted as correlates of clearance in the literature on this topic, covering both discretionary and nondiscretionary perspectives. These variables are 1) the age and 2) sex of the victim, 3) the number of offenders, 4) victims involved in the same event, 5) the decade in which the homicide occurred, 6) the agency that investigated the crime, 7) whether the same agency had to investigate another homicide in the same month, and finally 8) the U.S. state in which the event took place, to account for geographical variation. I then compute the average marginal effect (AME) of race per each data set, adjusting for the same matched variables along with additional information on the used weapon and the circumstances surrounding the event (available for both data sets), as well as information on the type of location in which the event took place and the type of urban context in which it occurred (these two latter sources were only available for NIBRS data). In parallel with the matching approach, I also estimate adjusted regression models on the unmatched samples for each data set, controlling for the same variables mentioned. The rationale of complementing the analysis with nonmatched data is to obtain effect sizes that do not suffer from excessive data loss due to matching and can further quantify the impact of race in a setting with no covariate balance. The variables used for matching and adjustment follow the extant empirical literature on homicide clearance, covering all the main theoretical frames developed over time. To enhance reliability, I compute AME via two distinct approaches: the traditional delta method and a simulation-based approach. I estimate and report the AME for the whole samples, as well as provide detailed analysis on potential effect heterogeneity between males and females and across decades, using group-average marginal effects.

Although I explain why current data and models do not suffer from the issue of unmeasured confounders, I employ two strategies to address the issue, strengthening the reliability of the study's results. First, I carry out extensive sensitivity analyses showing that, should unmeasured confounders be an issue, their impact on the models would need to be excessively large to meaningfully represent a problem for the derived estimates and consequently invalidate the outcomes of the study. Second, I link data from *The Washington Post*'s Murder with Impunity project with U.S. Census data to show that community-level socioeconomic characteristics do not alter the magnitude and significance of the race effect.

Robustness models testing 1) the impact of alternative preprocessing steps, 2) the inclusion of additional control variables, and 3) the stability of the findings using MAP data for the 1976–2020 period are provided in the online supporting information as corroboration of the main findings.[2] Finally, alternative models investigating disparity in time to clearance are also included in the online supporting information to provide a more nuanced empirical angle to the phenomenon.

The article proceeds as follows. The next section provides a detailed account of the main theoretical traditions in homicide clearance research. The third section connects the literature on racial disparities in homicide clearance with the broader empirical literature on racial inequalities in criminal justice and policing in the United States. In the Current Study section, I summarize the objectives of the work, offering three main hypotheses around which the analytical framework is built. In the fifth section, I describe the data sources employed in the analyses and present the analytical approach of the study. In the sixth section, I report and describe the results of the main analyses and models. Finally, I summarize the findings of the study and conclude by framing its limitations and providing reflections for policy and future research.

2 | THEORETICAL TRADITIONS IN HOMICIDE CLEARANCE RESEARCH

Scholarship on homicide clearance has been mostly characterized by two main concurrent perspectives. On the one hand, a tradition of scholarship departing from the "theory of law" proposed by Black (1976) has posited that the likelihood that a homicide is cleared is primarily explained by the characteristics of the victim or area where the homicide takes place. On the

[2] Additional supporting information can be found in the full text tab for this article in the Wiley Online Library at http://onlinelibrary.wiley.com/doi/10.1111/crim.2024.62.issue-1/issuetoc.

other hand, criminologists and sociologists inspired by the seminal works of Wolfgang (1958) and Gottfredson and Hindelang (1979) have argued that homicide clearance can be explained and predicted by factors that go beyond the characteristics of the victim or the spatial and social context in which the homicide occurred. Building on these two traditions, the following three complementary/alternative theoretical interpretations have been advanced: 1) the police devaluation perspective, 2) the victim lifestyle perspective, and 3) the police resources perspective. Below I provide an overview of these theoretical frames.

2.1 | Black's Theory of Law and the Discretionary Perspective

Scholars aligning with Black's "theory of law" (1976) subscribe to the so-called "discretionary" perspective.[3] Black's theory originates from the idea that law can be defined as governmental social control and that law is a quantifiable concept that varies across the following five dimensions of social life: 1) stratification, 2) morphology, 3) culture, 4) organization, and 5) social control. Concerning stratification, Black wrote that stratified social wealth is fundamental to understanding which subjects, when victimized, are more likely to receive higher attention from law enforcement. In this regard, the translation of Black's theory into homicide clearance research predicts that victims who are female, younger, and belonging to racial minorities are devalued compared with male, older, and White victims. Shifting the attention from people to places, homicides that occurred in areas with lower socioeconomic status are also less likely to be solved compared with homicides that occurred in communities characterized by higher social status and wealth. With regard to morphology, Black postulated that victims who are not close to the center of the productive life of a community are also at risk of receiving less law. One example is unemployed victims, who are devalued compared with employed ones. The same line of reasoning applies, according to Black, to areas characterized by different employment rates within urban contexts or regions. Concerning culture, his theory of law identifies areas with lower educational backgrounds as less likely to benefit from the full application of the law. With respect to the organization dimension, Black claimed that organized structures are more likely to receive more law than single individuals. Connecting this proposition with homicide clearance, Litwin (2004) hypothesized that, in general, areas with lower social organization would be characterized by lower clearance rates. Finally, with respect to social control, Black (1976) posited that the higher the social control one has been subjected to, the lower the respectability and, hence, the lower the amount of law one should expect. To exemplify, homicide victims that had prior contact with the criminal justice system faced lower odds of case clearance.

In subsequent work, Black (1980) moved from his general argument to specific examples regarding the behavior of law, stating that the murder of a person with high social status will be investigated with much more diligence and resources compared with the homicide of an individual that has less wealth and visibility.

A few years later, Paternoster (1984) published an article that has become another backbone of the discretional perspective—although, interestingly, Paternoster did not cite Black's work. Paternoster did not specifically focus on disparity in homicide clearance but on racial disparity in prosecutorial decisions regarding the death penalty for homicide perpetrators. The study reported that, *ceteris paribus*, Black homicide offenders were more likely to be sentenced to the death penalty compared with White offenders. Paternoster's article, which more naturally aligns

[3] The "discretionary" perspective has also been labeled "extralegal" and "victim devaluation".

with the vast literature on racial discrimination in courts, is referenced as one of the most striking early empirical accounts of race effects after Black published his two seminal works (1976, 1980) and its evidence has been applied to homicide research to suggest how race can explain different outcomes in case investigation even after controlling for event characteristics.

Empirical research over time, however, has produced mixed findings regarding the postulates of Black's (1976) theory. Marked by the scarcity of comprehensive data in terms of geographical and temporal coverage, research in criminology and sociology has been revolving around case studies involving single cities, counties, or states within the United States, often focusing on limited temporal windows. Within the limits imposed by data and measurement issues, no clear answers have been offered to corroborate (or falsify) the theory proposed by Black. In fact, inconclusive results have been provided regarding the alleged differential effects of victims' sex, race, and age on clearance likelihood, as well as the hypothesized lower clearance rates for homicides occurring in disadvantaged areas or communities.

Some studies detected higher odds of clearance when the victim is a woman (Lee, 2005; Petersen, 2017; Regoeczi et al., 2000), whereas others found null results (Addington, 2006; Puckett & Lundman, 2003; Wellford & Cronin, 1999) or even reported higher likelihood for male victims (Jiao, 2007). Concerning race, the literature is also characterized by mixed findings, with some works highlighting racial disparity in clearance probability (Addington, 2007; Alderden & Lavery, 2007; Fagan & Geller, 2018; Keel et al., 2009; Lee, 2005; Regoeczi et al., 2008; Vaughn, 2020), whereas other did not find any race effect (Addington, 2006; Jiao, 2007; Puckett & Lundman, 2003). Age-wise, even though most studies agree that child victims are related to a higher likelihood of clearance (Addington, 2007; Roberts, 2007), much less agreement exists when older victims are considered (Liem et al., 2019; Regoeczi et al., 2020). In terms of areas and community characteristics, divergence also exists. Few works have documented lower clearance rates in disadvantaged neighborhoods or communities (Kennedy et al., 2021; Litwin & Xu, 2007; Mancik et al., 2018), with others indicating that homicides occurring in disadvantaged areas are more likely to be solved (LoFaso, 2020; Petersen, 2017).

2.2 | The Solvability Perspective

Before Black's (1976) theory of law, Wolfgang (1958) argued that, given the salience of homicide as one of the most serious crimes occurring in a society, law enforcement ensures the same amount of attention, resources, and effort to all cases, regardless of the characteristics of the victim or the area in which the murder took place. Gottfredson and Hindelang (1979) complemented this view by explaining that discretion by police officers does not influence investigations and case outcomes precisely because of the inherent seriousness of homicide as a crime. Their alternative model relied on the idea that the "amount of law" one receives is a function of what happens between the victim and the offender, and that harm and seriousness is the only determinant of the quantity of law one should expect to receive. Their view encompassed the behavior of law in general, as Black's (1976), rather than a specific application to homicide clearance research. But the concepts of harm and seriousness clearly reconnect their general model to the study of the variation of the likelihood of solving murder cases. Since homicide is the most serious, damaging, harmful crime, it prompts strong police responses that are in no way influenced by discretionary factors related to the age, race, sex, or social status of the victim. The solvability perspective thus attributes variations of clearance likelihood to characteristics of the events such as the weapon used, the circumstances surrounding the event, the type of population area linked to the murder, as well as the location where the body was found.[4] According to sociologists and criminologists championing the solvability perspective, weapons are fundamental in shaping the likelihood of case clearance because different types of weapons are more or less likely to leave evidence on the crime scene. The circumstances are also critical to the work of investigators and detectives because the type of interaction and motives guiding the event can facilitate or hinder the search for the perpetrator. Wolfgang (1958) also highlighted the importance of the size of the community where the event took place (rather than its socioeconomic characteristics) as relevant in explaining the chances of solving a case, as highly populated communities might represent an opportunity for escaping from the spotlight of law enforcement. Finally, body location might signal a specific relationship between the victim and the perpetrator. Furthermore, different locations (such as outdoor and indoor) lead to different types of forensic evidence, as well as to different probabilities of witnesses.

Litwin (2004) integrated the solvability perspective by discussing how, given the hierarchical structure of police institutions, law enforcement agencies are interested in being evaluated positively and how case clearance is one of the most straightforward (albeit discussed) means of evaluation. Police agencies thus try to maximize their clearance rates, leveraging complex systems of incentives and pressure (both internal and external). As a result, Litwin argued that all homicide cases receive the same attention, effort, and resources.

Completely diverging from the hypotheses offered by Black's (1976) theory of law, the discretionary perspective has found a much higher agreement in terms of empirical results in the literature. Previous studies have demonstrated, for instance, that homicides committed with the use of a firearm are less likely to be solved compared with those committed with a knife or another object that requires direct contact between the perpetrator and the victim (Campedelli, 2022; Litwin, 2004; Roberts, 2007; Roberts & Lyons, 2011; Rydberg & Pizarro, 2014). For example, according to a recent study by Piquero (2024), the rate of firearm homicides with Black individuals as victims is 12 times greater than that experienced by Whites. Similarly, leveraging data from the Project on Human Development in Chicago Neighborhoods, Lanfear and colleagues (2023) also found evidence of disproportionate direct or indirect firearm victimization for Black compared with White respondents. Therefore, following the solvability framework, potential racial disparities in homicide clearance may simply be the byproduct of unequal rates of firearm-related victimization experienced by Black individuals. Additionally, those homicides that occurred in indoor locations have more chances to be solved because evidence can be better preserved, as well as because of the correlation between indoor locations and the fact that the victim and the perpetrator were not strangers (Addington, 2006; Litwin, 2004; Litwin & Xu, 2007; Regoeczi et al., 2000). Finally, evidence shows that homicides committed in conjunction with another felony are also less likely to be solved by law enforcement, underlying the importance of considering the circumstances surrounding the murder (Lee, 2005; Puckett & Lundman, 2003; Regoeczi et al., 2000; Roberts, 2007).

2.3 | Complementary and Alternative Theoretical Developments

The discretionary and solvability perspectives represent the two most prominent, debated, and tested theoretical explanations for unfolding variation and dynamics in homicide clearance

[4] The solvability perspective is also known as "nondiscretionary" or "event characteristics" perspective.

research. Nonetheless, scholars have departed from these two frameworks to delineate alternative or complementary theoretical explanations. These alternatives include the police devaluation perspective, the victim lifestyle perspective, and the police resources perspective.

On the one hand, the police devaluation perspective was first conceptualized by Keel et al. (2009). Analyzing a survey sent to law enforcement agencies across the United States to assess factors related to clearance rates, Keel and colleagues found, among other things, that the percentage of the non-White population has a negative effect on clearance rates. Although this result typically aligns with the discretionary perspective, the authors argued that the explanation mechanism functions the other way around; namely, clearance rates are lower in areas with a higher proportion of minorities because people living in these areas have lower trust and offer less cooperation to the police, thus, making it more difficult for law enforcement to solve homicide cases. Keel and colleagues framed this theoretical construction by taking inspiration from another work from Black (1993) in which he advanced a sociological explanation of conflict management through informal and extralegal practices, such as retaliation. The related empirical literature simplified the fundamental question of the police devaluation perspective focusing on the relationship between community disadvantage, segregation, and socioeconomic status to clearance rates or probability, rather than testing the proper mechanisms of trust and cooperation and how these directly interact with the likelihood of solving serious crimes. Nonetheless, as I anticipated, while overviewing the discretionary perspective, the findings remain inconclusive: some researchers found that clearance is lower in communities characterized by lower socioeconomic status (Litwin & Xu, 2007; Ousey & Lee, 2010), whereas others did not detect any effect in this regard (Puckett & Lundman, 2003; Xu, 2008).

On the other hand, the victim lifestyle perspective originates from the work of Hindelang (1977) on the differential effects experienced by different social groups in terms of crime victimization risk and, somehow, expands Black's (1976) theory of law by combining some elements of the solvability perspective, putting more emphasis on the victim's deviant lifestyles. Although this perspective has its roots in theoretical bases dating back decades, it was brought to attention only recently by Rydberg and Pizarro (2014). The authors contended that low clearance rates can be explained by the social environment and behavioral routines of individuals. Specifically, when fatal violence emerges in the context of deviant or criminal lifestyles, such as violence as a result of gang-related interactions, cases are less likely to be cleared (or take more time to be solved).

What emerges from these first two complementary approaches is that victim-level characteristics are deemed to be important, but scholars have proposed different explanations than those originally set forth by Black (1976; and subsequently, autonomously, by Paternoster (1984)]: Rather than police discretion in devoting equal efforts and resources to all homicides regardless of race and status (among others), variation in clearance probability is due to lower trust and cooperation linked with communities sharing the same broad characteristics of the victim or with lifestyles that hinder police investigations.

The third alternative theoretical frame, that is, the one I synthetically labeled the "police resources" perspective, purports that homicide clearance is influenced by the level of training, resources, staffing, and funding to which a law enforcement agency has access. This frame fits into the broad scholarship on the impact of policing on crime. Although a major line of research concentrates on the effects that police force size, training, and resources have on crime rates, a parallel strand considered how these dimensions relate to the ability of law enforcement to clear cases. The police resources perspective thus switches the attention from the single case or victim to the characteristics of the law enforcement institution in charge of investigating a case. Two recent works straightforwardly considered both police size and funding and assessed their impact on homicide clearance (Bjerk, 2022; Chalfin et al., 2020). In both cases, authors did not find any effect: More officers and more money do not increase clearance rates. Yet, this perspective is characterized by further multidimensionality in the sense that different dimensions linked with police agencies beyond staffing and funding are considered to be potentially relevant in explaining clearance rates and likelihood. The empirical and theoretical roots of the police resources perspectives reside in the several reports published by the RAND Corporation, which claimed that investigative efforts have a tiny impact on solving crimes, especially serious ones like homicide (Chaiken et al., 1977; Chaiken et al., 1974; Greenwood & Petersilia, 1975). According to Greenwood and Petersilia (1975), solving crimes was just a matter of favorable circumstances rather than of investigative work, with investigators spending more time on postarrest case processing. The findings of these reports have gone widely untested for many years, and only recently scholars have questioned them using new data and conceptual approaches. Wellford et al. (2019), for instance, analyzed police performance of homicide clearance through five dimensions (i.e., organization structures; leadership and resources; selection, training, and performance review; case assignment and the investigative process; and community interaction) and found qualitative differences between agencies with high and low clearance rates. In particular, among other findings, higher performing agencies have more structured between-unit oversight, greater ability to quickly respond to each case, and more specialized investigators.

3 | HOMICIDE CLEARANCE AND THE BROADER LITERATURE ON RACIAL INEQUALITY IN CRIMINAL JUSTICE

3.1 | Empirical Evidence of Racial Disparity in Policing and Criminal Justice in the United States

Racial disparity has long plagued, and continues to plague, policing and the criminal justice system in the United States. A rich literature spanning the social sciences documents the various ways through which this disparity is substantiated.

Scholarship on discrimination and unfair treatment against people of color, minorities, and disadvantaged communities by law enforcement, courts, and justice institutions has a long-standing history. Yet, the higher availability of data and the dramatic series of highly public events of the last decade— including the dozens of murders of Black individuals perpetrated by police officers in the country—significantly fostered academic attention on the issue. The literature is now exceptionally vast and heterogeneous: Prominent research lines focused, for example, on disparities in police stops (Kramer & Remster, 2018; Legewie, 2016; Pierson et al., 2020), disproportionate use of force against civilians (Chalfin et al., 2020; Edwards et al., 2019; Streeter, 2019), and concerns over discrimination and fairness perils posed by modern crime control technologies such as predictive policing (Brayne, 2017; Ferguson, 2016; O'Donnell, 2019).

In light of the often-chaotic abundance of police-related and police-generated data, scholars have also dedicated considerable efforts in methodological reasoning and tools to study racial disparity quantitatively, seeking to overcome structural limitations in available information, facilitating credible causal reasoning, and as a side effect, assessing the biases inherent with administrative and official data (Knox et al., 2020; Knox & Mummolo, 2020).

A wealth of research has also testified to the different treatments received by people of color, particularly Black individuals, in sentencing (Mustard, 2001; Rehavi & Starr, 2014; Yang, 2015) and, parallelly, in arrest (Bushway et al., 2022; Golub et al., 2007; Roehrkasse & Wildeman, 2022) and incarceration prevalence (Bales & Piquero, 2012; Duxbury, 2021a; Sykes & Pettit, 2014; Western et al., 2021).

Although comprehensively reviewing all the theoretical lenses through which racial disparity has been studied goes beyond the scope of this article, investigating racial inequalities in the likelihood of homicide clearance seeks to contribute to this broad and diverse area of research. Understanding the dynamics of homicide clearance offers empirical evidence that, while embedded in the domain literature detailed in the previous section, can be integrated into adjacent domains. In the next subsection, I will elaborate on the various effects and implications that racial disparity in homicide clearance can have on deterrence, legitimacy, legal cynicism, mental health, and trust in the police. All these effects speak to distinct areas of research that have been developed over the last few decades in sociology, criminology, economics, and political science. Therefore, considering racial disparity in homicide clearance research only in relation to its specific literature represents a limitation to the academic, as well as policy understanding of how inequality emerges in the administration of justice in the United States at various levels.

3.2 | The Relevance of Homicide Clearance Research

Homicide, along with violent crime, represents a far-reaching problem in the United States. Given the prevalence and salience of the phenomenon, scholars have sought to unfold the multifaceted ways in which violence affects individuals and communities. Among other consequences, exposure to homicide and violence has been demonstrated to increase the risk of crime involvement (Bingenheimer et al., 2005; Papachristos & Wildeman, 2014), curb economic mobility (Manduca & Sampson, 2019; Sharkey & Torrats-Espinosa, 2017), decrease life expectancy (Redelings et al., 2010), and influence adverse birth outcome (Goin et al., 2019) and children's cognitive performance (Sharkey, 2010). Furthermore, as recently shown, when violence is deliberately directed toward Black Americans, the adverse effects on health are particularly pronounced for individuals belonging to the African American community (Curtis et al., 2021). In such a context, the inability to effectively close homicide cases leads to additional negative ramifications.

The United States, in fact, has undergone significant reductions in the percentage of cleared homicides over the last few decades, fueling both academic (Cook & Mancik, 2023; Council on Criminal Justice, 2021) and public discussions regarding the causes and effects of this trend (Maxon et al., 2015; *The Washington Post*, 2019). As Riedel (2008) noted, however, the issue had gone overlooked for many years before attracting sufficient public attention. Nonetheless, the increasing availability of data from official sources (e.g., the UCR and the NIBRS), as well as from organizations and civil society (e.g., "Murder With Impunity" project from *the Washington Post*) has contributed to raising academic and public concerns and facilitating scrutiny.[5]

As a result of this wave of attention toward the phenomenon, scholars, reporters, and activists have underlined how the study of homicide clearance bears relevance that goes beyond the merely theoretical and academic dimensions. I reviewed and mentioned the various ways in which understanding homicide clearance contributes to sociological and criminological understanding. This line of research, however, also entails significant policy implications. Policy-wise, research on homicide clearance can be critical in unfolding dynamics and mechanisms that deserve attention and call for timely and effective solutions. Given the above-mentioned toll that violence

[5] Although homicide clearance research has predominantly focused on the United States, recent works have also concentrated on European countries. See for instance Liem et al. (2019) and Aziani and Persurich (2022).

and homicide have on communities in the United States, ensuring that homicides are solved and perpetrators are apprehended is of critical importance for several reasons.

First, failing to clear a case inhibits effective deterrence of criminal law sanctions (Braga & Dusseault, 2018). Second, effective police performance via clearance reduces the risk of recidivism and retaliation, further diminishing the sense of insecurity entrenched in communities affected by homicidal violence. Third, higher clearance rates avoid the multiplicative effects of the diverse negative consequences suffered by family members, friends, and colleagues of the victims, as well as by members of the communities in which the victim lived. Fourth, ensuring that homicides cases are cleared increases trust in law enforcement and reduces legal cynicism, a major sociological issue linked with interactions between citizens and justice and policing institutions (Kirk & Papachristos, 2011; Sampson & Bartusch, 1998). In turn, countering legal cynicism translates into strengthening the relationship between institutions and citizens, increasing cooperation and trust. Fifth, as noted by Fagan and Geller (2018), racial disparities in homicide clearances may trigger further disparities at later stages in the process of the administration of justice, such as the production of capital cases and sentencing more in general, hence, reinforcing racial inequalities to higher levels. This reflection is also in line with recent work from Kim and Kiesel (2018). For all these reasons, research has a fundamental role in offering empirical results that can guide effective reforms, interventions, and policies to guarantee that homicides are solved effectively, as well as ensure that all groups and communities are treated equally in the face of violent crimes such as homicides.

4 | THE CURRENT STUDY

The current study specifically investigates whether homicides involving Black victims are less likely to be cleared compared with homicides involving non-Black victims.[6] Therefore, the study tests one focal point of the discretionary perspective, namely, that the racial characteristics of the victims influence the outcomes of an investigation. The theoretical roots of this preposition reside in Black's (1976) theory of law and, in particular, in the concept of stratification, which views some specific groups of people as receiving less law compared with their counterparts of higher social status. Scholars in homicide clearance research over time have operationalized stratification mostly in a tripartite fashion, namely, considering racial minorities, females, and younger individuals (i.e., victims) as the archetypes of subjects receiving less law and, therefore, facing a lower clearance likelihood (Litwin, 2004). Concerning race, results have been mixed, periodically revamping the debate around the discretionary and solvability perspectives.

Shedding light on this inconclusiveness is the primary goal of this work. To answer its central question, the current study entails a microlevel approach that focuses on clearance likelihood at the event/victim level, considering together data pertaining to both the discretionary and the solvability traditions.

This study seeks to advance the literature on homicide clearance in four important ways. First, it goes beyond mere descriptive or correlational evidence by employing a research design intended to isolate the causal effect of race on clearance likelihood. Establishing a causal effect, rather than a correlational one, is critical to advancing theory and practice in this area of research, allowing future research to then concentrate on proper mechanisms behind the effect. Second,

[6] As it will be detailed in the Materials and Methods section, non-Black victims, in the data hereby used, practically translate to "White" victims.

it relies on two (plus one) distinct data sources offering the largest sample sizes ever analyzed in homicide clearance research, providing the most comprehensive and systematic perspective on the topic to date. Besides the systematic and more comprehensive nature of the analysis here proposed, comparing data sources advances the broad debate on data quality, representativeness, and coverage of the most important official sources of crime in the United States. Third, it considers a large time period covering three decades of data, significantly widening the temporal lenses that, besides notable exceptions [see Fagan & Geller (2018)], have been employed in the extant literature. Fourth, it focuses on homicides from all over the United States rather than just being limited to single urban contexts or counties, hence, guaranteeing the generalizability of findings at the country level.

To sum up reflections made in the previous sections, although this study's main theoretical contribution resides in the assessment of the race effect as discussed in the context of the contrasting views outlined by the discretionary and solvability perspectives, the current work also naturally adds to the wide and diverse literature on systemic racism in the American policing and criminal justice system. Numerous works in the last few years have documented how racial minorities are disproportionately affected by harmful police behavior, incarceration, and harsher sentencing. By considering whether homicides involving Black victims are less likely to be cleared, I also expand research on racial disparity by focusing on victims rather than on (alleged) perpetrators, seeking to detail how indeed disparity does not only affect individuals when they are seen as offenders but also when they are victims seeking justice. In light of these aspects, the present work is centered on the following hypothesis:

Hypothesis 1 (H1). Homicides involving Black victims are less likely to be cleared compared with homicides involving non-Black victims.

In addition, I also consider two complementary analyses that aim to provide a more nuanced view about the phenomenon. First, I will explore whether heterogeneity in the race effect occurs across males and females. Second, I will assess whether race effects have varied over time.

Disparity between males and females has been considered by scholars addressing the discretionary perspective, building on Black's (1976) idea that females receive less law than males do because they occupy a lower position in the structure of society. Yet, empirical research has provided contrasting results on this matter. When findings have pointed toward higher clearance likelihood for females, they have been interpreted from the standpoint of the discretionary and victim lifestyle perspectives, explaining that inequality lies in the fact that male and female victims are associated with different lifestyles and event circumstances that, in turn, translate to varying odds of solving a murder case (Rydberg & Pizarro, 2014). That considered, exploring race effect heterogeneity between males and females aims at further advancing empirical research addressing the theoretical debate around the drivers of homicide clearance, as well as adding to the abundant literature investigating patterns of victimization (and involvement in crime) across sexes (Gartner, 1990; Smith & Visher, 1980). To test this argument, I hence offer the following hypothesis:

Hypothesis 2 (H2). Racial disparity in the likelihood of homicide clearance is higher for male than for female victims.

Potential heterogeneity across decades instead is tested to investigate whether racial disparity has varied over time in the last 30 years in the United States. In this regard, I build on a rich scholarship targeting trends and developments in racial inequalities in the administration of justice in the United States (LaFree et al., 2010; Sampson & Lauritsen, 1997). Recent works investigating racial disparity in the country have documented that the relationship between racial minorities, law enforcement, and the criminal justice system in general has evolved in recent decades—in some cases worsening the inequality between racial groups and in other cases reducing it. On the one hand, for instance, research has shown that in the 1980–2019 period, racial minorities were increasingly affected by fatal violence by police (GBD 2019 Police Violence US Subnational Collaborators, 2021). In addition, considering the 1975–2012 time frame, Black communities were marginalized in the discussion of criminal sentencing law, which predominantly reflected the interests and objectives of White communities to protect their social interests (Duxbury, 2021b). On the other hand, data show that even though Black individuals remain disproportionately incarcerated compared with Whites, recent prison reforms have reduced the incarceration gap between racial groups (The Sentencing Project, 2021). To further highlight the importance of considering historical trends in homicide clearance specifically, Cook and Mancik (2023) recently demonstrated how declining trends in homicide clearance as measured by arrest data might in fact be interrelated with increased standards for arresting people, reflected by the increasing percentage of individuals convicted and sentenced to prison for committing murders. This finding would suggest that justice is better guaranteed today than in the past when higher arrest rates were coupled with lower odds of actual conviction and imprisonment. For these reasons, exploring temporal variations in the race effect on homicide clearance can contribute to the broader debate on the historical development of racial inequality in the context of the social, technological, legal, and political changes that marked the country in the past 30 years. I hence provide the following hypothesis:

Hypothesis 3 (H3). The magnitude of racial disparity in homicide clearance has not remained constant during the course of the three decades under analysis.

5 | MATERIALS AND METHODOLOGY

5.1 | Data

5.1.1 | Source 1: MAP data set

MAP is a nonprofit organization aimed at increasing awareness and disseminating information about homicides in the United States (Hargrove, 2019). The full MAP contains a total of 827,219 homicide victims associated with 789,664 homicide cases (the number of victims is higher because a homicide case can be associated with multiple victims) and refers to events that occurred from 1976 to 2020. The resulting MAP data set arguably represents the most comprehensive victim-based collection of data available to the public, sensibly reducing the well-known discrepancies between FBI homicide data and the WONDER data set compiled by the Centers for Disease Control and Prevention (CDC) (Kaplan, 2020). For each homicide victim, the MAP data set provides information on basic information regarding the victim and the offenders; temporal and geographic details such as the city, state, and month of the homicide; as well as data on the weapon used and the circumstances in which the victim was murdered. The restricted MAP data set applied in the main analyses of this work covers instead a period ranging from 1991 to 2020 and includes information on a total of 522,278 homicide victims associated with 497,187 homicide cases. The data collected by MAP originate from two sources: Most records in this 1991–2020 version ($N = 489{,}285$, related to 464,194 separate incidents) are based on the openly available Supplementary Homicide Reports (SHR), which are part of the FBI UCR system. In addition, MAP obtained information on additional 32,993 homicide victims (corresponding to as many homicide cases) that were not recorded into the UCR system through Freedom of Information Act requests. MAP data for homicide victims recorded from 1976 to 2020 ($N = 814{,}738$) are analyzed in the online supporting information (see section A.3.3 for further details).

Although the MAP data set ensures the highest available level of representativeness at the national level, the clearance indicator for each single case is not based on official data but is derived using an operationalization criterion. According to such criterion, a homicide is cleared if information about the offender's sex is reported as unknown. In this case, the murder is assumed to be unsolved. Although this criterion does not represent an entirely unreasonable assumption and similar operationalizations have been already used in the literature (Chalfin et al., 2020; Regoeczi et al., 2000), it may inflate clearance rates. For instance, even though an agency may know the sex of the offender, a case might still be unsolved. To overcome this structural limitation, I investigate the research question integrating MAP data with NIBRS and the 2019 "Murder With Impunity" data set curated by *The Washington Post* (details on it are available in section A.3.5 in the online supporting information). The exposure variable of interest is whether the victim was Black.

The 1991–2020 MAP data set (which follows the same structure as the FBI's SHR) uses six different race categories: Black (N = 257,415, 49.28 percent of the total), White (N = 246,770, 47.25 percent), Asian (N = 8,901, 1.70 percent), Unknown (N = 4,857, .9 percent), American Indian or Alaskan Native (N = 4,204, .8 percent), and Native Hawaiian or Pacific Islander (N = 131, .02 percent). I aggregated all non-Black categories. MAP race categorization does not include a standalone "Hispanic" category. This information is available in the "Ethnicity" variable that should map whether the victim was Hispanic. The variable, however, is rarely collected, and thus is sensibly flawed (Kaplan, 2020). For this reason, I have not relied on it, thus, distinguishing only between Black and non-Black victims (who are White in 93.16 percent of cases).

5.1.2 | Source 2: NIBRS data set

The second primary source used in this work is the NIBRS database. Specifically, a victim-based data set is assembled using all available years (from 1991 to 2020) in the NIBRS concatenated files relying on data from the victim, administrative, batch, and offense segments in the NIBRS files. For each year, I retrieve data on homicide victims on individuals that were labeled as victims, in at least one of the ten possible offense columns, of one among justifiable homicide, murder/nonnegligent manslaughter and negligent manslaughter. Victim-level information data were linked with information obtained from the administrative segment using an existing unique identifier. The administrative segment collects basic information about each crime incident, such as the date of the crime. The same procedure was deployed to link victim-level information with data from the offense and batch segments. The offense segment offers detailed information about the specific crime, such as the weapon used. The batch segment instead reports information on the jurisdiction in which the murder occurred, including information on the type of agency that investigated the crime. At the final stage, all these separate data sets were combined together using the unique identifier, mapping detailed information at the victim level. The NIBRS data set contains information on a total of 100,741 homicide victims from 1991 to 2020. After removing victims of unknown age, the total number of observations for the NIBRS data set is 98,677. The outcome variable (i.e., whether a case was cleared) is simply derived by checking information on the number of arrestees per each victim and the indicator on whether the crime was cleared by exceptional circumstances (e.g., death of the offender). Hence, in the NIBRS data set, a homicide event is considered cleared if at least one person has been arrested or if the case has been cleared by exceptional means.

Compared with the MAP data set, the variable mapping the outcome of a homicide event has a much more definitive nature because it is linked to official information and is not based on an assumption in the absence of specific information. Nonetheless, the NIBRS data set suffers from coverage and representativeness issues. Although homicide events have been available since 1991, only a few agencies have reported full data to the system since that time (Li & Lartey, 2022; Li & Ricard, 2023). In 2021, the FBI retired the UCR system, switching it to the once-voluntary NIBRS system. Yet, most agencies have still failed to send their data, creating substantial problems for reliable estimation of crime rates for many counties around the United States.

As for the MAP, in the NIBRS case, the exposure variable of interest is whether the victim is Black. The data set contains six race categories: Black victims (N = 47,871) account for 48.51 percent of the total and White (N = 47,395) for 48.03 percent. Then, the data set records 1,698 victims of Unknown race (1.72 percent), 969 Asian/Pacific Islander victims (.98 percent), 683 American Indian/Alaskan natives (.69 percent), and 61 Native Hawaiian or Other Pacific Islander (.06 percent). I followed the same procedure used in the MAP data set: Given the lack of reliable information on Hispanic ethnicity (Kaplan, 2021a), I aggregated all non-Black victims together (who, in 93.28 percent of the cases, were White).

5.2 | Analytical Strategy

5.2.1 | Exact matching

I investigate the effects of being a Black victim on the likelihood of homicide clearance focusing on data gathered from the MAP and NIBRS data sets. Per each data set, two different model specifications are tested: one with a matched sample and one using all available observations. Concerning the former, I use exact matching as the main nonparametric preprocessing technique to ensure comparability between Black and non-Black victims and allow for a causal explanation of Black race as the exposure of interest (Stuart, 2010). Matching refers to a family of methods employed in research on causal inference mostly in observational settings when no randomization in treatment assignment is available. Matching, which offers a broad suite of specific approaches, thus seeks to obtain a data sample in which observations in the treated and nontreated groups differ only for their treatment status and, potentially, for the outcome of interest but have similar or, preferably, identical distributions in terms of covariates. Mathematically:

$$\tilde{p}\,(X|T = 1) = \tilde{p}\,(X|T = 0) \tag{1}$$

with $\tilde{p}$ being the empirical density of the data and T being the treatment status. In this work, I rely on exact matching, which is the preferable matching approach because it only matches observations with identical values in all the selected covariates X. Here, each treated observation is matched with at least one control unit having the same characteristics in the entire matched covariate space.

Two fundamental requisites for selecting variables must be fulfilled to properly carry out the matching procedure. First, matching relies on the concept of ignorability, assuming that all variables related to both the exposure and the outcome are included. Second, variables that might have been affected by the treatment or exposure should be excluded.

In light of these requisites, for each set of models, matching is done using information on 1) the total number of victims in the same incident; 2) the total number of offenders in the same incident; 3) the sex of the victim; 4) the age of the victim (mapped in categories covering 5 years each); 5) the decade in which the homicide occurred; 6) the agency that investigated the crime; 7) whether another homicide occurred in the same month, in the same city, investigated by the same agency; and 8) the U.S. state in which the event took place.

These variables not only satisfy the two conditions mentioned (i.e., ignorability and lack of variables that might have been affected by treatment), but they have also been carefully chosen based on the rich correlational literature investigating homicide clearance. Table 1 reports details regarding the variables used in the matching and estimation phases. The table specifically includes information on the phases in which each variable has been used (i.e., matching and estimation or estimation alone), along with its format, and a brief summary of findings and an explanation of the rationale for inclusion, enhanced with relevant references. For a further description of these variables see figures S1 and S2 in the online supporting information, which measure covariate balance pre- and postmatching and prevalence and clearance ratios for each variable across data sets (figures S3–S14). In particular, the plots mapping prevalence and clearance ratio show, for each value or level in each variable contained in table 1, the share of homicides involving Black and non-Black victims and the share of cleared cases for both racial groups. At a descriptive level, these visualizations are helpful to identify possible correlations between a given variable and the race of the victim, along with possible differentials in clearance probability.

In addition, to avoid the issue of data loss consequential to the matching procedure leading to biased results, I also estimate covariate-adjusted models without matched samples, relying on the entire MAP and NIBRS samples. The matching process is carried out using the MatchIt library (Ho et al., 2011). Numerous robustness models are available in the online supporting information. These models include supplementary analyses using a 5-year variable to map temporal changes instead of the decade; models including the victim–offender relationship as additional control, along with models using MAP homicide data covering the 1976–2020 period; and models investigating disparity in time to clearance for solved cases in the NIBRS data set. Furthermore, robustness models that assess the role of being Black on the likelihood of homicide clearance using data from *The Washington Post*'s 2019 “Murder With Impunity” project are also available. All these robustness checks provide results in line with the ones presented in the main text, further corroborating the study findings.

5.2.2 | Estimation of the effect

The estimand of interest, assessed after the matching step, is the average treatment effect on the treated, also known as *ATT*, which is formalized as:

$$ATT = E\left[\delta_i | T_i = 1\right] = \sum_{i=1}^{N_T} (Y_i = 1 | T_i = 1) - \sum_{i=1}^{N_T} (Y_i = 0 | T_i = 1) \tag{2}$$

The ATT quantifies the average treatment effect for individuals in the exposed group. In our case, it maps the effect of being Black on homicide clearance. The estimation of the ATT is done

TABLE 1 Summary of variables used for matching and estimation, along with each variable's rationale and references to relevant works.

Variable	Inclusion	Format	Summary of Findings and Rationale	Representative Relevant Works
N of Victims	M+E	Count	Only marginally investigated in literature. Based on the available evidence, the hypothesis is that the higher the number of victims, the higher the likelihood of evidence leading to clearance.	(Addington, 2007; Lee, 2005; Sturup et al., 2015)
N of Offenders	M+E	Count	Homicides perpetrated in co-offending may lead to the commission of errors by the offenders or increase the probability of defection.	(Campedelli & Yaksic, 2021)
Victim's Sex	M+E	Categorical	This variable was central in the original theorizing by Black. The empirical literature focused on this extensively. Findings have been mixed or inconclusive.	(Alderden & Lavery, 2007; Avdija et al., 2022; Campedelli, 2022; Lee, 2005; Puckett & Lundman, 2003; Regoeczi et al., 2008; Riedel & Rinehart, 1996; Wolfgang, 1958)
Victim's Age	M+E	Categorical	Based on extensive research, the variable has been included as previous works highlighted how age is a significant predictor of clearance, although mixed findings for some age classes exist.	(Alderden & Lavery, 2007; Avdija et al., 2022; Lee, 2005; Puckett & Lundman, 2003; Regoeczi et al., 2000; Wolfgang, 1958)
Decade	M+E	Categorical	The rationale of the variable is to control for the sensible variations in homicide rates and clearance rates occurred over time, following also recommendations from previous works.	(Cook & Mancik, 2023; Litwin & Xu, 2007; Ousey & Lee, 2010; Xu, 2008)
Weapon	M+E	Categorical	The variable is in line with the nondiscretionary perspective. Numerous studies have highlighted that some weapons are correlated with higher chances of clearance.	(Addington, 2007; Campedelli, 2022; Litwin, 2004; Puckett & Lundman, 2003; Regoeczi et al., 2000; Regoeczi et al., 2008; Roberts, 2008)
Circumstances	E	Categorical	This variable is associated with the nondiscretionary perspective. The extant literature shows that considering the context in which a homicide occurred is helpful in predicting the outcome of the investigation because some homicides are much more straightforward to solve (e.g., homicides in domestic situations).	(Alderden & Lavery, 2007; Avdija et al., 2022; Litwin, 2004; Litwin & Xu, 2007; Lundman & Myers, 2012; Maxfield, 1989; Wolfgang, 1958)

(Continues)

TABLE 1 (Continued)

Variable	Inclusion	Format	Summary of Findings and Rationale	Representative Relevant Works
Agency Type	M+E	Categorical	The implicit rationale of the variable is to possibly capture differences in terms of resources and training across agencies.	(Braga & Dusseault, 2018; Carter & Carter, 2016; Campedelli, 2022; Keel et al., 2009; Wellford et al., 2019)
Monthly Agency Investigative Overlap	M+E	Categorical (Binary)	Coupled with the agency type information, this variable maps whether there was another homicide investigation by the same agency, in the same city and same month. Such information would control for the effect of high investigative workload, especially in towns/small cities.	(Campedelli, 2022; LoFaso, 2020)
State	M+E	Categorical	The State variable is included to account for geographical differences in homicide prevalence and clearance rates across States.	(Campedelli, 2022)
Location Type (Only for NIBRS)	E	Categorical	Previous works found that the location in which the homicide occurs/the body is found are relevant in clearing a case, aligning with the solvability perspective, because the location might provide useful leads or forensic evidence.	(Ferrandino, 2021; Jiao, 2007; Lee, 2005; Litwin & Xu, 2007; Riedel & Jarvis, 1999; Trussler, 2010)
Population Group (Only for NIBRS)	E	Categorical	This variable adds a layer of information on the type of city/town/area in which the homicide occurred. It serves as an additional proxy to control for investigative resources as well as the type of environment linked to the event, a feature that was originally theorized as important by champions of the nondiscretionary perspective.	(Braga & Dusseault, 2018; Borg & Parker, 2001; Carter & Carter, 2016; Davies, 2007; Wolfgang, 1958)

Note: Column "Inclusion" reports whether the variable was used in both the matching and the estimation phases (M+E) or only in the estimation (E) phase due to being possibly affected by the exposure (i.e., race of the victim).

using both the matched and the nonmatched data sets, relying on logistic regression models fitted with sandwich heteroskedasticity-robust standard errors. Models for MAP and NIBRS slightly differ: Both have as binary dependent variable the outcome of the case (Solved/Not Solved), the binary T of interest (being Black/not being Black), use all the controls used in the matching procedure (as suggested by Ho et al. [2007]), and add additional controls that can be theoretically thought as affected by the exposure. These controls are 1) the type of weapon and 2) the circumstances in which the homicide occurred for both MAP and NIBR 3) the location type,[7] and 4) the type of area (labeled population groups) for the NIBRS data set alone, given that these two variables were available only in this latter source. Mathematically, the MAP models are represented by the following equation:

$$\begin{aligned}\log\left(\frac{p(solved)}{1-p(solved)}\right) = {} & \beta_0 + \beta_1\left(\text{Victim's Race : Black}\right) + \beta_2\left(N\text{Victims}\right) + \beta_3\left(N\text{Offenders}\right) \\ & + \beta_4\left(\text{Victim's Age}\right) + \beta_5\left(\text{Victim's Sex}\right) + \beta_6\left(\text{Decade}\right) + \beta_7\left(\text{Weapon}\right) \\ & + \beta_8\left(\text{Circumstance}\right) + \beta_9\left(\text{Agency}\right) + \beta_{10}\left(\text{Monthly Agency Overlap}\right) \\ & + \beta_{11}\left(\text{State}\right)\end{aligned} \tag{3}$$

whereas the equation for NIBRS models is:

$$\begin{aligned}\log\left(\frac{p(solved)}{1-p(solved)}\right) = {} & \beta_0 + \beta_1\left(\text{Victim's Race : Black}\right) + \beta_2\left(N\text{Victims}\right) + \beta_3\left(N\text{Offenders}\right) \\ & + \beta_4\left(\text{Victim's Age}\right) + \beta_5\left(\text{Victim's Sex}\right) + \beta_6\left(\text{Decade}\right) + \beta_7\left(\text{Weapon}\right) \\ & + \beta_8\left(\text{Circumstance}\right) + \beta_9\left(\text{Agency}\right) + \beta_{10}\left(\text{Monthly Agency Overlap}\right) \\ & + \beta_{11}\left(\text{State}\right) + \beta_{12}\left(\text{Location Type}\right) + \beta_{13}\left(\text{Population Area}\right)\end{aligned} \tag{4}$$

In both cases, the models use the observation-level weights produced in the matching phase, accounting for the differential weight of the matched control units, given that not all units receive the same number of matches. As anticipated, for both data sets, a second set of adjusted models is estimated without the matched sample, thus, using all the available observations, without achieving covariate balance. For the matched and unmatched models, all coefficients are transformed into odds ratios, and the average marginal effect (AME) is computed for the variable of interest (i.e., being a Black victim). The AME allows for more straightforward effect interpretation given that all models computed are from the generalized least model family, thus, making the use of log odds and odds ratios uninformative of the true size of the effect, as well as noncomparable across models (Allison, 1999; Mood, 2010; Norton et al., 2018).

In the context of a dichotomous independent variable, the AME is the average difference in the adjusted prediction between those being Black and those not being Black. The AME can be interpreted in terms of probability, hence, facilitating comparisons between models and data. Besides the overall AME, which represents the marginal effect calculated by averaging the individual effect for each observation in the data set and is used to test H1, I also provided group-average marginal effects to test H2 and H3 focusing on two variables: the sex of the victim and the decade

[7] The circumstance variable bears a critical importance in the analysis of homicides as well as homicide outcomes and has been widely used in the literature on homicide clearance. Nonetheless, it presents issues, as documented by Pizarro and Zeoli (2013). The circumstance variable, in fact, is prone to errors related — among others — to different reporting methodologies across agencies and incomplete information at the time of the investigation. However, I decided to include it nonetheless because potential errors/discrepancies in reporting are likely not correlated with race of the victim, as demonstrated by the visualizations provided in the Supplementary Material Figure S9, in which ratios of prevalence per each circumstance type are practically identical between races across circumstance types.

in which an event took place. Group-average marginal effects are calculated by taking the average of the observation-level average marginal effects per each sex or decade group.[8] Beyond raw differences in AME across groups, I also test for significance in the computed values to verify that the detected group-level effects are statistically different. The analysis on marginal effects is carried out using the *marginaleffects* (Arel-Bundock, 2023) and *clarify* (Greifer et al., 2023) packages in R. The former uses the traditional delta method, whereas the latter is built relying on a simulation approach, as proposed by King et al. (2000). The two are compared because the delta method requires three main assumptions for a given model to be considered correct: 1) normally distributed coefficients in a given model, 2) normally distributed quantity of interest (namely, the AME), and 3) equality between the first-order approximation of the variance of the estimator and its true variance. If these assumptions are not met, the inference may not be accurate. Hence, to demonstrate the reliability of the finding hereby presented, I computed the AME using both approaches.

5.2.3 | Ignorability and sensitivity

The data available from MAP and NIBRS to measure the impact of race, and specifically of being a Black victim, on the likelihood of race are sufficient to fulfill the principle of ignorability, which is fundamental in observational studies seeking to perform causal inference tasks, avoiding biased effects of treatments or exposures of interest. In fact, theoretically and practically, these two data sources provide all the necessary information to avoid the presence of unmeasured confounders, which are defined as variables that lie along an open backdoor path from the treatment to the outcome (Cinelli et al., 2022). Nonetheless, objections may be raised concerning the absence—in both the MAP and NIBRS data sets—of granular information on the spatial context in which a homicide occurred, arguing that two homicides occurred in neighborhoods or communities with distinct characteristics that also have different odds of clearance. Although in fact this type of information is missing, we have two reasons for being reassured that its absence does not constitute an issue with concern to confounding.

First, the literature investigating whether neighborhood contexts impact the likelihood of clearance has so far provided inconclusive results (Borg & Parker, 2001; Ferrandino, 2021; LoFaso, 2020; Mancik et al., 2018; Petersen, 2017). Second, even if one assumes that the spatial context in which a homicide occurs may contribute to causing a given outcome in the case investigation, the spatial context does not cause the race of the victim, nor does it lie along an open backdoor path from the exposure to the outcome (I provide a more detailed explanation of this aspect in section A.2.2 in the online supporting information). I would argue that, theoretically, the community or spatial context in which a homicide occurs can act as a mediator to the role of race rather than as a confounder biasing the causal link between race and clearance.

Nonetheless, to ensure transparency and dispel any doubt about the reliability of the findings, I performed a sensitivity analysis analyzing two hypotheses based on the assumption that the spatial-ecological context surrounding the homicide can be thought of as a variable lying along an open backdoor path from being Black and homicide clearance: a case with a binary unmeasured confounder and a case with a continuous unmeasured confounder. Particularly, I assessed, across

[8] This approach, compared to an alternative traditional procedure using variable interactions, allows the covariate distribution as well as the moderator to naturally vary without setting subgroup-level counterfactual values that may represent impossible combinations of covariates, making proper interpretation challenging.

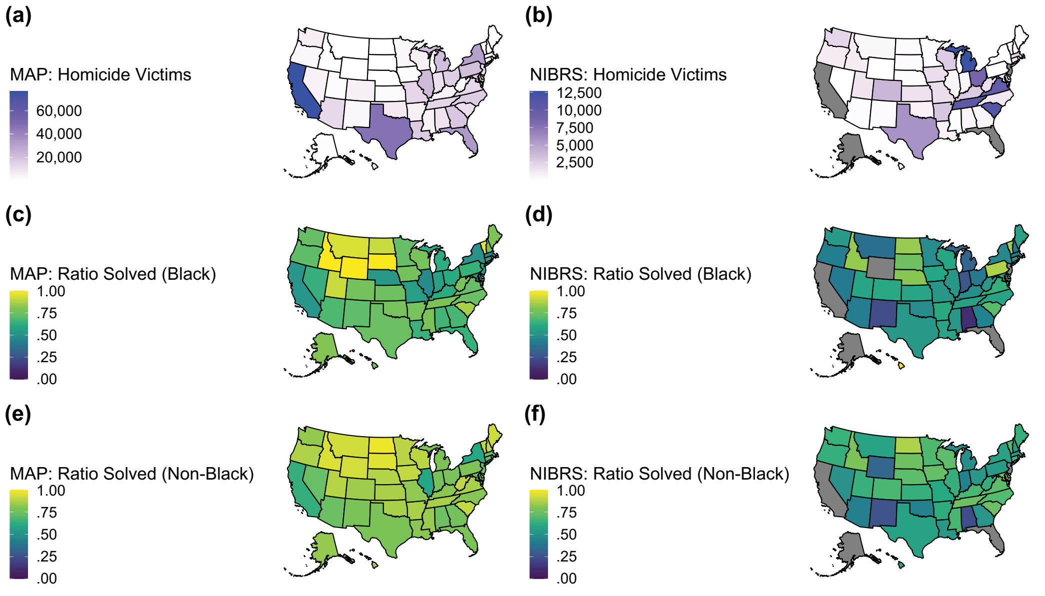

FIGURE 1 Count of homicide victims per state in the MAP (Panel a) and NIBRS (Panel b) data sets. Ratio of solved homicide cases (victim based) with Black victims in the MAP (Panel c) and NIBRS data sets (Panel d). Ratio of solved homicide cases (victim based) with non-Black victims in the MAP (Panel e) and NIBRS data sets (Panel f). [Color figure can be viewed at wileyonlinelibrary.com]

many scenarios, how large the effect of the unmeasured confounder should be to nullify the effects detected in the main MAP and NIBRS models. Theoretical details and full statistical outcomes of the sensitivity analyses are available in the online supporting information (section A.2). In general, for both the binary and the continuous hypothetically unmeasured confounders, the analyses, conducted with the tipr library in R (McGowan, 2022), demonstrate that the magnitude of the two variables should be unreasonably large to invalidate the coefficients obtained in the models. Such results thus reinforce the reliability of the results concerning the causal effect of race on the likelihood of homicide clearance.

6 | RESULTS

6.1 | Descriptive Evidence

Figure 1 provides a graphic illustration of the number of observations in the MAP and NIBRS data sets. All U.S. states, including the District of Columbia, are represented in the MAP data set. California (N = 76,522) is the state with the highest number of observations, accounting for 14 percent of the total homicide victims in the data set. Texas is ranked second (N = 46,712, 9 percent), Florida third (N = 33,358, 6 percent), and New York fourth (N = 31,127, 6 percent). North Dakota (N = 351), Vermont (N = 379), and Wyoming (N = 463) are instead the states with the lowest counts. On the contrary, the NIBRS data set does not guarantee full coverage in terms of states. California, Florida, New Jersey, and Alaska did not report any homicide data to the NIBRS system during the 1991–2020 period. The lack of data is particularly

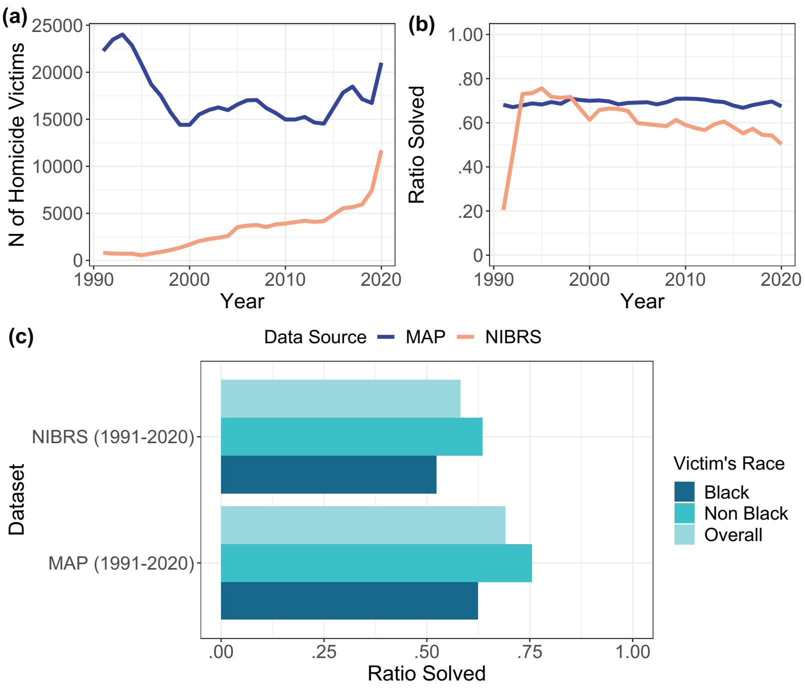

FIGURE 2 Yearly series of homicide victims in the MAP and NIBRS data sets (Panel a), yearly average of cleared homicides across both data sets (Panel b), and average clearance rates per victim's race: Black, Non-Black, and overall, across the MAP (1991–2020) and the NIBRS (1991–2020) data sets (Panel c). [Color figure can be viewed at wileyonlinelibrary.com]

relevant given that California and Florida are two of the most prevalent states in the MAP data set.

In general, also other states with high counts in the MAP data set are not as represented in the NIBRS one. Texas, for instance, only has 5,852 homicide victim observations (accounting for approximately 6 percent of the total). New York and Pennsylvania record strikingly low counts: only 22 and 21, respectively. Michigan ($N = 12{,}651$, 12 percent) South Carolina ($N = 11{,}166$, 11 percent), and Tennessee ($N = 10{,}528$, 10 percent) are the most represented in the NIBRS data set. These data highlight a significant difference in the distribution of homicide data and homicide victims across the two data sets, particularly unfolding the problems of coverage and representativeness in the NIBRS data set. Panel C and D also graphically show the ratio of solved homicides per state, considering Black victims, in MAP and NIBRS. Panel E and F provide the same information for the two same data sets, focusing instead on the clearance ratio for non-Black victims. In panel D, Wyoming is colored in gray because no data on homicides of Black victims were recorded.

In the MAP data set, the states with the lowest clearance ratio for Black victims are the District of Columbia (.40), Massachusetts (.45), Illinois (.47), Maryland (.50), and New York (.50). In the NIBRS data set, instead, the lowest clearance ratios for Black victims are reported for Alabama (.12), New Mexico (.23), Indiana (.27), and Michigan (.32).

The sensible differences in the two data sets are also outlined in figure 2. Panel A shows the number of observations in the two data sets overall. The absolute difference between the two is pronounced, peaking above 21,500 units in 1991. Notably, this gap has been reduced over time and in 2020 is set at 9,301 observations. Also, the two trends for both data sets signal an increase in homicide victims since 2000, although with substantial oscillations. Panel B shows the annual ratio of cleared victim cases instead. Even in this case, differences across data sets emerge. In the MAP one, the trend is almost flat, from 68.13 percent cleared cases in 1991 to 67.44 percent in 2020. The trend in the NIBRS data set, instead, is declining with remarkable steepness. Besides an increase from approximately 20 percent in 1991 to 72.54 percent in 1993—potentially explained by oscillations in agency reports to the system in the first few years—the ratio decreased from a peak of 75.63 percent in 1995 to the second-lowest point, slightly above 50 percent, in 2020.

Despite these apparent differences in representativeness and clearance rates, figure 2 (panel C) visualizes an important similarity between the MAP and NIBRS data sets. Besides absolute differences in clearance rates, in both cases, homicides involving Black victims reported lower clearance percentages on average. In the MAP data, the average number of solved cases with a Black victim is 62.32 percent, whereas it is 75.47 percent for non-Black victims (68.99 percent for the whole sample). This finding, in relative terms, holds in the NIBRS data set. The average number of solved homicides with Black victims is 52.27 percent, whereas it is approximately 63.52 percent for non-Black individuals (58.06 percent for the entire data set). This descriptive account already hints at the possible presence of racial disparity in homicide clearance in the United States.

6.2 | Inferential Evidence

6.2.1 | Main results

Besides descriptive indications, table 2 summarizes the statistical outcomes for the logistic regression models investigating the impact of being Black on homicide clearance at the national level. For each data set, I fit two models. The first uses the matched sample to estimate the effect of being a Black victim on the probability of clearance adjusting for the same covariates used in the matching phase, as well as variables (e.g., circumstance) that were not used for matching. The second is estimated using the entire samples without matching yet adjusting for the same covariates used for matching and adjustment in the adjusted-matched models. All coefficients (reported as odds ratios and AME) are statistically significant at the 99.9 percent level and below 1, indicating a negative relationship between being Black and the likelihood of clearance, regardless of the model specification, data set, and sampling strategy, corroborating H1.

Despite the considerable differences between the MAP and NIBRS data sets, the statistical estimates on the role of the victim's race in the likelihood of clearance are highly comparable. According to MAP data, the reduction in probability goes from 4.4 percent to 4.8 percent, depending on model specification and sampling strategy. According to NIBRS data, the reduction in likelihood goes from 3.4 percent to 4.1 percent, also depending on the approach used. In both cases, the smallest effects are estimated when using the matched samples. In the MAP data set, after exact matching, the likelihood of solving a homicide is reduced by 4.4 percent when the victim is Black (AME = −.044, 95 percent CI = [−.048; −.040], $p < .001$), whereas the effect increases to 4.8 percent when using the entire sample (AME = −.048, 95 percent CI = [−.051; −.046], $p < .001$). Models fit using the NIBRS data follow the same pattern, although with slightly lower estimates. Leveraging this source, being a Black victim reduces the likelihood of clearance by 3.4 percent in the matched case (AME = −.034, 95 percent CI = [.041; −.027], $p < .001$) and 4.1 percent in the unmatched one (AME = −.041, 95 percent CI = [−.048; −.034], $p < .001$).

Translating these figures in terms of raw numbers—and taking as reference the maximum and minimum AME estimated by the four models across both data sets—given 50,000 homicide

TABLE 2 Logistic regression models estimating the effects of being Black on the likelihood of homicide clearance—MAP and NIBRS data (1991–2020).

Variable	**MAP (1991–2020)**		**NIBRS (1991–2020)**	
	Adjusted Matched	**Adjusted Unmatched**	**Adjusted Matched**	**Adjusted Unmatched**
Victim's Race: Black (OR)	.754***	.727***	.840***	.813***
[95% CI]	[.681; .835]	[.715; .740]	[.810; .871]	[.785; .842]
Victim's Race: Black (AME)	−.044***	−.048***	−.034***	−.041***
[95% CI]	[−.048; −.040]	[−.051; −.046]	[−.041; −.027]	[−.048; −.034]
Observations	453,047	522,278	70,669	98,677
% Matched	86.744	/	71.616	/
Cragg-Uhler Pseudo R^2	.435	.438	.277	.251
χ^2	161,67.583	194,46.808	16,79.066	20,362.888
p-value	.000	.000	.000	.000

Notes: Estimates are reported as odds ratios (ORs) and as average marginal effects (AMEs). 95 percent confidence intervals (CIs) between parentheses. Models are computed using heteroskedasticity-robust standard errors.

$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

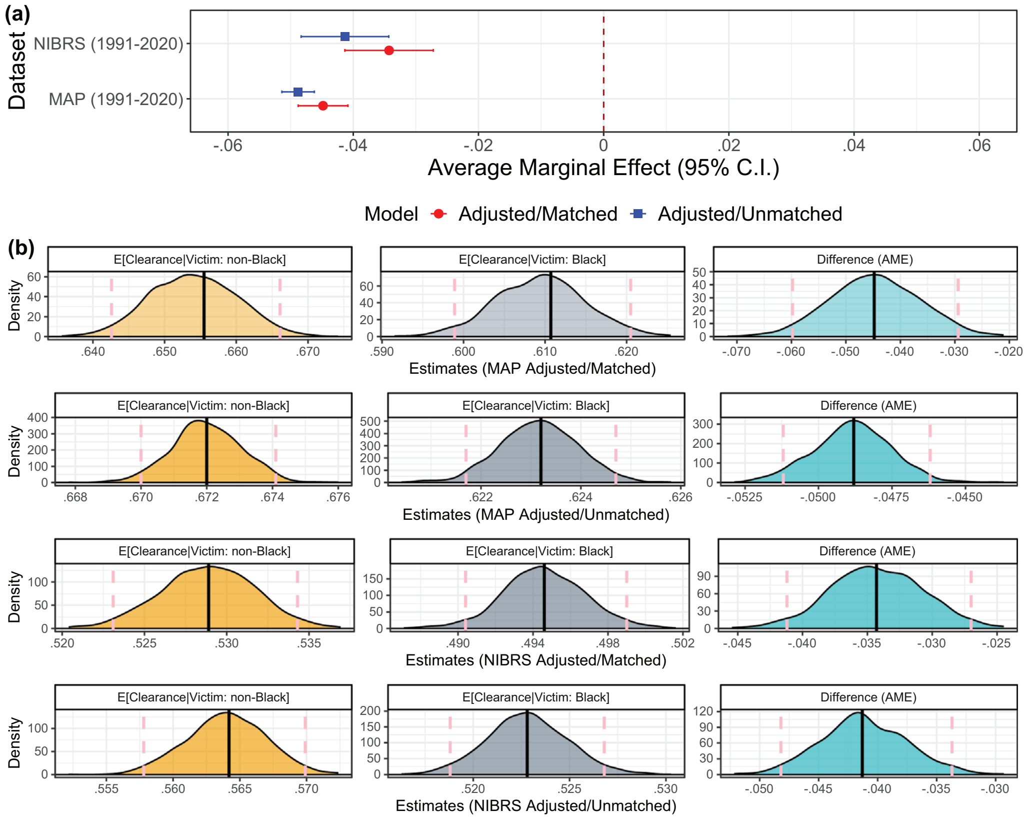

FIGURE 3 Panel a: Average marginal effects of being a Black victim on the probability of clearance, per model specification and data set, with 95 percent confidence intervals, computed through the delta method. Panel b: Simulation-based inference (*N*sim = 1,000) per each model specification and data set, visualizing the distribution of expected clearance probability per Non-Black victims (E[Clearance|Victim: Non – Black], expected clearance probability per Black victims (E[Clearance|Victim: Black] and the difference between the two (AME).
[Color figure can be viewed at wileyonlinelibrary.com]

Note: Dashed pink lines represent 95 percent confidence intervals of the distributions, whereas solid black lines represent the point estimate (average of the distribution).

victims, approximately 1,700–2,400 more homicides would have been cleared had the victims been non-Black. Figure 3 graphically illustrates the estimated AME of being a Black victim on the odds of clearance. The figure displays the AME point estimates (with 95 percent Cis) computed using the traditional delta method, as well as the results obtained via a simulation-based inferential approach. Simulation-based results in panel B report, for each model, the distribution of the expected probability of clearance for non-Black victims, the distribution of the expected probability of clearance for Black victims, and the distribution of the difference between the two, namely the AME, for a total of 1,000 simulations. The estimates across the two approaches are identical, further corroborating their reliability. Interestingly, the inferential results suggest that racial disparity is large and robust but less pronounced than the one that could be implied by simple descriptive statistics, as the one commented in the previous subsection. This finding underlines the importance of properly statistically comparing homicide cases rather than simply relying on crude percentages.

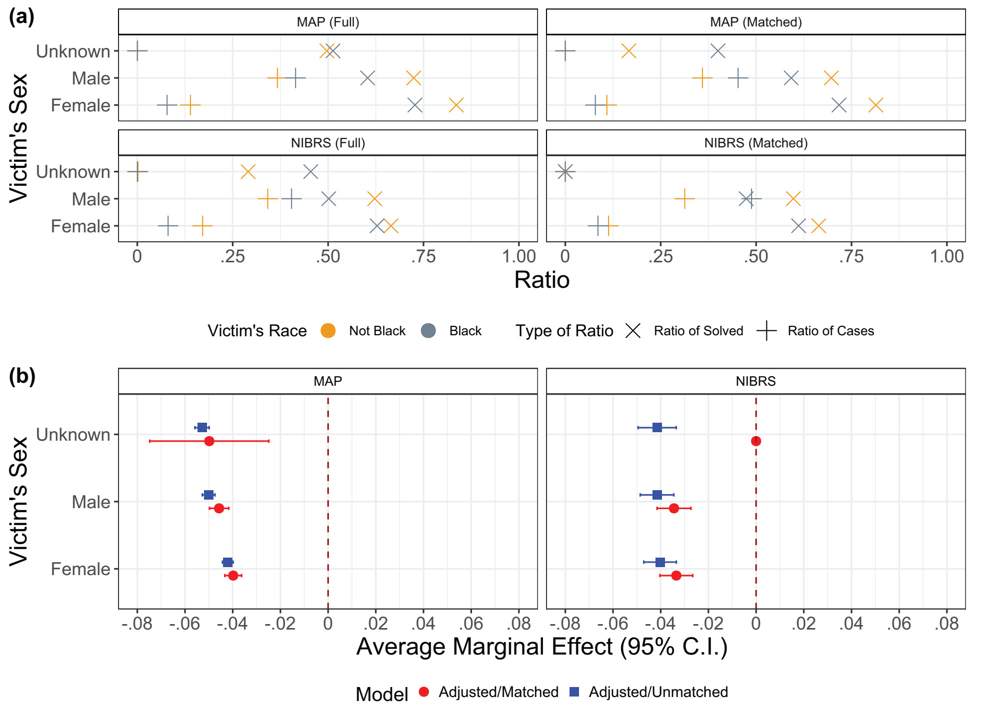

FIGURE 4 Panel a: Visualization of clearance and prevalence ratios of each sex category per race category (Black vs. Not Black) in each data set (full or matched). Panel b: Average marginal effects of each sex category in each data set and model (red is adjusted/ matched, blue is adjusted/unmatched). [Color figure can be viewed at wileyonlinelibrary.com]

Beyond the primary analysis providing the average effect of being a Black victim on the likelihood of clearance at the national level, across both data sets, I also computed group-average marginal effects focusing on two theoretically relevant variables used in the matching and adjustment phases: the sex of the victim and the decade in which the homicide occurred, seeking to understand whether race plays different roles between sex categories and has mutated its impact over time.

6.2.2 | Assessing race effects across males and females

Figure 4 visualizes both the prevalence and the clearance ratios for each sex category in the MAP and NIBRS data sets (in both the full and the matched cases), as well as the AME per each sex, across sources and models. Concerning descriptive evidence, males account for most homicide victims in the MAP and NIBRS data sets, and Black males in particular are the most represented category, regardless of source and sampling. On the contrary, non-Black females are more prevalent compared with Black female victims. The Unknown category, instead, represents a tiny proportion of all cases. When focusing on clearance patterns for males and females, Black males and females report substantially lower clearance ratios compared with their non-Black counterparts. In the full MAP data set, Black males have a clearance ratio equal to .60, whereas the clearance ratio for non-Black males is .72. In the matched MAP data set, the clearance ratio for

Black males is .59 and .69 for non-Black males. In the full NIBRS, the Black male clearance ratio is also far lower than the one reported for non-Black victims (.50 vs. .62). The same occurs in the matched NIBRS (.47 vs. .59). Similar gaps are appreciable for female victims. In the full MAP, Black females have a clearance ratio of .72 compared with the clearance ratio of .83 for non-Black victims. In the matched MAP, the difference only slightly decreases (.71 vs. .81). In the NIBRS, the difference is less pronounced but still reports higher clearance ratios for non-Black victims (.62 vs. .66 in the full NIBRS, .61 vs. .66 in the matched one).

The group-level analysis of AME reveals that statistically significant differences emerge across sex categories, although these are moderate, hence, partially confirming H2. Focusing on MAP, in the matched case, the AME for males is −.045 (95 percent CI = [−.049; −.041], $p < .001$) and is −.039 for females (95 percent CI = [−.043; −.036], $p < .001$) corresponding to an estimated difference equal to .005 ($p < .001$). In the unmatched case, instead the AME for males is −.050 (95 percent CI = [−.052; .047],$p < .001$) and −.042 for females (95 percent CI = [−.044; −.039],$p < .001$), with an estimated difference of .008 ($p < .001$). Differences across sex categories remain significant in the NIBRS data set, although with a lower magnitude. In the NIBRS matched case, the AME for males is equal to −.034 (95 percent CI = [−.041; −.027], $p < .001$), whereas the AME for females is −.033 (95 percent CI = [.040; −.026], $p < .001$), with a difference of .001 ($p < .001$). In the unmatched model, males have an AME equal to .041 (95 percent CI = [−.048; −.034], $p < .001$), whereas the AME for females is −.040 (95 percent CI = [−.047; −.033], $p < .001$), with an estimated differential of .001 ($p < .001$).

6.2.3 | Assessing race effects over the decades

Figure 5 displays the descriptive visualization of prevalence and clearance patterns across decades for Black and non-Black victims, as well as the inferential results of the AME for the three decades under analysis. Prevalence ratios clearly show that although the distribution across decades is homogeneous in the MAP data set, in the NIBRS, most homicides were recorded in the 2010s decade because in the 2000s and, foremost, in the 1990s, only a few agencies reported to the NIBRS system. Furthermore, in both data sets and across all samples, Black victims are always associated with sensibly lower clearance ratios compared with non-Black victims. In the MAP case, this divide grew over time. In the 1990s, focusing on the full data set, Black victims had a clearance ratio equal to .64, whereas the ratio for non-Black victims was .72. In the 2000s, Black victims' ratio was .63 (.75 for non-Black victims). In the 2010s, the difference equaled .20 (.59 vs. .79). In the matched case, this pattern is confirmed. In the 1990s, Black victims had a clearance ratio of .64, with non-Black victims having a ratio equal to .69. The difference in the 2000s was .11 (.62 vs. .72), whereas in the 2010s it was .18 (.57 vs. .75). In the NIBRS data, instead, the difference was almost constant in the 1990s and 2000s, whereas it slightly increased in the 2010s. Regarding the whole data set, in the 1990s, Black victims had a clearance ratio of .59, whereas non-Black victims had a clearance ratio of .66. In the 2000s, the difference slightly increased to .08 (.57 vs. .65). In the 2010s, the difference was equal to .13 (.49 vs. .62). In the matched NIBRS data set, the same dynamics emerge. In the 1990s and 2000s, the difference was .07 (.58 vs. .65 and .54 vs. .63); in the 2010s, when more homicides were reported, it grew to .14 (.46 vs. .60).

When considering the group-level AME, in fact, significant, yet moderate, differences across decades arise. Similarly to what has been detected with H2, H3 is thus corroborated, although variation across decades appears to be tiny. In the MAP-adjusted matched model, the AME for the 1990s is −.043 (95 percent CI = [−.047, −.039], $p < .001$), for the 2000s is −.045 (95 percent CI

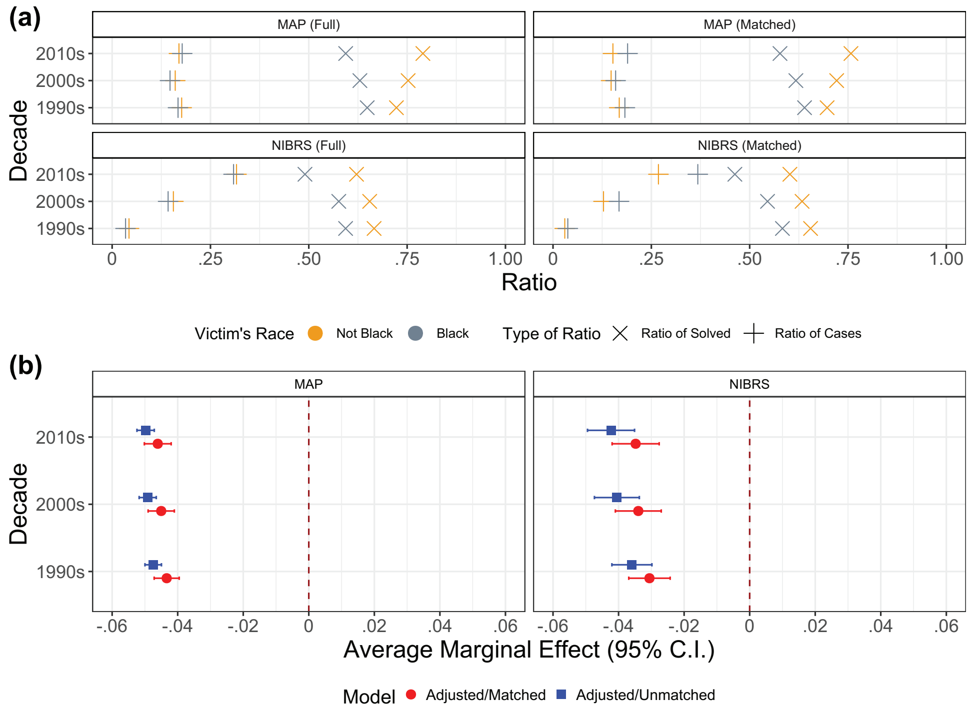

FIGURE 5 Panel a: Visualization of clearance and prevalence ratios of each decade per race category (Black vs. Not Black) in each data set (full or matched). Panel b: Average marginal effects of each decade in each data set and model (red is adjusted/matched, blue is adjusted/unmatched). [Color figure can be viewed at wileyonlinelibrary.com]

= [−.049; −.041], $p < .001$) and is equal to −.046 for the 2010s (95 percent CI = [−.050; −.042], $p <$ .001). The estimated differences in the AME are .001 between the 1990s and 2000s ($p < .001$), .002 between the 1990s and 2010s ($p < .001$), and .001 between the 2000s and 2010s ($p < .001$). These differences slightly shrink in the unmatched adjusted case, with the AME in the 1990s being .047 (95 percent CI = [−.049; −.044], $p < .001$), whereas it is −.049 in the 2000s and 2010s (in the 2000s, 95 percent CI = [−.051; −.046], $p < .001$; in the 2010s, 95 percent CI = [−.052; −.047], $p < .001$). The estimated differences in AME are .001 between the 1990s and 2000s, .002 between the 1990s and 2010s, and .0006 between the 2000s and 2010s ($p < .001$).

Focusing on the NIBRS data sets, in the matched-adjusted model, the AME for the 1990s is −.030 (95 percent CI = [−.036; −.024], $p < .001$), becoming larger in the 2000s (AME = −.033, 95 percent CI = [.040; −.026], $p < .001$) and in the 2010s (AME = −.034, 95 percent CI = [−.042; −.029], $p < .001$). The differences are estimated to be .003 between the 1990s and 2000s ($p < .001$), .004 between the 1990s and 2010s ($p < .001$), and .001 between the 2000s and 2010s ($p < .001$). The same rank appears in the adjusted unmatched model. In the 1990s, the AME is –.036 (95 percent CI = [−.042; .029], $p < .001$), in the 2000s is equal to –.040 (95 percent CI = [−.048; −.033], $p <$ .001), and in the 2010s reaches its peak, being equal to −.042 (95 percent CI = [−.049; −.035], $p <$ .001). In the adjusted unmatched case, the estimated differences in the AME are .004 between the 1990s and 2010s ($p < .001$), .006 between the 1990s and 2010s ($p < .001$), and finally, .001 between the 2000s and 2010s ($p < .001$).

6.2.4 | Robustness and sensitivity

For robustness purposes, a first set of models reports findings using 5-year categorical variables instead of decades in the matching and estimation steps of the MAP and NIBRS data sets (see subsection A.3.1 in the online supporting information). Using 5-year windows, the AME for MAP data is –.044 in the adjusted-matched case (95 percent CI = [−.049; −.040], $p < .001$) and −.049 in the adjusted unmatched case (95 percent CI = [−.051; −.046], $p < .001$). In the NIBRS case, instead, the AME in the adjusted-matched model is −.036 (95 percent CI = [−.043; −.028], $p <$ .001) and −.041 in the adjusted unmatched (95 percent CI = [−.048; −.034], $p < .001$).

A second set of models investigated racial disparity by adding a variable that maps the relationship between the victim and the offender as an additional control. Full results are available in subsection A.3.2 in the online supporting information. Previous research has found that homicides are often intraracial (Hewitt, 1988). Hence, adding the victim–offender relationship controls for potentially different propensities to cooperate with the police in criminal investigations among different racial groups. Although the magnitudes of effects slightly decrease (especially for MAP data), the disparity remains sizable and highly significant. Using MAP data, the effect is −.019 (95 percent CI = [−.023; −.014], $p < .001$) for the matched case and −.016 (95 percent CI = [−.018; −.014], $p < .001$) for the unmatched case. Models leveraging NIBRS data instead lead to identifying an effect equal to −.023 (95 percent CI = [.035; −.011], $p < .001$) for the matched case and −.019 (95 percent CI = [−.026; −.012], $p < .001$) for the unmatched case.

A third set of models reports the results from models using MAP data from 1976 to 2020, covering the entire period of data availability for MAP (section A.3.3). Based on events that occurred within the 45-year span, homicides involving Black victims were 2.26—2.27 percent less likely to be cleared compared with homicides with non-Black victims, depending on the type of model (adjusted matched: 95 percent CI = [−.28; −.025], $p < .001$; adjusted unmatched: 95 percent CI = [−.028; −.024], $p < .001$). Therefore, considering all three sets of models, being a Black victim significantly and negatively affects the probability of homicide clearance, with estimates aligning with those presented in the main analyses.

A fourth set of models investigated disparity In time to clearance relying solely on NIBRS data (MAP data do not record the date of the arrest of the homicide perpetrator). Poisson and quasi-Poisson models revealed that, all else being equal, homicides involving Black victims take an average of 1.99 more days to be solved in the matched case (95 percent CI = [.499; 3.470], $p <$ .01). In the unmatched case, the AME increases to 2.15 additional days but maintains its statistical significance (95 percent CI = [2.042; 2.256], $p < .001$). Full results are available in section A.3.4 in the online supporting information.

A fifth set of models offers robustness checks linking MAP and *The Washington Post* 2019 data, covering the 2007–2017 period (see section A.3.5 in the online supporting information for details). I fit models with and without U.S. Census data at the Block group level. Linking census data was possible using *The Washington Post* data set because each event includes latitude and longitude data. Census information is gathered through Geocodio, which allows for extrapolating block group-level data from latitude–longitude information. Models are enriched with census data to demonstrate that adding the sociodemographic variables concerning the location in which the homicide occurs only slightly decreases the race effect without eliminating its strong significance. Specifically, I include two census variables: The first one maps the percentage of Black-only households residing in the block group, and the second one maps the percentage of residing household earning more than US$100,000 per year.

Figure S22 and tables S15 and S16 in the online supporting information synthesize the model results in graphical and tabular formats. In table S15, the first model only uses concordant clearance outcomes between the MAP and The Washington Post data, whereas the second maintains all linked events, switching discordant outcomes according to the outcome of the investigation reported in *The Washington Post* data. In the equal outcomes case, the AME in the adjusted matched model is −.044 (95 percent CI = [−.060; −.030], $p < .001$), translating into a 4.4 percent reduction in the likelihood of clearance for homicides with Black victims, whereas it is −.042 in the adjusted unmatched case (95 percent CI = [−.054; −.030], $p < .001$). In the discordant outcome case, instead, the AME is −.033 (95 percent CI = [−.045; .021], $p < .001$) in the adjusted matched model and −.040 (95 percent CI = [−.052; −.029], $p < .001$) in the adjusted unmatched one. Table S16 has the same structure as table S15 but shows the results of the models including census data to control for community characteristics. In the equal outcomes case, the AME of the adjusted matched model is −.032 (95 percent CI = [−.048, −.016], $p < .001$), and it remains identical in the unmatched case (AME = −.032, 95 percent CI = [−.044; −.019], $p < .001$). In the discordant outcomes case, when the effect is estimated via the adjusted matched model, it becomes equal to −.019 (95 percent CI = [−.031, −.006], $p < .01$). Without matching, instead, it slightly increases to −.021 (95 percent CI = [−.033; .008], $p < .01$).

Concerning sensitivity tests focused on the main analyses hereby presented, section A.2 in the online supporting information provides a detailed analysis of the effects that unmeasured confounders might have on the detected effects, coupled with a discussion on why the current data and models most likely do not suffer from such a problem. The sensitivity analysis has been centered on two different scenarios: one with a continuous unmeasured confounder and one with a binary unmeasured confounder. The results, in both cases, show that the coefficients of these hypothetical variables would need to be unreasonably large to eliminate the effects presented in table 2 and figure 3, further suggesting the reliability of the statistical results commented above.

7 | DISCUSSION AND CONCLUSION

In one of his most debated works, Black (1976) theorized that law is a quantifiable object and that the amount of law one person receives depends on the characteristics of the individual. Departing from this theoretical frame, the discretionary perspective developed in homicide clearance research argued that the likelihood that a homicide is solved is explained by the sex, race, or socioeconomic condition of the victim because law enforcement agencies invest fewer efforts in investigating homicides against certain groups or categories of people within society. Over time, scholars have investigated clearance rates to test whether this "discretionary" perspective was adherent to reality. This inquiry was shaped by the contraposition between the discretionary perspective itself and the principal alternative school of thought, labeled "nondiscretionary," which explained the heterogeneity in clearance rates as a by-product of the characteristics of the event (e.g., the weapon used, the circumstance surrounding the homicide), rather than the characteristics of the victim (Gottfredson & Hindelang, 1979; Wolfgang, 1958). The role of race, in particular, has attracted notable attention from scholars in sociology and criminology. The findings in the literature (mostly consisting of descriptive accounts, correlational evidence, and temporally and geographically limited case studies) turned out to be mixed, however. In this study, I have addressed this research problem by tackling the various limits suffered by most studies produced so far.

I have investigated whether homicides involving Black victims are less likely to be cleared than homicides involving non-Black victims, comprehensively analyzing two primary sources of data in homicide research: the MAP data set ($N = 522{,}278$), which expands the well-known FBI's SHR data (Hargrove, 2019), and the NIBRS data set ($N = 98{,}677$), both referring to the 1991–2020 period (Kaplan, 2021b). The MAP data set guarantees a high coverage for the entire country but operationalizes clearance without having official information about the outcome of the investigation. The NIBRS data set, instead, has much lower coverage (and representativeness) due to reporting issues but provides an official measure of clearance. By analyzing the two, I balanced the extant issues of each and exploited their significant mutual advantages. I have studied racial disparity in homicide clearance at the national level relying on exact matching and regression adjustment to isolate as much as possible the effect of race on the outcome of the investigation. Exact matching was performed by considering a range of factors that the literature has shown to be correlated with clearance. These factors included the age and sex of the victim, the number of victims and offenders involved in the same event, the decade in which the homicide occurred, the agency which investigated the crime and whether it was already investigating another homicide in the same month, and the U.S. state where the event took place, to account for possible geographical variations across the country. I have also tested the hypothesis without covariate balance to avoid excessive data loss and derive useful comparative estimates.

I documented that being Black is strongly and significantly associated with a reduction in the likelihood of clearance, which is in line with the first (and central) hypothesis of this work. In the 1991–2020 time frame, depending on the source, sampling, and estimation approach, being a Black victim leads to a reduction in the probability of clearance falling between 3.4 percent and 4.8 percent, compared with an event with a non-Black victim. In absolute terms, then, given 50,000 homicide victims, being Black is estimated to lead on average to 1,700–2,400 less cleared cases, relative to a counterfactual scenario in which the victims are not Black. Even taking the most conservative AME estimate, obtained in the unmatched case using MAP data adding the victim–offender relationship variable, the disparity in cleared cases would still amount to a reduction of 800 cases, which remains an impressive figure. Importantly, the results obtained through this inferential approach also indicated how racial disparity seems to be less pronounced compared with the clearance gaps derived from simple descriptive and journalistic accounts, highlighting the importance of deploying a *ceteris paribus* approach to study this issue.[9]

All statistical results are confirmed across robustness models testing the impact of alternative preprocessing choices. In addition, I investigated the fundamental research question of the work by using a third data source, namely the 2019 "Murder With Impunity" data set collected by *The Washington Post*. The analysis provides the same outcomes as the ones presented in the main text.

Although I argue that the current data and model do not suffer from the issue of unmeasured confounders, I also carried out two methodological strategies to address the issue. First,

[9] Reports and journalistic accounts often only compare the percentage of solved homicides for Black and White (or Hispanic) victims without considering the circumstances of the events or other victim and event characteristics as done in this study. When only considering crude clearance rates, racial disparity appears larger. Vox, for instance, reports results from an analysis of data from the Scripps Howard News Service indicating that clearance rates for White victims in the 1980-2008 period was 78%, 11 percentage points higher than that for Black and Hispanic victims. Data from the "Murder with Impunity" project from the Washington Post have also been analyzed only using clearance percentages (see also this Prison Policy Initiative brief, showing that cases with Black victims are solved in 46% of the cases compared to 63% for White victims). Similar approaches have been used by CBS News and other news agencies. While descriptive statistics can be useful in conveying easily interpretable messages to the public, this approach for measuring racial disparity disregards important confounding or mediating factors that should be taken into account in proper inferential designs.

I have integrated data from *The Washington Post* with U.S. Census data at the block group level, leveraging latitude–longitude event coordinates, showing that including sociodemographic information on the area where the murder occurred did not cancel the race effect. Second, I conducted an extensive analysis of the possible impact of the issue on the main MAP and NIBRS data, demonstrating that the magnitude of such hypothetical unmeasured confounders should be unreasonably large to eliminate the sizable and strongly significant effects found throughout the data and models presented in the main analyses.

Beyond presenting AME for the entire samples, I also provided detailed evidence on potential effect heterogeneity between males and females and across decades, testing H2 and H3. Concerning the sex of the victim, statistical differences are determined indicating that the race effect is moderately stronger for males compared with females. Theoretically speaking, this finding is in line the victim's lifestyle perspective (Rydberg & Pizarro, 2014). Yet, the difference in the magnitudes of the AME between males and females is contained, indicating that sex has a limited moderating effect on the likelihood of clearance. With regard to the three decades under analysis, group-based analyses suggest that, although mildly and with different magnitudes, racial disparity increased over time. In this case, even though the difference in magnitudes is also tiny, the mildly negative trend signals an absence of improvement in the differential effect that race has on homicide clearance. This finding represents an additional empirical contribution aligning with those studies that show how, recently, certain patterns of discrimination against minorities have worsened in the United States (Duxbury, 2021b; GBD 2019 Police Violence US Subnational Collaborators, 2021).

The findings of the study bear both theoretical and policy relevance. Theoretically, this work confirms, in relation to race, the discretionary perspective proposition about clearance gaps across different groups of victims. Beyond a clear contribution to homicide clearance research, this study also adds to the abundant literature amassed over time documenting the existence of racial inequalities in the policing and criminal justice systems in the United States. In fact, the statistical results of this study quantify the reduction in clearance to be on the scale of thousands every 50,000 victims (or hundreds every 10,000 victims). To be fully appreciated, however, these striking figures should be contextualized in larger terms, considering the array of damages inflicted on those who represent the indirect victims of these events, such as family, friends, co-workers, and the broader involved communities. Indeed, an aspect that should not be overlooked—possibly opening future research venues—is the detrimental effect that uncleared cases can have on the relationship between citizens and communities, possibly causing legal cynicism, distrust, disillusion, rage, and sense of marginalization.

Given the research design of the current work, and the nature of the data it relies on, it is impossible to explain why racial disparity exists. This aspect represents a clear limitation of the study. Yet, these results call for future attempts to understand the mechanisms behind clearance gaps for Black and non-Black victims. Scholars adhering to the discretionary perspective suggested that marginalized people and minorities are valued differently by law enforcement, and hence, they receive "less" law compared with other groups within society. Although this suggestion may represent one option, others exist. Another explanation might be related to behavioral and ideological differences between officers and the communities they serve, following recent indications from the empirical work of Ba et al. (2022). Hawk and Dabney (2014), using ethnographic data from a U.S. metropolitan police department, concluded that unit culture and perception of victims' deservedness inexorably impact the outcome of homicide investigations. This impact, in turn, creates a hierarchy of victims (i.e., true victims and precipitating victims), underscoring the moral complexities at play in police work. Nothing more than hypotheses can be offered at this stage, but given the solid and clear evidence of racial disparity, scholars should further focus their attention on this issue, trying to disentangle the functioning of such disparate processes.

As anticipated, although racial disparity in homicide clearance has straightforward scientific implications, it also has practical ramifications. Policy-wise, these findings underline the urgency for effective and timely initiatives to eliminate this gap. Rapid and comprehensive initiatives should seek to restore trust between law enforcement and communities of color, ensuring fair and equal justice for all homicide victims, both direct and indirect. Understanding the reasons behind this divide can significantly facilitate the implementation of interventions to reduce it, hence, the importance of future research to focus on this aspect. Furthermore, targeting racial disparity in homicide clearance may in turn help in reducing disparity in other processes within the criminal justice system, as noted by Fagan and Geller (2018) and Kim and Kiesel (2018).

This work also prompts reflections on the importance of complying with the NIBRS. The NIBRS offers an extraordinary potential for analyzing crime in the United States (well beyond homicide), but its issues with coverage and representativeness undermine the possibility of researching critical questions and offering generalizable results, especially in cases when, contrarily to the current study, additional or complementary data sources are not available. Although the extraordinary effort by the MAP team to retrieve data on homicides that were not included in the original SHR was critical to sensibly reduce the gap with homicide counts documented by the WONDER data set collected by the CDC, NIBRS data are indeed characterized by huge problems of coverage. Li and Lartey (2022), for instance, showed that NIBRS data for 2021 were highly uninformative due to the burgeoning incompleteness deriving from missing data from approximately 35 percent of the U.S. population. More recently, Li and Ricard (2023) reported that in 2022 only 44 percent of all police agencies have submitted data for all 12 months to the NIBRS system, with 32 percent of agencies not participating at all, including the New York Police Department and the Los Angeles Police Department (24 percent of the agencies instead only submitted incomplete data). Although the trend in coverage is improving, the amount of missing data thus remains an open issue.

Given the far-reaching (often practical) relevance that the empirical study of crime has across sociology, criminology, economics, and political science, institutional efforts to ensure data compliance from law enforcement should hence be prioritized to guarantee that, in the future, academic research will continue to help policy makers reduce crime and increase fairness in the administration of justice through rich, informative, reliable data sources. In this work, for instance, discrepancies between MAP and NIBRS in terms of coverage have made it impossible to meaningfully investigate geographic patterns at the state, regional, or local scales, hindering potentially useful indications on meso- or microlevel variations across the country. The impossibility of properly conducting heterogeneity explorations at various geographical scales prevented me from assessing whether race effects are universal in the United States. The United States counts a total of approximately 18,000 police departments and is characterized by distinct experiences of policing, as well as by wildly different homicide rates across cities and counties. Including state effects is certainly useful at a higher level for controlling for possible macrolevel heterogeneity, but variance within states would be as crucial to capture how reporting practices change, as well as how racial disparity unfolds. States themselves in fact are complex patchworks of sensibly different contexts: the urban and the rural areas, those economically disadvantaged against the wealthier ones, segregated versus highly integrated cities, and racially homogeneous against diverse communities. Hypothetically, in some areas, racial disparity in homicide clearance might be sensibly larger than the effect detected in the models hereby presented. At the same time, there may be areas where no gap exists in the likelihood of clearance across racial groups. Current data sources do not enable us to target these issues, fundamentally limiting the range of questions that could be answered through homicide data. In other words, whereas race effects emerge as clear nationwide and across decades, whether they hold or how they vary across geographical areas altogether remains an open question.

Finally, one last aspect to consider concerning data limitations is the impossibility of discriminating between White and Latinx victim cases due to inconsistencies in the way in which the ethnicity variable is constructed and populated in both the MAP and NIBRS data sets. For this reason, as mentioned in the Data section, all non-Black victims have been aggregated together. Although most non-Black victims are indeed White (in more than 93 percent of the cases in both the MAP and NIBRS data sets), the inability to analyze Latinx cases separately also hampers a more nuanced analysis of racial disparities in homicide clearance. Does disparity emerge only between Black and non-Black victims, or does it extend to Latinx individuals? If more precise, detailed, and consistent reporting practices are promptly deployed, these kinds of questions may be meaningfully addressed in the future. Conversely, failing to address these issues will only leave us with a partial view of the multifaceted relationship between homicide, clearance, and race.

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REFERENCES

Addington, L. A. (2006). Using National Incident-Based Reporting System murder data to evaluate clearance predictors: A research note. *Homicide Studies*, *10*(2), 140–152.

Addington, L. A. (2007). Hot vs. cold cases: Examining time to clearance for homicides using NIBRS data. *Justice Research and Policy*, *9*(2), 87–112.

Alderden, M. A., & Lavery, T. A. (2007). Predicting homicide clearances in Chicago: Investigating disparities in predictors across different types of homicide. *Homicide Studies*, *11*(2), 115–132.

Allison, P. (1999). Comparing logit and probit coefficients across groups. *Sociological Methods & Research*, *28*(2), 186–208.

Arel-Bundock, V. (2023). *marginaleffects: Predictions, comparisons, slopes, marginal means, and hypothesis tests*. The Comprehensive R Archive Network. https://cran.r-project.org/web/packages/marginaleffects/marginaleffects.pdf

Avdija, A. S., Gallagher, C., & Woods, D. D. (2022). Homicide clearance rates in the United States, 1976–2017. *Violence & Victims*, *37*(1), 101–115.

Aziani, A., & Persurich, C. (2022). Homicide clearance: Discretionary and non-discretionary factors. *European Journal of Criminology*, Advance online publication. https://doi.org/10.1177/14773708221136049

Ba, B. A., Kaplan, J., Knox, D., Komisarchik, M., Mariman, R., Mummolo, J., Rivera, R., & Torres, M. (2022). *Who are the police? Descriptive representation in the coercive arm of government* [Working paper]. https://jmummolo.scholar.princeton.edu/sites/g/files/toruqf3341/files/ba_et_al_2022.pdf

Bales, W. D., & Piquero, A. R. (2012). Racial/ethnic differentials in sentencing to incarceration. *Justice Quarterly*, *29*(5), 742–773.

Bingenheimer, J. B., Brennan, R. T., & Earls, F. J. (2005). Firearm violence exposure and serious violent behavior. *Science*, *308*(5726), 1323–1326.

Bjerk, D. (2022). Does greater police funding help catch more murderers? *Journal of Empirical Legal Studies*, *19*(3), 528–559.

Black, D. (1976). *The behavior of law*. Academic Press.

Black, D. (1980). *The manners and customs of the police*. Academic Press.

Black, D. (1993). *Sociological justice*. Oxford University Press.

Borg, M. J., & Parker, K. F. (2001). Mobilizing law in urban areas: The social structure of homicide clearance rates. *Law & Society Review*, *35*(2), 435–466.

Braga, A. A., & Dusseault, D. (2018). Can homicide detectives improve homicide clearance rates? *Crime & Delinquency*, *64*(3), 283–315.

Brayne, S. (2017). Big data surveillance: The case of policing. *American Sociological Review*, *82*(5), 977–1008.

Bushway, S., Cabreros, I., Paige, J. W., Schwam, D., & Wenger, J. B. (2022). Barred from employment: More than half of unemployed men in their 30s had a criminal history of arrest. *Science Advances*, *8*(7), eabj6992.

Campedelli, G. M. (2022). Explainable machine learning for predicting homicide clearance in the United States. *Journal of Criminal Justice*, *79*, 101898.

Campedelli, G. M., & Yaksic, E. (2021). Survival of the recidivistic? Revealing factors associated with the criminal career length of multiple homicide offenders. *Homicide Studies*, Advance online publication. https://doi.org/10.1177/10887679211010882

Cardarelli, A., & Cavanagh, D. (1994). *Uncleared homicides in the United States: An exploratory study of trends and patterns*. Paper presented at the annual meeting of the American Society of Criminology, Miami, FL.

Carter, D. L., & Carter, J. G. (2016). Effective police homicide investigations: Evidence from seven cities with high clearance rates. *Homicide Studies*, *20*(2), 150–176.

Chaiken, J. M., Greenwood, P. W., & Petersilia, J. (1977). The criminal investigation process: A summary report. *Policy Analysis*, *3*(2), 187–217.

Chaiken, J. M., Lawless, M., & Stevenson, K. A. (1974). *The impact of police activity on crime: Robberies on the New York City Subway System* [Technical report]. RAND.

Chalfin, A., Hansen, B., Weisburst, E. K., & Williams, Morgan C. J., (2020). *Police force size and civilian race* (Working Paper 28202). National Bureau of Economic Research.

Cinelli, C., Forney, A., & Pearl, J. (2022). A crash course in good and bad controls. *Sociological Methods & Research*, Advance online publication. https://doi.org/10.1177/00491241221099552

Cook, P. J., & Mancik, A. (2023). The sixty-year trajectory of homicide clearance rates: Toward a better understanding of the great decline. *Annual Review of Criminology*, Advance online publication. https://doi.org/10.1146/annurev-criminol-022422-122744

Council on Criminal Justice. (2021). *Homicide trends: What you need to know*.

Curtis, D. S., Washburn, T., Lee, H., Smith, K. R., Kim, J., Martz, C. D., … Chae, D. H. (2021). Highly public anti-Black violence is associated with poor mental health days for Black Americans. *Proceedings of the National Academy of Sciences*, *118*(17), e2019624118.

Davies, H. J. (2007). Understanding variations in murder clearance rates: The influence of the political environment. *Homicide Studies*, *11*(2), 133–150.

Duxbury, S. W. (2021a). Fear or loathing in the United States? Public opinion and the rise of racial disparity in mass incarceration, 1978–2015. *Social Forces*, *100*(2), 427–453.

Duxbury, S. W. (2021b). Who controls criminal law? Racial threat and the adoption of state sentencing law, 1975 to 2012. *American Sociological Review*, *86*(1), 123–153.

Edwards, F., Lee, H., & Esposito, M. (2019). Risk of being killed by police use of force in the United States by age, race–ethnicity, and sex. *Proceedings of the National Academy of Sciences*, *116*(34), 16793–16798.

Fagan, J., & Geller, A. (2018). Police, race, and the production of capital homicides. *Berkeley Journal of Criminal Law*, *23*, 261.

Ferguson, A. G. (2016). Policing predictive policing. *Washington University Law Review*, *94*, 1109.

Ferrandino, J. (2021). Getting away with murder: Homicide clearance by arrest in Chicago and its community areas. *Homicide Studies*, *25*(2), 164–188.

Gartner, R. (1990). The victims of homicide: A temporal and cross-national comparison. *American Sociological Review*, *55*(1), 92–106.

GBD 2019 Police Violence US Subnational Collaborators. (2021). Fatal police violence by race and state in the USA, 1980–2019: A network meta-regression. *Lancet*, *398*(10307), 1239–1255.

Goin, D. E., Gomez, A. M., Farkas, K., Zimmerman, S., Matthay, E. C., & Ahern, J. (2019). Exposure to community homicide during pregnancy and adverse birth outcomes: A within-community matched design. *Epidemiology*, *30*(5), 713–722.

Golub, A., Johnson, B. D., & Dunlap, E. (2007). The Race/ethnicity disparity in misdemeanor marijuana arrests in New York City. *Criminology & Public Policy*, *6*(1), 131–164.

Gottfredson, M. R., & Hindelang, M. J. (1979). A study of the behavior of law. *American Sociological Review*, *44*(1), 3–18.

Greenwood, P. W., & Petersilia, J. R. (1975). *The criminal investigation process: Volume I: Summary and policy implications* [Technical report]. RAND.

Greifer, N., Worthington, S., Iacus, S., & King, G. (2023). *clarify: Simulation-based inference for regression models*. https://iqss.github.io/clarify/#:~:text=Simulation-based%20inference%20involves%20simulating%20model%20coefficients%20from%20their,distribution%20of%20the%20estimates%20as%20their%20sampling%20distribution

Hargrove, T. (2019). *Murder Accountability Project*. https://www.murderdata.org/

Hawk, S. R., & Dabney, D. A. (2014). Are all cases treated equal? Using Goffman's frame analysis to understand how homicide detectives orient to their work. *British Journal of Criminology*, *54*(6), 1129–1147.

Hewitt, J. D. (1988). The victim-offender relationship in convicted homicide cases: 1960–1984. *Journal of Criminal Justice*, *16*(1), 25–33.

Hindelang, M. J. (1977). *Victims of personal crime: An empirical foundation for a theory of personal victimization*. Ballinger.

Ho, D., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software*, *42*, 1–28.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*(3), 199–236.

Jiao, A. Y. (2007). Explaining homicide clearance: An analysis of Chicago homicide data 1965–1995. *Criminal Justice Studies*, *20*(1), 3–14.

Kaplan, J. (2020). Chapter 6 Supplementary Homicide Reports (SHR). In *Uniform Crime Reporting (UCR) Program data: A practitioner's guide*.

Kaplan, J. (2021a). Chapter 6 Victim segment. In *National Incident-Based Reporting System (NIBRS) data: A practitioner's guide*.

Kaplan, J. (2021b). *Jacob Kaplan's concatenated files: National incident-based reporting system (NIBRS) data 1991–2020*. https://www.openicpsr.org/openicpsr/project/118281/version/V5/view

Keel, T. G., Jarvis, J. P., & Muirhead, Y. E. (2009). An exploratory analysis of factors affecting homicide investigations: Examining the dynamics of murder clearance rates. *Homicide Studies*, *13*(1), 50–68.

Kennedy, L. W., Caplan, J. M., Piza, E. L., & Thomas, A. L. (2021). Environmental factors influencing urban homicide clearance rates: A spatial analysis of New York City. *Homicide Studies*, *25*(4), 313–334.

Kim, J., & Kiesel, A. (2018). The long shadow of police racial treatment: Racial disparity in criminal justice processing. *Public Administration Review*, *78*(3), 422–431.

King, G., Tomz, M., & Wittenberg, J. (2000). Making the most of statistical analyses: Improving interpretation and presentation. *American Journal of Political Science*, *44*(2), 341–355. https://gking.harvard.edu/files/making.pdf

Kirk, D. S., & Papachristos, A. V. (2011). Cultural mechanisms and the persistence of neighborhood violence. *American Journal of Sociology*, *116*(4), 1190–1233.

Knox, D., Lowe, W., & Mummolo, J. (2020). Administrative records mask racially biased policing. *American Political Science Review*, *114*(3), 619–637.

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

Kramer, R., & Remster, B. (2018). Stop, frisk, and assault? Racial disparities in police use of force during investigatory stops. *Law & Society Review*, *52*(4), 960–993.

LaFree, G., Baumer, E. P., & O'Brien, R. (2010). Still separate and unequal? A city-level analysis of the black-white gap in homicide arrests since 1960. *American Sociological Review*, *75*(1), 75–100.

Lanfear, C. C., Bucci, R., Kirk, D. S., & Sampson, R. J. (2023). Inequalities in exposure to firearm violence by race, sex, and birth cohort from childhood to age 40 years, 1995-2021. *JAMA network open*, *6*(5), e2312465.

Lee, C. (2005). The value of life in death: Multiple regression and event history analyses of homicide clearance in Los Angeles County. *Journal of Criminal Justice*, *33*(6), 527–534.

Legewie, J. (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.

Li, W., & Lartey, J. (2022). The problem with the FBI's missing crime data. *The Marshall Project*.

Li, W., & Ricard, J. (2023). 4 reasons we should worry about missing crime data. *The Marshall Project*.

Liem, M., Suonpää, K., Lehti, M., Kivivuori, J., Granath, S., Walser, S., & Killias, M. (2019). Homicide clearance in Western Europe. *European Journal of Criminology*, *16*(1), 81–101.

Litwin, K. J. (2004). A multilevel multivariate analysis of factors affecting homicide clearances. *Journal of Research in Crime and Delinquency*, *41*(4), 327–351.

Litwin, K. J., & Xu, Y. (2007). The dynamic nature of homicide clearances: A multilevel model comparison of three time periods. *Homicide Studies*, *11*(2), 94–114.

LoFaso, C. A. (2020). Solving homicides: The influence of neighborhood characteristics and investigator caseload. *Criminal Justice Review*, *45*(1), 84–103.

Lundman, R. J., & Myers, M. (2012). Explanations of homicide clearances: Do results vary dependent upon operationalization and initial (time 1) and updated (time 2) data? *Homicide Studies*, *16*(1), 23–40.

Mancik, A. M., Parker, K. F., & Williams, K. R. (2018). Neighborhood context and homicide clearance: Estimating the effects of collective efficacy. *Homicide Studies*, *22*(2), 188–213.

Manduca, R., & Sampson, R. J. (2019). Punishing and toxic neighborhood environments independently predict the intergenerational social mobility of black and white children. *Proceedings of the National Academy of Sciences*, *116*(16), 7772–7777.

Maxfield, M. G. (1989). Circumstances in Supplementary Homicide Reports: Variety and validity. *Criminology*, *27*(4), 671–696.

Maxon, J., Wright, K., & Rios, E. (2015). What determines if a murder case gets solved? Race. *Mother Jones*. https://www.motherjones.com/politics/2015/06/chester-gun-violence-black-deaths-matter/

McGowan, L. D. (2022). tipr: An R package for sensitivity analyses for unmeasured confounders. *Journal of Open Source Software*, *7*(77), 4495.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67–82.

Mustard, D. (2001). Racial, ethnic, and gender disparities in sentencing: Evidence from the U.S. federal courts. *The Journal of Law and Economics*, *44*(1), 285–314.

Norton, E. C., Dowd, B. E., & Maciejewski, M. L. (2018). Odds ratios—Current best practice and use. *JAMA*, *320*(1), 84–85.

O'Donnell, R. M. (2019). Challenging racist predictive policing algorithms under the Equal Protection Clause. *New York University Law Review*, *94*, 544.

Ousey, G. C., & Lee, M. R. (2010). To know the unknown: The decline in homicide clearance rates, 1980—2000. *Criminal Justice Review*, *35*(2), 141–158.

Paintsil, I. K. O. (2022). Does a victim's race influence violent crime arrest? A test of the victim devaluation thesis. *Crime & Delinquency*, Advance online publication. https://doi.org/10.1177/00111287221143938

Papachristos, A. V., & Wildeman, C. (2014). Network exposure and homicide victimization in an African American community. *American Journal of Public Health*, *104*(1), 143–150.

Paternoster, R. (1984). Prosecutorial discretion in requesting the death penalty: A case of victim-based racial discrimination. *Law & Society Review*, *18*(3), 437–478.

Petersen, N. (2017). Neighbourhood context and unsolved murders: the social ecology of homicide investigations. *Policing & Society*, *27*(4), 372–392.

Pierson, E., Simoiu, C., Overgoor, J., Corbett-Davies, S., Jenson, D., Shoemaker, A., Ramachandran, V., Barghouty, P., Phillips, C., Shroff, R., & Goel, S. (2020). A large-scale analysis of racial disparities in police stops across the United States. *Nature Human Behaviour*, *4*(7), 736–745.

Piquero, A. R. (2024). Racial Inequality in Firearm Homicide Victimization.but not Other Types of US Violence. *Cambridge Journal of Evidence-Based Policing*, *8*(1), 1.

Pizarro, J. M., & Zeoli, A. M. (2013). An assessment of the quality of homicide data in the supplementary homicide reports: A research note. *Justice Quarterly*, *30*(4), 711–731.

Puckett, J. L., & Lundman, R. J. (2003). Factors affecting homicide clearances: Multivariate analysis of a more complete conceptual framework. *Journal of Research in Crime and Delinquency*, *40*(2), 171–193.

Redelings, M., Lieb, L., & Sorvillo, F. (2010). Years off your life? The effects of homicide on life expectancy by neighborhood and race/ethnicity in Los Angeles County. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *87*(4), 670–676.

Regoeczi, W. C., Jarvis, J., & Mancik, A. (2020). Homicide investigations in context: Exploring explanations for the divergent impacts of victim race, gender, elderly victims, and firearms on homicide clearances. *Homicide Studies*, *24*(1), 25–44.

Regoeczi, W. C., Jarvis, J., & Riedel, M. (2008). Clearing murders: Is it about time? *Journal of Research in Crime and Delinquency*, *45*(2), 142–162.

Regoeczi, W. C., Kennedy, L. W., & Silverman, R. A. (2000). Uncleared homicides: A Canada/United States comparison. *Homicide Studies*, *4*(2), 135–161.

Rehavi, M. M., & Starr, S. B. (2014). Racial disparity in federal criminal sentences. *Journal of Political Economy*, *122*(6), 1320–1354.

Riedel, M. (2008). Homicide arrest clearances: A review of the literature. *Sociology Compass*, *2*(4), 1145–1164.

Riedel, M., & Jarvis, J. (1999). The decline of arrest clearances for criminal homicide: Causes, correlates, and third parties. *Criminal Justice Policy Review*, *9*(3-4), 279–306.

Riedel, M., & Rinehart, T. A. (1996). Murder clearances and missing data. *Journal of Crime and Justice*, *19*(2), 83–102.

Roberts, A. (2007). Predictors of homicide clearance by arrest: An event history analysis of NIBRS incidents. *Homicide Studies*, *11*(2), 82–93.

Roberts, A. (2008). Explaining differences in homicide clearance rates between Japan and the United States. *Homicide Studies*, *12*(1), 136–145.

Roberts, A., & Lyons, C. J. (2011). Hispanic victims and homicide clearance by arrest. *Homicide Studies*, *15*(1), 48–73.

Roberts, A., & Smith, H. R. (2023). Police diversity and crime clearance for Black and Hispanic victims. *Criminology & Public Policy*, *22*(2), 199–232.

Roehrkasse, A. F., & Wildeman, C. (2022). Lifetime risk of imprisonment in the United States remains high and starkly unequal. *Science Advances*, *8*(48), eabo3395.

Rydberg, J., & Pizarro, J. M. (2014). Victim lifestyle as a correlate of homicide clearance. *Homicide Studies*, *18*(4), 342–362.

Sampson, R. J., & Bartusch, D. J. (1998). Legal cynicism and (subcultural?) tolerance of deviance: The neighborhood context of racial differences. *Law & Society Review*, *32*(4), 777–804.

Sampson, R. J., & Lauritsen, J. L. (1997). Racial and ethnic disparities in crime and criminal justice in the United States. *Crime and Justice*, *21*, 311–374.

Sharkey, P. (2010). The acute effect of local homicides on children's cognitive performance. *Proceedings of the National Academy of Sciences*, *107*(26), 11733–11738.

Sharkey, P., & Torrats-Espinosa, G. (2017). The effect of violent crime on economic mobility. *Journal of Urban Economics*, *102*, 22–33.

Smith, D. A., & Visher, C. A. (1980). Sex and involvement in deviance/crime: A quantitative review of the empirical literature. *American Sociological Review*, *45*(4), 691–701.

Streeter, S. (2019). Lethal force in black and white: Assessing racial disparities in the circumstances of police killings. *The Journal of Politics*, *81*(3), 1124–1132.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: A review journal of the Institute of Mathematical Statistics*, *25*(1), 1–21.

Sturup, J., Karlberg, D., & Kristiansson, M. (2015). Unsolved homicides in Sweden: A population-based study of 264 homicides. *Forensic Science International*, *257*, 106–113.

Sykes, B. L., & Pettit, B. (2014). Mass incarceration, family complexity, and the reproduction of childhood disadvantage. *The ANNALS of the American Academy of Political and Social Science*, *654*(1), 127–149.

The Sentencing Project. (2021). *The color of justice: Racial and ethnic disparity in state prisons* [Technical report].

The Washington Post. (2019, January 7). *Murder with impunity*. https://www.washingtonpost.com/graphics/2018/national/murder-with-impunity/

Trussler, T. (2010). Explaining the changing nature of homicide clearance in Canada. *International Criminal Justice Review*, *20*(4), 366–383.

Vaughn, P. E. (2020). The effects of devaluation and solvability on crime clearance. *Journal of Criminal Justice*, *68*, 101657.

Wellford, C., & Cronin, J. (1999). *An analysis of variables affecting the clearance of homicides: A multistate study* [Technical report]. Justice Research and Statistics Association.

Wellford, C. F., Lum, C., Scott, T., Vovak, H., & Scherer, J. A. (2019). Clearing homicides. *Criminology & Public Policy*, *18*(3), 553–600.

Western, B., Davis, J., Ganter, F., & Smith, N. (2021). The cumulative risk of jail incarceration. *Proceedings of the National Academy of Sciences*, *118*(16), e2023429118.

Wolfgang, M. E. (1958). *Patterns in criminal homicide*. University of Pennsylvania Press.

Xu, Y. (2008). Characteristics of homicide events and the decline in homicide clearance: A longitudinal approach to the dynamic relationship, Chicago 1966–1995. *Criminal Justice Review*, *33*(4), 453–479.

Yang, C. S. (2015). Free at last? Judicial discretion and racial disparities in federal sentencing. *The Journal of Legal Studies*, *44*(1), 75–111.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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