Racial Discrimination against Crime Victims: Evidence from Violent Crime Investigations

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Abstract

I develop and apply a new test for a consequential but overlooked form of racial discrimination: by police detectives against victims of crime. I test whether detectives display racial bias using a marginal outcome test derived from a model of police investigations. By performing the test on novel data on all the investigations of violent crime conducted by the Chicago Police Department over the last two decades, I find evidence of racial bias against Black victims: cases that are classified as solved in the same amount of time are more likely to be rejected by the prosecution for insufficient evidence if the victim is Black rather than White. This is true for both homicides (-9.2%) and non-fatal violent crime (-2.5%). These differences are consistent with the police being more tolerant of a case failing to enter the court process when the victim is Black. Heterogeneity analysis leveraging the experience and race of the primary detective indicates that the results are driven by racial animus and not by inaccurate beliefs. These results suggest that efforts to increase oversight and transparency in policing should also extend to police investigations and the broader differential treatment of crime victims.

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1 Introduction

The overly punitive approach of US police towards minority civilians suspected of a crime has been a major topic of discussion in recent years (CNN, 2014; National Academies of Sciences and Medicine, 2022). Research has shown that non-White civilians are more likely to be stopped and searched for contraband or weapons (Antonovics and Knight, 2009; Anwar and Fang, 2006), receive a traffic ticket (Goncalves and Mello, 2021), be arrested (Raphael and Rozo, 2019), and subject to the use of force (Hoekstra and Sloan, 2022; Lieberman, 2024) by the police.[1] Related work has documented that these forms of oversanctioning by the police significantly erode trust in law enforcement institutions (Desmond et al., 2016; Ang et al., 2024).

Far less scrutinized is the alleged underperformance of the police in serving minority civilians when they are *victims* of a crime (Natapoff, 2006; Leovy, 2015). Minority residents of large US cities in fact report being discriminated against when victimized, arguing that police investigations are less thorough when the victim is not White. This is claimed to result in disproportionately many unsolved (i.e., not-*cleared*) crimes and lower levels of accountability for violence committed against these victims, with homicides cited as a leading example (Mueller and Baker, 2016; Tuerkheimer, 2017).[2] This differential treatment can have significant consequences. It can decrease confidence in the police among minority residents and reduce their future willingness to cooperate (Lowery et al., 2018a; Lowery et al., 2018b). Despite the importance of the issue, a rigorous examination of racial discrimination against crime victims is lacking.

In this paper, I fill this gap and test for racial discrimination against crime victims in the context of police investigations of violent crime. I develop a marginal outcome test for racial bias – as opposed to accurate statistical discrimination (Hull, 2021) – against crime victims

[1]These disparities extend beyond interaction with the police, as suspected criminals are less likely to be released on bail (Arnold et al., 2018; Arnold et al., 2022) and more likely to be sentenced to prison and for longer (Abrams et al., 2012; Rehavi and Starr, 2014) if they are not White.

[2]Investigation of violent crime is not the only setting where racial discrimination against crime victims might appear. For example, non-White residents of large US cities have reported experiencing slow response times and a lack of attention and care from responding police officers after calling 911 (Sabino, 2024; Mahr and Annie, 2024).

and apply it to data from Chicago. Following Becker (1957), I leverage a post-treatment (i.e., after solving the crime) outcome to test for biased preferences among investigators. The test is based on a simple model of police investigations. The detective has a clear objective: to gather sufficient evidence to ensure a successful prosecution of the perpetrator(s), thereby delivering justice to the victims and their families. Intuitively, the detective will wait to clear and submit a case for court proceedings until the expected success of her investigation has reached an acceptable level, given the evidence collected. Hence, all cases are cleared exactly when this desired threshold of evidence, and consequently of success, is achieved.[3]

Empirically, I consider an investigation to be successful upon clearance if the Cook County State Attorney's Office (CCSAO) – which is the prosecutor of reference for the Chicago police – accepts the case for prosecution. Since this decision is based on the quantity and quality of the evidence presented by the police, it is informative of the detectives' work (Smith, 2019; Charles, 2022). A case is then successful if cleared via arrest and prosecution and not successful if cleared without prosecution due to CCSAO's rejection.[4] Note that in both cases, the police can consider the crime solved and the investigation concluded, despite that in the latter case the suspect will not go to court. This is the first step in the court process for an investigation conducted by the Chicago Police Department (CPD) and the least affected by other agents' biases.

In the context of this model, I introduce the first testable definition of racial bias against crime victims in police investigations. Bias originates from a lower acceptable threshold of expected success upon submission, among cases solved in a given time, if the victim is not White. Simply put, under racial bias, cases closed in the same number of days are worked more poorly and are therefore less likely to enter the court process for the group subject to discrimination. At baseline, these thresholds of desired success are assumed to depend only on the race of the victim and the time elapsed from the offense, with the latter being relevant

[3]The model also allows for these thresholds to never be reached, which means that the case is never solved. This occurs if a case is suspended, formally or informally, and this decision can also be affected by the race of the victim.

[4]This outcome abstracts from the result of the prosecution and focuses solely on whether the CCSAO is willing to accept the case for court proceedings.

since evidentiary standards can become more lax over time. Other characteristics of the case can influence how fast evidence accrues but not the race-specific desired stopping points. I gradually relax this assumption in the empirical analysis. By studying the differential quality of work upon clearance by race of the victim, this test more precisely elicits racial bias on the intensive margin of investigation.[5]

I perform this marginal outcome test starting from novel data on 704,211 victims of violent crime and the related investigations handled by the CPD from 2000 to present. Importantly, the data include information about the victim, the incident, the primary detective assigned to the case, all the status updates of the investigation with the related date, and the type of clearance if the case ever reached a solution of some kind. I can then distinguish between clearances achieved via arrest and prosecution of a suspect and clearances where the prosecution refused to proceed with the case and when they were classified as such. Cases belonging to these two categories form the sample for the outcome test.

I find evidence of racial bias – on the intensive margin – against Black victims of all violent crimes and Hispanic victims of homicide. Specifically, I observe a 7.8 pp (-9.2%) and 3.9 pp (-4.6%) lower likelihood of clearance being achieved via successful arrest and prosecution for Black and Hispanic victims of homicide, respectively. Among non-fatal violent crimes, I find discrimination against Black victims, as their cases are 2.2 pp (-2.9%) less likely to enter the court process upon clearance than those of White victims. When breaking down the results by sub-type of non-fatal violent crime, I document that Black victims are mostly discriminated against in investigations of aggravated assaults and batteries. On the other hand, there seems to be racial bias in favor of Hispanic victims of non-fatal violent crime (relative to White victims), with the prosecution being 1.95 pp (+2.6%) more willing to accept cases of Hispanic victims than cases of White victims. I find that this positive discrimination in favor of Hispanic victims is concentrated mostly among cases of sexual assault and, to a lesser extent, robberies.

[5] Bias on the extensive margin instead corresponds to the detectives holding a higher perceived cost of labor if the victim is not White, all else equal. However, this decision cannot be studied through the lenses of an outcome test, as discussed in greater detail in the body of the paper.

The main estimates are relatively unaffected by the inclusion of several characteristics of the originating incident and other demographics of the victim. This suggests limited scope for bias originating from features other than, but correlated with, the race of the victim. This also limits concerns about the logical validity of the marginal outcome test (Canay et al., 2023).[6] Detective-level estimates reveal high variability in racial bias among investigators. Furthermore, roughly two-thirds of CPD's investigators discriminate against Black victims of violent crime. A remarkable share of detectives (46.2%) discriminate against Hispanic victims, despite average positive bias in the latter's favor.

I next explore the sources behind these results, which helps understanding what policies can alleviate this form of bias. Specifically, it is possible that the estimated racial bias does not originate from biased *preferences* against minority victims (racial animus) (Becker, 1957) but from biased *beliefs* held by the detectives about what makes an investigation successful upon completion (inaccurate statistical discrimination) (Bohren et al., 2023). If biased beliefs were driving these results, the success gap would reasonably shrink as detectives gain more experience. I find small and not significant interactions between the experience of the detective who clears the case and the race of the victim, for both fatal and non-fatal violent crime. Racial animus is therefore a more likely driver of the main estimates.

I then test for race concordance between victim and detective. If biased preferences were indeed behind the observed gaps, we would expect the rankings of the outcome by race of the victim, or at least the size of the gaps, to also depend on the race of the decision-maker (Anwar and Fang, 2006; Antonovics and Knight, 2009). Black and Hispanic detectives display remarkably smaller, and not significant, success gaps for homicides of same-race victims than other-race detectives. This is true also for non-fatal violent crime among Black detectives. This set of results suggests that racial bias in this setting more likely originates from biased preferences than from biased beliefs on evidentiary standards (Arnold et al., 2018; Bohren et al., 2022). I also show that biased preferences among detectives might

[6] This preserves the logical consistency of the test. Canay et al. (2023) shows that models of decision making underpinning outcome tests can be recast as Roy models. However, if the decision-maker follows a generalized Roy model, where unobserved characteristics enter both sides of the decision rule, we might conclude bias even if the decision-maker is unbiased or biased against the opposite group.

be consistent with the views of the public and/or scrutiny from the media: Black victims, and to a minor extent Hispanic victims, are less likely to receive media attention from the main local newspapers in Chicago, even after controlling for other features that determine the newsworthiness of the incident. These disparities in media coverage are consistent with reduced pressure on the detectives to achieve successful case outcomes for Black victims.

My findings suggest that transparency initiatives in policing, which focus on areas such as traffic stops and use of force, should also address police investigations and disparities in the treatment of crime victims more broadly. Additionally, using clearance rates as a metric for police performance is likely inadequate, as only a fraction of solved cases reach court proceedings, and they do so differentially by victim race.[7] Last, I find evidence that increased diversity among investigators may help ensure more equitable treatment for crime victims.

Related Literature: I contribute to the literature on discrimination against minority individuals in the US justice system. A rich body of work in economics has studied the overly punitive tendency of the US justice system, and the police in particular, towards minority individuals. Most such work has focused on racial discrimination against individuals who are *suspected criminals*. Few papers have instead considered the treatment of crime *victims*. An exception is Alesina and La Ferrara (2014), who tests whether Black defendants are more likely to be sentenced to death than White defendants by studying whether the ranking of error rates by defendant race changes with the race of the victim.[8] Their main question, however, remains whether Black defendants are over-sanctioned. Moreover, they cannot identify marginal individuals, requiring strong assumptions on the distribution of the unobservables. Criminologists have devoted more attention to the treatment of victims, finding mixed results (Taylor et al., 2009; Petersen, 2017; Fallik, 2018). Most of these studies leverage data voluntarily reported by police agencies to the FBI (NIBRS) and compare the probability of clearance across victim races while controlling for factors that are thought

[7] In Chicago, only 70% of homicides and 50% of non-fatal violent crimes that are considered solved also reach the stage of prosecution and thereby enter the court process.

[8] Another exception in economics is Bjerk (2022), which descriptively discusses differential patterns of clearance by victim and neighborhood, albeit in the context of a different research question.

to correlate with the difficulty of the case. Using these data and adopting a correlational approach raises identification concerns.[9] Moreover, this literature has overlooked the identity of individual detectives and the link between investigations and subsequent stages of the justice system. I attempt to address these limitations. First, I define discrimination within a model of investigative behavior to guide identification. Second, I leverage data on individual detectives. Third, I use a court-related outcome realized upon crime solution to elicit decision-makers' preferences.

I also contribute to the literature studying police behavior broadly defined. Most papers examining individual decisions made by the police have focused on the behavior of patrol officers. However, little is known about another crucial figure in law enforcement: the police detective. Detectives represent a relevant fraction of police employees and, importantly, significantly affect the probability of apprehension of criminals, determining the deterrent power of policing.[10] Economists tangentially analyze the work of detectives when treating clearance rates as proxies for a police department's performance, almost always as aggregates.[11] To the best of my knowledge, this is the first paper that focuses on the individual decisions made by these agents and how they vary by the race of the victim involved in the assigned case.

Methodologically, I contribute to a large literature that develops methods to measure discrimination. A long tradition in economics has used outcome tests, which are based on differences in post-decision outcomes across groups, to do so (Becker, 1957; Becker, 1993). A critical issue in this context is to identify individuals on the margin of being treated given the decision-maker thresholds for treatment assignment (the *"infra-marginality"* problem). A common solution is to impose strong distributional assumptions on the unobservables of the individuals involved (Knowles et al., 2001; Anwar and Fang, 2006, Alesina and La Ferrara,

[9]First, reporting to NIBRS is voluntary, poor and skewed towards smaller jurisdictions. This makes the results from these studies representative of medium- or small-sized cities, where policing and crime are radically different. Additionally, any null effect might be biased due to selection on consistently reporting to NIBRS. Moreover, these studies control for features that are either revealed only upon clearance or that directly affect investigative intensity, as noted by Cook and Mancik (2024).

[10]Of sworn officers employed by agencies with at least 100 officers, 27% reported working as investigators (Prince et al., 2021).

[11]For examples, see McCrary (2007); Mastrobuoni (2020); and Mastrorocco and Ornaghi (2020).

2014). Recent work has instead leveraged quasi-random assignment to decision-makers to identify marginal individuals (Arnold et al., 2018; Dobbie et al., 2021). In the absence of quasi-random assignment, I circumvent the issue and identify racial bias by exploiting the dynamic nature of police investigations. Detective operations are concluded precisely when a desired threshold of evidence is reached, making all the observed solved cases on the margin of being closed.

Outline: The remainder of the paper proceeds as follows. Section 2 provides relevant background on how police clear a crime and the diverging paths a cleared case can take, especially in Chicago. Section 3 describes the main data used in the paper. Section 4 sketches a model of investigations and derives the marginal outcome test for racial bias in investigations. Section 5 presents the main results from the marginal outcomes test. Section 6 analyzes the sources of the observed bias. Section 7 discusses the policy implications and concludes.

2 Background

2.1 How to Clear a Crime

According to FBI terminology, a solved crime corresponds to a "clearance", and 2 main types of clearance are typically considered (FBI, 2010).[12] First, a law enforcement agency can clear a crime by successfully arresting a suspect, which represents the vast majority of clearances. This occurs when the police have identified, arrested and turned over for prosecution at least one suspect. An alternative way of clearing a crime is by exceptional means. This occurs when the police have identified a suspect, gathered what they deem is sufficient evidence to support arrest and prosecution of the suspect, but encountered a circumstance beyond their control that prohibits them from doing so. Examples of these exceptional circumstances are victims' refusal to cooperate, the prosecution's refusal to press charges or the death of the

[12]The FBI defines these two types of clearance, and the circumstances leading up to them, mostly from a data collection perspective. In reality, law enforcement agencies sometimes deviate from these guidelines.

identified offender.[13] In essence, for the police to clear a crime, it often suffices to identify a credible suspect, regardless of whether they can apprehend and/or prosecute the individual.

Whether a crime is solved depends both on police behavior and incident-specific external factors, which determine the intrinsic difficulty of the investigation. For example, firearms leave less evidence than other weapons involving interpersonal contact, such as knives (Asher, 2021). Cooperation from witnesses (and/or victims if not a homicide), or the lack of thereof, is another influential factor that police report to strongly affect the likelihood of solving a crime (Asher, 2021). The actions police can take during a criminal investigation are numerous and multifaceted, ranging from the number and manner of interviews to the thoroughness of evidence collection and lab submissions, as well as persistence in follow-ups with witnesses, families, and victims.

2.2 Post-Clearance: The case of Chicago

While practices might vary by jurisdiction, whenever a suspect is found and is detained, the police typically decide whether to release her without charges or request that the prosecution press charges against her. In Cook County, where the post-clearance analysis is conducted, if the police opt for the latter, they contact the Felony Review Unit (FRU) at the CCSAO. This is typically a rotating group of Assistant State Attorneys (ASAs) who review the police's evidence and decide whether to approve or reject the charges against the suspect in custody (Cook County State's Attorney, 2018, Cook County State's Attorney's Office, 2024). The police contact the FRU for felonies, while they can bypass the FRU for misdemeanors and drug charges. The contacted ASA can decide whether to accept the charges based on the evidence presented, reject the charges or suggest that the investigation continue.[14] Whenever charges are not accepted, the police release the suspect but can resubmit for charges at a

[13]According to calculations made by Kaplan (2021) using 2019 NIBRS numbers from all agencies that reported data, approximately 50% of all exceptional clearances are due to a lack of cooperation from the victim, and 50% are due to the prosecution denial. These numbers mostly reflect trends for non-deadly crime, as homicides represent a very small share of total crime.

[14]From discussions with the CCSAO, continued investigation is suggested when there is a clear piece of evidence that is missing and is considered obtainable.

later time. This is an instance of clearance achieved by exceptional means, in this case due to prosecution denial. Whenever charges are accepted, the suspect(s) will be scheduled for a preliminary hearing before going to trial and, potentially, sentencing. Figure A.1 shows the arrest-to-court pipeline in Cook County, IL. This paper focuses on the first step, when after an arrest the police go to the CCSAO's FRU.

From a legal standpoint, a discrepancy between police work and the prosecution's opinion can arise because the standards for arrest and prosecution need not coincide. The law in fact requires that the totality of the evidence amounts to the level of *probable cause* for the police to be able to arrest and request charges on a suspect. However, for the prosecution to be able to convict the suspect(s), the threshold increases to *proof beyond a reasonable doubt*.[15] It is therefore at the discretion of the police whether to gather evidence exceeding probable cause before submitting a case for prosecution or they deem probable cause to be sufficient. Analogously, the prosecution can accept cases that are not (yet) backed by evidence amounting to proof beyond reasonable doubt. However, given the incentive on their part to maximize conviction rates, it is in their best interest to reject a case whenever they deem the evidence insufficient. The FRU's decision is therefore informative of the quality of the police work: acceptance of charges means that the CCSAO deemed the evidence to be good enough to seek a conviction, i.e., at the level of proof beyond reasonable doubt. Rejection can instead be interpreted as the CCSAO considering the evidence only at the level of probable cause. Note that even if charges are rejected, the police can consider the crime to be solved. In this case, the crime is classified as cleared by exceptional means. Upon rejection, the police decide whether to continue investigating and again seek charges or stop completely. The non-negligible rate of rejections by the CCSAO (see Table 1) has been repeatedly highlighted by the media as a problematic issue that can fuel a cycle of violence,

[15] Probable cause means that, based on the existing evidence, a reasonable person would believe that an offense occurred and that it is probable that this suspect committed that offense. On the other hand, proof beyond reasonable doubt also requires that there is no reasonable doubt that the defendant committed the crime. For reference, see the US Supreme Court rulings in Brinegar v. United States, 338 U.S. 160 (1949) and Maryland v. Pringle, 540 U.S. 366 (2003). Probable cause and proof beyond reasonable doubt are not to be confused with *reasonable suspicion*, which is an even lower standard that is grounds for an investigative stop by law enforcement.

especially in the context of murder investigations (Smith, 2019; Charles, 2022; Grimm, 2022).

3 Data

Through a series of FOIA requests, I obtained data on all 885,586 victims of violent crime reported to the CPD from 1/1/2000 to present and the related investigation. The data include information on both fatal violent rime (first-degree murder) and non-fatal violent crime (aggravated assault, aggravated battery, criminal sexual assault, robbery). I have 3 main datasets that can be merged through a unique identifier. First, I have information regarding the victim of the incident (race, ethnicity, gender, age), the incident itself (type of crime, weapon used, premises of incident, address, date and time, circumstances of the incident) and the current status of the investigation related to the incident (whether the crime was cleared and the type of clearance, if cleared). Second, I obtained data on all the detectives assigned as primary detectives to the case, including their demographic characteristics (race, gender, date of appointment as police officer) and the date of assignment to each case. Last, I obtained information on all the status updates related to a single case, which importantly include all the times a case is updated as cleared, with the specific type of clearance for that classification update, and the respective date of update.[16] I can then distinguish between clearances achieved via arrest and prosecution of a suspect and exceptional clearances where the prosecution refused to proceed with the case. I can also compute the time to clearance as the difference between the date when the crime is classified as cleared and the time of the offense. I also observe other types of updates, such when a case is reopened or suspended, with the latter being used later in the paper.

I drop all offenses that occurred after 12/31/2023 and keep only victims that are either White non-Hispanic (henceforth, White), Black or White Hispanic (henceforth, Hispanic).[17]

[16] Using these granular data on all updates however seems to come with a cost, as it appears to not distinguish as well between prosecution denials and deaths of offenders as the dataset with the current status does. I explain how I address this issue in Section 4.2.

[17] For non-fatal violent crime, I have to drop all crimes reported in 2000 due to missing geographic information.

I restrict the sample to cases that have ever been assigned to a detective and therefore ever investigated after the incident.[18] These two restrictions leave me with 704,211 victims. The dataset is kept at the victim level since there is variation in demographics, mostly in age and gender, and features of the crime even within within incidents.[19] Although there can be only one primary detective at a time assigned to a case, I address the fact primary detective on a case is in some instances replaced during the course of the investigation by leveraging the date of assignment of detectives to cases and the date of the update. Specifically, I do the following: For cases that are cleared, I keep the detective that was on the case at the time of clearance classification. For cases that are never solved, I keep the first detective ever assigned, although this pool of cases will not play a large role in the paper because the major focus is the sample of cases that are ever cleared. When I later examine the decision to suspend an investigation, I will consider the detective assigned to the case at the time as the relevant individual.

Table 1 reports summary statistics for this sample. There is a large gap in the raw probability of clearance between White and minority victims of homicides. Cases of minority victims are also less likely to be solved via arrest and prosecution, even conditional on clearance. White victims are more likely to be female and older, and they represent a small share of total victims of homicide. For non-fatal violent crime, in contrast, we observe a relatively small overall clearance gap; however, this gap becomes more substantial if we consider clearances that occurred via the successful arrest and prosecution of a suspect, at least for Black victims. Refusal to cooperate is also most common among Black victims. Robberies are by far the most common of the non-fatal violent crimes, especially for White and Hispanic victims.

[18] However, not all violent crimes seem to have a primary detective assigned. In response to a FOIA request, CPD communicated that a primary detective might not be assigned, for example, if an offender was immediately apprehended on the scene and no follow-up was required. A significant share of these crimes without a primary detective ever assigned (roughly 30%) are not yet solved. A majority of these are assaults without injuries involved. This means that cases without primary detectives are a mix of cases that are solved immediately and rightfully did not need a primary detective assigned and cases that were never solved but that we might expect should be investigated. Since I cannot disentangle these two categories, I drop violent crimes that were never assigned to a detective, regardless of the reason for this choice.

[19] Of the incidents in my data, 86.7% have only 1 victim, 97% of incidents have 1 or 2 victims, and only 0.91% have more than 3 victims.

While we cannot assess whether Chicago is an outlier in terms of the outcome used for the marginal outcome test (acceptance/rejection by the prosecution upon clearance), due to unavailability of such data for more cities, we can study the gap in homicide clearance rates by race of victim across several cities. To do so, I leverage data collected by the Washington Post on homicides committed between 2007 and 2017 and their clearance status for 47 large US cities, with related information about the victim and coordinates of the incident. I then estimate city-level clearance gaps between Black and White victims and between Hispanic and White victims, using a model that interacts city fixed effects with dummies for Black and Hispanic victims. I control for city-by-year fixed effects and cluster the standard errors at the ZIP code level. The results of this exercise, plotted in Figure A.2, show that Chicago does not appear to be an outlier, at least when it comes to this outcome. Adding further controls, such as age and gender of the victims and the demographic characteristics of the neighborhood, does not dramatically change the conclusion (Figure A.3).

4 Model and Marginal Outcome Test

I next sketch a model of police investigations that allows me to develop a marginal outcome test for racial bias. Following Becker (1993), I leverage a post-decision (i.e., post-clearance), downstream outcome to elicit the agents' preferences. The model explicitly considers two key decision variables that can lead to a clearance. These are *i)* the time when the detective desires to clear and close the case; *ii)* the time when she would instead suspend altogether the investigation of a case that would therefore never be solved.[20]

[20]The test derived in this paper is similar to those in Anwar and Fang (2015) and Lodermeier (2023). They leverage the evolution of a relevant variable over time and use the (first) period when a decision is made by the relevant agent to identify marginal cases in the parole and eviction settings, respectively. Lodermeier (2023), in particular, does so without imposing strong parametric assumptions and is the closest in spirit to my approach.

4.1 A Model of Police Investigations

Setup: The police receive case i, which is then assigned to an investigator. The investigator observes the race $R_i \in \{w, m\}$ of the victim, as well as other characteristics U_i that are in part unobserved to the econometrician. The investigator chooses how many days T_i to keep the case open and work on it before submitting it for clearance and, ultimately, for prosecution of the arrestee(s). She has the option of submitting the case on any day t following a decision rule that tells her whether the case is ready for submission. Let $D_i(t) = 1$ denote the investigation being concluded and the case being cleared – and submitted for prosecution – at time t.

Upon clearance and submission, the case can be successful or not, and this partly depends on how much time was spent on the case. As a measure of success, I use the DA's decision to accept the case and proceed to prosecution. Let $Y_i^*(t) \in \{0, 1\}$ indicate the potential success when days $T_i = t$ are spent on the case before submission, and write the observed outcome as $Y_i = Y_i^*(T_i)$. The true probability of success upon submission of the case at the end of each period t is $p(t, r, u) = E[Y_i^*(t) \mid R_i = r, U_i = u, T_i = t]$. To simplify notation, expected success is denoted as $p(t)$. I assume that $p(t)$ is weakly increasing in t, all else fixed: the more time is spent on the case, the more evidence is collected, and the more successful the case is going to be in expected terms. I further assume that $p(0) = 0$ and that time is continuous.

The investigator also pays a subjective cost $c(R_i, t)$ of submitting a case with a given evidence level to court. I allow the cost to depend on race, with $c(w, t) \neq c(b, t)$ signifying racial discrimination. The lower $c(R_i, t)$ is, the more the detective is willing to submit at low values of $p(t)$, i.e., with worse evidence. The submission cost therefore identifies the desired evidentiary standard that has to be met before submission at time t for a victim of race R_i. The cost $c(R_i, t)$ can be further micro-founded by assuming that the detective minimizes the costs of type I errors (submitting potentially failing cases) and type II errors (not submitting potentially successful cases). $c(R_i, t)$ can be then recast as the relative cost of type I errors, i.e., submitting a potentially failing case, for a victim of race R_i after t

days of investigation.[21] Therefore, if she discriminates against minority victims, we expect $c(m,t) < c(w,t)$: failures are relatively less costly if the victim is not White. This cost is also reasonably decreasing over time: any given value of $p(t)$ becomes more acceptable to the investigator (and her supervisor) as time passes, as new cases keep arriving.[22] Equivalently, a potential failure becomes more tolerable over time. Furthermore, I allow racial bias to vary flexibly over time by not assuming separability in race and time to clearance in $c(\cdot)$.

Clearance: The investigator's desire to clear, submit and close the case can then be represented as follows:

$$D_i(t) = \mathbf{1}[p(t) \geq c(R_i, t)] \tag{1}$$

There exists a period t_i^* satisfying the indifference condition $p(t_i^*) = c(R_i, t_i^*)$, at which point the investigator submits and closes the case. This is equivalent to the investigator having race-specific thresholds of minimum expected success that she is willing to tolerate before submitting, $\underline{p}(w,t)$ and $\underline{p}(m,t)$, at any point in time. If she has a distaste for investigating cases of non-White victims, we expect a lower probability of success for non-White cases filed on the margin than White cases filed on the margin, i.e., $\underline{p}(m,t) < \underline{p}(w,t)$.

Note that these thresholds are assumed to depend on the race of the victim and the time elapsed from offense to clearance, but not on the other characteristics of the case, which jointly determine the difficulty of the investigation. These characteristics are assumed to affect the pace at which evidence accrues and how fast the case reaches the desired quality but not the desired thresholds of expected success themselves. In the empirical analysis, I relax this assumption and test whether any differential standards that I might find vary with observables other than race but potentially correlated with it. This assumption also preserves the logical validity of the marginal outcome test, a point stressed by Canay et al. (2023).

Suspension: Not all cases, however, will reach submission and clearance. The inves-

[21] See Appendix B.2 for the derivation.

[22] An evidence level only above probable cause is acceptable after three years but not after one week of investigation, when there remains a concrete possibility of obtaining new evidence. Similarly, a detective is more likely to be sanctioned if she brings a low level of evidence for submission to the supervisor after one week than if she brings it after three years.

tigator can also suspend the investigation at any point in time even before submission if she considers the investigation not worth being kept open, by either formally or informally abandoning the case. This can be captured by the investigator also paying a subjective cost for actively investigating the case on day t, $l(R_i, U_i, t)$, which is potentially race-dependent and is strictly increasing over time. If she discriminates against non-White victims and dislikes investigating their cases, we expect $l(m, u, t) > l(w, u, t)$: she finds spending time on cases of non-White victims more costly than investigating cases of White victims. [23] If the investigation is suspended, the case will not be cleared or brought to court. Let $S_i(t) = 1$ denote the investigation being suspended at time t. The investigator will do so if the cost of investigation at time t exceeds the maximum effort that she is willing to exert on a case, $\bar{l}$:

$$S_i(t) = \mathbf{1}[l(R_i, U_i, t) \geq \bar{l}] \tag{2}$$

There is then a period t_i^0 such that the indifference condition along this margin holds, i.e., $l(R_i, U_i, t_i^0) = \bar{l}$. Equation 2 plays then the role of a (subjective) resource constraint forcing the detective into a corner solution, with the investigation not resulting in a clearance. While perhaps simplistic, Equation 2 is meant to capture the fact that the investigation will be suspended if it is considered unproductive and unlikely to reach the desired threshold of evidence/success for submission.

A case is therefore cleared and submitted if there is both enough evidence to do so, according to the investigator's subjective thresholds of success, as pinned down by $c(\cdot)$, *and* the investigation was never abandoned. The case is instead suspended if the investigation becomes too demanding before reaching an acceptable level of evidence. The realized time spent on the case is then either the time of suspension or the time of clearance, depending on whether the case was ever suspended, i.e., $T_i = S_i t_i^0 + (1 - S_i) t_i^*$. Clearance status will be equal to 1 only if the case was never suspended: $D_i = (1 - S_i)$.[24] Success will always

[23] While the suspension decision could be modeled in even greater detail, the decision is kept as simple as possible due to the lack of appropriate outcomes and data for an outcome test. Here, for example, I assume that the detectives know their cost of investigation. However, we can relax this assumption and make $l(R_i, U_i, t)$ an expected cost: $l(R_i, U_i, t) = E[l(t)|R_i, U_i]$.

[24] While there exist periods t s.t. $D_i(t) \neq (1 - S_i(t))$, in the observed data, where S_i and D_i do not vary

be equal to 0 if the case is never solved/submitted: $Y_i = D_i Y_i^*(T_i) = (1 - S_i) Y_i^*(T_i)$. Cases that are suspended will not arrive at the DA's office, and we therefore never observe their potential success.

A test for racial bias: In this model, there is room for discrimination along two margins: the investigator could both *i)* assign a lower chance of clearance to cases of Black victims by suspending potentially workable cases – discrimination on the extensive margin – and *ii)* set lower desired success rates even conditional on clearance/submission for cases of minority victims – discrimination on the intensive margin. Note that suspension and clearance here follow two decision processes that evolve in parallel. This setting is close in spirit to use of force by the police: officers both decide whether to use force, potentially in a discriminatory way (Fryer Jr, 2019; Hoekstra and Sloan, 2022), and what *level* of force to use conditional on using force, also in a potentially in a discriminatory way (Lieberman, 2024).

While the suspension decision does not involve a downstream potential outcome that is linked to the treatment, the submission decision does. Clearance is in fact determined once the expected downstream outcome Y_i, the successful submission for prosecution, is optimized relative to the costs. Moreover, all cleared cases are closed at the time of indifference, t_i^*. We can therefore perform a marginal outcome test for racial bias on the intensive margin by studying cases that are cleared and their success probabilities once they reach the DA's office. Recall that for cleared cases, we observe $T_i = t_i^*$ in the data. The observed disparity in success rates between cases involving non-White and White victims that take the same amount of time before closure therefore identifies the difference in costs of submission, i.e., desired evidentiary standards, $c(r,t) - c(r',t)$. Since we defined this difference as racial bias, and cases are closed on the margin, i.e., when they equate the race-specific cost, we can state the following:

Proposition 1 *If* $\Delta_t^Y \equiv E[Y_i \mid R_i = m, D_i = 1, T_i = t] - E[Y_i \mid R_i = w, D_i = 1, T_i = t] < 0$*, the investigator displays racial bias on the intensive margin against non-White victims.*

time, this cannot occur.

We would therefore conclude that the police display bias against non-White victims (at relative time to clearance t) if we estimate $\Delta_t^Y < 0$. By averaging over the range of time to clearance, we obtain a total measure of racial bias, Δ^Y.[25] For the proof of Proposition 1, see Appendix B.1. Note that the suspension decision will affect which t_i^*s are observed for each race group: we do not observe t_i^* if $t_i^* > t_i^0$, making Δ^Y representative not of all investigations but only those that are brought to the end. However, conditional on observing $t_i^* = t$ for both races, the gap in success rates identifies the differential costs of submission at such t.

4.2 Empirical Approach

I next describe how I empirically estimate Δ^Y. In the data, I observe when the police classify a case as cleared, which can be used to impute time to clearance t_i^*. I also observe whether the case was cleared by arrest or exceptional means. For homicides, exceptional clearances occur due either to the death of the offender or prosecution denial. I then construct my measure of success Y_i as follows: a case is considered successful if clearance has occurred via an arrest that has been approved by the DA's office, which is then followed by prosecution, which represents the majority of clearances. If instead the case is considered cleared but this was not achieved via arrest and prosecution, the case will not be considered successful. Since the clearance status of a case can be updated multiple times, I consider the first clearance update as the main measure of success and the relative time elapsed to impute the time to closure t_i^*. Whenever possible, clearances due to the death of the offender are dropped from the sample since I do not observe the counterfactual decision of the DA in the scenario where the offender did not die. For non-fatal violent crime, there is another relevant category of clearance: exceptional clearance due to the complainant's refusal to cooperate. Since I do not know the counterfactual success of these cases, as they never reach the DA's office, they are also dropped from the analysis.[26]

[25] Note that I follow Hull (2021) and allow bias to arise via non-race characteristics.

[26] For homicides, I observe if a case was *ever* cleared due to the death of the offender. In all the status updates, however, this is rarely recorded as such. Many homicides that are, at least at some point, cleared

By then restricting to cases that are cleared either via arrest and prosecution or exceptionally due to prosecution denial, I estimate the following baseline model:

$$Y_{ijay} = \alpha + \beta^B BlackVictim_i + \beta^H HispanicVictim_i + f(T_i) + \delta_j + \delta_{ay} + \varepsilon_{ijay} \quad (3)$$

where $f(T_i)$ is a function of time to clearance. I first control for time to clearance with a quadratic in T_i and then non-parametrically using fixed effects of weekly bins of T_i. This means that cases cleared within a week of the offense are binned together, as are cases solved between 7 and 14 days of assignment, and so forth. I always include detective area fixed effects, δ_{ay}, since investigative operations (e.g., detective assignment, supervisor review) are conducted at this geographic level, and they can differ widely in their internal functioning and personnel. I interact these fixed effects with the year when the offense was committed, and hence when the case assigned to a detective, as the boundaries of the areas changed substantially over the years.[27] This further accounts for average changes in personnel, such as the area commander and operations within areas, in addition to time trends in the outcome. I also add a set of fixed effects for the identity of the primary detective assigned to the case at the time of clearance, δ_j. When analyzing non-fatal violent crimes, both time to clearance, area-year fixed effects and detective fixed effects are interacted with crime type (assault, battery, sexual assault, robbery). The coefficients of interest are β^B and β^H, which estimate total racial bias in closure decisions, against Black and Hispanic victims, respectively. Recall that the dataset is kept at the victim level; although the vast majority of incidents involve

due to the death of the offender are recorded as generic exceptional clearances in the update data. For homicides, I drop cases that are ever cleared due to the death of the offender and the first clearance was not a clearance by arrest, which suggests that the suspected offender was dead at the time of the first clearance. For nonfatal crime, I do not observe whether the crime was *ever* cleared due to the death of the offender. As discussed in Section 2, however, it is unlikely that a large share of exceptional clearances for nonfatal violent crime are due to the death of the offender. Moreover, death of offender seems disproportionately more likely among homicides of White victims than among homicides of minority victims.

[27] Detective areas are partitions of the city where detectives are stationed. They include a handful of districts, and when an incident warranting investigation occurs, a detective from the corresponding area is called and assigned. For budgetary reasons, CPD cut these areas from 5 to 3 in March 2012 and reverted back to 5 in April 2020. This creates three major periods when the functioning of the detective areas are radically different: before the closures in 2012, after the closures in 2012/before the reopening in 2020, and after the reopening in 2020. See Figure ?? for the respective maps.

only 1 victim, or at most 2 victims, I weight each victim by the inverse of the total number of victims involved in the incident. The basic model is then augmented with additional fixed effects and controls to explore how the gap in success rates, if any, changes once we account for other factors that potentially correlate with race. Standard errors are clustered at the detective-area-year-of-offense level.

Figure A.5 shows the distributions of the number of days elapsed from the date of the offense to the date when the case is classified as cleared, for cases that are ever cleared. The sample is already restricted as described above, with exceptional clearances due to death of the offender or refusal to cooperate by the victim being dropped when possible. The distributions are shown separately for homicides and nonfatal violent crime. To improve visualization, the distributions are truncated at 3 years and 1 year for homicides and other violent crime, respectively. The homicides in this sample are mostly recorded as cleared in a couple of months, but the probability of clearance does not drop to 0 thereafter, and it gradually decreases over time. For nonfatal crimes, in contrast, most seem to be classified as cleared within a week or two, and they will virtually never be cleared if this does not occur within the first three or four months.

5 Results

5.1 Graphical Evidence

Figure 1 shows the raw probability of success among the cases that will be used for the marginal outcome test, as outlined in Section 4, by race of the victim and separately for homicides and non-fatal violent crime. Black victims experience the lowest probability of their case being closed successfully with an arrest and prosecution, with the confidence interval never overlapping with that of White victims. The gap is 8.7 pp for homicides and 3.8 pp for other violent crime. Hispanic victims also experience lower average success for homicides than White victims, although not significantly, and virtually no difference relative to cases of White victims for non-fatal violent crime. While this exercise is informative, as all cases are in fact closed on the margin, these numbers do not consider *who* investigates these cases (detectives) and *where* they are investigated (detective areas), which can significantly affect the gaps in success rates. Moreover, the evidentiary standard required to close the marginal investigation can become more lax over time and differentially so for victims of different races, as argued in Section 4.

Figure 2, on the other hand, provides a more accurate visual representation of what Equation 3 will estimate. It shows a quadratic fit of the relationship between the probability of success and the days between incident and first clearance by race of the victim. Success is first residualized with respect to the main fixed effects used for the test, other than time to clearance: detective area-year and primary detective at the time of clearance. The range of time to clearance is truncated at 1 year for homicides and 3 months for nonfatal violent crime to limit the sample to a range where a reasonable number of cases are cleared and improve visualization. For all three racial groups, the probability of success decreases with the time it took to clear the case, providing suggestive evidence in favor of the assumption that the desired threshold for success decreases over time. We observe a gap between the Black and White curves, with cases of Black victims being systematically less likely to be successful than cases of White victims and this difference remaining roughly constant over time. Strikingly, even cases that are solved soon after the incident, which typically have clear evidence against a suspect and require a relatively low amount of effort, are less likely to be approved by the CCSAO if the victim is Black rather than White. The picture is more nuanced for Hispanic victims: the average gap is smaller in magnitude and virtually null for cases closed early.

For other violent crimes (Figure 3), we again observe an overall gap in success rates between cases of Black and White victims concentrated in the first month, when most nonfatal crime is solved. We instead observe better cases being systematically handed to CCSAO if the victim is Hispanic rather than White. Since robberies represent a disproportionately large share of non-fatal violent crimes, potentially obfuscating any pattern in other violent crimes, Figure A.8 reproduces the same figure but excluding robberies. A starker pattern emerges for Black victims, with a roughly constant gap in success rates over time that also resembles what is observed for homicides. Cases of Hispanic victims seem again to be more likely to be cleared via successful arrest and prosecution than cases of White victims, but the difference is smaller in magnitude. For both types of comparisons, the success rates decrease less dramatically over the range of time to clearance. Equation 3 takes an average of the gap between the two curves over the entire range of time to clearance.

5.2 Main Results

Table 2 shows the results from the estimation of Equation 3, separately for homicides and non-fatal violent crime. Columns 1 and 2 report the results for homicides. Column 1, which controls for time to clearance using a quadratic polynomial, shows that Black and Hispanic victims' cases are 8.2 pp and 4.6 pp significantly less likely to be successful (i.e., approved by the CCSAO) than cases of White victims. This is consistent with the police displaying bias against Black and Hispanic victims. These effects are sizable: they correspond to a 9.7% and 5.4% reduction for Black and Hispanic victims, respectively, when compared with the average probability of success of a White case (84.8%). Column 2 replaces the quadratic in time to clearance with a set of fixed effects that bins time to clearance in weeks to clearance: the gap in success rates slightly decreases for both Black and Hispanic victims, and the difference is significant only at the 10% level for Hispanic victims. The gaps are 9.2% and 4.6% with respect to the White mean for Black and Hispanic victims of homicide, respectively. Overall, Table 2 presents evidence of racial bias against Black and Hispanic victims of homicide.

Columns 3 and 4 report the results for the sample of victims of non-fatal violent crime. Recall that this sample excludes crimes that are exceptionally cleared due to the victim's refusal to prosecute because we do not observe the counterfactual success outcome for these crimes. These estimates, therefore, are representative of how the police differentially treat Black and Hispanic victims who are willing to cooperate relative to White victims who are willing to cooperate. The police display bias against Black victims of non-fatal violent crime, as their cases are 1.9 pp and 2.2 pp less likely to succeed when compared with White victims when controlling parametrically or non-parametrically for time to clearance, respectively.

Given a baseline success rate of 75.7% for White victims, taking the estimates in Column 4, we can conclude that Black cases are 2.9% less likely to succeed. Conversely, the police appear to hand investigations over for prosecution with better evidence when the victim is Hispanic than when the victim is White, as cases of Hispanic victims are more likely to be approved by the FRU. As reported in Column 4, Hispanic cases are 1.95 pp (2.6%) more successful than when the victim is White.

5.3 Robustness

I next test the robustness of the main results. I start by controlling for time to clearance in different and more demanding ways. Results are shown in Table A.1 are for both homicides and non-fatal violent crime. I first use an alternative version of time to clearance that takes the first day when the case is assigned to a detective, rather than the date of the offense, as the starting point of the investigation. These dates can sometimes differ due to a lag in reporting or a lag in assignment. The results remain largely unchanged (Columns 1 and 3). For homicides, I then interact time to clearance with the detective area where the investigation is conducted: this allows required evidentiary standards to change over the course of investigation in a different way for each area. Due to the low number of observations, I utilize a quadratic in days to clearance rather than week-bins fixed effects. The results are again similar to those in Table 2 (Column 2). The large sample size for non-fatal violent crime allows the use of more demanding specifications. In Column 4, I interact week-bins fixed effects of time to clearance with detective fixed effects, and in Column 5, I instead bin time to clearance into 3-day bins, so that we compare crimes that are solved in nearly the same number of days in a flexible way. The results are qualitatively unchanged.

I further test the robustness of the main results to a series of other potential concerns, with the results jointly plotted in Figure A.9 for homicides and in Figure A.10 for non-fatal violent crime. First, it is possible that the police close the gap in success rates by returning to the FRU after being rejected and that the ultimate result of the investigation is actually unbiased. To test this, I use the *final* clearance status observed in the data, rather than the first, to create my measure of success. According to this alternative measure, the case of victim i is successful if the last time I observe the case updated as cleared is as a clearance achieved via arrest and prosecution. The time to clearance is adjusted accordingly as the time elapsed from the offense to the *last* observed clearance update. Overall, success gaps do not appear to be closed by returning to the prosecution for a new evaluation.

Second, I test whether the results are driven by cases that are solved very early or very late, which might be unique, outlier investigations. For homicides, I drop cases solved in less than 1 month or after 2 years. For non-fatal violent crimes, I drop cases solved in less than 2 weeks or more than 2 months. Different cutoffs are adopted due to the different ranges of time to clearance for homicides and non-fatal crime, with the former spanning a wider time frame. The only noticeable differences with respect to the main results are found for homicides of Hispanic victims, where the estimates are remarkable larger when dropping cases solved early, and for non-fatal violent crime involving Black victims, where bias seems concentrated in the short-run.

Last, I use the identity of the first primary detective assigned to the case rather than the detective who is on the case at the time of clearance. While the latter seems the most relevant for the decision of when to stop the investigation, the former can also have a significant impact on the investigation, thereby limiting the actions that the next detective assigned can take. Note that 71% of cases in the sample used for the marginal outcome test have only one primary detective ever assigned. The results are virtually unchanged.

5.4 Indirect Bias: Adding Non-Race Characteristics

The model upon which the test is based assumes that characteristics other than race can affect the expected rate of success of the case, and hence how fast evidence accrues and reaches the desired level, but they do not enter the cost function that pins down the required thresholds for submission. We can relax this assumption and test how the gap in success rates changes when we account for other observable characteristics of the victim, or the incident, that might correlate with race – and success. Racial bias could in fact originate *indirectly* from another characteristic that correlates with race and success (Bohren et al., 2022). In that case, by controlling for these characteristics, the estimates would shrink towards zero. However, we would still be in the presence of racial bias, despite it not *directly* originating from the race of the victim.

Table 3 performs this exercise for homicides, starting from the basic model. The addition of a quadratic in age of the victim, gender of the victim and fixed effects for the ZIP code where the incident occurred slightly increase the estimates in magnitude (Column 1). In Column 2, I further control for whether the victim was injured during a domestic violence-related or gang-related incident. The estimates are virtually unaffected. Accounting for other dimensions of the incident that are typically considered to capture most of the objective difficulty of an investigation (weapon used, premises of the incident, hour-month when the incident occurred) reduces the success gap for Black victims, while the gap increases for Hispanic victims. Controlling for the totality of these features does not dramatically alter the results, and especially for Black victims, the final point estimate is very similar in magnitude to the baseline estimate in Table 2, where none of these features were included. This suggests that detectives are already factoring in all of these additional variables when closing an investigation, at least for Black victims.

Table 4 estimates the same series of models for nonfatal violent crimes. In this sample, the success gaps decrease overall by 0.5 pp and 0.6 pp for Black and Hispanic victims, respectively, when comparing estimates from the most saturated model (Column 3 in Table 4) with the the baseline estimates (Column 4 in Table 2). This set of results confirms that the police display racial bias against Black victims of violent crime and Hispanic victims of homicides by accepting a higher probability of the case not entering the court system. However, they treat more favorably Hispanic victims of non-fatal violent crime more favorably than White victims.[28]

[28]Another characteristic that is not the race of the victim but might correlate with it and with the success rates of different cases is the race of the suspect/arrestee. Since violent crime tends to be committed within-race, for the race of the suspect/arrestee to explain the results and make the true gaps null, the CCSAO and/or the police would have to be particularly lenient towards minority suspects/arrestees, which seems unlikely given prior work on policing and prosecution behavior (Rehavi and Starr, 2014; Goncalves and Mello, 2021). I further use two, rather imperfect, sources of data to test for this: data on all suspects linked to the

Non-fatal violent crime is however highly heterogeneous, and it is worth exploring each type separately. I estimate a heterogeneous version of the main model including all controls (Column 3 in Table 4) where I interact the race of the victim with dummies for the specific type of non-fatal violent crime (assault, battery, sexual assault, robbery). All controls are also interacted with crime type. Figure 4 shows the results. Bias against Black victims of non-fatal violent crime seems to originate from aggravated assaults and batteries, while no bias is found when considering sexual assaults and robberies. For Hispanic victims, we observe an almost opposite pattern: the bias in their favor is concentrated among sexual assaults and robberies, with a particularly large coefficient for sexual assaults.

5.5 Detective-level Estimates

An important question in studies of discrimination in policing, and the criminal justice system more broadly, is how widespread discrimination is (Goncalves and Mello, 2021). I address this issue in my setting by estimating detective-level racial bias. The ultimate goal is to estimate two meaningful quantities: the variation (standard deviation) in bias and the share of detectives who discriminate. The average detective-level bias is obviously also of interest, but we have already obtained a first estimate of this parameter in the main results. I start by estimating the following model, which interacts the race of the victim with detective fixed effects:

$$Y_{ijay} = \alpha + \beta_j^B BlackVictim_i + \beta_j^H HispanicVictim_i + f(T_i) + \gamma' X_i + \delta_j + \delta_{ay} + \varepsilon_{ijay} \quad (4)$$

I also include the non-race characteristics of the victim and incident that were introduced in Section 5.4, X_i. These estimates are informative insofar as detectives close a sufficient number of cases for victims of all three demographic groups considered here. Therefore, I restrict the sample to detectives that close at least 10 cases for each group. I then follow Arnold et al. (2022): they compute the mean and standard deviation of bias using empirical

case (who are not necessarily ever apprehended) and data on arrestees (which has the caveat that it appears to be selected on charges being actually accepted). Both datasets are obtained via FOIA request. Juvenile suspects/arrestees are absent for privacy concerns, and the race is also missing in many other instances.

Bayes methods as in Morris (1983) and then the share of agents who discriminate, in this case corresponding to detectives with negative success gaps, using the posterior average effect calculation of Bonhomme and Weidner (2022). Standard errors for each of these quantities are obtained by bootstrapping shrunken estimates again derived following Morris (1983).[29]

Figure 5 plots the posterior distribution of detective-level bias separately for Black and Hispanic victims.[30] The mean bias against Black victims (-2 pp, SE=.05 pp) is, if anything, slightly larger in magnitude than in the main estimates. On the other hand, the average bias in favor of Hispanic victims (.05 pp, SE=.06 pp) is reduced in size, suggesting that the favorable treatment observed in the full sample is largely due to detectives handling few cases, who are dropped for this exercise. Nearly two-thirds of the detectives in this sample discriminate against Black victims (SE=1.5 pp), while less than half discriminate against Hispanic victims (SE=1.5 pp). Importantly, there is wide variability in both types of bias, as standard deviations of 6.3 pp (SE=.07 pp) and 7.4 pp (SE=.09 pp) are estimated for Black and Hispanic victims, respectively, which is roughly 10% of the White outcome mean.

5.6 Differential Suspension of Investigations

The model in Section 4 illustrates how clearance disparities by race can arise on the intensive and extensive margin. Recall that this occurs because detectives adopt different thresholds for submission and suspension, respectively. While the first type of threshold is based on an outcome and can be therefore studied through the lenses of a marginal outcome test, the second is not. For this reason, the suspension decision is kept very simple. However, we can learn something about the suspension margin, even from this basic setup, since the

Missing race and selection is most sizable in the first dataset for homicides and in the second dataset for nonfatal violent crimes. Tables A.3 and A.4 show the main results while controlling for the race of suspects and arrestees, respectively. For the reasons explained above, the preferred models for homicides are those in Table A.4, while those for non-fatal violent crime are in Table A.3. Overall, the results are not dramatically affected by the inclusion of the race of the suspects/arrestees for Black victims, while the estimates become smaller in magnitude and not significant for Hispanic victims. The coefficients on the indicators for the race of the victim are also largely consistent with previous estimates in the literature. Given the limitations of these data sources, the preferred estimates remain those in the main body of the paper.

[29] Table A.2 reports the main estimates in this sample.

[30] Figure A.11 plots kernel density distributions of raw estimates and their shrunken version, with the latter obtained following Morris (1983).

time of suspension is observed in the data. Specifically, I observe in the data whether a case is suspended as well as the date when the case was classified as such.[31] Importantly, by studying the extensive margin by leveraging suspensions (which are actual decisions thus far unexplored in the literature), rather than a clearance indicator (which is the more common practice but ultimately the byproduct of many decisions), we can gain more nuanced insights into investigation disparities along this margin.

Suspending an investigation has a clearly adverse impact on the expected clearance of the case, as well as success upon clearance.[32] Importantly, suspensions can be administered in a discriminatory way. The model in Section 4 allows for this by explicitly including the suspension decision, with potentially race-dependent costs of investigation. The suspension decision can be written as a threshold rule in time to suspension, where similar cases are suspended earlier if the victim is non-White.[33] I test this claim by leveraging a rich set of observable characteristics of all non-fatal crimes investigated by CPD in the last two decades (Table 5). I estimate the following model:

$$Y_{ijay} = \alpha + \beta^B BlackVictim_i + \beta^H HispanicVictim_i + \gamma' X_{iy} + \delta_j + \delta_{ay} + \varepsilon_{ijay} \tag{5}$$

where Y_{ijay} is the number of days elapsed from offense to suspension. I include detective fixed effects, δ_j, area-year fixed effects, δ_{ay}, and other victim and incident characteristics X_{iy}, which include controls for age and gender of the victim, neighborhood, weapon, premises, hour and month of the offense, and whether the incident is gang or domestic violence related.

By taking the days elapsed from the offense to suspension as an outcome, we see that

[31] Investigations are officially suspended only for non-fatal crime, and this is done mostly for efficient resource management: a case that is deemed not worthy of effort is suspended, and this typically occurs when the investigator thinks that there are no actionable leads. Although homicide investigations are not officially suspended, they can obviously be unofficially abandoned if the case has stalled.

[32] Some suspended investigations are in fact reopened and ultimately solved, but if the case had not been worked for some time, evidence might have been lost, or at least deteriorated, cooperative witness might have become more hostile, and so forth. Therefore, even if the case were to reach the required bar for clearance, a successful entry into the court process is less likely. Detectives can therefore reach the bar represented by probable cause but not proof beyond a reasonable doubt. It will be up to them whether submission is warranted. This latter decision, and its dependence on race, is precisely what is captured by the intensive margin decision in my model.

[33] See Appendix B.3 for the derivation.

violent crime investigations are suspended on average one day earlier (-4%) if the victim is Black than if she is White (Column 1). This difference is relatively unaffected if we also control for the potentially gang-related or domestic violence-related nature of the incident (Column 2). Cases of Hispanic victims are not suspended significantly earlier or later than cases of White victims. Although these results should be interpreted with caution given that they are not based on an outcome but on a benchmarking exercise relying on observable features, they provide suggestive evidence of racial bias, this time on the extensive margin, against Black victims. Importantly, these results also give credibility to the model and are consistent with the results from the marginal outcome test.

6 Mechanisms

In this section, I explore the mechanisms behind the observed racial bias, estimated using my marginal outcome test, in greater detail. I first leverage the characteristics of the detective who closes the case and then investigate an external form of accountability that might contribute to the main results: the media.

6.1 Sources of Racial Bias: Leveraging Detective Characteristics

The literature on discrimination has pointed out that what models of discrimination generally attribute to biased preferences against minority individuals (racial animus) (Becker, 1957) could instead originate from biased beliefs (inaccurate statistical discrimination). Here, these would be biased beliefs held by the detectives about what makes an investigation successful upon completion (Bohren et al., 2023). It is in fact difficult to distinguish between the two, and both correspond to forms of bias (Arnold et al., 2018; Arnold et al., 2022). For policy reasons, however, it is important to understand whether we should intervene on beliefs and information to correct racial inequities or if some other levers have to be pulled, such as de-biasing training. I attempt to distinguish between these two forms of bias by leveraging the characteristics of the detectives who clear the case similarly to what Arnold et al. (2018)

do with judges.

If inaccurate statistical discrimination explains the main results, cases of Black victims would be disproportionately more likely to be rejected by the DA because detectives hold inaccurate beliefs regarding evidentiary quality and/or standards rather than biased preferences. If this is the case, the more experienced the detective is, the smaller the gap in success rates due to correction to her beliefs. If we do not find any significant interaction between experience of the detective and the race of the victim, racial animus is a more likely explanation for the observed bias. Specifically, to test the role of – potentially inaccurate – beliefs, I estimate the following model:

$$\begin{aligned} Y_{ijay} = &\alpha + \beta^B BlackVictim_i + \beta^H HispanicVictim_i + \theta Experience_{jy} + \\ &+ \theta^B BlackVictim_i \times Experience_{jy} + \theta^H HispanicVictim_i \times Experience_{jy} \\ &+ f(T_i) + \gamma' X_{iy} + \delta_j + \delta_{ay} + \varepsilon_{ijay} \end{aligned} \tag{6}$$

We can corroborate this by also testing for concordance between race of the victim and the race of the detective. Previous work on discrimination by law enforcement agents has tested for biased preferences by studying whether the rankings of the outcome, by race of civilian, are a function of the race of the decision-maker (Anwar and Fang, 2006, Antonovics and Knight, 2009, West, 2018). I do so by estimating the following model:

$$\begin{aligned} Y_{ijay} = &\alpha + \beta^B BlackVictim_i + \beta^H HispanicVictim_i + \theta Experience_{jy} + \\ &+ \rho^B BlackVictim_i \times BlackDetective_j + \rho^H HispanicVictim_i \times HispanicDetective_j + \\ &+ f(T_i) + \gamma' X_{iy} + \delta_j + \delta_{ay} + \varepsilon_{ijay} \end{aligned} \tag{7}$$

Table 7 shows the results of these exercises for both homicides and non-fatal violent crime. Experience is calculated as the number of years between the clearance of a specific case and the year of first appointment as a police officer for the respective detective.[34] It is

[34]The year of first appointment as a detective is not available. Officers are promoted to the rank of detective years after their first appointment as patrol officers.

further de-meaned so that the baseline coefficient for Black and Hispanic victims represents the gap in success rates for the detective with average experience. We see that experience does not seem to be a relevant factor in the detectives' submission decisions. Both the interactions between Black and Hispanic victims and experience of the detective are small and not significant, meaning that as detectives gain experience, the gap in success rates does not significantly decrease. Moreover, the baseline coefficient on experience of the detective is not significant either. This further confirms that outcomes at closure are indeed driven by preferences and not ability. If the latter were the originating factor of the gaps in success rates, we might expect a significant positive relationship between success and experience, as ability should positively correlate with experience. Overall, inaccurate beliefs on what is expected by the CCSAO to achieve equal success rates, and how this might differ by race, is an unlikely explanation for the main results.

When testing for race concordance (Table 7), on the other hand, we see that Black and Hispanic detectives display significantly smaller success gaps for homicides of same-race victims (Column 1). While the coefficients on these interactions are not significant, they are positive, large in magnitude and make the overall gaps no longer significant, despite still being negative. For non-fatal violent crimes (Column 2), where the estimates are more precise due a larger sample size, I observe statistically significant evidence of race concordance between Black victims and detectives in such a way that the success gap among Black detectives between Black and non-Black victims is essentially null. Hispanic detectives seem to treat Hispanic victims even more favorably than do different-race detectives, although the point estimate is not significant and relatively small when compared with the baseline estimate for Hispanic victims of nonfatal violent crime. Ultimately, these estimates collectively suggest that racial bias in this setting more likely originates from biased preferences than from biased beliefs on evidentiary standards (Arnold et al., 2018; Bohren et al., 2022).

Importantly, the fact that the gaps in success rates do not vary with experience but do vary with the race of the detective also indicates that bias as measured here indeed originates, at least in part, from the decisions of the police investigators. If the gaps in success rates were solely due to the CCSAO's biased decisions, the FRU would have to be adopting practices that are tailored to both the race of the victim *and* the race of the detective, which seems unlikely. Note that part of the observed disparities might still originate from the CCSAO's propensities: it is possible that the police submit the same evidence for every case after the same number of days of investigation but the FRU systematically requires disproportionately more evidence for cases of Black victims. Detectives, however, do not seem to adjust investigation practices to close the gaps in success rates and still accept that cases of Black victims have a higher probability of not entering the court process, which is precisely the definition of bias adopted here.

6.2 Related Bias from Non-Police Agents: Local Newspapers

Detectives might not be the only agents displaying bias against Black and Hispanic victims of homicide. Their actions might in fact be reflecting the views of the public and/or the amount of external scrutiny they face. Lower coverage of minority homicides decreases the pressure on detectives to deliver successful outcomes, which in terms of my model would translate into a lower desired evidentiary standards for these victims, $c(m, t)$. I test this claim by collecting all the mentions of each victim of homicide in Chicago from 1/1/2000 to 12/31/2023 that appeared in the print version of the Chicago Tribune or Chicago Sun Times, the main local newspapers in Chicago, within $k \in [1, 7]$ days of the homicide.[35] I can then compute whether a victim is mentioned and how many articles are published. Figure 6 plots the cumulative probability of mention by either of the two newspapers in Chicago within the first 7 days after the death of the victim. We observe that if a victim is not mentioned by day 3, they are rarely mentioned thereafter. A wedge between White and Black victims is visible from the very first days. Hispanic victims are less likely to be mentioned than White victims but more likely to be mentioned than Black victims.[36]

Given that coverage plateaus after the third day and that the more time passes, the more coverage is itself influenced by policing activities, I focus on cumulative coverage by the third

[35] I only use homicides because for nonfatal crimes, the names of the victims are not disclosed by the police or the newspaper. Moreover, to be precise, I use the day of death rather than the day of the offense, again because names are rarely disclosed before the victim is deceased.

[36] Figure A.12 shows the results separately for Chicago Tribune and Chicago Sun Times.

day – third day included. I test whether coverage differs by race of victims in the first days after they die, controlling for their other demographics (age, gender), time variables that affect whether the news can appear in the printed paper and media-related time trends (day of the week, hour of day, month, year), or the newsworthiness of the homicide (weapon, whether it is gang related, whether is is domestic violence related, ZIP code). Specifically, I estimate the following model:

$$Y_{iy} = \alpha + \beta^B BlackVictim_i + \beta^H HispanicVictim_i + \gamma' X_{iy} + \varepsilon_{iy} \tag{8}$$

where Y_{iy} is either a dummy for whether the victim i, who died at time y has been mentioned by local newspapers by the third day after the event or the the total number of mentions by the third day. Given the skew in the distribution of total mentions, a Poisson model is used for this second dependent variable rather than OLS.

I document two main facts (Table 8): *i)* Black victims, and to a lesser extent Hispanic victims, are less likely than White victims to be mentioned in the paper at all, and ii) fewer articles are written about their death. Note that White–Black disparities persist even within neighborhoods, although they are smaller and less precisely estimated.[37] Although estimating the causal effect of this gap in coverage on the clearance and success gaps is beyond the scope of this paper, this set of results provides suggestive evidence that the equilibrium in the media market is one of lesser interest in non-White victims. Detectives might therefore best-responding to the amount of scrutiny they face from the media and the public. Nevertheless, they display bias against non-White victims.

7 Policy Implications and Conclusion

This paper provides the first evidence that the police discriminate by race when interacting with victims of crime. I do so by focusing on police investigations of violent crime. I develop

[37] Tables A.5 and A.6 show the results separately for the Chicago Tribune and Chicago Sun Times, respectively.

a novel marginal outcome test for racial bias that does not require random assignment of cases to decision-makers and exploits the dynamic nature of the treatment. By leveraging the prosecution's decision to accept or reject a case based on the evidence presented as the outcome of interest, I show that the Chicago Police Department chooses to close, in the same amount of time, systematically lower-quality investigations if the victim is Black relative to when the victim is White. For both fatal and non-fatal violent crime, Black victims are in fact less likely to ever see their assailant go to court. Instead, I observe that Hispanic victims are discriminated against when they are victims of homicide but receive preferential treatment when victims of non-fatal violent crime. As detectives' experience does not seem to reduce these gaps, while the race of the investigator appears to be a more important determinant of the estimates, bias in this setting is likely driven by racial animus.

My results highlight several policy implications. First, calls for oversight and transparency in policing, which have been increasing in recent years, should also consider investigations, not only activities such as traffic stops and use of force, which have come under major scrutiny. While less salient in the public's mind than other policing activities when discussing policing reforms, the decisions of police investigators can also be biased, and they should be the object of external monitoring. Moreover, this paper documents that only a share of all crimes that are considered solved by the police actually end up entering the court process, due to the prosecution deeming the evidence presented by the police to be insufficient. The issue becomes even more sizable if we consider non-fatal violent crime and the remarkable share of clearances achieved due to the victim's refusal to cooperate. For these reasons, the overall clearance rate seems an inadequate metric to measure the performance of a police department, a concern echoed by Cook and Mancik (2024) and Baughman (2020). Last, I also provide suggestive evidence that increasing racial diversity among investigators could mitigate these inequities.

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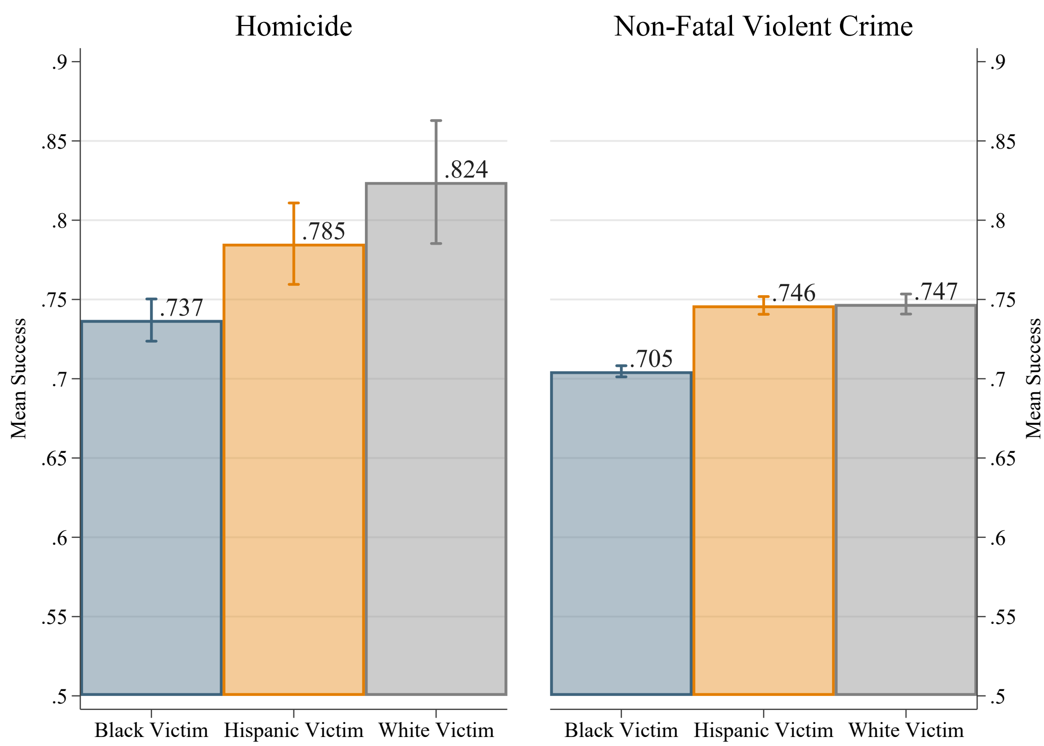
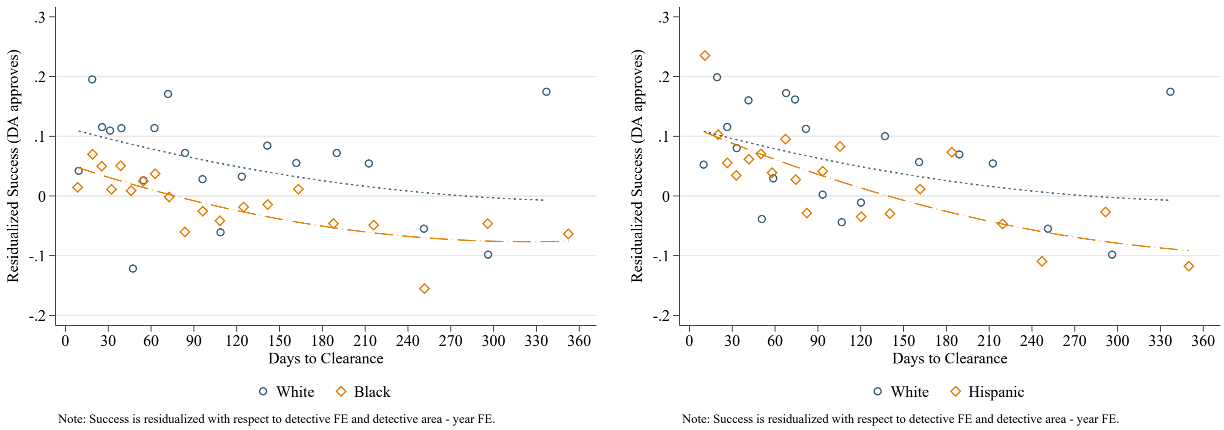
Figures and Tables

Figure 1: Probability of Clearance Being Achieved via Arrest and Prosecution, by Race of the Victim



Notes: This figure plots the probability of clearance being achieved via a successful arrest and prosecution in the sample used for the marginal outcome test. This is shown separately by race of the victim and for homicide and non-fatal violent crime; 95% confidence intervals are also reported.

Figure 2: Relationship between Success and Days to Clearance, by Race of the Victim – Homicides

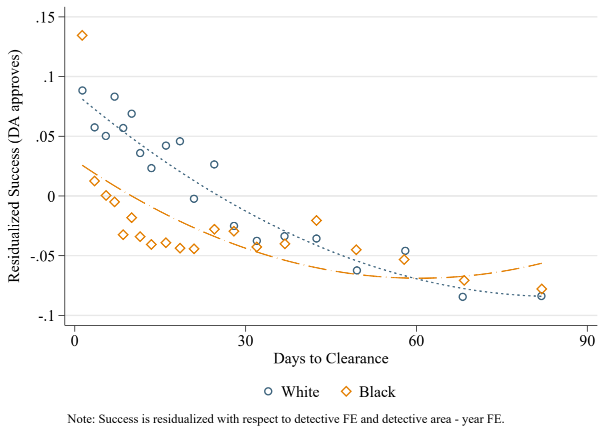


(a) White Victim vs. Black Victim

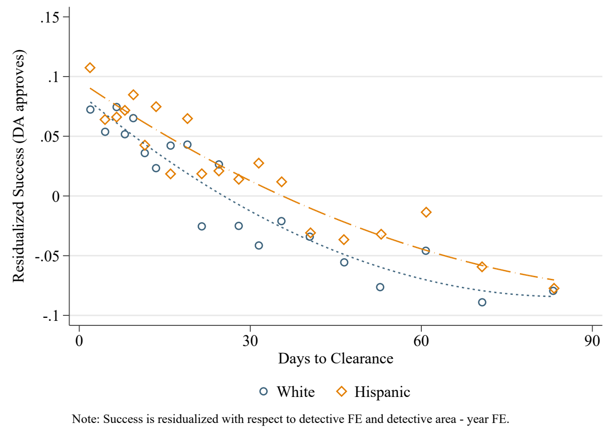
(b) White Victim vs. Hispanic Victim

Notes: This figure shows a quadratic fit of the relationship between the probability of success of a homicide investigation and the days between offense and clearance, by race of the victim. Success is first residualized with respect to detective areas and the primary detective at the time of clearance. The range of time to clearance is truncated at 1 year to limit the sample to a range where a reasonable number of cases are cleared. Given the low number of homicides of White victims solved around day 365, cases solved between 1 year and 1 year and 3 months after the offense are kept as well to increase precision at the boundary. This is done for all racial groups.

Figure 3: Relationship between Success and Days to Clearance, by Race of the Victim – Non-fatal Violent Crime



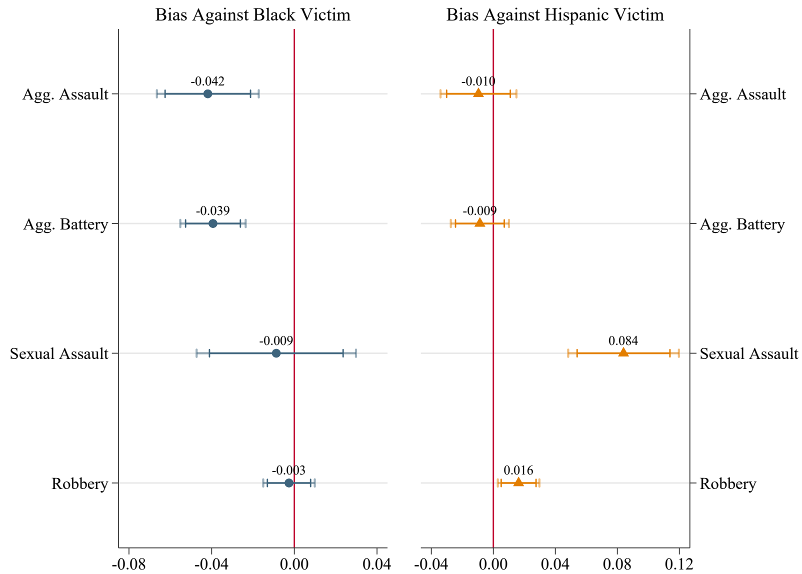
(a) White Victim vs. Black Victim



(b) White Victim vs. Hispanic Victim

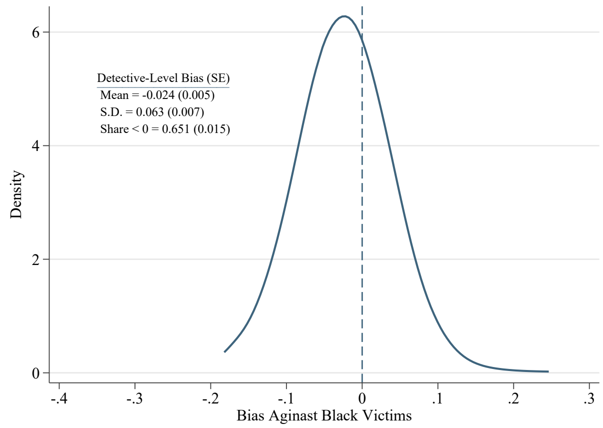
Notes: This figure shows a quadratic fit of the relationship between the probability of success of an investigation of a nonfatal violent crime and the days between assignment and clearance, by race. Success is first residualized with respect to detective areas and the primary detective at the time of clearance, both interacted with fixed effects for the type of non-fatal violent crime. The range of time to clearance is truncated at 3 months to limit the sample to a range where a reasonable number of cases are cleared.

Figure 4: Heterogeneity in Racial Bias by Type of Nonfatal Violent Crime

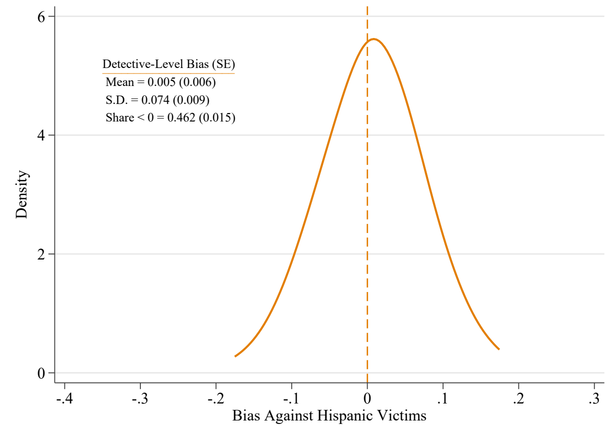


Notes: This figure plots the coefficient from a heterogeneous version of the model used in Column 3 of 4 by type of nonfatal violent crime. Race dummies for Black and Hispanic victims are interacted with fixed effects for the type of nonfatal violent crime. All controls are further interacted with fixed effects for the type of nonfatal violent crime.

Figure 5: Detective-level Estimates of Bias



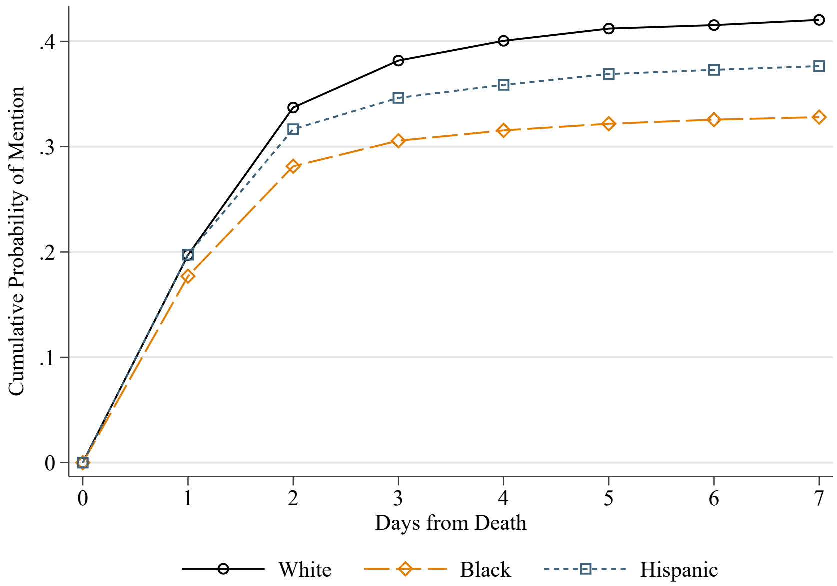
(a) White Victim vs. Black Victim



(b) White Victim vs. Hispanic Victim

Notes: This figure plots the posterior distribution of detective-level bias. Detective-level estimates of bias are obtained from Model 4, specifically as the interaction between dummies for the race of the victim with detective fixed effects. The distribution of detective-level bias and fractions of discriminators are computed from these estimates as posterior average effects following Arnold et al. (2022), who build from Bonhomme and Weidner (2022). Standard errors, reported in parentheses, are obtained by bootstrapping posterior estimates of detective-level bias obtained using Morris (1983)'s Empirical Bayes approach.

Figure 6: Cumulative Probability of Mention of Homicide Victims in Chicago by Race of the Victim



Notes: This figure plots the cumulative probability that a victim is mentioned in the print version of either the Chicago Tribune or the Chicago Sun Times in the first 7 days after the death of the victim. The statistics are shown separately for White, Black and Hispanic victims.

Table 1: Characteristics of Victims by Race in Chicago

	White Victims	***Black Victims***	***Hispanic Victims***
	Homicide		
Cleared	0.67	0.46	0.47
Cleared by Arrest and Prosecution	0.50	0.31	0.34
Female	0.24	0.11	0.11
Age	38.94	29.42	27.08
Number of Victims	651	10,281	2354
	Other Violent		
Cleared	0.28	0.26	0.26
Cleared by Arrest and Prosecution	0.17	0.12	0.15
Cleared by Victim's Refusal	0.06	0.10	0.06
Female	0.36	0.40	0.30
Age	34.96	31.23	29.76
Aggravated Assault	0.11	0.17	0.16
Aggravated Battery	0.18	0.36	0.27
Sexual Assault	0.07	0.06	0.06
Robbery	0.64	0.41	0.50
Number of Victims	97,800	451,104	142,021

Notes: This table shows the characteristics of the victims of violent crime, and related incidents, in the sample used in Sections 4 and 5, separately for White, Black and Hispanic victims and for homicides and nonfatal violent crime. Only White, Black and Hispanic victims are kept in the sample.

Table 2: Gap in Success Rate by Race of the Victim – Other Violent Crime

	Homicides		Non-Fatal Violent Crime	
	(1)	(2)	(3)	(4)
	Success	Success	Success	Success
Black Victim	-0.082***	-0.078***	-0.019***	-0.022***
	(0.023)	(0.023)	(0.005)	(0.005)
Hispanic Victim	-0.046**	-0.039*	0.021***	0.020***
	(0.023)	(0.023)	(0.005)	(0.005)
Quadratic in Days to Clearance	✓		✓	
Days (Week Bins) × Type FE		✓		✓
Detective × Type FE	✓	✓	✓	✓
Detective Area × Year × Type FE	✓	✓	✓	✓
White Victim Mean	0.848	0.848	0.757	0.757
Observations	5,156	5,156	108,288	108,288
R^2	0.293	0.362	0.341	0.363

Notes: This table shows the results from the estimation of Equation 3. In Columns 1 and 2, the sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. In Columns 3 and 4, the sample is restricted to non-fatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. The main regressors of interest are dummies that take value 1 if the victim is Black or Hispanic. Columns 1 and 3 control for time to clearance using a quadratic polynomial, estimated separately for each type of nonfatal violent crime in Column 3. Every model includes detective fixed effects and detective-area-year-of-offense fixed effects, which are further interacted with type-of-crime fixed effects in Columns 3 and 4. Columns 2 and 4 replace the quadratic polynomials with a set of fixed effects that bin time to clearance in weeks to clearance, separately for each type of nonfatal violent crime in Column 4. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Adding Non-Race Characteristics of the Victim and the Incident – Homicides

	(1) Success	(2) Success	(3) Success
Black Victim	-0.087***	-0.083***	-0.078***
	(0.025)	(0.025)	(0.027)
Hispanic Victim	-0.046**	-0.046*	-0.062**
	(0.023)	(0.024)	(0.027)
Days (Week Bins) FE	✓	✓	✓
Detective Area-Year FE	✓	✓	✓
Detective FE	✓	✓	✓
Age, Age^2, Gender, ZIP FE	✓	✓	✓
Gang, DV FE		✓	✓
Weapon, Premises, Hour-Month FE			✓
White Victim Mean	0.848	0.848	0.848
Observations	5,156	5,156	5,156
R^2	0.379	0.385	0.451

Notes: This table shows the results from the estimation of Equation 3 with additional controls. The sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. The main regressors of interest are dummies that take value 1 if the victim is Black or Hispanic. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects. Column 1 controls for gender and a quadratic in age of the victim and includes fixed effects for the ZIP code where the incident occurred. Column 2 further controls for whether the incident was gang or domestic violence related. Column 3 adds fixed effects for the weapon used against the victim, premises of the incident and hour-month of offense. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Adding Non-Race Characteristics of the Victim and the Incident – Other Violent Crime

	(1) Success	(2) Success	(3) Success
Black Victim	-0.021***	-0.020***	-0.019***
	(0.005)	(0.005)	(0.005)
Hispanic Victim	0.016***	0.016***	0.016***
	(0.005)	(0.005)	(0.005)
Days (Week Bins)-Type FE	✓	✓	✓
Detective Area-Year-Type FE	✓	✓	✓
Detective-Type FE	✓	✓	✓
Age, Age^2, Gender, ZIP FE	✓	✓	✓
Gang, DV FE		✓	✓
Weapon, Premises, Hour-Month FE			✓
White Victim Mean	0.757	0.757	0.757
Observations	108,288	108,288	108,288
R^2	0.364	0.365	0.373

Notes: This table shows the results from the estimation of Equation 3 with additional controls. The sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. The main regressors of interest are dummies that take value 1 if the victim is Black or Hispanic. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects. Column 1 controls for gender and a quadratic in age of the victim and includes fixed effects for the ZIP code where the incident occurred. Column 2 further controls for whether the incident was gang or domestic violence related. Column 3 adds fixed effects for the weapon used against the victim, premises of the incident and hour-month of offense. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Differential Suspensions of Investigations by Race of the Victim

	(1) Days to Suspension	(2) Days to Suspension
Black Victim	-1.221***	-1.165***
	(0.196)	(0.195)
Hispanic Victim	0.156	0.062
	(0.213)	(0.211)
Detective FE	✓	✓
Area-Year-Type FE	✓	✓
Age, Age^2, Gender	✓	✓
ZIP FE	✓	✓
Weapon, Premises, Hour-Month FE	✓	✓
Gang, DV FE		✓
White Victim Mean	29.525	29.525
Observations	497907	497903
R^2	0.296	0.296

Notes: This table shows the results from the estimation of Equation 5 with additional controls. The sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that have been investigated by the Chicago Police Department between 2001 and 2023 and officially suspended at some point. The dependent variable is the number of days elapsed from the offense to the day of first suspension. The main regressors of interest are dummies that take value 1 if the victim is Black or Hispanic. All regressions include detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects. Column 1 controls for gender and a quadratic in age of the victim and includes fixed effects for the ZIP code where the incident occurred, fixed effects for the weapon used against the victim, premises of the incident and hour-month of offense. Column 2 adds fixed effects for whether the incident was gang or domestic violence related. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneity by Detective's Experience at Clearance

	Homicides	Other Violent Crime
	(1)	(2)
	Success	Success
Black Victim	-0.093***	-0.020***
	(0.027)	(0.005)
Hispanic Victim	-0.057**	0.016***
	(0.026)	(0.005)
Experience	-0.002	0.003
	(0.017)	(0.005)
Black Victim × Experience	-0.002	0.001
	(0.004)	(0.001)
Hispanic Victim × Experience	0.001	0.001
	(0.004)	(0.001)
Detective × Type FE	✓	✓
Detective Area × Year × Type FE	✓	✓
Days (Week Bins) × Type FE	✓	✓
All Controls	✓	✓
White Victim Mean	0.849	0.757
Observations	5,041	107,680
R^2	0.388	0.366

Notes: This table shows the results from the estimation of Equation 6. In Column 1, the sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. In Column 2, the sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects in Column 2 and all the non-race controls included in Column 3 of Tables 3 and Table 4. Experience of the detective is calculated as the difference between the year of clearance of the case and the year of hiring as police officer and is further demeaned. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heterogeneity by Detective's Race

	Homicides	Other Violent Crime
	(1)	(2)
	Success	Success
Black Victim (β^B)	-0.097***	-0.022***
	(0.027)	(0.005)
Hispanic Victim (β^H)	-0.065**	0.016***
	(0.026)	(0.005)
Black Victim × Black Detective (ρ^B)	0.087	0.026**
	(0.075)	(0.011)
Hispanic Victim × Hispanic Detective (ρ^H)	0.045	-0.001
	(0.043)	(0.010)
Detective × Type FE	✓	✓
Detective Area × Year × Type FE	✓	✓
Days (Week Bins) × Type FE	✓	✓
All Controls	✓	✓
$\beta^B + \rho^B$	-0.010	0.004
	(.07)	(.01)
$\beta^H + \rho^H$	-0.020	0.015
	(.048)	(.01)
White Victim Mean	0.849	0.757
Observations	5,041	107,680
R^2	0.388	0.366

Notes: This table shows the results from the estimation of Equation 7. In Column 1, the sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. In Column 2, the sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects in Column 2 and all the non-race controls included in Column 3 of Tables 3 and Table 4. All regressions further control for the experience of the detective at time of closure of the case. $\beta^B + \rho^B$ reports the same for the coefficient for Black victims alone (i.e., when the detective is non-Black) and the coefficient for the interaction between the dummy for a Black victim and the dummy for a Black detective, thereby representing the racial bias against Black victims among Black detectives. $\beta^H + \rho^H$ reports the same for the coefficient for Hispanic victims alone (i.e., when the detective is non-Hispanic) and the coefficient for the interaction between the dummy for a Hispanic victim and the dummy for a Hispanic detective, thereby representing the racial bias against Hispanic victims among Hispanic detectives. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

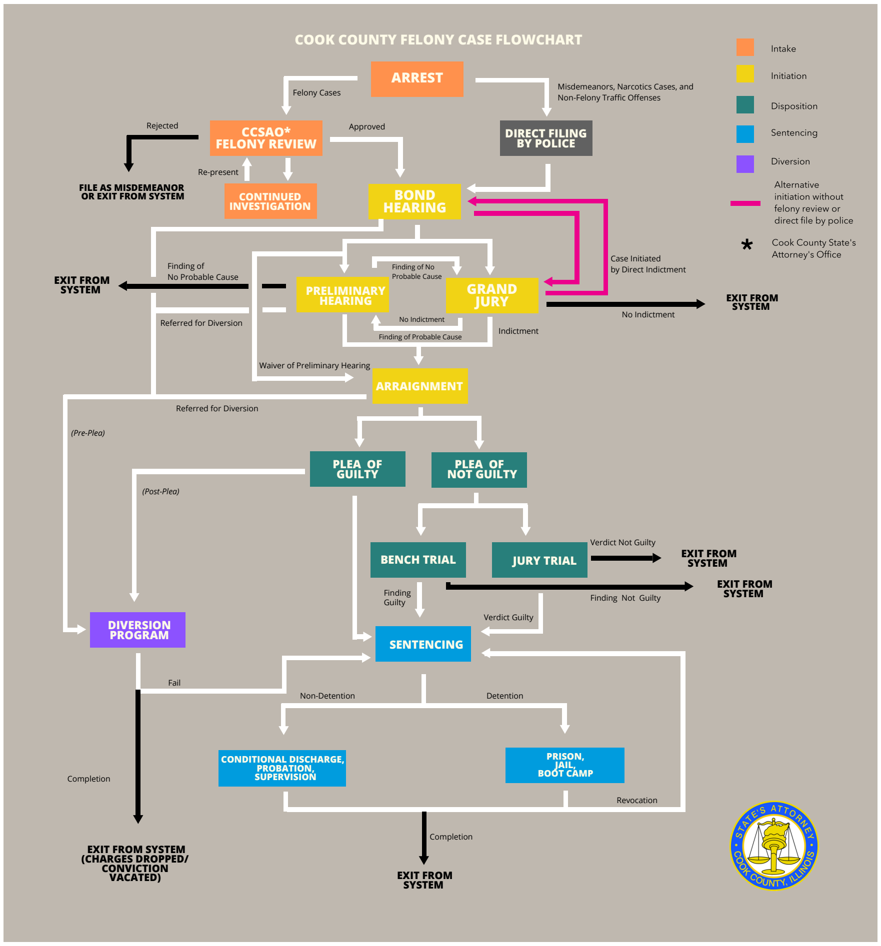
Table 8: Differential Media Coverage by Race of the Victim

	(1) OLS	(2) OLS	(3) OLS	(4) Poisson	(5) Poisson	(6) Poisson
	Any Mention by Day 3	Any Mention by Day 3	Any Mention by Day 3	Mentions by Day 3	Mentions by Day 3	Mentions by Day 3
Black Victim	-0.076***	-0.066***	-0.033*	-0.494***	-0.406***	-0.234***
	(0.018)	(0.018)	(0.019)	(0.093)	(0.081)	(0.078)
Hispanic Victim	-0.035*	-0.040*	-0.017	-0.337***	-0.296***	-0.155**
	(0.020)	(0.022)	(0.022)	(0.091)	(0.083)	(0.067)
Age, Age^2, Gender		✓	✓		✓	✓
Weapon, Gang, DV FE		✓	✓		✓	✓
Offense Hour, DOW FE		✓	✓		✓	✓
Offense Month, Year FE		✓	✓		✓	✓
ZIP FE			✓			✓
% β^B				38.996***	33.351***	20.864***
				(5.662)	(5.420)	(6.135)
% β^H				28.577***	25.603***	14.364**
				(6.496)	(6.175)	(5.766)
White Outcome Mean	0.395	0.395	0.395	0.978	0.944	0.945
Observations	12778	12708	12707	12778	12708	12707

Notes: This table shows the results from the estimation of Equation 8, where the sample is restricted to homicides committed against White, Black or Hispanic victims that are committed in Chicago between 2000 and 2023. The dependent variable is either a dummy for whether the victim i, who died at time y has been mentioned by local newspapers by the third day after the event (Columns 1 through 3) or the the total number of mentions by the third day (Columns 4 through 6). Columns 2 and 4 control for other demographics of the victim (age, gender), time variables that affect whether the news can appear in the printed paper and media-related time trends (day of the week, hour of day, month, year), or the newsworthiness of the homicide (weapon, whether it is gang related, whether is is domestic violence related). Columns 3 and 6 further add fixed effects for the ZIP code where the incident occurred. Given the skew in the distribution of total mentions, a Poisson model is used for this second dependent variable rather than OLS. Effects in percentage terms with related standard errors are also reported for Models 4 through 6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

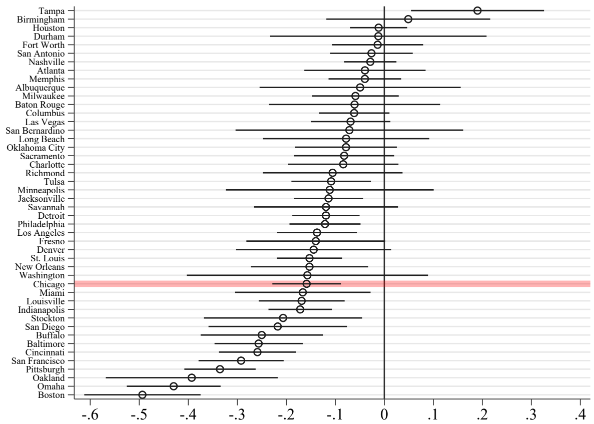
Appendix A: Supplemental Figures and Tables

Figure A.1: The Arrest-to-Court Pipeline in Cook County, IL

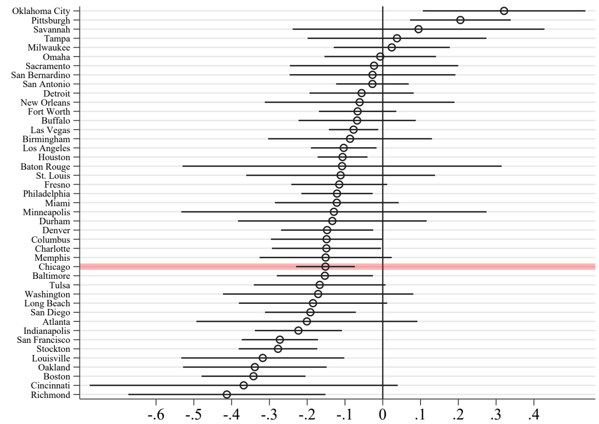


Notes: This figure shows the process that goes from entry to exit in the criminal justice system in Cook County, IL. Source: Cook County State Attorney's Office.

Figure A.2: City-level Estimates of the Gap in Clearance Rates



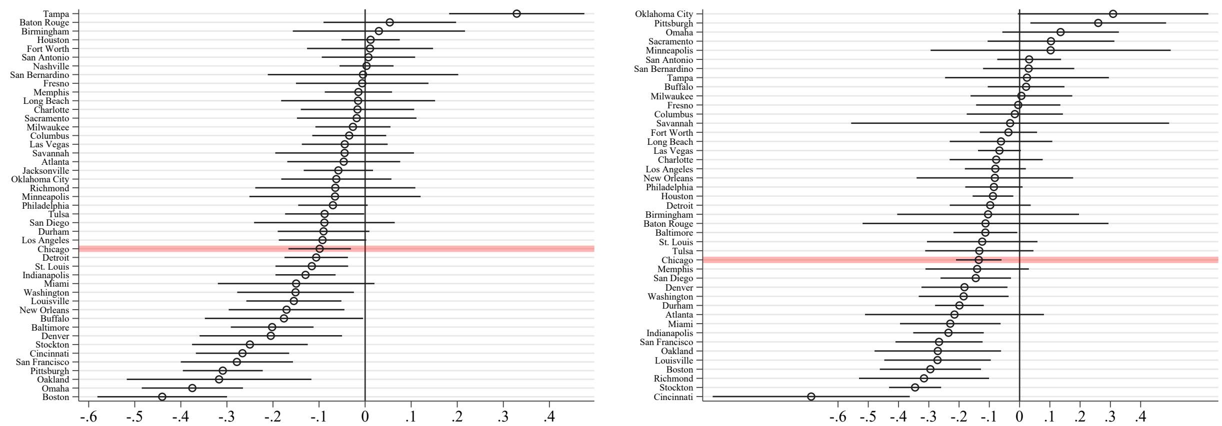
(a) White Victim vs. Black Victim



(b) White Victim vs Hispanic Victim

Notes: This figure plots $beta_c^B$ and β_c^H estimates from $Y_{icy} = \alpha + \beta_c^B BlackVictim_i + \beta_c^H HispanicVictim_i + \delta_{cy} + \varepsilon_{icy}$. The coefficients are city-specific estimates of the gap in clearance rates between cases of victims of different races. The outcome variable is a dummy that takes value 1 if the homicide is solved. Dummies for whether the victim is Black or Hispanic are interacted with city fixed effects. The model includes city-year fixed effects, δ_{cy}. Standard errors are clustered at the ZIP code level.

Figure A.3: City-level Estimates of the Gap in Clearance Rates, Adding Controls

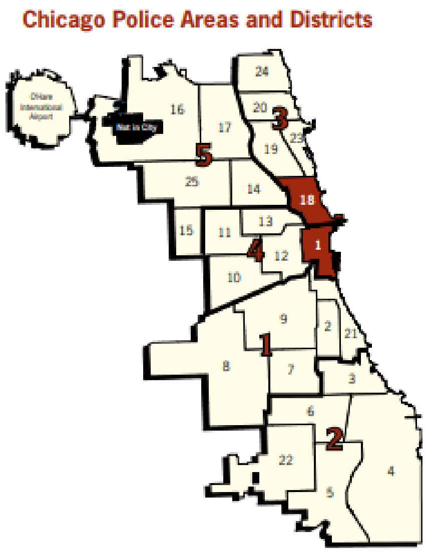


(a) White Victim vs. Black Victim

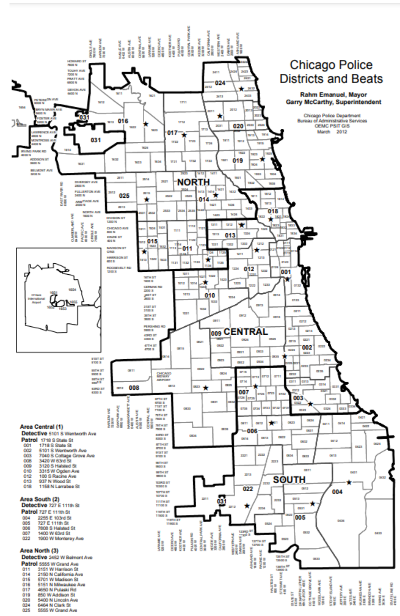
(b) White Victim vs. Hispanic Victim

Notes: This figure plots $beta_c^B$ and β_c^H estimates from $Y_{icy} = \alpha + \beta_c^B BlackVictim_i + \beta_c^H HispanicVictim_i + \gamma' X_i + \delta_{cy} + \varepsilon_{icy}$. The coefficients are city-specific estimates of the gap in clearance rates between cases of victims of different races. The outcome variable is a dummy that takes value 1 if the homicide is solved. Dummies for whether the victim is Black or Hispanic are interacted with city fixed effects. The vector X_i includes a quadratic in age of the victim, the gender of the victim, and the share of Black and Hispanic residents of the neighborhood, obtained from the 2010 Census. The model includes city-year fixed effects, δ_{cy}. Standard errors are clustered at the ZIP code level.

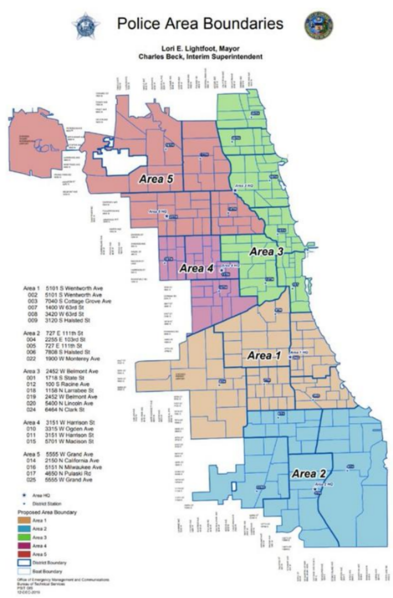
Figure A.4: Map of the City of Chicago with Detective Areas and Districts Labeled



(a) Before Closures in 3/2012



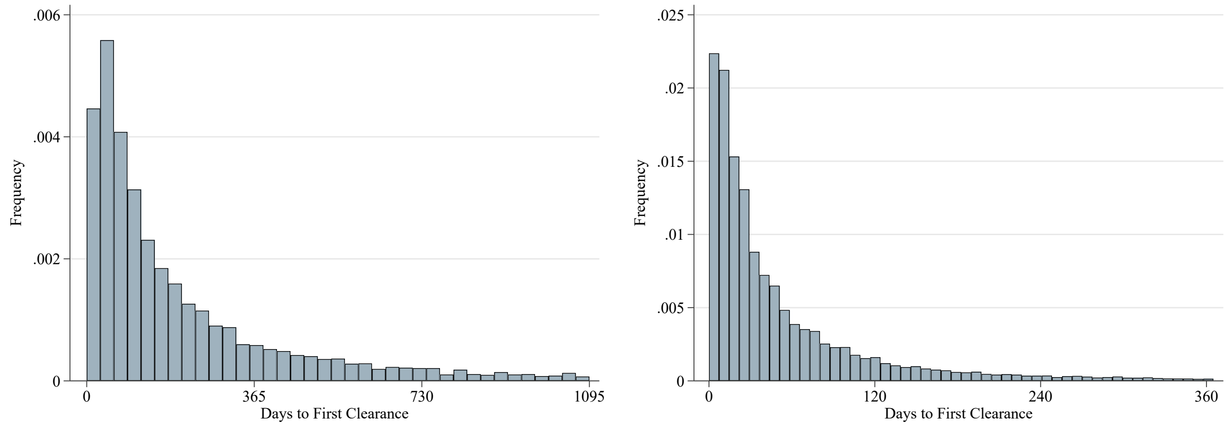
(b) After Closures in 3/2012 and Before Reopenings in 4/2020



(c) After Reopenings in 4/2020

Notes: This figure shows the evolution of the detective areas' boundaries over time in Chicago, before closures in 3/2012 (Panel a), after closures in 3/2012 and before reopenings in 4/2020, and after reopenings in 2/2020

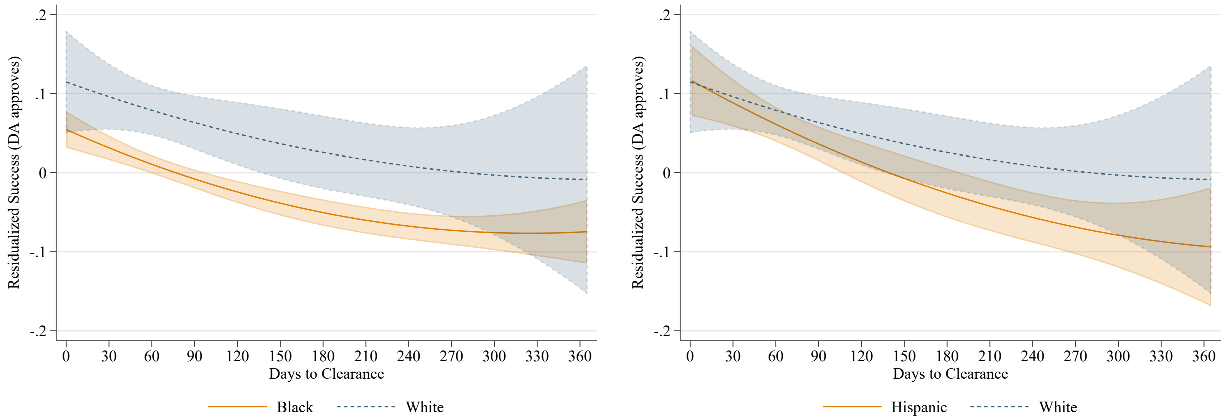
Figure A.5: Distribution of Days Elapsed from Offense to Clearance, by Race



(a) Homicide (b) Nonfatal Violent Crime

Notes: This figure plots the kernel distributions of the number of days elapsed from the date of the incident to the first time the case is considered cleared, only for cases that are ever cleared. Exceptional clearances due to death of the offender or victim's refusal to cooperate are dropped whenever possible. The distributions are shown separately for homicides and nonfatal violent and crime, and each of these is also broken down by race of the victim. For visualization reasons, the distributions are truncated at two years and one year, for homicides and nonfatal crime, respectively.

Figure A.6: Relationship between Success and Days to Clearance, by Race – Homicides

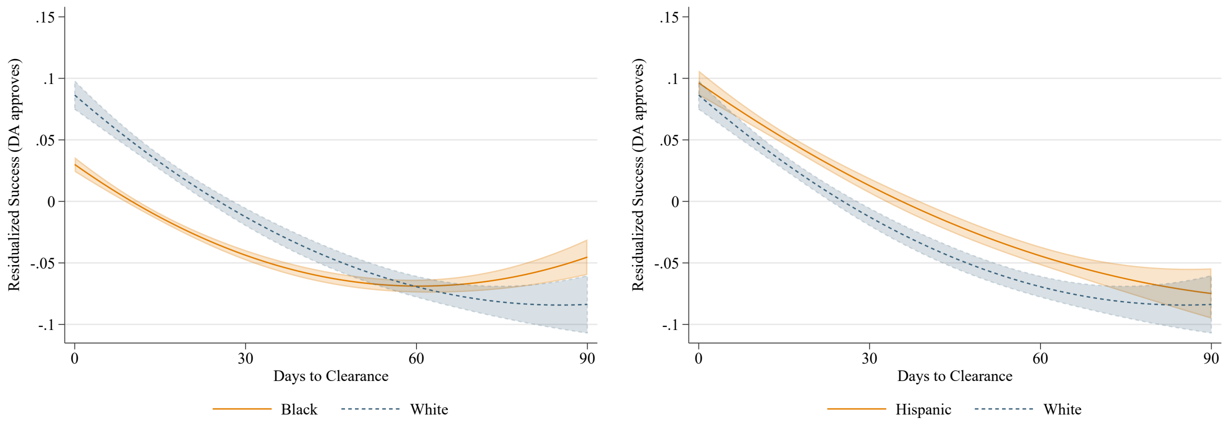


(a) White Victim vs. Black Victim

(b) White Victim vs. Hispanic Victim

Notes: This figure shows a quadratic fit of the relationship between the probability of success of a homicide investigation and the days between offense and clearance, by race of the victim, with 90% confidence intervals. Success is first residualized with respect to detective areas and the primary detective at the time of clearance. The range of time to clearance is truncated at 1 year to limit the sample to a range where a reasonable number of cases are cleared. Given the low number of homicides of White victims solved around day 365, cases solved between 1 year and 1 year and 3 months after the offense are also retained to increase precision at the boundary. This is done for all racial groups.

Figure A.7: Relationship between Success and Days to Clearance, by Race – Nonfatal Violent Crime

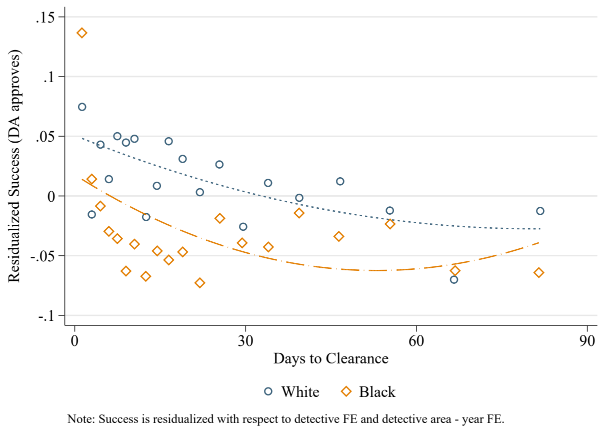


(a) White Victim vs. Black Victim

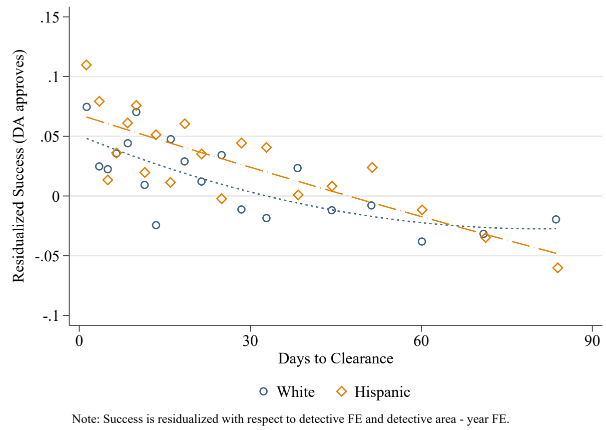
(b) White Victim vs. Hispanic Victim

Notes: This figure shows a quadratic fit of the relationship between the probability of success of an investigation of a nonfatal violent crime and the days between assignment and clearance, by race of the victim, with 90% confidence intervals. Success is first residualized with respect to detective areas and the primary detective at the time of clearance, both interacted with fixed effects for the type of nonfatal violent crime. The range of time to clearance is truncated at 3 months to limit the sample to a range where a reasonable number of cases are cleared.

Figure A.8: Relationship between Success and Days to Clearance, by Race – Nonfatal Violent Crime, Excluding Robberies



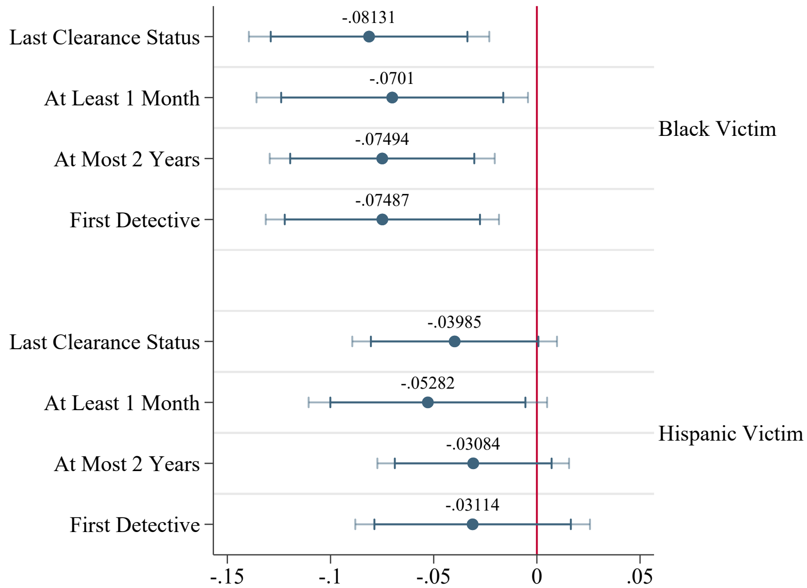
(a) White Victim vs. Black Victim



(b) White Victim vs. Hispanic Victim

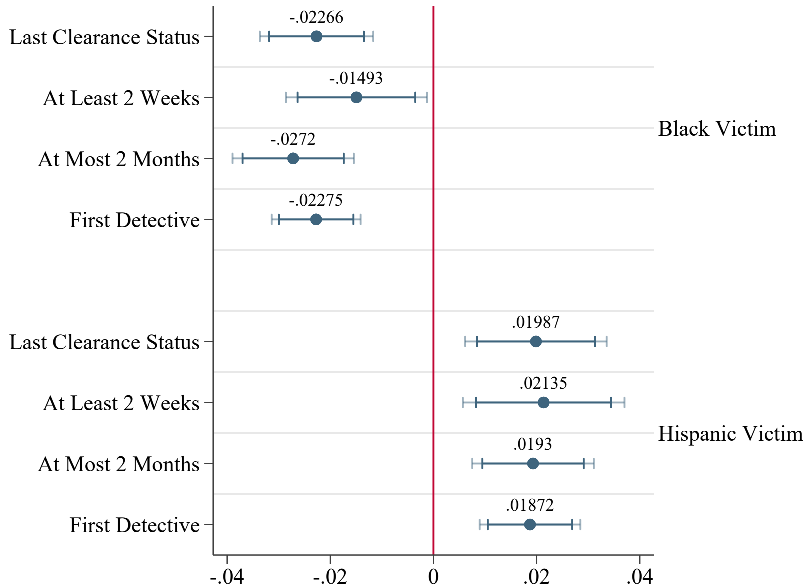
Notes: This figure shows a quadratic fit of the relationship between the probability of success of an investigation of a nonfatal violent crime, excluding robberies, and the days between assignment and clearance, by race of the victim. Success is first residualized with respect to detective areas and the primary detective at the time of clearance, both interacted with fixed effects for the type of nonfatal violent crime. The range of time to clearance is truncated at 3 months to limit the sample to a range where a reasonable number of cases are cleared.

Figure A.9: Robustness Checks – Homicides



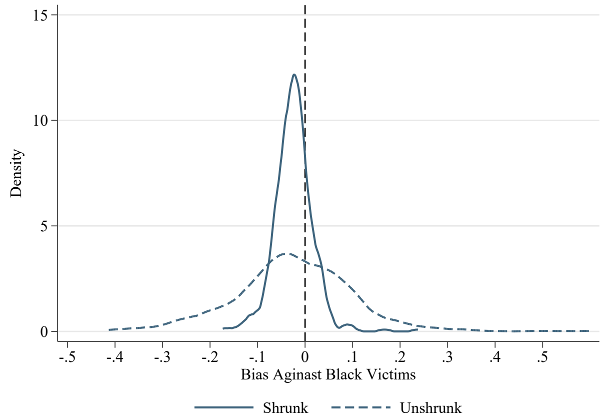
Notes: This figure plots the coefficients from a series of robustness checks for the main results for the sample of homicides, obtained by estimating variations of the main model in Equation 3. While coefficients for Black and Hispanic victims are shown separately, they are estimated from the same model. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects. I first use the last status update rather than the first to define the success outcome, with the time to clearance adjusted accordingly as the time elapsed from the offense to the last observed clearance update. I then drop cases solved in less than 1 month from the full sample. I next drop cases solved in more than 2 years from the full sample. Last, I use the identity of the first primary detective assigned to the case rather than the detective who is on the case at the time of clearance.

Figure A.10: Robustness Checks – Nonfatal Violent Crime

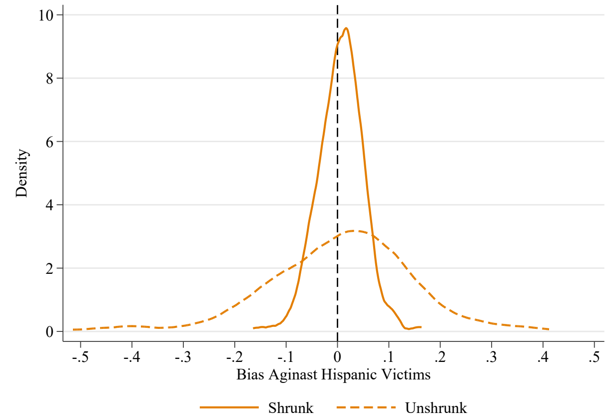


Notes: This figure plots the coefficients from a series of robustness checks for the main results for the sample of nonfatal violent crimes, obtained by estimating variations of the main model in Equation 3. While coefficients for Black and Hispanic victims are shown separately, they are estimated from the same model. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects. I first use the last status update rather than the first to define the success outcome, with the time to clearance adjusted accordingly as the time elapsed from the offense to the last observed clearance update. I then drop cases solved in less than 2 weeks from the full sample. I next drop cases solved in more than 2 months from the full sample. Last, I use the identity of the first primary detective assigned to the case rather than the detective who is on the case at the time of clearance.

Figure A.11: Detective-level Estimates of Bias



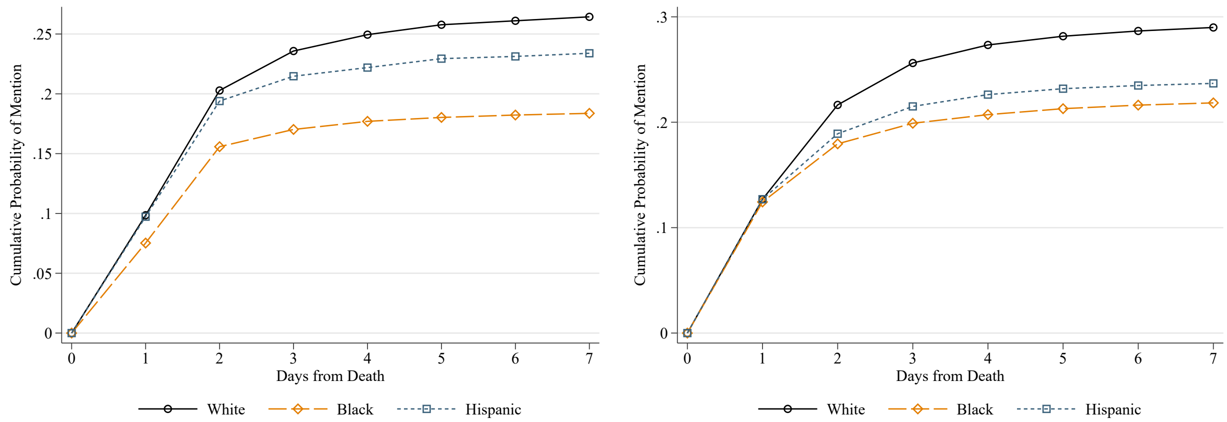
(a) White Victim vs. Black Victim



(b) White Victim vs. Hispanic Victim

Notes: This figure plots kernel density distribution of detective-level estimates of bias, before and after shrinkage using Morris (1983)'s empirical Bayes approach. The original estimates are obtained from Model 4, specifically as the interaction between dummies for the race of the victim with detective fixed effects.

Figure A.12: Cumulative Probability of Mention of Homicide Victims in Chicago by Race of the Victim



(a) Chicago Tribune

(b) Chicago Sun Times

Notes: This figure plots the cumulative probability that a victim is mentioned in the printed version of either the Chicago Tribune or the Chicago Sun Times in the first 7 days after the death of the victim, separately for the two newspapers. The statistics are further shown separately for White, Black and Hispanic victims.

Table A.1: Time to Clearance Robustness Checks

	Homicides		Other Violent Crime		
	(1)	(2)	(3)	(4)	(5)
	Success	Success	Success	Success	Success
Black Victim	-0.074**	-0.078***	-0.022***	-0.029***	-0.022***
	(0.029)	(0.022)	(0.005)	(0.005)	(0.005)
Hispanic Victim	-0.033	-0.042*	0.019***	0.017***	0.021***
	(0.029)	(0.022)	(0.005)	(0.005)	(0.005)
Days from Assignment (Week Bins) × Detective × Type FE	✓		✓		
Quadratics in Days × Detective Area		✓			
Days (Week Bins) × Detective × Type FE				✓	
Detective × Type FE	✓	✓	✓	✓	✓
Detective Area × Year × Type FE	✓	✓	✓	✓	✓
Days (3-Days Bins) × Type FE					✓
White Victim Mean	0.842	0.848	0.756	0.773	0.758
Observations	5,175	5,156	108,388	93,049	107,637
R^2	0.436	0.300	0.375	0.513	0.365

Notes: This table shows a series of robustness checks for the main results controlling for time to clearance in different and more demanding ways, starting from Equation 3. All regressions include detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects in the sample of nonfatal violent crime. Columns 1 and 3 use an alternative version of time to clearance that takes as a starting point of the investigation the first day when the case is assigned to a detective, rather than the date of the offense, again as fixed effects in week bins. Column 2 interacts time to clearance, as a quadratic in days to clearance, with the detective area where the investigation is conducted. In Column 4, I interact week-bin fixed effects of time to clearance with detective fixed effects. In Column 5, I instead bin time to clearance into 3-day bins. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Gap in Success Rate by Race of the Victim in the Sample Used to Estimate Detective-Level Bias

	(1) Success	(2) Success
Black Victim	-0.026***	-0.022***
	(0.006)	(0.006)
Hispanic Victim	0.018***	0.013*
	(0.006)	(0.007)
Days (Week Bins) × Type FE	✓	✓
Detective × Type FE	✓	✓
Detective Area × Year × Type FE	✓	✓
All Controls		✓
White Victim Mean	0.740	0.740
Observations	55,817	55,817
R^2	0.392	0.405

Notes: This table shows the results from the estimation of the main model in the sample used for the estimation of detective-level bias. All regressions include week bins of time-to-clearance fixed effects and detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects. Column 2 further adds all the non-race controls included in Column 3 of Tables 3 and Table 4. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Gap in Success Rate by Race of the Victim, Controlling for Suspects' Race

	Homicides			Other Violent Crime		
	(1) Success	(2) Success	(3) Success	(4) Success	(5) Success	(6) Success
Black Victim	-0.092**	-0.091**	-0.092**	-0.025***	-0.029***	-0.026***
	(0.046)	(0.045)	(0.046)	(0.005)	(0.005)	(0.006)
Hispanic Victim	-0.055	-0.055	-0.056	0.014**	0.011*	0.006
	(0.042)	(0.042)	(0.042)	(0.006)	(0.006)	(0.006)
Any White Suspect		-0.022			-0.026***	
		(0.054)			(0.007)	
Any Black Suspect			0.048			0.018**
			(0.051)			(0.007)
Any Hispanic Suspect			0.046			0.033***
			(0.056)			(0.007)
Days (Week Bins) × Type FE	✓	✓	✓	✓	✓	✓
Detective × Type FE	✓	✓	✓	✓	✓	✓
Detective Area × Year × Type FE	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓
White Victim Mean	0.842	0.842	0.842	0.758	0.758	0.758
Observations	3,017	3,017	3,017	88,299	88,299	88,299
R^2	0.549	0.549	0.549	0.384	0.384	0.385

Notes: This table shows the results from the estimation of the main model further controlling for the race of the suspects associated with the case. In Columns 1 through 3, the sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. In Columns 4 through 6, the sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The samples are further restricted to incidents that have a positive number of suspects linked to the case with none of them having missing race. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects for nonfatal violent crimes and all the non-race controls included in Column 3 of Tables 3 and Table 4. Columns 1 and 4 report the baseline estimates in these samples. I control for race of the suspect by first including an indicator for whether any White civilian was suspected of the crime and then with two separate indicators for whether any Black or Hispanic civilians were suspected of the crime. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective area-year-crime type of offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Gap in Success Rate by Race of the Victim, Controlling for Arrestees' Race

	Homicides			Other Violent Crime		
	(1)	(2)	(3)	(4)	(5)	(6)
	Success	Success	Success	Success	Success	Success
Black Victim	-0.052*	-0.055*	-0.062**	-0.011**	-0.012**	-0.010**
	(0.027)	(0.030)	(0.031)	(0.005)	(0.005)	(0.005)
Hispanic Victim	-0.040	-0.043	-0.040	0.006	0.005	0.002
	(0.029)	(0.032)	(0.032)	(0.005)	(0.005)	(0.005)
Any White Arrestee		-0.010			-0.004	
		(0.033)			(0.006)	
Any Black Arrestee			0.027			0.001
			(0.037)			(0.006)
Any Hispanic Arrestee			0.010			0.013**
			(0.035)			(0.006)
Days (Week Bins) × Type FE	✓	✓	✓	✓	✓	✓
Detective × Type FE	✓	✓	✓	✓	✓	✓
Detective Area × Year × Type FE	✓	✓	✓	✓	✓	✓
All Controls	✓	✓	✓	✓	✓	✓
White Victim Mean	0.882	0.882	0.882	0.908	0.908	0.908
Observations	4,385	4,385	4,385	65,296	65,296	65,296
R^2	0.457	0.457	0.457	0.253	0.253	0.253

Notes: This table shows the results from the estimation of the main model further controlling for the race of the arrestees associated with the case. In Columns 1 through 3, the sample is restricted to homicides committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2000 and 2023. In Columns 4 through 6, the sample is restricted to nonfatal violent crimes committed against White, Black or Hispanic victims that are cleared by the Chicago Police Department between 2001 and 2023. The samples are further restricted to incidents that have a positive number of arrestees linked to the case with none of them having missing race. The sample of arrestees appears to be heavily selected on charges being actually approved, with the issue being particularly relevant for nonfatal violent crime. The dependent variable is a dummy that takes value 1 if clearance is achieved via arrest and prosecution and 0 if via exceptional means due to prosecution denial. All regressions include week bins of time-to-clearance fixed effects, detective-area-year fixed effects and detective fixed effects, which are all further interacted with crime type fixed effects for nonfatal violent crimes and all the non-race controls included in Column 3 of Tables 3 and Table 4. Columns 1 and 4 report the baseline estimates in these samples. I control for race of the arrestee by first including an indicator for whether any White civilian was arrested for the crime and then with two separate indicators for whether any Black or Hispanic civilians were arrested for the crime. Observations are weighted by the inverse of the number of victims involved in the incident. Standard errors are clustered at the detective-area-year-crime-type-of-offense level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Differential Media Coverage by Race of the Victim – Chicago Tribune

	(1) OLS	(2) OLS	(3) OLS	(4) Poisson	(5) Poisson	(6) Poisson
	Any Mention by Day 3	Any Mention by Day 3	Any Mention by Day 3	Mentions by Day 3	Mentions by Day 3	Mentions by Day 3
Black Victim	-0.066***	-0.034**	-0.008	-0.630***	-0.405***	-0.212**
	(0.019)	(0.017)	(0.018)	(0.125)	(0.121)	(0.100)
Hispanic Victim	-0.021	-0.015	0.007	-0.409***	-0.300**	-0.114
	(0.019)	(0.018)	(0.018)	(0.120)	(0.120)	(0.094)
Age, Age^2, Gender		✓	✓		✓	✓
Weapon, Gang, DV FE		✓	✓		✓	✓
Offense Hour, DOW FE		✓	✓		✓	✓
Offense Month, Year FE		✓	✓		✓	✓
ZIP FE			✓			✓
% β^B				46.755***	33.284***	19.077**
				(6.653)	(8.085)	(8.095)
% β^H				33.536***	25.928**	10.810
				(7.966)	(8.879)	(8.347)
White Outcome Mean	0.254	0.251	0.252	0.556	0.514	0.515
Observations	12778	12708	12707	12778	12708	12707

Notes: This table shows the results from the estimation of Equation 8, where the sample is restricted to homicides committed against White, Black or Hispanic victims that are committed in Chicago between 2000 and 2023. The dependent variable is either a dummy for whether victim i, who died at time y has been mentioned by the Chicago Tribune by the third day after the event (Columns 1 through 3) or the the total number of mentions by the third day (Columns 4 through 6). Columns 2 and 4 control for other demographics of the victim (age, gender), time variables that affect whether the news can appear in the printed paper and media-related time trends (day of the week, hour of day, month, year), or the newsworthiness of the homicide (weapon, whether it is gang related, whether is is domestic violence related). Columns 3 and 6 further add fixed effects for the ZIP code where the incident occurred. Given the skew in the distribution of total mentions, a Poisson model is used for this second dependent variable rather than OLS. Effects in percentage terms with related standard errors are also reported for Models 4 through 6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Differential Media Coverage by Race of the Victim – Chicago Sun Times

	(1) OLS	(2) OLS	(3) OLS	(4) Poisson	(5) Poisson	(6) Poisson
	Any Mention by Day 3	Any Mention by Day 3	Any Mention by Day 3	Mentions by Day 3	Mentions by Day 3	Mentions by Day 3
Black Victim	-0.057***	-0.065***	-0.039**	-0.351***	-0.396***	-0.243**
	(0.017)	(0.017)	(0.017)	(0.098)	(0.090)	(0.101)
Hispanic Victim	-0.041**	-0.049**	-0.027	-0.256**	-0.276***	-0.172*
	(0.019)	(0.019)	(0.018)	(0.110)	(0.100)	(0.104)
Age, Age^2, Gender		✓	✓		✓	✓
Weapon, Gang, DV FE		✓	✓		✓	✓
Offense Hour, DOW FE		✓	✓		✓	✓
Offense Month, Year FE		✓	✓		✓	✓
ZIP FE			✓			✓
% β^B				29.598***	32.677***	21.586***
				(6.883)	(6.079)	(7.935)
% β^H				22.570**	24.095***	15.790*
				(8.503)	(7.622)	(8.769)
White Outcome Mean	0.263	0.267	0.268	0.422	0.431	0.431
Observations	12778	12708	12707	12778	12700	12695

Notes: This table shows the results from the estimation of Equation 8, where the sample is restricted to homicides committed against White, Black or Hispanic victims that are committed in Chicago between 2000 and 2023. The dependent variable is either a dummy for whether victim i, who died at time y has been mentioned by the Chicago Sun Times by the third day after the event (Columns 1 through 3) or the the total number of mentions by the third day (Columns 4 through 6). Columns 2 and 4 control for other demographics of the victim (age, gender), time variables that affect whether the news can appear in the printed paper and media-related time trends (day of the week, hour of day, month, year), or the newsworthiness of the homicide (weapon, whether it is gang related, whether is is domestic violence related). Columns 3 and 6 further add fixed effects for the ZIP code where the incident occurred. Given the skew in the distribution of total mentions, a Poisson model is used for this second dependent variable rather than OLS. Effects in percentage terms with related standard errors are also reported for Models 4 through 6. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Theory Appendix

B.1 Proof of Proposition 1

We can show that if there is a gap in success rates between Black and White cases that are solved and handed over to the prosecutor after the same number of days t_i^*, the investigator displays racial bias:

$$
\begin{aligned}
&E[Y_i \mid R_i = b, D_i = 1, T_i = t] - E[Y_i \mid R_i = w, , T_i = t] \\
=&E[Y_i^*(t) \mid R_i = b, T_i = t_i^* = t] - E[Y_i^*(t) \mid R_i = w, T_i = t_i^* = t] \\
=&E[Y_i^*(t) \mid R_i = b, p_i(t) = c(b,t)] - E[Y_i^*(t) \mid R_i = w, p_i(t) = c(w,t)] \\
=&E[E[Y_i^*(t) \mid R_i, U_i] \mid R_i = b, p_i(t) = c(b,t)] - \\
&E[E[Y_i^*(t) \mid R_i, U_i] \mid R_i = w, p_i(t) = c(w,t)] \\
=&E[p_i(t) \mid R_i = b, p_i(t) = c(b,t)] - E[p_i(t) \mid R_i = w, p_i(t) = c(w,t)] \\
=&c(b,t) - c(w,t).
\end{aligned} \tag{9}
$$

The first equality follows because $Y_i = Y_i^*(T_i)$ and $T_i = t_i^* \iff D_i = 1$. The second equality follows because $T_i = t_i^* = t \iff p_i(t_i^*) = p_i(t) = c(r,t) = c(r,t_i^*)$. The third equality follows by the law of iterated expectations. The fourth equality follows because $p_i(t) = E[Y_i^*(t)|R_i, U_i]$. The fifth equality follows by the conditioning on $p_i(t)$.

B.2 Microfoundation of the thresholds $c(R_i, t)$

A detective decides whether to bring the case of victim i to the DA's office, represented by $D_i \in \{0, 1\}$. If the case is submitted, this can either be successful if the DA accepts the charges against the suspect related to the case of victim i ($Y_i^* = 1$) or a failure if the DA rejects charges ($Y_i^* = 0$). In each period, the detective has beliefs $p_i(t)$ over the success of the case. Upon clearance, she receives utility κ regardless of the success status of the case. She dislikes making both false positives ($D_i = 1, Y_i^* = 0$) and false negatives ($D_i = 0, Y_i^* = 1$). Define the cost of these errors as $\beta(t)$ and $\gamma(t)$, respectively. Her utility in period t is therefore:

$$U(t) = \kappa - \beta(t)D_i(1 - Y_i^*) - \gamma(t)(1 - D_i)Y_i^*, \tag{10}$$

with expected utility for different actions $d \in \{0, 1\}$ being

$$
\begin{aligned}
E[U(t)|D_i = 0] &= \kappa - \gamma(t)p_i(t) \\
E[U(t)|D_i = 1] &= \kappa - \beta(t)(1 - p_i(t))
\end{aligned} \tag{11}
$$

Her optimal decision rule is then

$$
\begin{aligned}
D_i &= \mathbf{1}[-\beta(t)(1 - p_i(t)) \geq -\gamma(t)p_i(t)] \\
&= \mathbf{1}[p_i(t) \geq \frac{\beta(R_i,t)}{\beta(R_i,t) + \gamma(R_i,t)} = c(R_i,t)]
\end{aligned} \tag{12}
$$

From the last equation, we see that $c(R_i, t)$ can be recast as the relative cost of type I error upon submission at period t of a case of victim of race R_i. We can therefore redefine racial bias, $c(b, t) < c(w, t)$, as the detective having a lower relative cost of an unsuccessful submission when the victim is Black rather than White. This difference in relative costs can arise in several ways. The detective can perceive, for example, race-neutral costs of false negatives ($\gamma(b, t) = \gamma(w, t)$) but a lower cost of false positives for Black victims than for White victims ($\beta(b, t) < \beta(w, t)$): submitting a shoddy investigation at time t is less costly if the victim is Black rather than White. Alternatively, the detective can perceive, for example, race-neutral costs of false negatives ($\beta(b, t) = \beta(w, t)$) but a larger cost of false positives for Black victims than for White victims ($\gamma(b, t) > \gamma(w, t)$): the detective dislikes keeping potentially successful cases with Black victims open more than those of White victims since keeping a case open entails additional investigative effort, which under discrimination against Black victims is more costly for the latter group than for White victims. A combination of these two scenarios ($\beta(b, t) < \beta(w, t)$ and $\gamma(b, t) > \gamma(w, t)$) can also yield a lower relative cost of failure for cases with Black victims than for cases with White victims.

B.3 Derivation of Threshold Rule in Time to Suspension t_i^0

Recall that the suspension decision is:

$$S_i(t) = \mathbf{1}[l(R_i, U_i, t) \geq \bar{l}] \tag{13}$$

with a period t_i^0 such that the indifference condition along this margin holds, i.e., $l(R_i, U_i, t_i^0) = \bar{l}$. For simplicity, assume that $l(\cdot)$ is separable in race: $l(R_i, U_i, t) = l(U_i, t) + l(R_i)$, with $l(m) > l(w)$. Now, the indifference condition can be rewritten as:

$$l(U_i, t_i^0) = \bar{l} - l(R_i) \tag{14}$$

Set $\bar{l} - l(R_i) = \bar{l}_{R_i}$, with $\bar{l}_m < \bar{l}_w$. The latter condition means that under discrimination on the extensive margin, the investigator has a lower threshold of labor that she is willing to invest in the case if the victim is non-White. We can invert $l(\cdot)$ to obtain a expression for t_i^0:

$$t_{R_i}^0 = l^{-1}(\bar{l}_{R_i}, U_i) \tag{15}$$

Since $\bar{l}_m < \bar{l}_w$, for given non-race characteristics, we have that $t_m^0 < t_w^0$.