Racial Bias by Prosecutors: Evidence from Random Assignment

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Abstract

Racial disparities in criminal justice outcomes are well-documented. However, there is little evidence on the extent to which racial bias by prosecutors is responsible for these disparities. This paper tests for racial bias in convictions by prosecutors. To identify effects, I leverage as-good-as-random variation in prosecutor race using detailed administrative data on the case assignment process and case outcomes in New York County, New York. I show that the assignment of an opposite-race prosecutor leads to a 5 percentage point (~ 8 percent) increase in the likelihood of conviction for property crimes, and this result is robust to adjusting for multiple comparisons. I find no evidence of effects for other types of crimes. Additional results indicate racial bias for property crime convictions is driven by fewer dismissals for opposite-race defendants.

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1 Introduction

In the United States, there is widespread recognition of racial disparities in criminal justice outcomes. Black Americans are four times as likely to have a criminal record and to have been incarcerated compared to non-blacks (Shannon et al., 2017). Despite public concern that the system is unfair to black and Hispanic Americans (Rasmussen Reports, 2014; Pew Research Center, 2019), little is known about whether these disparities are caused by bias. Recently, legal scholars and judges have hypothesized that prosecutors could play a central role in perpetuating these racial disparities (Foster v. Chatman, 2016; State v. Monday, 2011; Pfaff, 2017; Rehavi and Starr, 2014; Smith and Levinson, 2011). This is because prosecutors have arguably more discretion than any other party when it comes to the handling of alleged crimes (Luna and Wade, 2015; Pfaff, 2017; Sklansky, 2016; Stith, 2008). In particular, prosecutors choose whether and how to dismiss a case, assign charges, offer plea deals, strike potential jury members, and handle a case at trial. However, there is little causal evidence on whether prosecutors exhibit racial bias in making these decisions. The purpose of this paper is to test for prosecutor racial bias in convictions.

The primary difficulty in testing for racial bias by prosecutors is the nonrandom matching of prosecutors and defendants. Non-random matching is commonplace, as prosecutors are often allowed to choose their cases during screening. To overcome this endogeneity concern, I exploit the random assignment, conditional on screening date, of defendants to prosecutors in New York County through the Early Case Assessment Bureau. Within each shift at the Early Case Assessment Bureau, cases are assigned on a rotational basis depending on a case's timestamp or when the case was received. The assignment works as follows: when prosecutors arrive at the office, they are given the earliest timestamped case available by the office administrator, who strictly enforces the case assignment procedure. They cannot screen, or even look at, the case before they begin to work on it. When they finish writing up their case, they return to the office administrator and are again assigned the earliest timestamped case available.

This as-good-as-random assignment of prosecutors implies a prosecutor's race is uncorrelated with a defendant's underlying guilt. Consequently, some defendants are randomly assigned, conditional on case screening date, to prosecutors of their own race, while others are paired with opposite-race prosecutors. I provide empirical evidence for this random assignment by showing that prosecutor race is uncorrelated with defendant and case characteristics. I use this quasi-random variation in prosecutor race to identify opposite-race effects. Specifically, I estimate opposite-race effects by differencing out the role of defendant and prosecutor race, similar to other studies on racial bias (e.g., Price and Wolfers, 2010; Parsons et al., 2011; Anbarci and Lee, 2014; West, 2018).

I identify effects using detailed administrative data from the New York County District Attorney's Office and collected by the Vera Institute (Kutateladze, 2017). The New York County District Attorney's Office prosecutes all cases originating in New York County (Manhattan). This totals over 100,000 cases per year from a jurisdiction of over 1.6 million, making it the nation's fourteenth largest prosecutors' office (City of New York, 2015). The New York County District Attorney's Office also promotes itself as being especially progressive due to its commitment to criminal justice reform, community partnerships, and reducing bias (Manhattan District Attorney, 2018b). The data collected include information on the case assignment (as well as dismissal) process and conviction decisions for all cases assigned via the Early Case Assessment Bureau.

My results show significant evidence of prosecutorial bias against opposite-race defendants for property crimes, though not for other crimes. I estimate that being assigned an opposite-race prosecutor increases the probability of guilt by 5 percentage points ($\sim$ 8 percent) for property crimes. This difference represents 50 percent of the black-white gap in conviction rates for property crimes. Additional results indicate these differences are driven by decreased dismissal of cases by opposite-race prosecutors. Further, an analysis of individual prosecutors suggests that more than 77 percent of prosecutors exhibit racial bias for property crime offenses. This indicates the results cannot be explained by a few "bad apple" prosecutors; rather, bias is more systemic. The results are also robust to multiple inference correction.

Although criminology and law studies have long described the power and discretion of prosecutors, lack of data availability and use of selection-on-observables approaches has left many important questions regarding prosecutor racial bias unanswered.[1] To my knowledge, this is the first paper to use as-good-as-random variation in opposite-race prosecutors to estimate racial bias. This paper primarily contributes to the literature on prosecutors and complements existing work on defense attorneys, in-group bias, and discrimination in the criminal justice system.

In addressing the role of opposite-race prosecutors, this paper contributes to the empirical literature on prosecutor behavior in general (Arora, 2019; Rehavi and Starr, 2014; Tuttle, 2019; Yang, 2016). Some existing papers focus on how prosecutors respond to financial and electoral pressures. Yang (2016) uses pension eligibility and judge deaths as instruments

[1]There are several papers that use a selection-on-observables method to conclude defendant race may alter prosecutor decision-making at multiple stages such as initial screening (Albonetti and Hepburn, 1996; Bishop et al., 2010; Franklin, 2010; Freiburger and Jordan, 2011; Kingsnorth et al., 1998; Kingsnorth and Macintosh, 2004; Kutateladze et al., 2014; Leiber and Johnson, 2008; Holleran et al., 2010; Riedel and Boulahanis, 2007; Sorensen and Wallace, 1999; Spears and Spohn, 1997; Spohn and Spears, 1997; Pyrooz et al., 2011; Wooldredge and Thistlethwaite, 2004), pretrial detainment (Demuth and Steffensmeier, 2004; Demuth, Demuth; Freiburger and Hilinski, 2010; Kutateladze et al., 2014) dismissal (Franklin, 2010; Kutateladze et al., 2014; Spohn and Homey, 1993; Wooldredge and Thistlethwaite, 2004), guilty pleas (Albonetti, 1992), and sentencing (Hartley et al., 2007; Johnson, 2005; Johnson and Betsinger, 2009; Kutateladze et al., 2014; Shermer and Johnson, 2010; Spohn and Fornango, 2009; Ulmer et al., 2007). These papers are summarized in Kutateladze and Andiloro (2014) and Kutateladze et al. (2012).

for judicial vacancies and resources constraints, concluding these cause more prosecutor case dismissals. Using a regression discontinuity created by close elections, Arora (2019) finds that Republican prosecutors assign defendants longer prison sentences than Democratic ones.

This paper is most closely related to previous work by Rehavi and Starr (2014) and Tuttle (2019). In a seminal paper, Rehavi and Starr (2014) use a selection-on-observables approach and report that prosecutors may be responsible for racial disparities in federal sentencing. However, this finding can also be explained by prosecutor selection of cases. Their approach also does not rule out the possibility that unobservable baseline differences between black and white defendants, rather than prosecutor racial bias, explain the sentencing disparities. In this paper, I address these concerns by using the randomization of defendants to prosecutors, which allows me to isolate the role of opposite-race bias in prosecutor decisions. The level of detail in my data also allow me to be more thorough and investigate the degree of bias for each prosecutor. Tuttle (2019) examines abnormal bunching in crack cocaine amounts used for federal sentencing and shows that black and Hispanic defendants receive harsher drug sentences. These results are likely driven by prosecutors shifting drug amounts just over a quantity threshold, triggering mandatory minimum sentences. This study differs from Tuttle (2019) in that I can test for racial bias in multiple prosecutor decisions across different types of cases, where the level of prosecutorial discretion, and thus the scope for racial bias to matter, can differ.

More generally, this paper also complements a larger related literature documenting the effects of other actors in the criminal justice system. Several of these papers have examined the effects of defense attorneys (e.g., Abrams and Yoon, 2010; Agan et al., 2018; Anderson and Heaton, 2012; Cohen, 2014; Iyengar, 2007; Roach, 2012; Shem-Tov, 2016). In addition, there has been considerable research on racial and gender bias by police officers (e.g., Antonovics and Knight, 2009; Anwar and Fang, 2006; Goncalves and Mello, 2018; Grogger and Ridgeway, 2006; Horrace and Rohlin, 2016; Knowles et al., 1999; Pierson et al., 2017; Sanga, 2009; West, 2018), judges (e.g., Depew et al., 2017; Eren and Mocan, 2018; Gazal-Ayal and Sulitzeanu-Kenan, Gazal-Ayal and Sulitzeanu-Kenan; Johnson, 2014; Knepper, 2017; Lim et al., 2016; Schanzenbach, 2005; Shayo and Zussman, 2011; Steffensmeier and Hebert, 1999), and juries (e.g., Depew et al., 2017; Eren and Mocan, 2018; Gazal-Ayal and Sulitzeanu-Kenan, Gazal-Ayal and Sulitzeanu-Kenan; Johnson, 2014; Knepper, 2017; Lim et al., 2016; Schanzenbach, 2005; Shayo and Zussman, 2011; Steffensmeier and Hebert, 1999).

The results of this paper have several important implications. First, my results imply that in-group bias can persist despite the widespread focus on prosecutor training on equal treatment. For example, the American Bar Association's standards for prosecutors states, "The prosecutor should not manifest or exercise, by words or conduct, bias or prejudice based upon race" (American Bar Association, 2018). These guidelines even go so far as to advocate active resistance to bias: "A prosecutor's office should be proactive in efforts to detect, investigate, and eliminate improper biases, with particular attention to historically persistent biases like race, in all of its work" (American Bar Association, 2018). This study's finding of racial bias for property crimes is particularly striking given that I study the New York County District Attorney's Office, which is known for actively trying to combat racial discrepancies in criminal justice outcomes (Manhattan District Attorney, 2018b). For example, in 2010, the New York County District Attorney's Office stopped prosecuting most low-level infractions and began offering a treatment program instead of probation for low-level drug crimes. Both policies are described as being particularly important for communities of color (Cyrus Vance For District Attorney, 2017). The New York County District Attorney's Office also employ a chief diversity officer and diversity committee because they believe a diverse staff can help reduce racial bias (Manhattan District Attorney, 2018a).

Second, as the majority of defendants are black and the majority of prosecutors are white, the consequences of opposite-race bias are disproportionately borne by black Americans. These costs often extend beyond penalties imposed by courts. Perhaps the most significant of these costs is the worsened labor market outcomes attributed to increased convictions and thus criminal records (Holzer et al., 2007; Finlay, 2008; Mueller-Smith and Schnepel, 2017; Pager, 2003; Raphael, 2014). Other long-term ramifications, such as the increased use of welfare programs, decreased mental health, less access to public housing, and some negative impacts on children, are also associated with having a criminal record (e.g., Curtis et al., 2013; Dobbie et al., 2018; Johnson, 2009; Murray and Farrington, 2012; Wolff and Shi, 2012).

Finally, the results of this paper have compelling implications for designing policies aimed at reducing racial disparities. Estimates presented here suggest that fair treatment by prosecutors could reduce the black-white gap in property crime convictions by about one-third. Therefore, targeting prosecutor behavior could be a productive policy tool for reducing disparities. However, it is also important to recognize that for about half (62 percent) of the crimes in my sample, and 41 percent of prosecutors, I do not find evidence of racial bias. Therefore, I note that some prosecutors may be treating cases fairly already. In light of these differences across prosecutors and cases, it may be optimal to target specific prosecutors and crimes to better eliminate bias. This also highlights the need to better understand why bias is only committed by some prosecutors and only occurs in certain contexts.

2 Background and Data

2.1 Case Assignment and the Prosecutor's Role in New York County

The primary problem in assessing the effect of prosecutor race is the nonrandom matching of cases. To overcome this problem, I chose to study New York County, which gives no discretion in case selection to prosecutors for certain crimes. In New York County, after a defendant is arrested, the police are responsible for recording all arrest charges and prior arrest history during booking. If the case is a less serious offense, an infraction, or a violation, the defendant is often given a desk appearance ticket or court summons, and the case is not assigned to a prosecutor. Next, the police fax or email misdemeanor and felony cases to the Early Case Assessment Bureau, where misdemeanors and felonies are assigned to a prosecutor. Felony and misdemeanor cases follow a different assignment procedure. For felonies, a head prosecutor screens each case and assigns it to another prosecutor based on their experience with particular types of cases. Because the assignment of felony cases is not as good as random at the Early Case Assessment Bureau, I exclude them from my analysis.

In contrast to felonies, the assignment of misdemeanor cases is as good as random. Within each shift at the Early Case Assessment Bureau, cases are assigned on a rotational basis depending a case's timestamp, which is when the bureau received it. The assignment works as follows: when prosecutors arrive at the office, the office administrator gives them the earliest timestamped case available. The timestamp on the case is essential. During my visit to the Early Case Assessment Bureau, multiple prosecutors and administrators mentioned the importance of handling cases in the order they arrived. To this end, an administrator works 24 hours a day to handle arrests that come in outside of typical work hours, ensuring timestamps are correct. A prosecutor cannot screen, or even look at, a case before she begins working on it. When she is finished writing up her case, she will return to the administrator and is again assigned the earliest timestamped case available. I was able to observe this prosecutor case assignment when I visited the Early Case Assessment Bureau. The as-good-as-random assignment of cases was also confirmed by the researchers who originally collected these data, although they do not consider the effects of opposite-race prosecutors, nor do they solely examine cases with as-good-as-random assignment (Kutateladze and Andiloro, 2014). In short, this assignment procedure means prosecutor and defendant pairing is as good as random within each screening day.

Nearly all first-year prosecutors will work at the Early Case Assessment Bureau as part of their training. Each month, a group of first-year prosecutors is assigned to work at the bureau to handle misdemeanor cases by a supervisor. Because of these rotations, I can observe the decisions of many different prosecutors. However, they are primarily less experienced. When first-year prosecutors are not working at the Early Case Assessment Bureau, they are also exposed to the many different bureaus and units within the District Attorney of New York's Office. These bureaus and units specialize in specific types of crimes, as prosecutors tend to believe that decision-making differs enough across case types to require specialization.

After a case is assigned to a prosecutor at the Early Case Assessment Bureau, the prosecutor has multiple opportunities to alter case outcomes. Specifically, the prosecutor can decide to decline to prosecute the case, change a defendant's charges, endorse pretrial detainment, pursue a case dismissal through adjournment in contemplation of dismissal (ACD), offer a plea deal, and design the plea deal. All of these decisions may alter a defendant's most crucial case outcome: guilty or not guilty.

The first decision a prosecutor makes is whether to decline to prosecute a case. In contrast to many other settings, prosecutors in New York County decline relatively few cases, likely due to a close relationship between the New York County's District Attorney's Office and the New York City Police Department (Kutateladze and Andiloro, 2014). This outcome is rare because most cases are only declined if the case has a complete lack of evidence or if the defendant was arrested for a crime that the District Attorney's Office has decided not to prosecute anymore.

Next, the prosecutor decides which charges to bring against a defendant at screening. Often this includes the option of increasing or decreasing the severity of charges assigned to a defendant's case.[2] For example, a defendant may be booked for a Class B misdemeanor crime, punishable by up to 90 days in jail, but a prosecutor may increase the crime to a Class A misdemeanor, punishable by up to 1 year in jail, at screening (New York State, 2018). The severity of charges is critical because prosecutors often choose to follow department norms for pretrial detainment, plea deals, and sentencing based on charge severity (Frederick and Stemen, 2012).

The prosecutor also has the option of offering and designing a plea deal for all defendants. A plea deal can include charges that are higher or lower than the initial charges for which a defendant is booked. During plea bargaining, a prosecutor can also recommend a particular sentence to the judge. While a judge must approve of any plea or sentence, prosecutors play a significant role in designing the attributes of the plea deal and sentencing request. If a defendant accepts a plea deal, she will be considered guilty.

Instead of a plea deal, the prosecutor can also offer the defendant a particular type of dismissal, referred to as an ACD. This acts as an agreement to dismiss a case in 6 to 12

[2] Prosecutors in Manhattan are specifically trained to be very careful in assigning screening charges. For example, prosecutors are told not to merely rerecord the arresting charges because the police officer may be unaware of the criminal history of a defendant or the details of the characteristics of a specific charge.

months if there are no subsequent arrests. In New York, an ACD is not a conviction or an admission of guilt.[3] It is also extremely rare that an ACD will be reopened, let alone lead to a guilty outcome. During 2010 and 2011 in New York County, 36,411 court events had an ACD outcome. Of these events, only 1 percent (384) had a later recalendaring. A recalendaring implies that the case could have been reopened but not that the defendant was tried again and found guilty. Like a plea deal, an ACD must be approved by a judge, but it cannot be offered without the approval of the prosecutor.[4]

Finally, a case can be disposed through a dismissal. A dismissal can be the result of a motion brought by a judge, defendant, or prosecutor. Misdemeanor cases can also be dropped unilaterally by a prosecutor (Kutateladze and Andiloro, 2014). For dismissals, charges against the defendant are immediately dropped. The most common reason for a dismissal in New York County is lack of speedy prosecution, which makes up 34 percent of dismissals. A prosecutor's decision to prioritize certain cases could influence which cases are dismissed. Specifically, a prosecutor could choose to work on particular cases first, knowing nonprioritized cases are more likely to be dismissed if the evidence is not gathered in time.

Cases may also be disposed through a trial. However, in my sample, which is primarily misdemeanors, only 0.01 percent of cases go to trial. Therefore, I do not separately investigate the probability of guilt through a trial or an acquittal. Cases with these outcomes are included in my measure of guilty or not.

Finally, for most cases, the New York County District Attorney's Office practices vertical prosecution, which means that the same prosecutor remains with the case from screening through disposition. Specifically, for 60 percent of misdemeanor cases, the prosecutor as-

[3] New York Criminal Procedure §170.55

[4] There are also special marijuana ACDs that can be offered without the approval of the prosecutor. These can only be offered in marijuana drug cases.

signed to the case at the Early Case Assessment Bureau is the only one on the case. Other cases are reassigned to another prosecutor after arraignment. Importantly, in regard to those cases, I observe both prosecutors in my data. This allows me to conduct my entire study as an intent-to-treat analysis using the first assigned prosecutor to the case.

2.2 Data

I use data from the New York County District Attorney's Office, a large prosecutor's office responsible for prosecuting all crimes in the Manhattan borough of New York City. The dataset was compiled by the Vera Institute and is housed by the National Archive of Criminal Justice Data (Kutateladze et al., 2012).

I use the New York County District Attorney's Office's detailed administrative data on all misdemeanor cases assigned through the Early Case Assessment Bureau in 2010–2011 for New York County. I focus my analysis on black defendants, black prosecutors, white defendants, and white prosecutors, the majority of my sample. The third largest demographic group is Hispanics. Hispanic prosecutors only make up 4 percent of prosecutors at the New York County District Attorney's Office, making subgroup analysis difficult. All data are collected at the case level.

Police officers record their perception of defendant race on the New York Police Department's arrest reports. The New York County District Attorney's Office reports prosecutor race. Unfortunately, information on defendant and prosecutor race is missing for 1.63 percent and 1.82 percent of cases, respectively. I also do not observe defendant date of birth for 17 cases and gender for 160 cases. For the remaining analysis, I only show results for the sample of cases where I observe all case and defendant characteristics. Although these missing characteristics are likely the result of clerical mistakes and are not related to the race of the defendant, prosecutor, or case outcomes, I address this minor issue in Section 4.4. Specifically, I show that my results are robust to the inclusion of cases with missing characteristics and to numerous assumptions about the value of missing characteristics.

Data from the New York County District Attorney's Office include the race of the defendant and prosecutor and other characteristics about the case, defendant, and prosecutor. For each case in the dataset, I observe arrest, screening and sentencing charges, type of crime, prior arrest history, prior conviction history, prior incarceration history, gender, and age for the defendant. I also have information on the gender and race of the prosecutor, as reported by the New York County District Attorney's Office. Finally, I observe the disposition of every case that originated at the Early Case Assessment Bureau. Potential dispositions include conviction through trial, acquittal through trial, plea deal, decline to prosecute, dismissal, and dismissal through ACD. Importantly, I also observe the screening date for each case. Because as-good-as-random variation in prosecutor race only requires I condition on the screening date of a case, I show in Section 4.1 that prosecutor race is uncorrelated with other case and defendant characteristics.

My primary outcome of interest is an indicator for whether the defendant was found guilty at the case level. This means that if a defendant is guilty of any charge on her case, she is considered guilty. Importantly, this includes all cases, even the ones dismissed. A defendant can be found guilty one of two ways: by accepting a plea offer or by conviction through a trial. A defendant is considered not guilty if her case is declined or dismissed or if her trial ends in an acquittal. As mentioned before, the vast majority (99.9 percent) of guilty outcomes come from plea deals.[5]

[5]Two hundred and twenty-one cases go to trial, and 127 trial cases end in a conviction.

Next, I also consider other decisions influenced by prosecutors that may determine a defendant's final case outcome (guilty or not guilty) to investigate what mechanism may drive the results. These outcomes include declined prosecution, case dismissal, dismissal through ACD, charge increases, and pretrial detention. Declined prosecution means a case was dropped in the Early Case Assessment Bureau by a prosecutor, and case dismissal is a dismissal by a judge or prosecutor. An ACD is an agreement to dismiss a case in 6 to 12 months if there are no subsequent arrests. Declined prosecution, case dismissal, and ACD all directly lead to a not guilty outcome. Charge increases, meaning a case's charges are changed to a higher severity at any point before disposition, and pretrial detention may indirectly influence a case outcome. Finally, pretrial detention means being detained after arraignment.

Crime type is defined by the researchers who originally collected the data according to New York law.[6] The three most common types are drug crimes, property crimes, and person crimes. All other crimes are classified as other.[7] Although I do not observe the specific crime type associated with a case, the most common drug misdemeanor in New York County is possession of marijuana (Kutateladze and Andiloro, 2014). Most property misdemeanors are petit larceny (theft of property worth less than $1,000), and the most common person crime is third degree assault (Kutateladze and Andiloro, 2014; Chauhan et al., 2014). Drug crimes account for 25 percent of all cases, property crimes 38 percent, person crimes 7 percent, and other crimes 31 percent. I am missing crime type for 1.53 percent of cases. I also address this minor issue in Section 4.4.

[6] Kutateladze et al. (2012) defines crime types using the New York Penal Law: person offenses, New York Penal Law §120.00–135.75; property offenses, §140.00–165.74; and drug offenses, §220.00–221.55.

[7] Unfortunately, I do not observe the specific crimes that fall into the other category. I do know the most common crime types in the "other" category are escape and others relating to custody (PL §205), firearms, and other dangerous weapons (PL §265) and offenses against public order (PL §240).

Table 1 displays summary statistics. I have a total of 87,461 cases. The average defendant has been arrested and convicted of a crime more than four times. On average, 20 percent of cases are dismissed, 20 percent are dismissed through ACD, and 58 percent end with a guilty verdict. As my cases are primarily misdemeanors, 99.9 percent of convictions come from plea deals. The majority, 82 percent, of defendants are male with an average age of 34 years. Across all cases, 41 percent of prosecutors are male.

Black defendants make up 79 percent (68,798 cases) of my sample, and black prosecutors handle 14 percent of cases in my sample (11,937 cases). There are 2,488 (3 percent) cases with white defendants and black prosecutors, 9,449 (11 percent) cases with black prosecutors and black defendants, 59,349 (68 percent) cases with white prosecutors and black defendants, and 16,175 (18 percent) cases with white prosecutors and white defendants. In total, there are 83 black prosecutors and 495 white prosecutors.

3 Model

The conditional random assignment of cases to prosecutors provides an ideal setting for investigating the effect of prosecutor race on defendant outcomes. I use a generalized difference-in-differences model to estimate the effect of being assigned an opposite-race prosecutor on conviction. Formally, I estimate the following:

$$\begin{aligned} Guilty_c = \beta_0 + \beta_1 I(BlackDefendant)_c + \beta_2 I(WhiteProsecutor)_c + \\ \beta_3 I(BlackDefendant * WhiteProsecutor)_c + X_c + ScreeningDate_c + \epsilon_c, \quad (1) \end{aligned}$$

where *Guilty* is a binary variable equal to one when the defendant is considered guilty for case c and zero for all other case dispositions; $Black\ Defendant$ takes on a value of one when the defendant is black and zero when the defendant is white; β_1 captures differences in the probability of guilt across defendant race; and $White\ Prosecutor$ is equal to one when the prosecutor is white and zero when the prosecutor is black and controls for differences in probability of guilt across prosecutor race. The coefficient of interest, β_3, on $BlackDefendant * WhiteProsecutor$ captures the effect of being assigned an opposite-race prosecutor.[8] X_c includes control variables at the case level. Specifically, X_c includes defendant race, age, date of birth, gender, number of arrest charges, number of prior arrests, number of prior convictions, and number of prior incarcerations; indicators for any prior arrest, any prior convictions, any prior incarcerations, drug crime, property crime, person crime, and arrest zipcode; and prosecutor gender. All specifications include $ScreeningDate$ fixed effects. Robust standard errors are clustered at the prosecutor level to allow observations to be correlated across cases for a particular prosecutor. As I present results for multiple subgroups of crime, I also correct standard errors for multiple comparisons, as suggested by Anderson (2008).

Intuitively, the difference-in-differences compares differences in the probability of guilt between black defendants and white defendants for black prosecutors and white prosecutors. This model allows for black defendants to be more or less likely to be found guilty than white defendants. Similarly, black prosecutors may have different propensities for earning convictions than white prosecutors.

[8]This paper focuses on the effect of opposite-race prosecutors. However, I also estimate the effect of prosecutor race on conviction. Results are shown in Table A2. Here I regress *Guilty* on indicators for prosecutor race. Overall, I find evidence that white prosecutors increase the probability of defendant guilt by 2.1 percentage points (3.6 percent) for the entire sample. I also show that being assigned a white prosecutor increases the probability of guilt by 2.7 percentage points (4.5 percent) for property crimes only. This result is robust to the inclusion of controls in column 2.

The identifying assumption of this model is that the differences in probability of guilt between black and white defendants across white and black prosecutors would be the same in the absence of opposite-race bias. Identification relies on the random assignment of cases to prosecutors. The identifying assumption could fail if prosecutor race is correlated with other factors that also alter the probability of conviction. For instance, in other settings, black prosecutors may choose to prosecute cases for white defendants only when they have a strong enough case to ensure a guilty verdict and choose to accept any case with a black defendant. In this case, I would conclude my treatment effect was due to opposite-race bias, when it could actually be attributed, in part, to the initial quality of the case. I avoid this problem by using the random assignment of prosecutors to cases conditional on screening date. I can illustrate empirically that prosecutor race is uncorrelated with all observed defendant and case characteristics that would alter conviction rates.

The identifying assumption could also fail if prosecutors are responding to characteristics about a case that are correlated with defendant race. For example, if black prosecutors always earn more guilty verdicts for drug crimes and white defendants are more likely to commit drug crimes, I would find evidence of opposite-race bias. To address this potential failure, I interact all case and defendant characteristics with prosecutor race. If the inclusion of these interactions altered my estimate of opposite-race bias, then I could conclude the treatment effect could, perhaps in part, be attributed to prosecutors' responses to observed characteristics correlated with defendant race but not necessarily defendant race itself. For example, if white defendants are more likely to commit drug crimes and black prosecutors always earn more guilty verdicts for drug crimes, some of the opposite-race treatment effect I estimate could be due to black prosecutors' differential treatment of drug crimes but not defendant race.

In equation (1), β_3 captures the average opposite-race bias of prosecutors. I also consider the opposite-race bias of specific prosecutors separately because the average estimate may mask important heterogeneities. In particular, it could be the case that my average estimates are only driven by a few bad apple prosecutors, or the bias could be more systemic. To do so, I must consider two different models, one for white prosecutors and one for black prosecutors. Precisely, to estimate heterogeneous treatment effects for white prosecutors, I consider the following equation:

$$Guilty_c = \beta_0 + \beta_1 I(BlackDefendant)_c + ProsecutorID_p +$$
$$\Sigma_{p=1}^{121} \beta_{3p} I(BlackDefendant * WhiteProsecutor)_c * I(Prosecutor)_p + X_c + ScreeningDate_c + \epsilon_c. \quad (2)$$

Here I build on the original specification in equation (1) by estimating prosecutor-specific fixed effects and interaction terms.[9] For a particular white prosecutor, the difference-in-differences compares differences in the probability of guilt between black defendants and white defendants for average black prosecutors and a specific white prosecutor. Here β_{3p} captures the effect of being assigned a white prosecutor p. I use a similar specification for

[9]Note that prosecutor-specific fixed effects subsume a prosecutor race fixed effect.

black prosecutors:

$$Guilty_c = \beta_0 + \beta_1 I(WhiteDefendant)_c + Prosecutor_p +$$
$$\Sigma_{p=1}^{24} \beta_{3p} I(WhiteDefendant * BlackProsecutor)_c * I(Prosecutor)_p + X_c + ScreeningDate_c + \epsilon_c. \tag{3}$$

In this case, β_{3p} compares differences in the probability of guilt between black defendants and white defendants for average white prosecutors and a particular black prosecutor.

4 Results

4.1 Exogeneity of Prosecutor Race

I start by showing prosecutor race is not correlated with confounding factors. While I expect this to be true based on the case assignment process at the New York County District Attorney's Office, I also provide empirical evidence. To begin, I regress defendant and case characteristics (determined before the case is assigned to a prosecutor) on prosecutor race. Each specification includes screening date fixed effects. Specifically, I examine if defendant race, age, date of birth, gender, number of prior arrests, felony arrests, convictions, felony conviction, jail sentences, prison sentences, and non-incarceration sentences are correlated with the race of the prosecutor. I also examine whether the cases's number of current arrest charges, number of current arrest counts, misdemeanor type, type of crime—drug, property, person, and other—are correlated with prosecutor race.

Results are reported in Table 2. Of the 20 coefficients presented, only 1 is statistically significant at conventional levels, which is consistent with random chance. Additionally, the coefficients are also close to zero. For example, compared to white prosecutors, black prosecutors are 0.66 percentage points more likely to be on cases with a black defendant. I conclude defendant and case characteristics are not correlated with prosecutor race. These results indicate that case and defendant characteristics are orthogonal to prosecutor race and are consistent with the institutional background that cases are as good as randomly assigned to prosecutors conditional on screening date.

I also include another test to show that race is not correlated with confounding factors. The intuition behind this test is to show that the underlying probability of guilt for a defendant, as predicted before a case is assigned to a prosecutor, is unrelated with the race of her prosecutor. To do so, I predict the probability of guilt for each defendant using all observable characteristics about the defendant and case except for the race of the prosecutor. Specifically, I predict *Guilty* (after removing screening date fixed effects) using column 2 controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode. Next, I compare the predicted probability of guilt for black and white defendants across white and black prosecutors. If the predicted values are the same for black and white defendants regardless of prosecutor race, then I provide further evidence that the underlying probability of guilty for defendants is not correlated with prosecutor race.

Results for the predicted values test are shown in Figure 1 for the full sample. The predicted probability of guilt is 50.7 percent for white defendants assigned to white prosecutors and 51.1 percent for white defendants assigned to black prosecutors. These predicted values are not statistically different from each other (p-value = 0.598).[10] Similarly, the predicted probability of guilt for black defendants assigned to white prosecutors and black prosecutors are not statistically different (59.4 percent and 59.9 percent, respectively, p-value = 0.425). Figure 1 is also replicated for only property crimes in Figure 2. Again, predicted values are similar for white and black defendants no matter the race of the prosecutor (p-values = 0.784 and 0.205, respectively). This further suggests prosecutor race is unrelated to a defendant's predetermined likelihood of guilt, which is consistent with my identifying assumption.

4.2 Effect of Opposite-Race Prosecutors on Defendant Guilt

Next, I present results for my entire sample of cases in Table 3. Each column includes screening date fixed effects along with standard errors clustered at the prosecutor level. The outcome variable for each column is the probability of guilt. *Guilty* takes on a value of one if the defendant is convicted of a crime in any manner and zero for all other case outcomes.

Column 1 presents the estimate for opposite-race prosecutors for all case types. The coefficient on $BlackDefendant * WhiteProsecutor$ is 0.0252 and is statistically significant at the 5 percent level. This shows that being assigned an opposite-race prosecutor increases conviction by 2.52 percentage points (4 percent).

Column 2 adds controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode and gender of the pros-

[10] Formally, I regress predicted probability of guilt for white defendants on an indicator for prosecutor race.

ecutor. The coefficient is somewhat smaller (0.0167) and is significant at the 10 percent level.

Along with case-level controls, column 3 adds prosecutor fixed effects, which account for unobserved time-invariant prosecutor characteristics, having little effect on the magnitude of the coefficient. The coefficient of interest remains similar in magnitude—slightly decreasing to 0.0115 and not significant at conventional levels—although it is not statistically different from the estimate in column 1.

Column 4 explicitly addresses a potential threat to identification. If prosecutors are responding to case characteristics that are correlated with defendant race, but not defendant race itself, then I could incorrectly categorize different treatment of case characteristics as opposite-race bias. For example, if black defendants are more likely to commit drug crimes and white prosecutors are more likely to win guilty verdicts for drug crimes, then I would incorrectly attribute differences in prosecuting drug crimes to opposite-race bias. To directly investigate this threat, I add a separate interaction for each case characteristic and defendant control added in column 2, interacted with prosecutor race; this allows black and white prosecutors to respond differently to case characteristics. The coefficient of interest remains about the same with the inclusion of interactions, slightly increasing from column 3 to 0.259, and is significant at the 5 percent level. Taken together, these columns provide suggestive evidence that opposite-race prosecutors increase the probability of conviction by 1.6–2.6 percentage points (3 percent to 4.5 percent).

Next, I explore effects by crime type, as different types of crimes are also often handled uniquely based on their quality of evidence (Frederick and Stemen, 2012; Ratledge et al., 1982; Spohn and Holleran, 2001; Spohn and Spears, 1997). In general, property crimes also tend to have less physical evidence (Peterson et al., 2010; Schroeder and Elink-Schuurman-Laura, 2017). This means I might expect greater bias for property crimes, which tend to have less quality evidence and therefore have more room for discretion. Further, earlier research suggests that racial disparities may differ by crime type (e.g., Albonetti, 1997; Mustard, 2000; Steffenmeier et al., 2006). In particular, I consider effects for drug, property, person, and other crimes in Table 4.

In Table 4, each panel represents a different type of crime. The column layout of Table 4 is similar to Table 3. For each crime type, I first present results for the specification with screening date effects only. The second column adds controls, the third column adds prosecutor fixed effects, and the fourth column adds interactions.

I find little evidence of opposite-race bias for drug, person, or other offenses, as shown in panels A, B, and C. Results in panel D present robust and significant opposite-race effects for property crimes. In column 1 the baseline estimate, including screening date fixed effects, of 0.0549 indicates that being assigned an opposite-race prosecutor increases the likelihood of a guilty verdict by 5.5 percentage points (9 percent) for property crimes. Column 2 adds controls for defendant and case characteristics, such as the criminal history of the defendant and indicators for the type of crime committed. Specifically, column 2 adds controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode and gender of the prosecutor. Consistent with my identifying assumption, the coefficient remains similar in magnitude (0.049) and is statistically significant at the 1 percent level.

Column 3 adds prosecutor fixed effects to the case-level controls, which account for unobserved time-invariant prosecutor characteristics, having little effect on the magnitude of the coefficient. The coefficient of interest remains similar in magnitude—slightly decreasing to 0.0489 and is again significant at the 1 percent level.

Finally, column 4 explicitly addresses a potential threat to identification. If prosecutors are responding to case characteristics that are correlated with defendant race, but not defendant race itself, then I could incorrectly categorize different treatment of case characteristics as opposite-race bias. Here, I add a separate interaction for each case characteristic and defendant control, included in column 2 and interacted with prosecutor race; this allows black and white prosecutors to respond differently to case characteristics. The coefficient of interest remains about the same with the inclusion of interactions, slightly increasing from column 3 to 0.0547, and is significant at the 1 percent level. These results indicate that opposite-race prosecutors increase the probability of a guilty verdict by 5 to 5.5 percentage points (8 percent to 9 percent).

Because I report results for multiple types of crimes, I also include false discovery rate (FDR) adjusted q-values for the estimates presented in Table 4. I compute the FDR q-values using the method proposed by Anderson (2008), adjusting for four different crime categories. The FDR q-values can be interpreted as adjusted p-values. The FDR q-values for the property crime estimates in panel D are statistically significant at the 1 percent level for each specification. Therefore, I conclude that the effects I find are large enough not to be attributed to chance. In combination, these results show strong opposite-race bias for property crimes only.

4.3 Heterogeneous Effects by Prosecutor

To this point, I have established that there is opposite-race bias *on average* for property crimes. This is important because it is valuable to consider the typical bias a potential defendant with no choice over their prosecutor could face. However, what is less clear from the results in Table 4 is whether the bias is driven by a handful of prosecutors or if it is systemic across prosecutors. Establishing whether the *average* bias I estimate is systemic could be important when designing policies aimed at reducing bias. For example, a district attorney's office may wonder if the best policy to reduce bias targets specific prosecutors or is -wide.

I next analyze my data at the prosecutor level. For each prosecutor, I estimate a separate opposite-race bias term. To do so, I plot the coefficient β_{3p}, the prosecutor-specific opposite-race bias term, from equation (2) for white prosecutors and from equation (3) for black prosecutors. I present results for all crimes in Figure 3 and by crime type in Figure 4. I restrict my analysis to only include prosecutors with more than 75 cases (145 unique prosecutors), which leaves 90 percent of cases.

There are two important features of my analysis. First, there is substantial heterogeneity in the direction and magnitude of prosecutor racial bias. For instance, opposite-race bias estimates range from –0.28 to 0.28 for all crimes and –0.21 to 0.27 for Property Crimes. These estimates are more than at least six times the average estimates I find in column 2 of Tables 3 and 4. Finally, I do not find evidence that the distribution of opposite-race bias estimates are different for black and white prosecutors for all crimes, Drug Crimes, Other

Crimes or Property Crimes.[11] These results imply that both black and white prosecutors may be contributing to opposite-race bias.

Second, a substantial proportion of prosecutors have opposite-race bias terms greater than zero. In particular, 57 percent of prosecutors have a coefficient greater than zero in the entire sample. The same is true of 77 percent of prosecutors for Property Crimes. Further, 46 percent and 52 percent of the opposite-race bias estimates are positive and are statistically different from zero at the 95 percent level for the entire sample and Property Crimes, respectively. Even for Drug Crimes, Other Crimes, and Person Crimes, where I do not find strong evidence of opposite-race bias, a meaningful number of prosecutor have positive opposite-race bias terms (47 percent, 32 percent, and 66 percent, respectively). These results suggest that prosecutor opposite-race bias is not driven by a few bad apple or extreme prosecutors, but rather the majority of prosecutors could be responsible for some opposite-race bias.

Finally, I consider how many prosecutors would need to change their behavior to eliminate bias for the average defendant. This could be important to consider when thinking about what policies a district attorney's may pursue in an attempt to reduce or eliminate bias. Intuitively, I am asking whether the *average* estimate can be driven to zero by removing those estimated to be most biased. As with the above analysis, for this analysis I only use data from the 133 prosecutors with more than 75 cases. To investigate this, I reestimate equation (1) multiple times, iteratively dropping prosecutors by the size of their opposite-race bias coefficient estimated from equations (2) and (3). Specifically, I rank prosecutors in order of their opposite-race bias coefficient show in Figures 3 and 4. Next, I drop the

[11]The results from chi^2 tests of equality are the following: all crimes (χ^2 = 145, p-value = 0.461), Drug Crimes (χ^2 = 86, p-value = 0.449), Other Crimes (χ^2 = 100, p-value = 0.453), or Property Crimes (χ^2 = 97, p-value = 0.452). I do not consider the difference between black and white prosecutors for Person Crimes because there are only 3 black prosecutors that see more than 75 Person Crimes.

highest rank prosecutor, then the second and highest ranked, then the third highest ranked prosecutors, and so on. The average opposite-race bias terms, β_3, from equation (1) for this procedure are shown in Figures 5 and 6 for all crimes and by crime type, respectively. For all crimes, after dropping the 21 highest ranked prosecutors, the top 16 percent of my sample, the estimate of opposite-race bias is less than zero. For Property Crimes, after dropping the 34 highest ranked prosecutors, the top 39 percent of my sample, the estimate of opposite-race bias is less than zero. These results suggest that targeted attempts to remedy opposite-race bias would likely need to focus on the worst 16 percent to 39 percent of prosecutors.

4.4 Missing Values

As described earlier, one limitation of the data is that I do not observe certain covariates for every case. In particular, defendant age, gender, and race; crime type; and prosecutor race are missing for some observations in my sample. In this section, I show that these minor data limitations do not alter the results of this paper.

First, I show that including cases with missing information on defendant age and gender does not change my estimates for property crimes. Defendant age and gender are missing for 0.02 percent and 0.2 percent of cases, respectively (17 and 170 cases). Results are shown in Table A3. Each specification in the table includes screening date fixed effects, case-level controls, and interactions, just as in column 4 of earlier result tables. Column 1 repeats the result for property crimes in Table 4 for comparison. In column 2, I include dummy variables for missing defendant age and gender and interact each of these dummies with prosecutor race. I also replace the values of defendant gender and age with zeros for observations where I do not observe true gender or age. My coefficient on $Black\ Defendant * White\ Prosecutor$

is almost identical in magnitude and is significant at the 1 percent level. This indicates that missing information for defendant age and gender does not alter my results.

Next, I consider missing crime type. In column 3, I assume all missing crime types are property crimes. In column 4, I randomly assign case type based on the probability of property crime in my data (38 percent of cases are property crimes). Then I estimate my result using screening date fixed effects, case-level controls, and interactions. I then repeat this exercise 10,000 times. I present the average coefficient for these iterations and the 2.5th and 97.5th percentiles (95 percent confidence interval). In both columns, my estimate is similar in magnitude. I can also rule out zero in my confidence interval.

Second, I consider missing values of defendant and prosecutor race. Defendant race is missing for 1.6 percent of the sample (887 defendants), and prosecutor race is missing for 1.8 percent of the sample (3 prosecutors and 780 cases). Next, I show my results are robust to various assumptions about missing prosecutor and defendant race. First, I address missing values for prosecutors. Because 777 (99 percent) of the cases with missing values have the same prosecutor, I simply replace prosecutor race with either white or black. In column 5, I replace missing prosecutor race as white and reestimate my results. In column 6, I replace missing prosecutor race as black. Both estimates (0.0542 and 0.0542, respectively) are very similar in magnitude to the original estimate and are statistically significant at the 1 percent level.

In columns 7–12, I make various reasonable assumptions about the race of defendants whose race is missing. In columns 7 and 8, I replace all missing defendant races as black and white, respectively. Next, I replace defendant race as 0.5 black and 0.79 black, the sample average, in columns 9 and 10. These results are, again, very similar in magnitude to my original estimate and are statistically significant at the 1 percent level.

Of course, there are many different combinations of defendant race that could occur beyond the results presented so far in Table A3. To address these possible scenarios, I conduct a simulation where I randomly replace defendant race based on the distribution of defendant race I observe in my data (79 percent of defendants are black). Specifically, I randomly assign defendant race and estimate my result using arrest category and prior arrest fixed effects, case-level controls, and interactions. I then repeat this exercise 10,000 times. I present the average coefficient for these iterations and the 2.5th and 97.25th percentiles (95 percent confidence interval) in columns 11 and 12. I also assume all missing prosecutors are white in column 11 and black in columns 12. The average coefficient for both columns (0.0555 and 0.0549 is close to the original estimate, and both confidence intervals do not include zero). These results show that under reasonable assumptions about which cases have opposite-race pairings of prosecutors and defendants, results still show strong evidence of opposite-race bias for property crimes.

4.5 Potential Mechanisms

Given how my results show strong evidence of opposite-race bias in the probability of guilt for property crimes, I investigate potential mechanisms through which a prosecutor could affect the disposition of a case. As mentioned previously, there are many ways a prosecutor can alter the final outcome of a case: guilty or not guilty. First, a prosecutor could indirectly affect whether a defendant is convicted by altering pretrial detainment or by increasing charges. A prosecutor can also directly affect whether a defendant is guilty or not though declining prosecution, dismissing the case, or applying for an ACD. To examine the effect of opposite-prosecutors on potential mechanisms, I first estimate equation (1) using pretrial detainment, increasing charges, declined prosecution, pretrial detainment, case dismissal, and ACD as outcome variables. Results are shown in Table 5.

Each specification in the table includes screening date fixed effects, case-level controls, and interactions, just as in column 4 of Tables 3 and 4. First I consider pretrial detention in column 1 because prosecutors often have the power to recommend pretrial detention for defendants. Existing literature documents that pretrial detention can lead to increases in conviction for defendants because they are more likely to accept a plea deal while detained (Dobbie et al., 2018; Heaton et al., 2017; Stevenson, 2018). However, I only find suggestive evidence of opposite-race bias in pretrial detention for both the entire sample and the subsample of property crimes. As both coefficients, 0.0065 and 0.0053, are positive, but statistically insignificant, these results suggest opposite-race prosecutors might increase pretrial detention by 7 percent.

Results for charge increases are shown in column 2. A prosecutor's decision to increase the severity of charges may make it more difficult for a defendant to be released pretrial or may make the prosecutor more likely to seek out a guilty plea based on the new higher charges (Frederick and Stemen, 2012). Results indicate that for all cases and property crimes, an opposite-race prosecutor could charge severity by 3 percent to 8 percent, although neither coefficient is statistically significant at conventional levels.

I also show results for declined prosecution in column 3. It is possible that prosecutors could exhibit bias by declining to prosecute certain cases for certain same-race defendants. In column 1, I find evidence of opposite-race bias in the decision to decline to prosecute for all cases. When a defendant is assigned an opposite-race prosecutor, they are 26 percent less likely to have their case declined. However, I find no evidence of this bias for property crimes. This finding suggests that prosecutors are more likely to decline to prosecute a case for some cases, although not property ones.

Next, I consider case dismissal as a potential mechanism in column 4. Some misdemeanor dismissals are determined unilaterally by the case's prosecutor. Most dismissals are due to lack of speedy prosecution, which is officially determined by a judge, but a prosecutor's prioritization decisions can alter how long it takes to gather evidence on a case. For example, a prosecutor could decide to first work on cases where the defendant is opposite race versus own race. For all cases and property crimes, an opposite-race prosecutor decreases the chance of a case dismissal by 3 percent to 5 percent, although neither coefficient is statistically significant at conventional levels. This indicates that prosecutors could be altering case outcomes through increased dismissals for opposite-race defendants. However, estimates suggest this effect is unlikely to be the primary mechanism through which prosecutors exhibit opposite-race bias.

In column 5, I present results for ACD, the third most common case outcome (after a guilty plea and case dismissal). For the entire sample, the estimate of opposite-race bias is statistically insignificant, but its magnitude suggests that being assigned an opposite-race prosecutor decreases the likelihood of case dismissal through ACD by 0.095 percentage points or 5 percent. Among defendants who have committed property crimes, being assigned an opposite-race prosecutor decreases the chance of dismissal through ACD by 4.5 percentage points or 19 percent. These results suggest a substantial portion of the opposite-race bias I estimate could be attributed to prosecutors not dismissing cases for defendants. My result for ACDs is also in line with the argument that prosecutors may exhibit bias on cases with more room for discretion. This is because ACDs are sometimes criticized because they could allow a prosecutor who is "faced with inconclusive evidence . . . to find a way to keep a potentially dangerous person on a short legal leash" (Worden et al., 2012).

5 Discussion

These results show strong evidence of opposite-race bias for property crimes, although not for other crime types. This raises questions as to why prosecutors exhibit bias for only one type of crime. Further, it is natural to wonder if these results matter for overall racial disparities in the criminal justice system if prosecutors are only biased for one specific type of case.

While I cannot definitively conclude why prosecutor bias exists for only property crimes, one important factor may be evidence quality. When there is hard evidence on whether a crime occurred, prosecutors may have less ability to exhibit taste-based bias. Similarly, the availability of hard evidence may reduce the tendency of prosecutors to statistically discriminate.

Prosecutors and scholars agree that evidence quality is important for deciding how to prosecute a case. Based on one survey of two large urban district attorney's s, researchers conclude "the most important factor considered in determining whether a case will go forward is the strength of the evidence" (Frederick and Stemen, 2012). Other studies also confirm that prosecutors rely heavily on evidence strength when making case decisions (Spohn and Spears, 1997; Ratledge et al., 1982; Spohn and Holleran, 2001).

It is also generally believed that most property crimes have less hard evidence than other types of crimes. For example, physical evidence is considered the most reliable type of evidence by prosecutors, and prosecutors agree that physical evidence in property cases is typically weaker than in drug cases (Frederick and Stemen, 2012; Kutateladze et al., 2016). Using data from five different jurisdictions, Peterson et al. (2010) finds that for randomly selected property crimes (burglary and robbery in their setting), physical evidence is only collected for 9 percent to 17 percent of cases, compared to 22 percent to 83 percent of person crimes cases (homicide, assault, rape) and nearly 100 percent of drug cases. Schroeder and Elink-Schuurman-Laura (2017) also confirms that person crimes, such as homicides and rapes, tend to have higher evidence collection rates than property crimes.

Without quality evidence in property crimes, prosecutor decisions may rely more on person assessments of the likelihood of conviction, which could be altered by bias. In fact, some scholars have suggested that prosecutors may interpret weak evidence in a more "negative light" for minority defendants (Smith and Levinson, 2011; Kutateladze et al., 2016). Therefore, prosecutors may be able to exercise bias in the decision to dismiss a case through ACD, encourage dismissal, and increase charges, as property cases may have more room for discretion. Suppose that a defendant is arrested for a property crime, but the case lacks solid evidence. In this case, the prosecutor would have more leeway to choose to push for a dismissal or a plea deal, compared to a case where a person is arrested with drugs, as hard evidence on them. In this context, at least, it seems prosecutors are more likely to fairly prosecute crimes when they lack room for discretion.

Prosecutors having greater potential for discretion and bias in crimes with less quality evidence, like property crimes, is less concerning if property crimes are uncommon. However, property cases are the most common type of crime in New York County. Further, in 2016 there were 7,919,035 property crime offenses in the nation, and 25 percent of jail inmates were incarcerated for property offenses (FBI: UCR, 2016; Sawyer and Wagner, 2019). Finally, although there are not many sources for nation-wide misdemeanor arrests, the best estimates suggest over 1.4 million individuals were arrested for property crimes in 2014 (Stevenson and Mayson, 2018). This indicates there are many cases with greater room for discretion.

In addition, in many ways, one might expect effects found in this setting to be a lower bound for racial bias in other prosecutors' s across the country. This is because the Manhattan District Attorney has actively tried to address racial bias. For example, since 2010, the New York County District Attorney's Office stopped prosecuting most low-level infractions and started offering a treatment program, instead of probation, for low-level drug crimes. Both policies are described as being particularly important for communities of color (Cyrus Vance For District Attorney, 2017). It also employs a chief diversity officer and diversity committee because it believes a diverse staff can help reduce racial bias (Manhattan District Attorney, 2018a). For this reason, larger effects might be expected elsewhere. Because of the prevalence of property crimes and the progressive nature of the District Attorney of New York, finding effects for property offenses is nontrivial.

Finally, the results I find in New York County have important implications for racial disparities in the criminal justice system. Opposite-race bias by prosecutors could account for about 50 percent ($\frac{Estimate of Opposite Race Bias * Pr(White Prosecutor)}{Estimated Black White Disparity} = \frac{0.055*0.86}{0.049+0.055*0.86}$) of the difference in guilt across race for property crimes.[12] Even if prosecutors are acting fairly in other types of cases, the magnitude of the opposite-race bias I estimate should warrant further

[12] 0.86 is the probability of being assigned a white prosecutor for property crimes, 0.055 is my estimate of opposite-race bias for property crimes, and 0.049 is the β_1 I estimate in the same regression (Table 4). Referring to the model I present in equation (1), I estimate that the difference in conviction races between black and white defendants is $[(\beta_0 + \beta_1) * Pr(BlackProsecutor|BlackDefendant) + (\beta_0 + \beta_1 + \beta_2 + \beta_3) * Pr(WhiteProsecutor|BlackDefendant)] - [\beta_0 * Pr(BlackProsecutor|WhiteDefendant) + (\beta_0 + \beta_2) * Pr(WhiteProsecutor|WhiteDefendant)]$. Because cases are randomly assigned, $Pr(BlackProsecutor|WhiteDefendant) = Pr(BlackProsecutor|BlackDefendant)$, and similarly $Pr(WhiteProsecutor|WhiteDefendant) = Pr(WhiteProsecutor|BlackDefendant)$. Further, Pr(Black Prosecutor) = 1-Pr(White Prosecutor). Using this information to simplify, I determine the difference in black and white conviction rates is $\beta_1 + Pr(WhiteProsecutor)\beta_3$, where β_3 is my estimate of opposite-race bias. Therefore $\frac{\beta_3 * Pr(WhiteProsecutor)}{\beta_1 + \beta_3 * Pr(WhiteProsecutor)}$ represents the amount of the black-white gap explained by my estimate of opposite-race bias.

investigation into prosecutor bias.

6 Conclusion

In this paper, I test for opposite-race prosecutor bias in criminal convictions. To overcome potential endogenous case selection by prosecutors, I exploit the as-good-as-random assignment of cases to prosecutors in New York County, under which assignment is random conditional on screening date. The resulting variation in prosecutor race, combined with variation in defendant race, allows me to estimate the extent to which prosecutors are biased against opposite-race defendants.

My results indicate that the assignment of an opposite-race prosecutor leads to a 5 percentage point ($\sim$ 8 percent) increase in the probability of being found guilty for property crimes only. In addition, I explore the potential mechanisms through which opposite-race bias affects the probability of guilt. I show that being assigned an opposite-race prosecutor decreases the likelihood that a case is dismissed through an ACD. I interpret the reason for these findings as likely because prosecutors can more easily exercise discretion for crimes with weaker evidence, although I cannot rule out other interpretations.

The finding of prosecutor bias against opposite-race defendants lends support to recent movements to increase the training of prosecutors and to curb the ability of prosecutors to exercise discretion based on race (U.S. Department of Justice, 2016). Further, these results are striking because the New York County District Attorney's Office promotes itself as being especially progressive, expressed through its commitment to criminal justice reform, community partnerships, and reducing bias. My results add to existing evidence documenting opposite-race bias, though it is important to highlight I find no evidence of bias in person, other, or drug crimes. However, it is possible that a meaningful portion of the black-white disparity in convictions, 30 percent, could be contributed to prosecutors exhibiting opposite-race bias even if prosecutors do not display bias on all cases.

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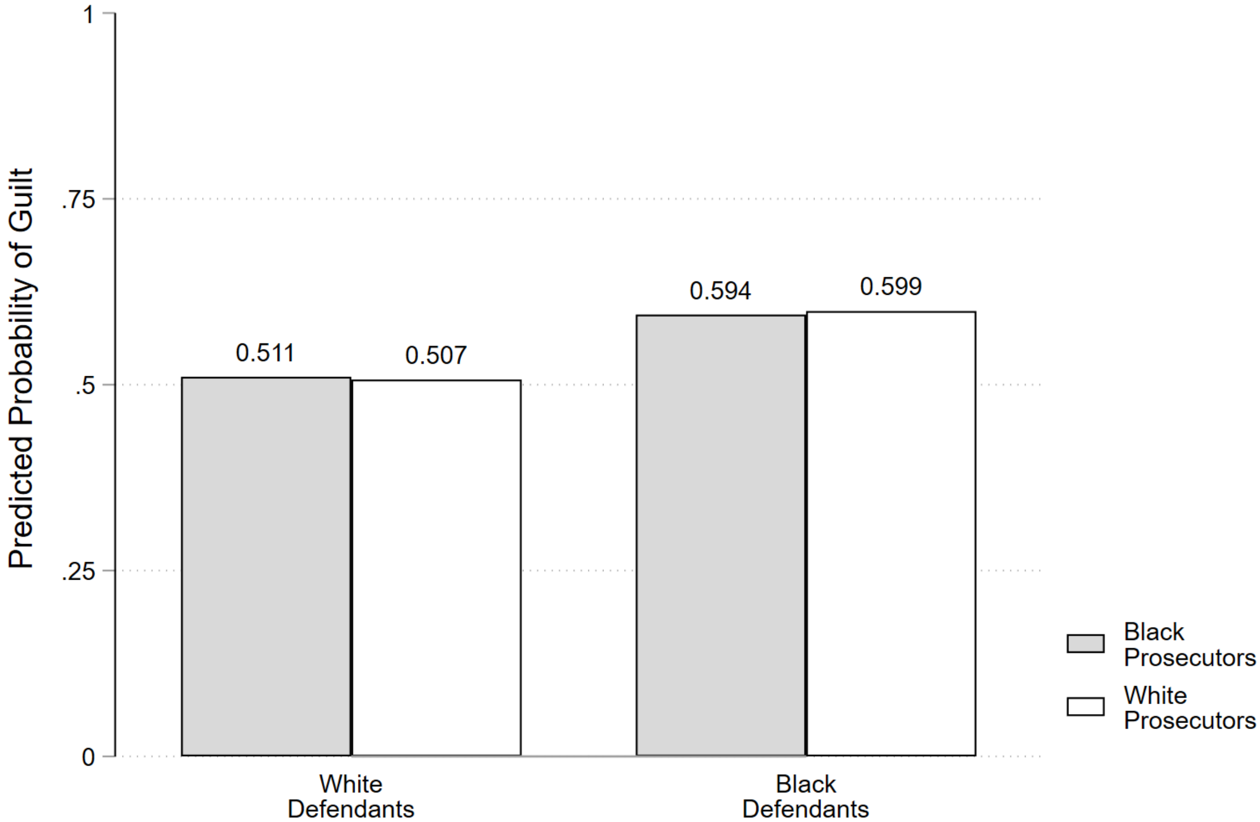
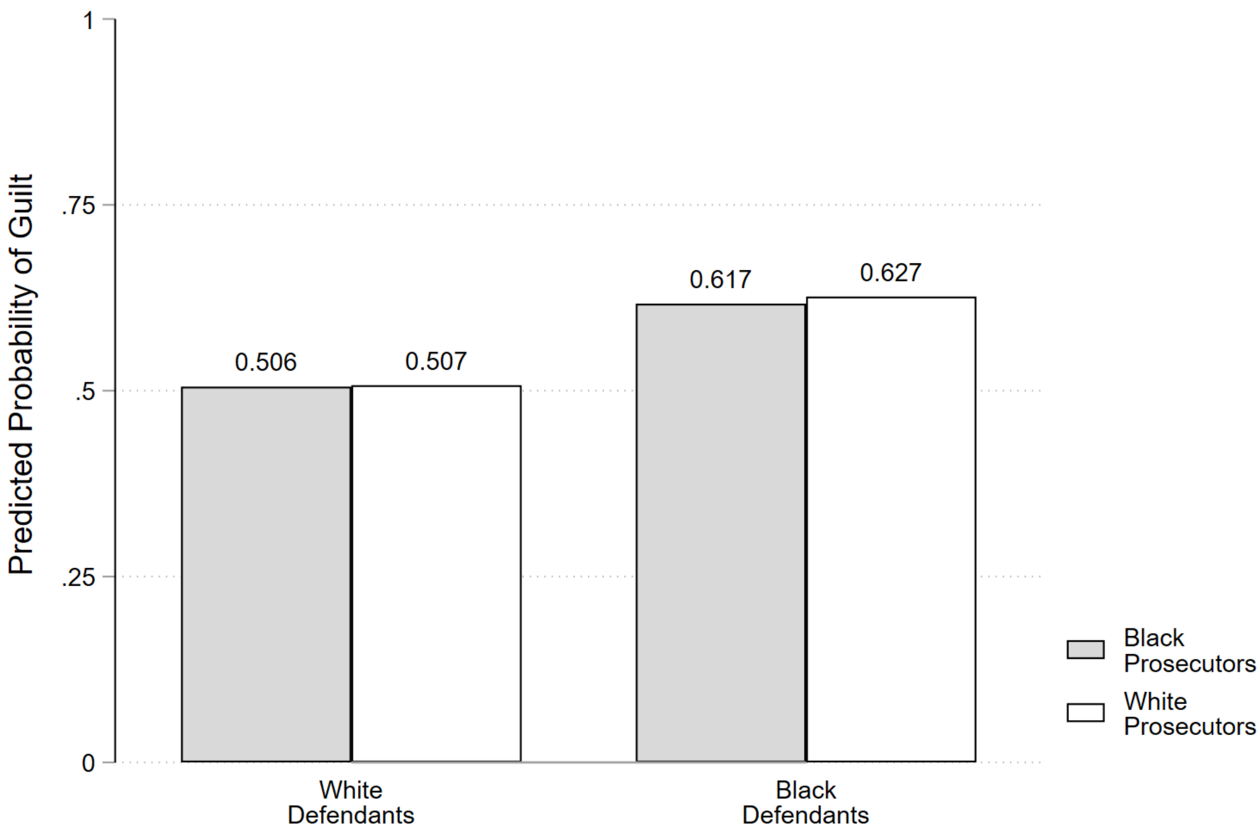
7 Tables and Figures

Figure 1: Predicted Values of Guilt



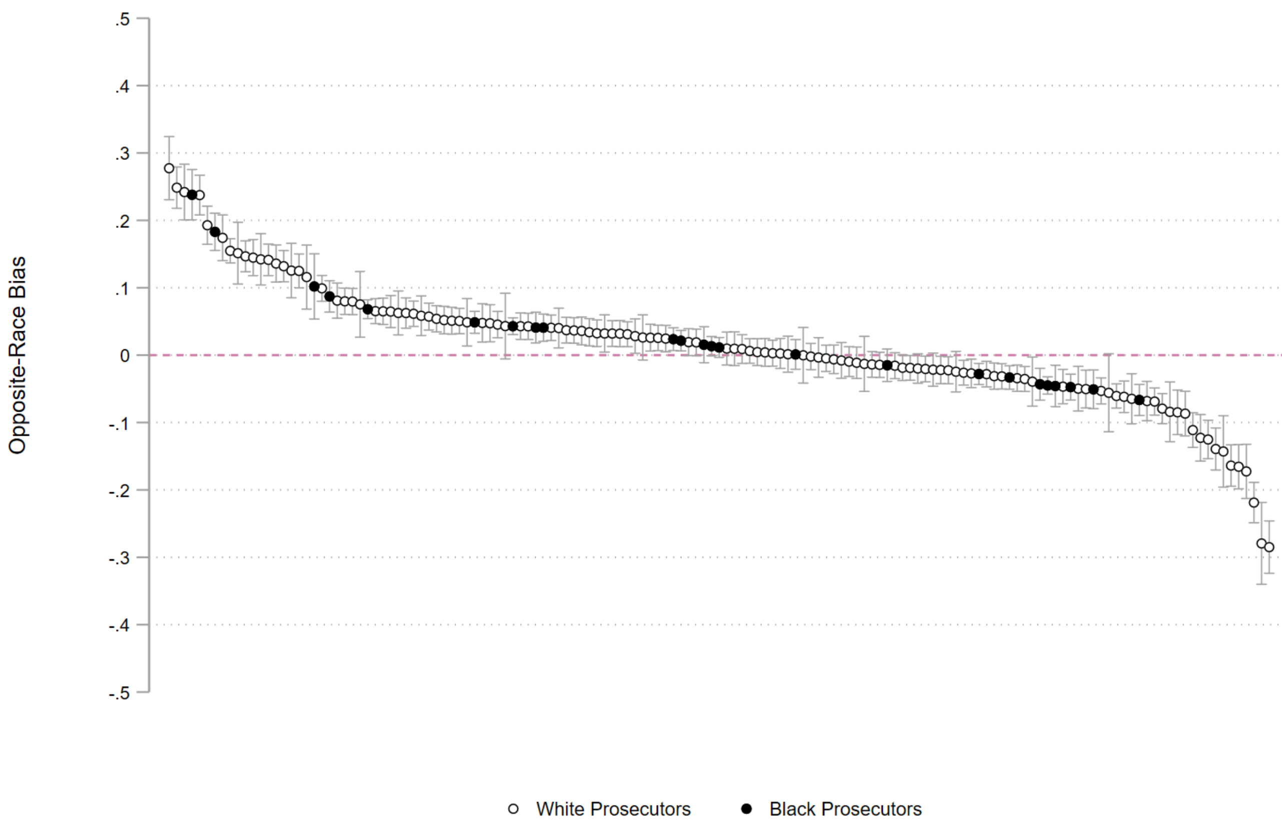
Notes: This figure reports predicted guilt for black and white defendants assigned to black and white prosecutors. The predicted value is calculated by regressing *Guilty* on all observable characteristics about the defendant and case that was determined before the case was assigned to the prosecutor except for prosecutor race. Specifically, *Guilty* is predicted (after removing screening date fixed effects) using defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode. There is no statistical difference in predicted guilt for white defendants assigned to white or black prosecutors. The same is true for black defendants.

Figure 2: Predicted Values of Guilt for Property Crimes



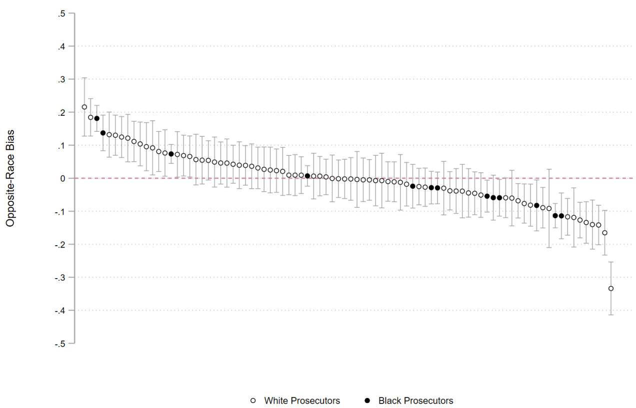
Notes: This figure reports predicted guilt for black and white defendants assigned to black and white prosecutors. The predicted value is calculated by regressing *Guilty* on all observable characteristics about the defendant and case that was determined before the case was assigned to the prosecutor except for prosecutor race. Specifically, *Guilty* is predicted (after removing screening date fixed effects) using defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode. There is no statistical difference in predicted guilt for white defendants assigned to white or black prosecutors. The same is true for black defendants.

Figure 3: Heterogeneous Treatment Effects by Prosecutor

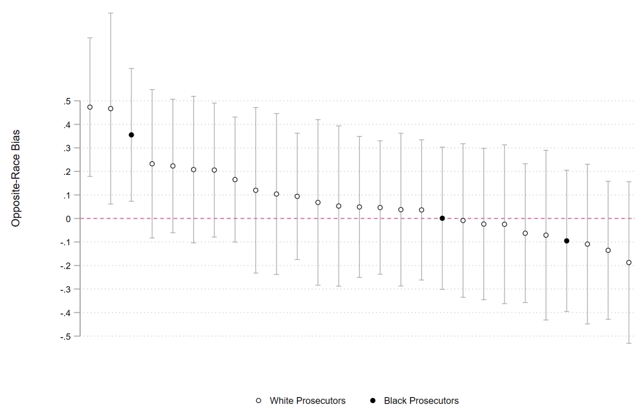


Notes: Each point represents a prosecutor-specific estimate of opposite-race bias (i.e., the coefficient β_{3p} from equation (2) or (3)). β_{3p} can be thought of as the effect of a specific opposite-race prosecutor on a defendant guilt. For a specific white prosecutor, the difference-in differences compares differences in the probability of guilt between black defendants and white defendants for average black prosecutors and a particular white prosecutor. Ninety-nine percent confidence intervals are shown. I only include prosecutors with more than 75 cases.

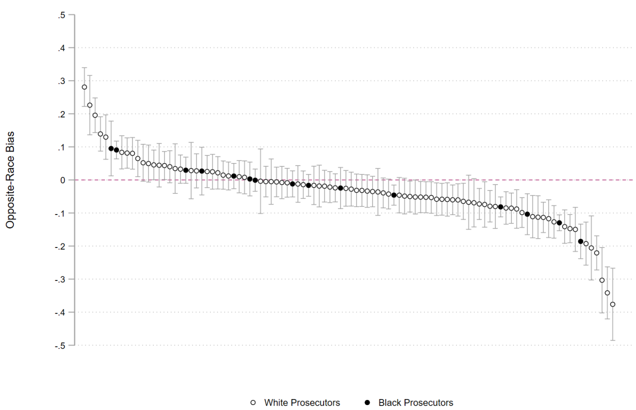
Figure 4: Heterogeneous Treatment Effects by Prosecutor



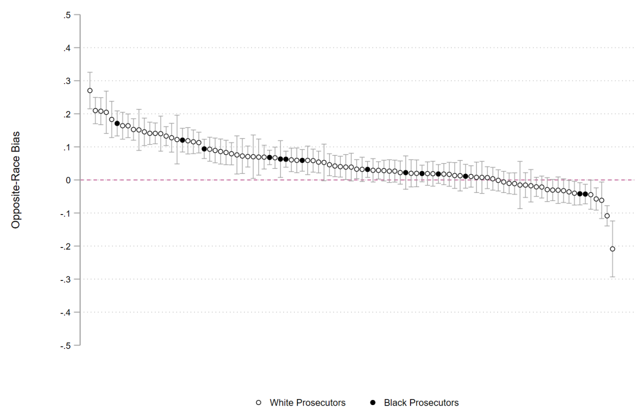
(a) Drug Crimes



(b) Person Crimes



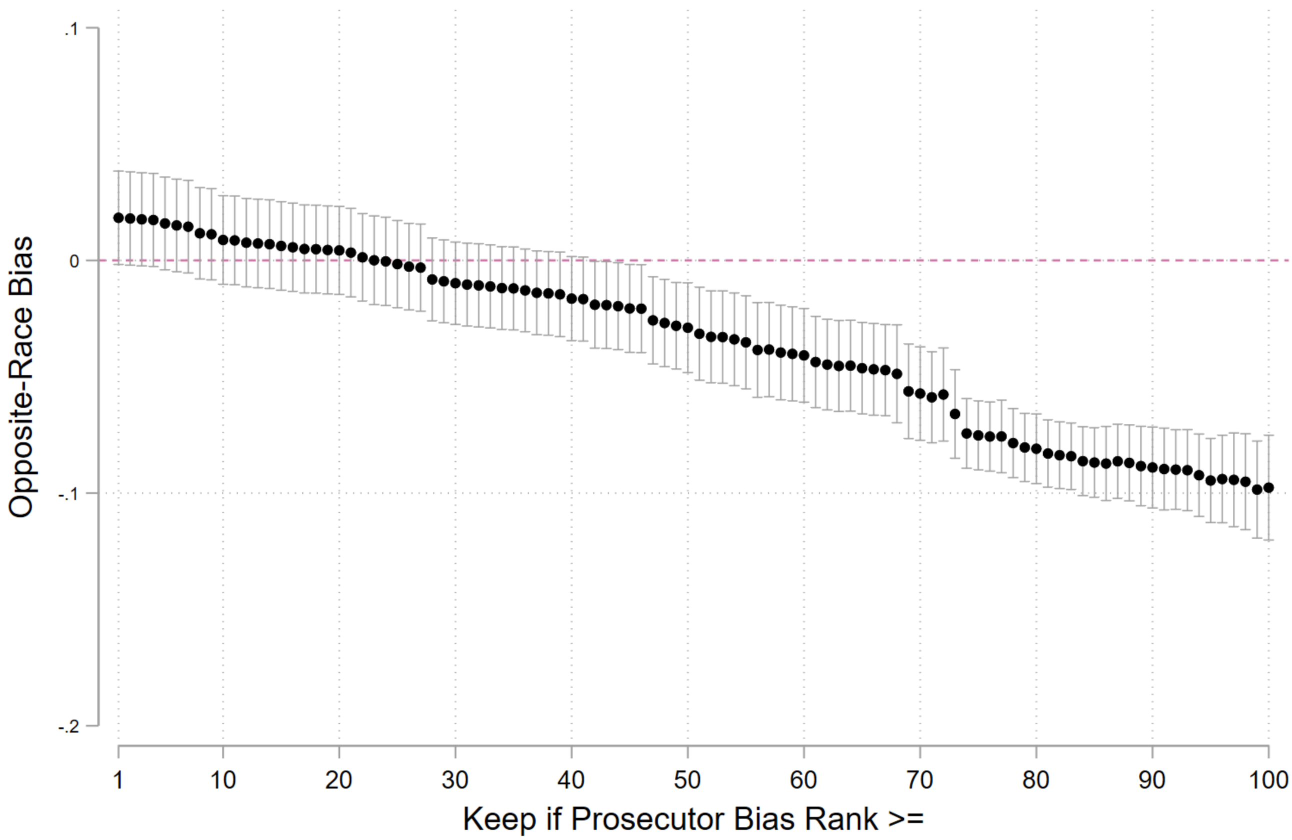
(c) Other Crimes



(d) Property Crimes

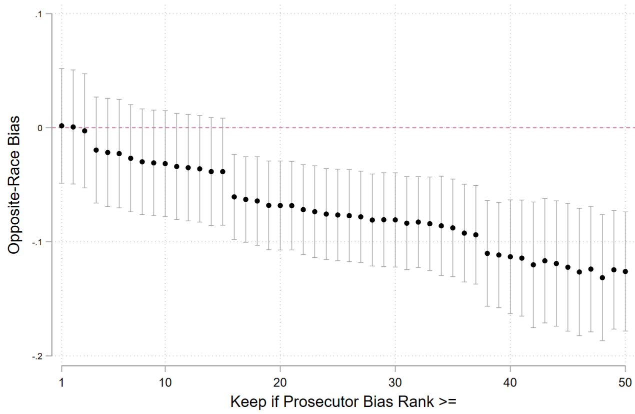
Notes: Each point represents a prosecutor-specific estimate of opposite-race bias (i.e., the coefficient β_{3p} from equation (2) or (3)). β_{3p} can be thought of as the effect of a specific opposite-race prosecutor on a defendant guilt. For a specific white prosecutor, the difference-in differences compares differences in the probability of guilt between black defendants and white defendants for average black prosecutors and a particular white prosecutor. Ninety-nine percent confidence intervals are shown. For Figures 4a, 4c, 4c, and 4d, I only include prosecutors with more than 75 drug, person, other, and property crimes, respectively.

Figure 5: The Effect of Dropping Prosecutors on Opposite-Race Bias Estimates

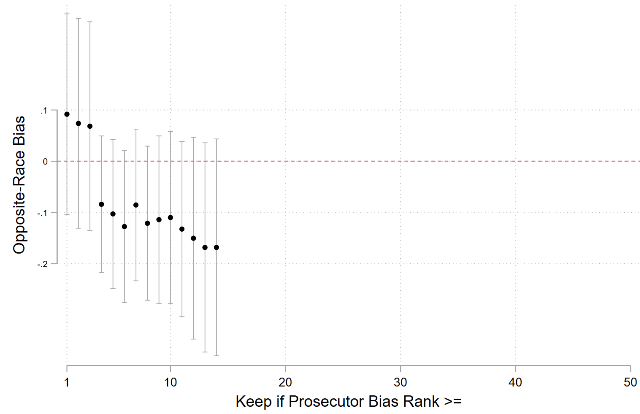


Notes: Each point represents the average estimate of opposite-race bias (i.e., the coefficient β_3 from equation (1)). Each coefficient is estimated from a separate regression. Ninety-nine percent confidence intervals are shown.

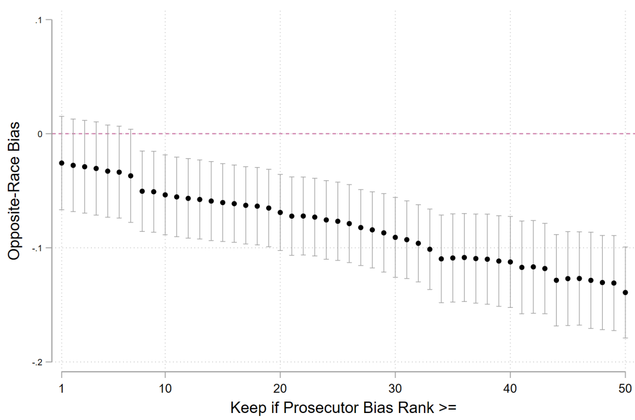
Figure 6: The Effect of Dropping Prosecutors on Opposite-Race Bias Estimates by Crime Type



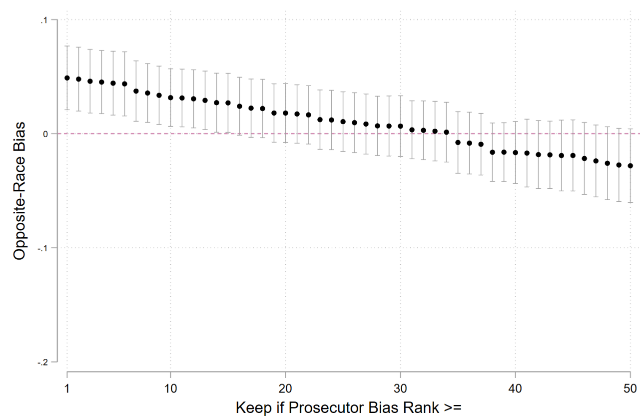
(a) Drug Crimes



(b) Person Crimes



(c) Other Crimes



(d) Property Crimes

Notes: Each point represents the average estimate of opposite-race bias (i.e., the coefficient β_3 from equation (1)). Each coefficient is estimated from a separate regression. Ninety-nine percent confidence intervals are shown. Because person crimes are only a small portion of my sample, I cannot complete the exercise for person crimes beyond dropping the 15th highest prosecutor.

Table 1: Summary Statistics

	(1) All	(2) Black Defendants	(3) White Defendants	(4) Drug Crimes	(5) Property Crimes	(6) Person Crimes	(7) Other Crimes
Panel A: Outcomes							
Pretrial Detention	0.0892	0.100	0.0487	0.0858	0.0862	0.209	0.0689
Charges Increased	0.0501	0.0522	0.0423	0.0225	0.0738	0.0802	0.0366
Decline to Prosecute	0.0189	0.0203	0.0139	0	0.00865	0	0.0513
Case Dismissed	0.204	0.208	0.189	0.196	0.140	0.594	0.203
ACD	0.196	0.169	0.298	0.261	0.243	0.0984	0.108
Guilty	0.579	0.601	0.497	0.543	0.607	0.303	0.636
Panel B: Case Characteristics							
Black Defendant	0.787	1	0	0.796	0.797	0.770	0.770
Defendant Age	34.01	34.02	33.98	34.12	33.12	32.92	35.28
	(12.84)	(12.97)	(12.34)	(12.69)	(13.32)	(12.32)	(12.35)
Defendant Male	0.819	0.825	0.800	0.874	0.756	0.780	0.861
	(0.385)	(0.380)	(0.400)	(0.331)	(0.429)	(0.414)	(0.346)
Prior Arrest	4.013	4.645	1.685	5.172	4.511	2.118	2.877
	(9.282)	(9.894)	(6.001)	(10.45)	(9.865)	(5.216)	(7.957)
Prior Felony Arrests	0.792	0.933	0.270	1.070	0.847	0.561	0.548
	(1.985)	(2.149)	(1.047)	(2.282)	(2.109)	(1.451)	(1.599)
Prior Convictions	4.152	4.804	1.747	5.280	4.888	1.732	2.865
	(9.873)	(10.54)	(6.305)	(11.10)	(10.42)	(5.017)	(8.612)
Prior Felony	0.214	0.253	0.0710	0.269	0.238	0.159	0.152
Convictions	(0.584)	(0.626)	(0.354)	(0.636)	(0.624)	(0.493)	(0.492)
Prior Jail Sentences	1.851	2.150	0.747	2.448	2.377	0.594	0.997
	(5.654)	(6.094)	(3.369)	(6.693)	(6.210)	(2.596)	(4.159)
Prior Incarcerations	0.135	0.160	0.0406	0.171	0.159	0.0882	0.0862
	(0.473)	(0.511)	(0.270)	(0.519)	(0.521)	(0.371)	(0.376)
Prior	2.146	2.470	0.952	2.637	2.337	1.036	1.759
Non-Incarceration Sentence	(4.899)	(5.188)	(3.384)	(5.105)	(4.884)	(2.703)	(5.059)
Black Prosecutor	0.136	0.137	0.133	0.142	0.136	0.133	0.133
Prosecutor Male	0.405	0.407	0.398	0.388	0.412	0.404	0.411
Observations	87,461	68,798	18,663	21,798	32,959	5,984	26,720

Mean coefficients; sd in parentheses

Notes: ACD stands for adjournment in contemplation of dismissal.

Table 2: Correlation Between Case Characteristics and Prosecutor Race

Panel A: Defendant Characteristics	Black Defendant	Defendant Age	Defendant Date of Birth	Male Defendant	Number Prior Arrests	Number Prior Felony Arrests	Number Prior Convictions	Number Prior Felony Convictions	Number Prior Jail Sentences	Number Prior Prison Sentences	Number Prior No-Incarceration Sentences
Black Prosecutor	0.00659	-0.0709	25.50	-0.00189	-0.0979	-0.00465	-0.162	-0.00232	-0.0966	-0.00107	-0.0642
	(0.00499)	(0.203)	(74.01)	(0.00533)	(0.154)	(0.0316)	(0.162)	(0.00674)	(0.0811)	(0.00480)	(0.0828)
Observations	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461
Outcome Mean	0.787	34.01	5645.7	0.819	4.013	0.792	4.152	0.214	1.851	0.135	2.146

Panel B: Case Characteristics	Number Arrest Charges	Number Arrest Counts	Class A Misdemeanor	Class B Misdemeanor	Class U Misdemeanor	Drug Crime	Property Crime	Person Crime	Other Crime
Black Prosecutor	-0.0227*	-0.0202	-0.00596	0.00712	-0.00116	0.00779	0.00701	-0.00459	-0.0102
	(0.0123)	(0.0143)	(0.00805)	(0.00772)	(0.00501)	(0.0112)	(0.0148)	(0.00568)	(0.00973)
Observations	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461	87,461
Outcome Mean	1.671	1.735	0.618	0.231	0.151	0.249	0.377	0.0684	0.306

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on *Black Prosecutor* from separate regressions of case and defendant characteristics on a binary variable representing prosecutor race. Each regression includes screening date fixed effects. Standard errors are clustered at the prosecutor level.

Table 3: Estimates of Opposite-Race Bias for Defendant Guilt

	(1)	(2)	(3)	(4)
Outcome: Guilty				
Black Defendant*White Prosecutor	0.0252**	0.0167*	0.0159	0.0259**
	(0.0115)	(0.00981)	(0.00975)	(0.0110)
Observations	87,461	87,461	87,461	87,461
Outcome Mean	0.579	0.579	0.579	0.579
Prosecutor and Defendant Race Indicators	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y
Case-Level Controls	N	Y	Y	Y
Prosecutor FE	N	N	Y	N
Interactions	N	N	N	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on the interaction of *Black Defendant* and *White Prosecutor* from the regression of *Guilty* on indicators for prosecutor race, defendant race, and the interaction term. Each specification includes screening date fixed effects. Column 2 adds controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode and gender of the prosecutor. Column 3 includes the same controls as column 2, with the exception of prosecutor gender, and adds individual prosecutor fixed effects. Column 4 adds interactions for every case and defendant control added in column 2, interacted with prosecutor race. Standard errors are clustered at the prosecutor level.

Table 4: Estimates of Opposite-Race Bias in Defendant Guilt by Crime Type

	(1)	(2)	(3)	(4)
Panel A: Drug Crimes				
Outcome: Guilty				
Black Defendant*White Prosecutor	0.0211	0.0149	0.0128	0.0129
	(0.0257)	(0.0228)	(0.0243)	(0.0274)
Observations	21,798	21,798	21,798	21,798
Outcome Mean	0.543	0.543	0.543	0.543
FDR q-value	0.825	0.633	0.824	0.948
Panel B: Person Crimes				
Outcome: Guilty				
Black Defendant*White Prosecutor	-0.0125	-0.0264	0.00211	-0.0130
	(0.0562)	(0.0552)	(0.0560)	(0.0585)
Observations	5,984	5,984	5,984	5,984
Outcome Mean	0.303	0.303	0.303	0.303
FDR q-value	0.825	0.633	0.824	0.97
Panel C: Other Crimes				
Outcome: Guilty				
Black Defendant*White Prosecutor	-0.00740	-0.0238	-0.0278	-0.0101
	(0.0199)	(0.0184)	(0.0191)	(0.0207)
Observations	26,720	26,720	26,720	26,720
Outcome Mean	0.636	0.636	0.636	0.636
FDR q-value	0.825	0.393	0.294	0.948
Panel D: Property Crimes				
Outcome: Guilty				
Black Defendant*White Prosecutor	0.0549***	0.0490***	0.0489***	0.0547***
	(0.0159)	(0.0133)	(0.0136)	(0.0144)
Observations	32,959	32,959	32,959	32,959
Outcome Mean	0.607	0.607	0.607	0.607
FDR q-value	0.002	0.001	0.003	0.002
Prosecutor and Defendant Race Indicators	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y
Case-Level Controls	N	Y	Y	Y
Interactions	N	N	Y	N
Prosecutor FE	N	N	N	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on the interaction of *Black Defendant* and *White Prosecutor* from the regression of *Guilty* on indicators for prosecutor race, defendant race, and the interaction term. Each specification includes screening date fixed effects. Column 2 adds controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode and prosecutor gender. Column 3 includes the same controls as column 2, with the exception of prosecutor gender, and adds individual prosecutor fixed effects. Column 4 adds interactions for every case and defendant control added in column 2, interacted with prosecutor race. Robust standard errors are clustered at the prosecutor level. False discovery rate (FDR) q-values are adjusted for multiple inference given the four categories of crime examined. FDR q-values are estimated using the method proposed by Anderson (2008) and are interpreted as two-sided p-values.

Table 5: Mechanism

	(1) Pretrial Detention	(2) Charges Increased	(3) Declined Prosecution	(4) Case Dismissed	(5) Adjournment in Contemplation of Dismissal
Panel A: Entire Sample					
Black Defendant*White Prosecutor	0.00646	0.00148	-0.00597*	-0.00652	-0.00975
	(0.00665)	(0.00560)	(0.00353)	(0.00792)	(0.0120)
Observations	87,461	87,461	87,461	87,461	87,461
Outcome Mean	0.0892	0.0501	0.0189	0.204	0.196
Panel B: Property Crimes					
Black Defendant*White Prosecutor	0.00529	0.00681	0.000923	-0.00631	-0.0450***
	(0.0120)	(0.00727)	(0.00328)	(0.0104)	(0.0162)
Observations	32,959	32,959	32,959	32,959	32,959
Outcome Mean	0.0862	0.0738	0.00865	0.140	0.243
Prosecutor and Defendant Race Indicators	Y	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y	Y
Case-Level Controls	Y	Y	Y	Y	Y
Prosecutor FE	N	N	N	N	N
Interactions	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on the interaction of *Black Defendant* and *White Prosecutor* from the regression of *Declined Prosecution*, *Pretrial Detention*, *Case Dismissed*, *Charges Increased*, and *Adjournment in Contemplation of Dismissal* on indicators for prosecutor race, defendant race, and the interaction term. All specifications include screening date fixed effects, controls, and prosecutor race interactions. Robust standard errors are clustered at the prosecutor level.

A Appendix

Table A1: Summary Statistics

	(1) All	(2) Black Defendants	(3) White Defendants	(4) Drug Crimes	(5) Property Crimes	(6) Person Crimes	(7) Other Crimes
Panel A: Outcomes							
Decline to Prosecute	0.0184	0.0197	0.0135	0	0.00840	0	0.0494
Charges Increased	0.0533	0.0555	0.0447	0.0232	0.0759	0.0916	0.0411
Pretrial Detention	0.0910	0.103	0.0502	0.0863	0.0889	0.210	0.0708
Case Dismissed	0.210	0.213	0.195	0.200	0.147	0.592	0.208
ACD	0.196	0.168	0.295	0.261	0.242	0.0986	0.110
Guilty	0.575	0.599	0.494	0.539	0.602	0.306	0.631
Panel B: Case Characteristics							
Black Defendant	0.786	1	0	0.796	0.796	0.769	0.770
Defendant Age	33.98	34.00	34.01	34.06	33.08	32.95	35.25
	(12.83)	(12.97)	(12.36)	(12.67)	(13.32)	(12.32)	(12.33)
Defendant Male	0.819	0.824	0.799	0.875	0.755	0.782	0.863
	(0.385)	(0.381)	(0.401)	(0.331)	(0.430)	(0.413)	(0.344)
Any Prior Arrests	0.497	0.569	0.250	0.604	0.516	0.414	0.408
	(0.500)	(0.495)	(0.433)	(0.489)	(0.500)	(0.493)	(0.492)
Prior Arrest	3.943	4.615	1.668	5.112	4.444	2.114	2.811
	(9.187)	(9.849)	(5.951)	(10.38)	(9.791)	(5.226)	(7.823)
Any Prior Conviction	0.440	0.507	0.213	0.522	0.462	0.345	0.368
	(0.496)	(0.500)	(0.409)	(0.500)	(0.499)	(0.475)	(0.482)
Prior Convictions	4.071	4.765	1.736	5.214	4.805	1.745	2.786
	(9.765)	(10.48)	(6.281)	(11.01)	(10.34)	(5.067)	(8.462)
Any Prior Incarceration	0.268	0.313	0.119	0.330	0.315	0.178	0.183
	(0.443)	(0.464)	(0.324)	(0.470)	(0.464)	(0.382)	(0.386)
Prior Incarcerations	1.946	2.291	0.786	2.585	2.491	0.693	1.052
	(5.739)	(6.212)	(3.468)	(6.770)	(6.345)	(2.729)	(4.197)
Black Prosecutor	0.136	0.137	0.133	0.142	0.136	0.132	0.133
	(0.343)	(0.344)	(0.340)	(0.349)	(0.343)	(0.339)	(0.340)
Prosecutor Male	0.410	0.412	0.403	0.392	0.418	0.405	0.415
	(0.492)	(0.492)	(0.490)	(0.488)	(0.493)	(0.491)	(0.493)
Missing Defendant Race	0.0163	0	0	0.00999	0.0130	0.0147	0.0257
	(0.127)	(0)	(0)	(0.0994)	(0.113)	(0.121)	(0.158)
Missing Prosecutor Race	0.0182	0.0180	0.0183	0.0136	0.0242	0.00570	0.0172
Observations	91,533	70,813	19,228	22,432	34,512	6,311	28,278

Mean coefficients; sd in parentheses

Table A2: The Effect of Prosecutor Race on Defendant Guilt

	(1)	(2)	(3)	(4)
	Guilty	Guilty	Guilty	Guilty
Panel A: Entire Sample				
Black Defendant	0.0933***	0.0694***	0.0693***	0.0688***
	(0.00513)	(0.00472)	(0.00472)	(0.00473)
White Prosecutor	0.0208*	0.0176*		
	(0.0118)	(0.0102)		
Observations	87,461	87,461	87,461	87,461
Outcome Mean	0.579	0.579	0.579	0.579
Panel B: Property Crimes				
Black Defendant	0.122***	0.0969***	0.0968***	0.0966***
	(0.00641)	(0.00632)	(0.00631)	(0.00623)
White Prosecutor	0.0273**	0.0187*		
	(0.0125)	(0.0103)		
Observations	32,959	32,959	32,959	32,959
Outcome Mean	0.607	0.607	0.607	0.607
Prosecutor and Defendant Race Indicators	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y
Case-Level Controls	N	Y	Y	Y
Prosecutor FE	N	N	N	Y
Interactions	N	N	Y	N

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on *White Prosecutor* from the regression of *Guilty* on an indicator for prosecutor race. Each specification includes screening date fixed effects. Column 2 adds controls for defendant race, age, date of birth, gender, number of arrest charges, number of arrest counts, number of prior arrests, number of prior felony arrests, number of prior convictions, number of prior felony arrests, number of prior jail sentences, number of prior incarcerations, number of prior non-incarceration sentences, misdemeanor type, drug crime, property crime, person crime, and arrest zipcode. Robust standard errors are clustered at the prosecutor level.

Table A3: Missing Values for Property Crimes

	Original Estimate	Missing Controls	Missing Crime Type		Missing Prosecutor Race		Missing Defendant Race					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
				Average [95% CI]							Average [95% CI]	
Outcome: Guilty												
Black Def*White Pros.	0.0547***	0.0545***	0.0592***	0.0590	0.0542***	0.0542***	0.0569***	0.0509***	0.0549***	0.0564***	0.0554	0.0549
	(0.0144)	(0.0144)	(0.0155)	[0.0547,0.0598]	(0.0145)	(0.0145)	(0.0147)	(0.0141)	(0.0145)	(0.0146)	[0.0501,0.0605]	[0.0498,0.0598]
Observations	32,959	32,991	34,330	34,330	32,959	32,959	33,385	33,385	33,385	33,385	32,959	32,959
Outcome Mean	0.607	0.607	0.583	0.583	0.607	0.607	0.606	0.606	0.606	0.606	0.607	0.607
Pros. & Def. Race Ind	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Case-Level Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Prosecutor FE	N	N	N	N	N	N	N	N	N	N	N	N
Interactions	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Missing Control Indicators	-	Y	Y	Y	-	-	-	-	-	-	-	-
Missing Defendant Race	-	-	-	-	-	-	Black	White	0.5 Black	0.79 Black	-	-
Missing Prosecutor Race	-	-	-	-	White	Black	-	-	-	-	White	White

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports the coefficient on the interaction of *Black Defendant* and *White Prosecutor* from the regression of *Guilty* on indicators for prosecutor race, defendant race, and the interaction term. All specifications include screening date fixed effects. Each specification also includes controls, and interactions, similar to column 4 in Table 3 and 4. Column 1 repeats the estimate for Table 4 panel D, column 4. Standard errors are clustered at the prosecutor level. Column 2 includes indicators for missing defendant characteristics. Columns 3 replaces all missing crime types as property crimes, and column 4 presents the average and 95 percent confidence interval from 10,000 iterations of randomly replacing crime type. Columns 5–6 replace missing prosecutor race as white or black respectively. Columns 7–10 replace missing defendant race as black, white, 0.5 black or 0.79 black (sample mean). Columns 11–12 present the average and 95 percent confidence interval from 10,000 iterations of randomly replacing defendant race.