Racial Disparities in Riverside County's Death Penalty System

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I. INTRODUCTION

1. This report presents my statistical analyses from two distinct but related studies focusing on death-penalty decision-making in Riverside County, California. The first study analyzed death-penalty prosecutorial charging practices and jury decision-making in Riverside County from 2006 through 2019 based on information from court documents and other official sources (hereafter the charging study). The second study examines broader death-sentencing trends in Riverside County from 1976 through 2018 using information gathered about death-sentencing and the Supplemental Homicide Report (SHR) (hereafter the SHR study). Before reviewing each study's methodology and statistical findings, I briefly introduce general methodological and conceptual issues pertinent to both studies.

II. ANALYSIS STRATEGY

Population Data on Death-Penalty Decision-Making

2. The charging study examines death-penalty prosecutorial charging and jury decision-making among the full *population* of court cases resulting from murders committed in Riverside County from 2006 through 2019, which includes over 800 defendants. Manslaughter cases were removed from the analysis as they are ineligible for the death penalty under Penal Code section 190.2. The SHR study examines a *population* of nearly 3,000 homicide incidents that occurred in Riverside County from 1976 through 2018. Homicide incident data was combined with a *population* of death verdicts in Riverside County from 1976 through 2018 to examine aggregate death-sentencing trends across all homicides during this period. Because the dataset for the SHR study does not contain information on charging decisions, the results of this study demonstrate broader death-sentencing trends rather than prosecutorial behavior. The SHR study complements the charging study by demonstrating larger patterns of possible racial[1] disparities in death-penalty outcomes for homicides in Riverside County across a much wider timeframe. As we shall see below, the fact that both of these studies utilize population data on death penalty decision-

[1] Throughout this report, I use the terms "race" and "racial" as shorthand for "race/ethnicity" and "racial/ethnic." While I acknowledge that Hispanic is an ethnicity rather than a racial category, I use the term "race" and "racial" for two reasons. First, both the charging and SHR datasets use the term "race" rather than "race/ethnicity." Second, much of the death penalty literature refers to "racial" rather than "race/ethnicity" disparities. Thus, the terms "race" and "racial" are more consistent with the data and prior literature.

making in California has important methodological implications for interpretations of statistical and practical significance.

Death-Penalty Decisions Analyzed

3. My analyses focus on three areas of death-penalty decision making: 1) special circumstance allegation filing, 2) death notice filing, and 3) death verdict. While the charging study examines all three of these decisions, the SHR study is limited to death verdicts due to the lack of publicly available state-wide data on special circumstance allegations and death notice filings.[2]

4. All three of these death penalty decisions are measured using binary variables, where the data were coded as "1" if the decision was present and "0" if otherwise.[3] For example, if a special circumstance allegation was filed, the variable was coded as "1" because it was present. In contrast, cases in which a special circumstance was not filed are coded as "0."

5. The first binary dependent variable I tracked was: Whether the prosecution alleged a special circumstance under Penal Code section 190.2.[4] Cases in which special circumstances were alleged were coded as "1." Cases in which no special circumstances were alleged were coded as "0." This is a critical decision in the death penalty process because it determines which cases become death-eligible under Penal Code section 190.2. The second binary dependent variable I tracked was: Whether the prosecution sought the death penalty (i.e., a death notice was filed). Cases in which the death penalty was sought were coded as "1." Cases in which the death penalty was not sought were coded as "0." This decision is central to determining whether a special circumstance allegation will become a capital case and thus has been the subject of extensive empirical analysis in other jurisdictions as well.[5] The third binary dependent variable I tracked

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[2] CCFAJ, *Official Recommendations on the Fair Administration of the Death Penalty in California* (2008), http://www.ccfaj.org/documents/reports/dp/official/FINAL%20REPORT%20DEATH%20PENALTY.pdf.

[3] "Binary" or "dichotomous" variables are categorical variables with only two categories, which are coded as "0" and "1." "Categorical" variables are those with multiple categories, each representing a different characteristic or group. For example, victim race is a categorical variable with three categories (0 = White, 1 = Hispanic, 2 = Black). The actual numeric values assigned to categorical variables do not influence regression results as they represent qualitative categories rather than precise numerical values. ALAN AGRESTI, ANALYSIS OF ORDINAL CATEGORICAL DATA (2010).

[4] All Penal Code citations herein are to California law.

[5] David Baldus, George Woodworth & Neil Weiner, *Perspectives, Approaches, and Future Directions in Death Penalty Proportionality Studies*, *in* THE FUTURE OF AMERICA'S DEATH PENALTY: AN AGENDA FOR THE NEXT GENERATION OF CAPITAL PUNISHMENT RESEARCH (Charles S. Lanier, William J. Bowers, & James R. Acker eds., 2009).

was: Whether the jury sentenced the defendant to death (i.e., a death verdict). Cases in which the jury rendered a death verdict were coded as "1." Cases in which a non-death verdict was rendered were coded as "0."

6. For the purposes of this research, a "death-eligible case" or "special circumstance case" refers to a case in which a special circumstance allegation enumerated in Penal Code section 190.2 was alleged by the prosecution. In contrast, a "capital case" or "death penalty case" refers to a case in which the prosecution sought the death penalty. Finally, a "death sentence" refers to a case wherein the prosecution sought the death penalty, and the jury rendered a death verdict. Thus, a "death sentence" case necessarily involves a death notice and special circumstance allegation, while a "capital case" or "death penalty case" necessarily involves a special circumstance allegation but may or may not result in a death penalty trial or a death verdict.

Statistical Estimation

7. To estimate the likelihood of a special circumstance allegation, death notice, or death sentence, I employed logistic regression models in these studies. I use regression models to analyze these data because they are the "most widely used vehicle for empirical analysis in economics and other social sciences," and they allow me to isolate the independent effect of victim/defendant race on death penalty outcomes for similarly situated cases.[6]

8. The regression analyses discussed below enabled me to test whether the likelihood of a prosecutor alleging a special circumstance or filing a death notice or the jury reaching a death verdict varies by race (of both the suspect/defendant and the victim), holding constant a host of non-racial factors that could influence death penalty decision-making by prosecutors and juries. This is necessary to ensure that any observed racial disparities are not spurious.[7] To the extent that legally relevant factors (e.g., number of victims, offense severity) correlate with race, my

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[6] Jeffrey Wooldridge, INTRODUCTORY ECONOMETRICS: A MODERN APPROACH (2012). As used here, "similarly-situated" refers to the fact that logistic regression models hold constant all of the non-racial predictors in the model, and thus regression estimates refer to cases that are mathematically similar in every other respect except for defendant race.

[7] "Spurious" is a term commonly used in quantitative analysis in the social sciences. A relationship is spurious if the link between an independent variable and the dependent variable is explained by variables other than those being analyzed. For example, the relationship between victim race and capital charging decisions would be spurious if it were explained by the number of homicide victims, but the number of homicide victims had not been included in the analysis. *Id.*

regression analyses account for these factors and isolate the independent effect of race on capital decision-making.

9. Regression models control for numerous non-racial factors (independent variables) that could impact death penalty decision-making (the dependent variable). In this context, the phrases "controlling for" or "holding constant" non-racial factors mean that the regression models compare the likelihood of a death penalty decision for two similarly situated defendants except for race. For example, with such an analysis, one can compare the likelihood that a Black, Hispanic, or White[8] defendant will receive a death notice in cases with similar independent variables corresponding to victim/defendant demographics (e.g., age, gender, etc.) and case characteristics (e.g., felony-murder charge, multiple-victim charge, etc.).

10. In statistical parlance, the dependent variable refers to "the main factor that you're trying to understand or predict,"[9] whereas independent variables are the "the factors you suspect have an impact on your dependent variable."[10] For the purposes of this report, the dependent variables analyzed correspond to death penalty outcomes: special circumstance allegation, death notice, or death verdict. In contrast, independent variables refer to victim/defendant demographics and case characteristics. Key independent variables of interest include victim/defendant race, as prior research has identified these are strong predictors of death penalty outcomes.[11]

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[8] Consistent with prior death penalty research, I use the term "Black" rather than "African-American" as the former is much broader in that it includes Black individuals who are not African-American such as Black immigrants. DAVID BALDUS, GEORGE WOODWORTH & CHARLES PULASKI, EQUAL JUSTICE AND THE DEATH PENALTY: A LEGAL AND EMPIRICAL ANALYSIS (1990); David Baldus et al., *Empirical Studies of Race and Geographic Discrimination in the Administration of the Death Penalty: A Primer on the Key Methodological Issues*, *in* THE FUTURE OF AMERICA'S DEATH PENALTY: AN AGENDA FOR THE NEXT GENERATION OF CAPITAL PUNISHMENT RESEARCH (Charles S. Lanier, William J. Bowers, & James R. Acker eds., 2009); Nick Petersen, *Examining the Sources of Racial Bias in Potentially Capital Cases A Case Study of Police and Prosecutorial Discretion*, RACE JUSTICE 2153368716645842 (2016); Nick Petersen, *Cumulative Racial and Ethnic Inequalities in Potentially Capital Cases: A Multistage Analysis of Pretrial Disparities*, CRIM. JUSTICE REV. 1–25 (2017); Baldus, Woodworth, and Weiner, *supra* note 5. I use the term "Hispanic" rather than "Latino" or "Latinx" because that is how it appears in the charging and SHR datasets.

[9] Amy Gallo, *A Refresher on Regression Analysis*, HARVARD BUSINESS REVIEW, 2015, https://hbr.org/2015/11/a-refresher-on-regression-analysis (last visited Jul 19, 2021).

[10] *Id.*

[11] BALDUS, WOODWORTH, AND PULASKI, *supra* note 8; Baldus et al., *supra* note 8; Petersen, *supra* note 8; Petersen, *supra* note 8; Baldus, Woodworth, and Weiner, *supra* note 5; Glenn Pierce & Michael Radelet, *Impact of Legally Inappropriate Factors on Death Sentencing for California Homicides, 1990-1999, The*, 46 ST. CLARA REV 1 (2005); Michael L. Radelet & Glenn L. Pierce, *Race and Death Sentencing in North Carolina, 1980-2007*, 89 NCL REV 2119 (2010).

11. Logistic regression is the specific type of regression used in both studies, as it is appropriate for binary dependent variables like those I used. It estimates the likelihood of a factor being "present" versus "absent" based on a series of predictors, where "presence" is coded as "1" and "absence" is coded as "0" (e.g., "1" if special circumstance alleged or "0" if none alleged).[12] Consistent with prior empirical research on the death penalty, I used logistic regression models to estimate the likelihood of having a special circumstance allegation, death notice, or death sentence by race while holding other non-racial predictors variables constant as described below. Logistic regressions are displayed as odds ratios where values larger than 1 indicate an increased likelihood of a case resulting in a particular death penalty outcome, whereas odds ratios less than 1 indicate a decreased likelihood of a homicide resulting in a particular death penalty outcome.[13] For the charging study, defendants represent the unit of analysis because the focus is on court case outcomes.[14] For the SHR study, the unit of analysis is the homicide incident because the SHR is an incident-based dataset.[15]

Predicted Probabilities

12. Results from logistic regression models are displayed as predicted probabilities to help visualize the relevant statistical comparisons and to improve the interpretability of my findings. Logistic regression models generate odds ratios, which can be difficult to interpret because there is no inherent scale for odds ratios as they represent nonlinear trends.[16] In contrast,

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12 BALDUS, WOODWORTH, AND PULASKI, *supra* note 8; Baldus, Woodworth, and Weiner, *supra* note 5; Baldus et al., *supra* note 8; WOOLDRIDGE, *supra* note 6.

13 For the purposes of this document, logistic regression estimates are discussed as percentage changes in terms of odds ratios, with 1 corresponding to equal odds (i.e., "no effect"). Binary variables estimated in a logistic equation can be interpreted as a percentage change in the odds/hazard using the following formula: 1-[(βxi) X 100]. For example, the odds of a homicide resulting in a death sentence are 73% higher for homicides with white victims than for those with black victims [1-($\beta_{0.27}$ X 100) = 73%] Baldus et al., *supra* note 8; WOOLDRIDGE, *supra* note 6..

14 By "unit of analysis," I mean that each row in the database corresponds to a defendant, regardless of the number of victims involved in the case. As such, multi-defendant cases produce separate rows for each defendant in the database. However, this does not imply that co-defendants within a single case are unrelated; clustered standard errors account for the presence of multiple defendants within a single court case. Baldus et al., *supra* note 8.

15 By "unit of analysis," I mean that each row in the database corresponds to a homicide incident, regardless of the number of victims involved in the homicide. As such, multi-suspect homicides produce separate rows for each suspect in the database since these result in separate court cases. Samuel R. Gross & Robert Mauro, *Patterns of Death: An Analysis of Racial Disparities in Capital Sentencing and Homicide Victimization*, STANFORD LAW REV. 27–153 (1984); Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

16 In a logistic regression model, odds (O) and probabilities (P) have the following relationship: Odds = P/1-P and Probability = O/1+O. Baldus, Woodworth, and Weiner, *supra* note 5.

predicted probabilities range from 0% to 100%, making them easier to interpret.[17] The use of predicted probabilities to display logistic regression analyses is helpful to overcome these interpretation difficulties and is common in my own published research[18] as well as the broader social scientific literature.[19] Predicted probabilities are calculated by "plugging in" the mean value for non-racial control variables into the model. Thus, predicted probabilities rates highlight the likelihood of a particular death penalty outcome among an "average" homicide that differs by victim or defendant race. That is, predicted probabilities display the likelihood of a particular death penalty outcome (special circumstance allegation, death notice, or death sentence) by victim/defendant race after controlling for (or net of) all the other non-racial variables in the logistic regression model. For example, the predicted probability of a Black defendant receiving a special circumstance in an "average" case is 34% according to Figure 4, net of other victim and defendant demographics, case characteristics, and other variables in the logistic regression model.

Adjusted vs. Unadjusted Results

13. Predicted probabilities described above correspond to "adjusted" statistics in the sense that the logistic regression models that "adjust" for important non-racial legal factors such as the presence of multiple victims or a felony. In contrast, "unadjusted" results correspond to the raw statistics for various measures without adjusting for other non-racial factors. For example,

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17 J. Scott Long & Jeremy Freese, REGRESSION MODELS FOR CATEGORICAL DEPENDENT VARIABLES USING STATA (Third Edition ed. 2014), https://www.stata.com/bookstore/regression-models-categorical-dependent-variables/ (last visited Nov 14, 2020); Alan C. Acock, A GENTLE INTRODUCTION TO STATA (3rd ed. 2013).

18 Petersen, *supra* note 8; Marisa Omori & Nick Petersen, *Institutionalizing Inequality in the Courts: Decomposing Racial and Ethnic Inequality in Detention, Conviction and Sentencing*, CRIMINOLOGY (2020); Nick Petersen, *Low-Level, but High Speed?: Assessing Pretrial Detention Effects on the Timing and Content of Misdemeanor versus Felony Guilty Pleas*, JUSTICE Q. DOI: 10.1080/07418825.2019.1639791 (2019); Brandon P. Martinez, Nick Petersen & Marisa Omori, *Time, Money, and Punishment: Institutional Racial-Ethnic Inequalities in Pretrial Detention and Case Outcomes*, CRIME DELINQUENCY 0011128719881600 (2019); George Wilson et al., *Particularism and racial mobility into privileged occupations*, 78 SOC. SCI. RES. 82–94 (2019); Petersen, *supra* note 8.

19 LONG AND FREESE, *supra* note 17. In this leading book on categorical data analysis, including logistic regression, Sociology Professors Scott Long and Jeremey Freese spend considerable time discussing the importance of predicted probabilities for making results more interpretable. In particular, they note: "Models for categorical outcomes are nonlinear, and this nonlinearity is the fundamental challenge that must be addressed for effective interpretation. Most simply, this means that you cannot effectively represent your model by presenting a list of estimated parameters. Instead, we believe the most effective way to interpret your models is by first fitting the model and then computing and estimating postestimation predictions [i.e., predicted probabilities] for the outcomes" *Id.* at p. 133. They go on to note that: "The primary methods for interpretation presented in this book are based on predictions from the model. The model is fit and the estimated parameters are used to make predictions at values of the independent variable that are (hopefully) useful for understanding the implications of the nonlinear model" *Id.* at p. 136.

Figure 1 below, showing the unadjusted results, indicates that 26% of all defendants charged with a special circumstance are Black, whereas the adjusted results in Figure 4 indicate that 41% of all special circumstance defendants are Black even after adjusting for other non-racial factors. Thus, after adjusting for other non-racial factors, Figure 4 suggests that Black defendants are even more overrepresented among those charged with a special circumstance.

Main Race Effects vs. Victim-Defendant Racial Dyad Interactions

14. Logistic regression analyses below occur in two major phases: 1) main effects of victim/defendant race independent of one another; 2) victim-defendant racial dyad interactions. As a baseline, I begin by examining the independent effects of victim/defendant race on death penalty outcomes to establish whether victims or defendants from particular racial groups are more or less likely to receive a special circumstance, death notice, or death sentence. Since prior research on the death penalty in California[20] and elsewhere[21] points to the interactive influence of victim/defendant racial groupings on case outcomes, I then examined interaction effects for victim/defendant racial dyads. Here, I examine whether victim and defendant race work together to shape death penalty outcomes. For example, whether cases with White victims and minority defendants are more likely to receive a death notice than cases with other victim-defendant racial dyads (e.g., White victims killed by White defendants, minority victims killed by White defendants, or minority victims killed by minority defendants). Using victim/defendant dyads is particularly important for understanding whether death penalty outcomes differ across intra- vs. inter-racial cases, net of other factors.[22]

Practical vs. Statistical Significance

15. Many scientific studies rely on statistical significance when discussing results from sample data. Statistical significance permits the researcher to extrapolate the results from their data analysis to locations and time frames beyond their dataset.[23] However, the American Statistical

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20 Petersen, *supra* note 8; Petersen, *supra* note 8.

21 Baldus et al., *supra* note 8; David Baldus & George Woodworth, *Race Discrimination and the Legitamacy of Capital Punishment: Reflections on the Interaction of Fact and Perception*, 53 DEPAUL REV 1411 (2003).

22 Petersen, *supra* note 8; Petersen, *supra* note 8.

23 In regression models, tests of statistical significance involve comparing the parameter estimate (β) for group 1 and group 2 based on the amount of variability in β from sample to sample. If β significantly differs from the null hypothesis value of β = 0 (i.e., "no effect") after taking into account sampling variability in β, this means that there is

Association (ASA) has sought to move away from focusing solely on statistical significance in recent years, noting that practical significance is also an essential consideration in any scientific study, particularly when researchers are analyzing population.[24] As such, my report includes discussions of both statistical *and* practical significance.

16. Focusing on practical significance is important given that the charging study involves a much smaller population of cases than the SHR study, making it more difficult to detect statistically significant relationships should they exist. Analyses with a smaller number of cases will necessarily have greater sampling variability,[25] as there is more variability across smaller groups being compared. This means that some of the charging study results may be too small to detect statistically significant relationships, should they exist. For example, regression models examining death notice filings and death verdicts among a much smaller sup-population of special circumstance cases may be unable to detect statistical significance should it exist. However, these smaller sub-populations are not a problem if one is simply describing the population of interest, as I am doing here, rather than making inferences to other possible sub-population "realizations."

17. Focusing on practical significance rather than statistical significance simply means that comparisons between races shed light on possible racial disparities for the particular location (Riverside County) and time periods of interest (2006-2019 and 1976-2018, respectively), and cannot necessarily be generalized to other possible historical/future "realizations" of the population. This approach is consistent with Professor Scott Phillips' analysis of death-penalty decision-making among a full population of homicide court cases from Harris County, Texas. As Phillips notes, "ignoring statistical significance in population data is legitimate and appropriate if a researcher is attempting to describe the population rather than draw inferences." [26] In such contexts, he explains, "researchers should focus more on substantive significance and less on

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a statistically significant difference that cannot be explained by random sampling variability as measured by sampling variability. In this regard, the major advantage of statistical significance is that it allows researchers to make inferences about a population based on sample data since the sampling variability is factored into the equation. WOOLDRIDGE, *supra* note 6; ACOCK, *supra* note 17. In the death penalty context, p-values correspond to the probability that "a [racial] disparity could occur by chance." Baldus et al., *supra* note 8 at 171. In the social sciences, p-values less than 0.05 are typically considered "statistically significant."

[24] Ronald L. Wasserstein & Nicole A. Lazar, *The ASA Statement on p-Values: Context, Process, and Purpose*, 70 AM. STAT. 129–133 (2016).

[25] Finlay and Agresti note that sampling variability, as measured by the standard error, decreases as the sample size increases, making it more difficult to detect statistically significant relationships should they exist. BARBARA FINLAY & A. AGRESTI, STATISTICAL METHODS FOR THE SOCIAL SCIENCES 92 (2009).

[26] Scott Phillips, *Status disparities in the capital of capital punishment*, 43 LAW SOC. REV. 807–838, 821 (2009).

statistical significance." [27] Following his advice, I focus more on practical significance, although I do highlight statistically significant relationships as well.

III. THE CHARGING STUDY

Data and Methodology

18. This study examines whether victim and defendant racial disparities exist among death penalty charging and sentencing decisions for adult murder[28] cases in Riverside County, California, from 2006 to 2019.[29] In 2020, the State Public Defender obtained a list of murders committed in Riverside County between 2006 and 2019 from the Riverside County District Attorney (DA) Office with information about whether each murder involved a special circumstance allegation or death notice. Using this list, electronic dockets were pulled for each case via the Riverside County Clerk of Court's website. Data on court decisions (e.g., charges, disposition, etc.) were obtained from these electronic dockets and were entered into an electronic spreadsheet. In addition, data on death sentences were obtained from the State Public Defender's Office. Finally, these death penalty data were merged with a California Department of Justice database containing information on murder victim demographics and incident characteristics.[30] By combining these data sources, a comprehensive dataset tracking death penalty charging decisions for all murders charged in Riverside County from 2006 to 2019 was constructed.

Dependent variables:

19. As previously noted, the charging study examines three death-penalty decisions: 1) special circumstance allegation, 2) death notice filing, and 3) death verdict. These outcomes represent binary variables coded as described above.

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27 *Id.* at 821.

28 I removed non-murder homicide cases (i.e., manslaughter) because they are not death penalty eligible under Penal Code section 190.2. CCFAJ, *supra* note 2.

29 I removed cases with offenders less than 18 years old since California's death penalty does not apply to juvenile defendants. Penal Code section 190.5 (a) notes that "the death penalty shall not be imposed upon any person who is under the age of 18 at the time of the commission of the crime."

30 CDOJ, *Homicide*, OPENJUSTICE (2021), https://openjustice.doj.ca.gov/data (last visited Aug 23, 2021).

Victim and Defendant Race:

20. Victim and defendant race was coded using a series of categorical variables: 0 = White ("reference" group), 1 = Hispanic, 2 = Black.[31] White victims/defendants represent the "reference" group, meaning that the regression estimates directly compare data for Black and Hispanic victims/defendants to the data for White victims/defendants. Like Pierce and Radelet[32], I limit the sample to murders involving victims and defendants that are White, Black, and Hispanic.

Case Characteristics from Court Files:

21. Consistent with prior research, I measured various features of the case using information from court files obtained from the Riverside County Clerk of Court's website.[33] Using a binary variable, I controlled for the presence of co-defendants in a case (1=co-defendant case, 0=single defendant case) because prosecutors may be more likely to offer a charge or a sentence reduction where one co-defendant cooperates with the prosecution.[34] As a continuous measure of offense severity, I controlled for the number of criminal counts charged related to non-murder offenses (e.g., possession of controlled substance, firearm violations, etc.); this variable was log-transformed to reduce skewness in its distribution. The special circumstances of murder while engaged in the commission of a felony[35] and multiple-murder[36] are among the most commonly

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[31] Following prior research, I coded multiple-victim cases with at least one White victim as "White-victim" cases and multiple-victim cases with at least one Black victim but no White victims as "Black-victim" cases. For example, a case involving one White victim and one Hispanic victim would be coded as a "White-victim" case since at least one White victim was killed in the case, whereas a case with one Black victim and one Hispanic victim would be coded as a "Black-victim" case since the case involved at least one Black victim and no White victims. For a similar approach, see Gross and Mauro, *supra* note 15; Petersen, *supra* note 8; Petersen, *supra* note 8.

[32] Pierce and Radelet, *supra* note 11.

[33] David Baldus & George Woodworth, *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2003); BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.

[34] CCFAJ, *supra* note 2.

[35] Penal Code, § 190.2(a)(17).

[36] Penal Code § 190.2(a)(3).

filed special circumstances in California and other states,[37] so I included binary variables that captured whether the case involved a contemporaneous felony or multiple murder victims.[38]

22. Given the importance of prior criminal history in shaping case outcomes,[39] I controlled for various forms of prior criminality in the logistic regression models. Although the Riverside County electronic case files do not contain a complete criminal history record for each defendant, I rely on charging and sentencing enhancements as a proxy for criminal history. In particular, I constructed a binary variable measuring whether the defendants' charges or sentencing enhancements indicated a pattern of prior criminal history (1=prior criminal history alleged, 0=no prior criminal history alleged). Examples of charges and enhancements used to define this binary variable included the following: "Carry loaded firearm having prior felony convictions" PC25850(C)(1), "Convicted felon and narcotic addict own or possesses firearm" PC29800(A)(1), "Habitual Offender" PC667(A)(1), "Prior Felony Conviction" PC1202(E)(5), "Prior serious felony conviction" PC667, etc.

23. Since some murder cases were still being actively litigated when data collection commenced, I controlled for whether the case was active (1=yes, 0=no) at the time of data collection. Because all the pending cases included a special circumstance allegation, I dropped these cases from the analysis predicting the likelihood of a special circumstance filing. In contrast, for the models predicting the filing of a death notice or rendering of a death sentence, I include the aforementioned binary variable measuring whether the case was active. Since all the pending cases involved a special circumstance allegation, it was not possible to control for case status in a regression model predicting the likelihood of a special circumstance filing due to issues of perfect prediction (i.e., active case status perfectly predicts the presence of a special circumstance because

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37 James Acker & Charles Lanier, *Aggravating circumstances and capital punishment law: Rhetoric or real reforms*, 29 CRIM. LAW BULL. 467–501 (1993); Ellen Kreitzberg, *A Review of Special Circumstances in California Death Penalty Cases* (2008), http://www.ccfaj.org/documents/ reports/dp/ expert/Kreitzberg.pdf; Nick Petersen & Mona Lynch, *Prosecutorial Discretion, Hidden Costs, and the Death Penalty: The Case of Los Angeles County*, 102 J. CRIM. LAW CRIMINOL. 1233 (2013); Ruth D. Peterson & William C. Bailey, *Felony murder and capital punishment: An examination of the deterrence question*, 29 CRIMINOLOGY 367 (1991); Steven F. Shatz, *Eighth Amendment, the Death Penalty, and Ordinary Robbery-Burglary Murderers: A California Case Study, The*, 59 FLA REV 719 (2007); Steven F. Shatz & Nina Rivkind, *California Death Penalty Scheme: Requiem for Furman, The*, 72 NYUL REV 1283 (1997).

38 These refer to the presence of a co-occurring felony or multiple murder victims, not necessarily the filing of that special circumstance for those factors under PC § 190.2(a)(17) or PC § 190.2(a)(3), respectively. Thus, these variables measure whether a felony or multiple murder special circumstance *could* be alleged based on the case facts, not whether *it* was alleged.

39 BALDUS, WOODWORTH, AND PULASKI, *supra* note 8; Baldus and Woodworth, *supra* note 33.

only special circumstance cases were pending). Given that that regression models cannot estimate the likelihood of an outcome (special circumstance) for a variable (case status) that is perfectly correlated with the outcome variable (i.e., there is no variation),[40] pending cases were dropped from regression models predicting the filing of a special circumstance allegation. In contrast, case status was included in the regression models predicting the likelihood a death notice or death verdict because whether a case was pending did not perfectly predict whether a death notice was alleged or a death sentence was rendered. In other words, among the pool of special circumstance cases, some pending cases resulted in a death notice or death sentence while others did not, making it possible to estimate whether case status influenced these outcomes. In the end, the substantive conclusions outlined below regarding the impact of victim/defendant race do not differ depending on whether I control for case status in the regression models or exclude these cases from the analysis.[41] Thus, my results are robust to the inclusion or exclusion of pending cases.

DOJ Victim and Case Characteristics:

24. In addition to variables drawn from the court files and DA records, information on victim demographics and case characteristics were derived from the California Department of Justice (DOJ) homicide database.[42] Information gathered from the DOJ dataset included: victim age (measured in years), victim gender (1=male, 0=female), murder weapon (1=firearm, 2=knife, 3=other weapons), location (1=street, 2=residence, 3=other locations), and victim-offender relationship (1=stranger, 2=relationship unknown, 3=family member).[43]

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40 LONG AND FREESE, *supra* note 17.

41 In supplementary models excluding pending cases, the results for defendant/victim race the results are similar to those outlined below. In these supplementary models, Black defendants are more likely to receive a death notice (β=11.14, $p<.05$) or a death sentence (β=15.30, $p<.10$) compared to White defendants. Similarly, Hispanic defendants are more likely to receive a death notice (β=3.90, $p>.10$) or a death sentence (β=7.53, $p>.10$) compared to White defendants. Compared to cases with White victims, the supplementary models also indicate that cases with Black victims are less likely to result in a death notice (β=0.61, $p>.10$) or a death sentence (β=0.33, $p>.10$), whereas cases with Hispanic victims are slightly more likely to result in a death notice (β=1.04, $p>.10$) but less likely to result in a death sentence (β=0.36, $p>.10$).

42 CDOJ, *supra* note 30.

43 For multi-victim cases, the average age was used to calculate victim age, and the most common value (i.e., the mode) was used in the case of categorical variables pertaining to case characteristics. For example, a case with a 40-year-old and a 30-year-old victim would have an average victim age of 35 (i.e., [40+30]/2=35). Similarly, a case with three victims where two were killed by a firearm and one victim was killed by a knife would be coded as a "firearm" case since firearm usage represents the most common means of death (i.e., the mode). Given prior research indicating that cases with female victims are more likely to be prosecuted capitally or result in a death sentence, any case with at least one female victim was coded as a "female" victim case. For instance, a case with one female victim and one

25. Since the DOJ database does not include victim or perpetrator names, I used probabilistic matching to merge these data to the official court records. In particular, I used the "reclink2" package in a statistical software called "Stata"[44] to link these datasets based on the following variables: offense date, victim race, police agency, multiple victims, a concomitant felony (arson, robbery, burglary, kidnapping, rape, or other sex crime), street gang murder, murder for financial gain, murder by poison, murder of a police officer, or murder involving torture. While my "reclink2" algorithm allows for probability matching for most of these characteristics, it required a perfect match for the county and homicide offense date (month and year).[45] Probability matching is commonly used in various social sciences when an exact match cannot be achieved, such as linking names with misspellings or variations in street address names.[46] Moreover, probability matching has been used in previous death penalty studies to link capital cases to homicide data.[47]

26. Using this approach, I was able to match 75% of cases between DOJ and death penalty datasets. For the remaining 25% of court cases where no appropriate match was found in the DOJ data, multiple imputation was used to address this missing data. Multiple imputation was also used to address missing data for victim race (4.74%) in the original death penalty dataset derived from electronic court files. Ten imputed datasets, that is, datasets that replace missing values with a predicted value based on a series of independent variables (also known as multiple imputation),[48] were constructed as this amount is sufficient to introduce random error into the

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male victim would be coded as a "female" victim case because at least one victim was a female, whereas a case with two male victims would coded as a "male" victim case since no female victims were killed in the case. Marian R. Williams, Stephen Demuth & Jefferson E. Holcomb, *Understanding the influence of victim gender in death penalty cases: the importance of victim race, sex-related victimization, and jury decision making*, 45 CRIMINOLOGY 865–891 (2007).

44 Nada Wasi & Aaron Flaaen, *Record linkage using Stata: Preprocessing, linking, and reviewing utilities*, 15 STATA J. 672–697 (2015).

45 In a "reclink2" algorithm using the default minimum match score of .75, I force the county and homicide date (month and year) to match exactly by including them in the "required" subcommand. Moreover, I assigned greater matching weights using the "wmatch" subcommand to victim race, multiple homicide victims, felony murder, number of suspects, lewd/lascivious, poison, and arson, while assigning lesser weight to carjacking, rape, robbery, or gang activity. Per Wasi and Flaaen's advice, a visual inspection of each homicide with matched ties was conducted using Stata's clinical review package "clrevmatch." *Id.*

46 *Id.*

47 Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

48 Specifically, chained multiple imputation equations were used in Stata via the "mi impute chained" command. All of the variables in the logistic regression models were included in the multiple imputation equation as well as the dependent variable because doing so improves model specification. ACOCK, *supra* note 17; Alan C. Acock, *Working with missing values*, 67 J. MARRIAGE FAM. 1012–1028 (2005).

process.[49] The multiple imputation equation included the following binary variables as predictors: special circumstance allegation filed (1=yes, 0=no), multiple special circumstance allegations filed (1=yes, 0=no), multiple defendants (1=yes, 0=no), and multiple victims (1=yes, 0=no).

Analysis Strategy:

27. As previously noted, logistic regression models were employed given the categorical nature of the dependent variables. Logistic regressions predicting the likelihood of a special circumstance filing included all murders occurring in Riverside County between 2006 and 2019 because prior research indicates that most California murders are potentially eligible for at least one special circumstance under Penal Code section 190.2.[50] In contrast, since a death notice or death sentence is only applicable in cases involving at least one special circumstance under Penal Code section 190.2, I limit my analyses of death notice or death sentence decisions to cases where the prosecution alleged at least one special circumstance. Thus, I use the prosecutorial filing of a special circumstance to define death penalty eligibility. In this way, I take prosecutorial special circumstance filings at face value[51], asking whether racial disparities exist in death notice filings and death sentencing among the pool of cases that prosecutors themselves determined were death-eligible.

28. Given this two-stage selection process leading to death notice filings and death sentences, I utilize a two-part modeling approach consistent with prior research.[52] First, I estimated

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49 Joseph L. Schafer, *Multiple Imputation: A Primer*, 8 STAT. METHODS MED. RES. 3–15 (1999); Xia Wang & Daniel P. Mears, *Examining the direct and interactive effects of changes in racial and ethnic threat on sentencing decisions*, J. RES. CRIME DELINQUENCY (2010); Xia Wang & Daniel P. Mears, *A multilevel test of minority threat effects on sentencing*, 26 J. QUANT. CRIMINOL. 191–215 (2010).

50 Shatz, *supra* note 37; Shatz and Rivkind, *supra* note 37; CCFAJ, *supra* note 2.

51 By "face value," I simply mean that I am agnostic about how prosecutors define death penalty eligibility based on special circumstance filling. Thus, while I acknowledge and test whether there are racial disparities in special circumstance filings, I am merely using the prosecutorial filing of a special circumstance to define death-eligibility.

52 For a similar approach, see Stephen Demuth, *Racial and Ethnic Differences in Pretrial Release Decisions and Outcomes: A Comparison of Hispanic, Black, and White Felony Arrestees*, 41 CRIMINOLOGY 873–908 (2003); Thomas J. Keil & Gennaro F. Vito, *Race and the death penalty in Kentucky murder trials: An analysis of post-Gregg outcomes*, 7 JUSTICE Q. 189–207 (1990); Michael J. Leiber & Kristan C. Fox, *Race and the impact of detention on juvenile justice decision making*, 51 CRIME DELINQUENCY 470–497 (2005); Michael J. Leiber & Kristin Y. Mack, *The individual and joint effects of race, gender, and family status on juvenile justice decision-making*, 40 J. RES. CRIME DELINQUENCY 34–70 (2003); Nancy Rodriguez, *The cumulative effect of race and ethnicity in juvenile court outcomes and why preadjudication detention matters*, 47 J. RES. CRIME DELINQUENCY 391–413 (2010); Sara Steen, Rodney L. Engen & Randy R. Gainey, *Images of Danger and Culpability: Racial Stereotyping, Case Processing, and Criminal Sentencing*, 43 CRIMINOLOGY 435–468 (2005); Darrell Steffensmeier & Stephen Demuth, *Ethnicity and Judges' Sentencing*

the likelihood of a special circumstance filing for all murder cases in Riverside County from 2006 through 2019 and then used the predicted probabilities to calculate the hazard rate of a special circumstance filing. Second, among the sub-population of cases resulting in a special circumstance, I used the hazard rate of a special circumstance allegation as a predictor for the filing of a death notice or death sentence. One major benefit of this two-part analysis approach is the ability to control for selection bias.[53]

29. Logistic regression models utilized clustered standard errors at the case level. Clustered standard errors allow me to account for the fact that two defendants from the same case are likely more similar to each other than two defendants from different cases since they may share common characteristics (e.g., same victim, same offense circumstances).[54]

30. While 0.05 p-value cut-off levels are commonly used in the social sciences[55], given the small sample size of the charging study, I use the 0.1 p-value level to evaluate claims of statistical significance. Increasing the p-value cut-off level from 0.05 to 0.1 is commonly done in studies with small sample sizes[56], including death penalty analyses presented to Supreme Courts in other states.[57]

Decisions: Hispanic-Black-White Comparisons, 39 CRIMINOLOGY 145–178 (2001); Jeffery T. Ulmer & Brian Johnson, *Sentencing in context: A multilevel analysis*, 42 CRIMINOLOGY 137–178 (2004).

53 Selection bias arises when researchers rely on information from a non-random sub-sample of the population. This type of bias is amplified when observations are selected in a way that is not independent from the outcome of interest. Richard Berk, *An introduction to sample selection bias in sociological data*, AM. SOCIOL. REV. 386–398 (1983); Shawn Bushway, Brian D. Johnson & Lee Ann Slocum, *Is the magic still there? The use of the Heckman two-step correction for selection bias in criminology*, 23 J. QUANT. CRIMINOL. 151–178 (2007). In the research presented here, the inclusion of the hazard rate of arrest helps to mitigate the potential of selection bias by explicitly modeling the process by which homicide cases enter into the criminal justice system.

54 Clustered standard errors allow for intergroup correlation, relaxing the usual regression assumption of statistically independent observations when constructing standard errors. More specifically, this technique applies a weighting algorithm when calculating the standard errors that take into account the intergroup correlation between observations in the same group (i.e., "cluster"). WOOLDRIDGE, *supra* note 6.

55 FINLAY AND AGRESTI, *supra* note 25; ACOCK, *supra* note 17.

56 FINLAY AND AGRESTI, *supra* note 25; ACOCK, *supra* note 17.

57 State v. Gregory, , 427 P 3d 621 (2018); Katherine Beckett & Heather Evans, *Race, death, and justice: Capital sentencing in Washington state, 1981-2014*, 6 COLUM J RACE L 77, 1981–2014 (2016).

Results

Unadjusted Summary Statistics:

31. Table 1 shows "unadjusted" summary statistics. That is, Table 1 lists the raw statistics for various measures without controlling for any other variables. Roughly 35% of all Riverside County murder cases involved a special circumstance from 2006 to 2019, while 10% involved a death notice and 3% resulted in a death sentence. Among special circumstance cases, 28% involved a death notice, and 8% resulted in a death sentence. Finally, 29% of death notice cases result in a death sentence. Thus, death notices and death sentences are relatively rare occurrences, even among special circumstance cases.

Table 1. Summary Statistics for Death Penalty Outcomes in Riverside County.

	(1) All murders	(2) Special circumstance	(3) Death notice	(4) Death sentence
Death penalty outcomes:				
Special circumstance	35%	100%	100%	100%
Death notice	10%	28%	100%	100%
Death sentence (yes/no)	3%	8%	28%	100%
Defendant race:				
Black defendant	20%	26%	39%	36%
Hispanic defendant	55%	55%	52%	60%
White defendant	25%	18%	9%	4%
Prior criminal history enhancement	12%	17%	27%	32%
Victim race:				
Black victim	16%	18%	26%	20%
Hispanic victim	49%	49%	47%	40%
White victim	35%	32%	27%	40%
Victim age	34.7875	33.8998	34.1192	28.6562
Male victim	70%	69%	62%	68%
Multiple victims	13%	23%	31%	36%
Multiple defendants	19%	33%	29%	36%
log # non-murder charges	1.4123	1.7617	1.9515	2.031
Case characteristics:				
Death-eligible felony	8%	14%	17%	16%
Pending case	6%	18%	21%	12%
Weapon: Firearm	43%	49%	48%	44%
Weapon: Knife	15%	11%	13%	20%
Weapon: other	42%	40%	38%	36%
Victim-defendant relationship: stranger	23%	30%	34%	36%
Victim-defendant relationship: family	17%	12%	12%	20%
Victim-defendant relationship: other	41%	40%	33%	32%
Victim-defendant relationship: unknown	19%	17%	21%	12%
Location: residence	42%	44%	52%	48%
Location: street	20%	22%	20%	24%
Location: other	38%	33%	28%	28%

32. Figure 1 and Figure 2 show opposing trends with respect to death penalty outcomes for White victims and White defendants. Across the stages of the death penalty process, the percentage of White victims slightly increases, while the percentage of White defendants dramatically decreases. On the other hand, we see a large increase in the percentage of Black defendants across the stages and a smaller increase in the percentage of Black victims. For example, 20% of all cases involve a Black defendant, yet 39% and 36% of death notice and death

verdict cases (respectively) involve a Black defendant. We see some changes in the percentage of Hispanic victims and defendants across the death penalty process, although the changes are much smaller compared to the differences between Whites and Blacks.

Figure 1. Unadjusted Defendant Racial Breakdown by Outcome

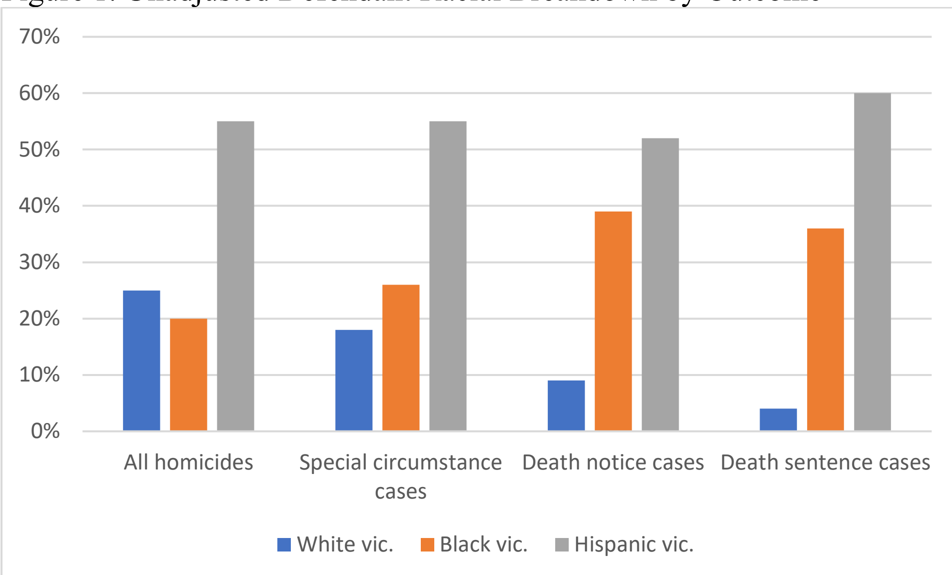
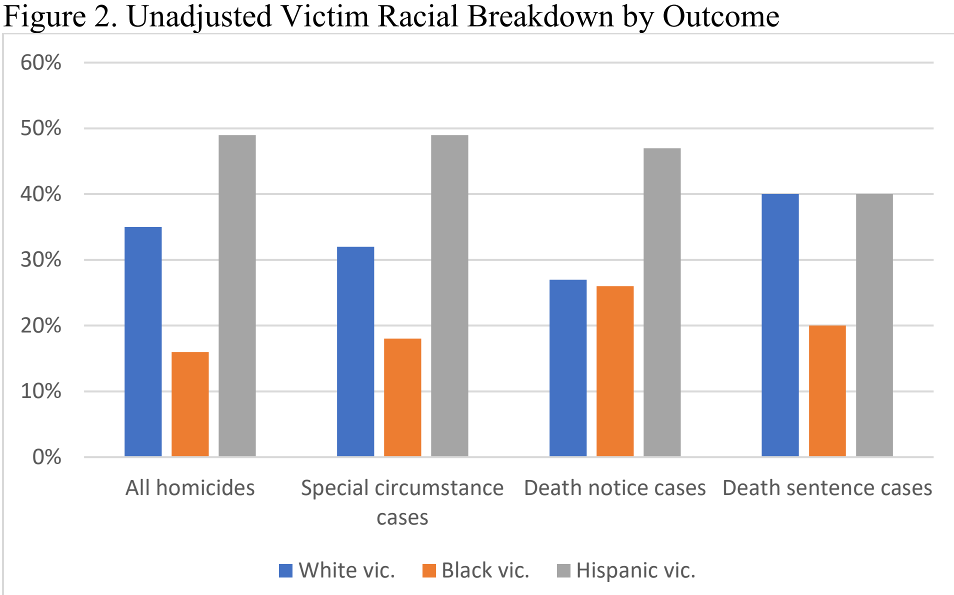


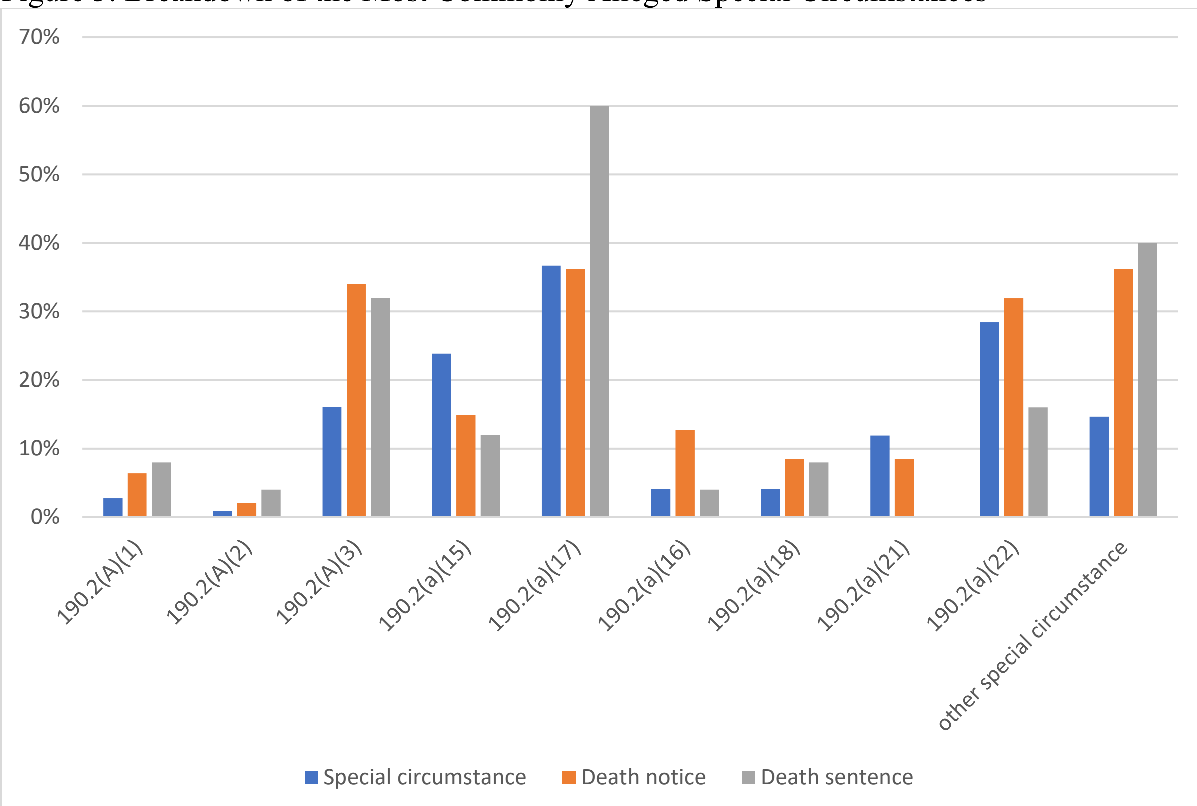
Figure 2. Unadjusted Victim Racial Breakdown by Outcome



33. Figure 3 displays the most commonly alleged special circumstances in Riverside County. These include 190.2(a)(3) - multiple victims, 190.2(a)(15) - lying in wait, 190.2(a)(17) -

felony murder, 190.2(a)(21) - drive-by murder, 190.2(a)(22) - street gang, and other special circumstances. Among death notice cases, the most commonly alleged special circumstances are 190.2(a)(3) - multiple victims, 190.2(a)(17) - felony murder, 190.2(a)(21) - drive-by murder, 190.2(a)(22) - street gang.

Figure 3. Breakdown of the Most Commonly Alleged Special Circumstances



Main Effects of Victim and Defendant Race:

34. Next, I turn to "adjusted" regression estimates in Table 2. These are "adjusted" in the sense that the regression models control for other important legal factors such as the presence of multiple victims or a felony. According to logistic models, murders involving multiple victims or a felony are more likely to result in a special circumstance, death notice, and death sentence. These findings are consistent with California's death penalty laws, which suggest that murders with multiple victims [PC190.2(a)(3)] or a felony [PC190.2(a)(17)] are more aggravated, and thus are eligible for the death penalty.

35. Even after controlling for these important legal factors, however, defendant race shapes death penalty outcomes in Table 2. Compared to White defendants, Black defendants are 1.71 times more likely to be charged with a special circumstance, are 9.06 times more likely to receive a death notice, and are 14.09 times more likely to be sentenced to death. All these White-Black disparities are statistically significant at the 0.1 p-value level (i.e., $p < 0.1$), meaning that there is less than a 10% chance of obtaining these results by random chance.[58] Compared to White defendants, Hispanic defendants are 1.08 times more likely to be charged with a special circumstance, are 3.73 times more likely to receive a death notice, and are 10.85 times more likely to be sentenced to death. While White-Hispanic disparities are only statistically significant at the 0.1 p-value level for the death sentence model, this is due to the large standard errors derived from this small sub-population of the 313 special circumstance defendants. However, as we shall see below, many of these disparities are quite stark in practical terms, as illustrated by the predicted probabilities.

36. Table 2 also highlights racial disparities based on victim race, particularly when comparing Black and White victims. Compared to cases with White victims, cases with Black victims are 1% less likely to involve a special circumstance, are 5 % less likely to involve a death notice, and are 61% less likely to result in a death sentence. Compared to cases with White victims, cases with Hispanic victims are 13% more likely to involve a special circumstance, are 9% more likely to involve a death notice, and are 66% less likely to result in a death sentence. None of these differences are statistically significant at the 0.1 p-value level. Again, this is most likely due to the small number of murders examined. That being said, the predicted probabilities below highlight significant victim race disparities in practical terms.

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58 FINLAY AND AGRESTI, *supra* note 25; BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.

Table 2. Logistic Regressions Predicting Death Penalty Outcomes in Riverside County.

Model #	(1)	(2)	(3)
Population	All charged murders	Special circumstance murders	
Outcome	Special circumstance	Death notice	Death sentence
	OR(SE)	OR(SE)	OR(SE)
Defendant demographics:			
Black defendant	1.71* (0.53)	9.06** (8.49)	14.09* (20.85)
Hispanic defendant	1.08 (0.30)	3.73 (3.07)	10.85* (15.26)
Prior criminal history enhancement	0.82 (0.22)	1.81 (0.77)	3.68* (2.69)
Victim demographics:			
Black victim	0.99 (0.32)	0.95 (0.62)	0.39 (0.35)
Hispanic victim	1.13 (0.30)	1.09 (0.54)	0.34 (0.23)
Victim age	1.00 (0.01)	1.00 (0.01)	0.97 (0.02)
Male victim	0.62* (0.17)	0.46 (0.27)	0.64 (0.52)
Case characteristics:			
Multiple victims	1.81** (0.50)	2.59* (1.34)	2.73 (1.94)
Multiple defendants	3.34*** (0.71)	1.07 (0.73)	3.09 (3.09)
Death-eligible felony	1.90* (0.73)	2.49 (1.59)	2.13 (2.03)
Pending case		1.42 (0.66)	0.45 (0.32)
Weapon: Firearm	1.24 (0.29)	1.14 (0.50)	1.03 (0.81)
Weapon: Knife	0.91 (0.31)	2.50 (1.47)	2.84 (2.14)
Victim-defendant relationship: stranger	2.79** (1.14)	0.98 (0.96)	0.78 (0.95)
Victim-defendant relationship: other	2.14** (0.74)	0.36 (0.33)	0.31 (0.34)
Victim-defendant relationship: unknown	1.45 (0.62)	0.77 (0.73)	0.16 (0.22)
log # non-murder charges	2.72*** (0.45)	2.69* (1.57)	2.67 (2.15)
Location: residence	1.64* (0.46)	1.19 (0.70)	1.11 (1.00)
Location: street	1.69* (0.51)	1.13 (0.67)	1.40 (1.22)
Hazard rate: special circumstance		2.58 (2.28)	3.80 (4.39)
Observations	836	313	313

Exponentiated coefficients; Standard errors in parentheses
Notes: Listwise deleted sample. Reference groups = White victim; White defendant; not a death-eligible felony; single victim; single defendant case; other murder weapons; family victim-offender relationship; other incident locations.
* p < .10, ** p < .05, *** p < .01

37. While predicted probabilities reveal both defendant and victim racial disparities in special circumstance filing, the victim-based racial disparities are much smaller in scale. According to Figure 4, Black defendants are more than 10% more likely to receive a special circumstance than White defendants, net of other factors. Similarly, Hispanic defendants are slightly more likely to receive a special circumstance than White defendants, although the disparity is much smaller at only 2%. Turning to victim race in Figure 5, we see that cases with Hispanic

victims are most likely to involve a special circumstance (27%), followed by those with a White (26%) and Black (25%) victim.

Figure 4. Predicted Probability of Special Circumstance by Defendant Race

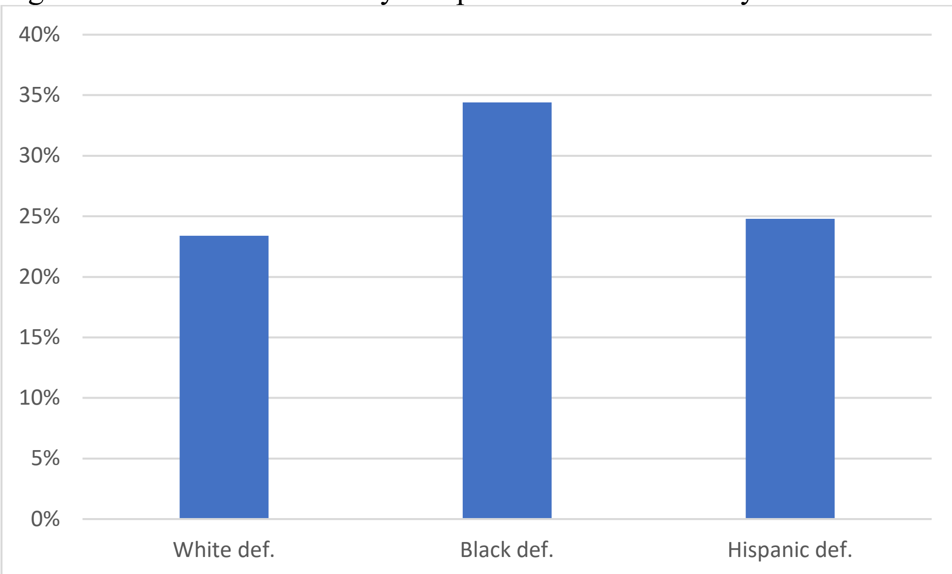
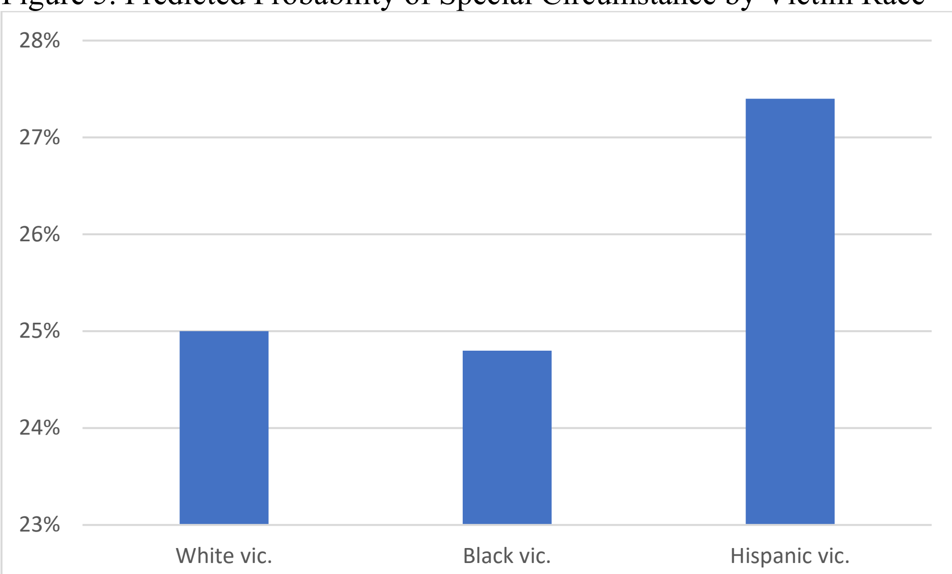


Figure 5. Predicted Probability of Special Circumstance by Victim Race



38. Similar disparities emerge when explaining death notice filing. Figure 6 indicates that cases with Black (46%) or Hispanic (25%) defendants are more likely to involve a death notice than those with a White defendant (8%). In contrast, racial disparities in death notice filing

displayed in Figure 7 are smaller for cases involving White (27%) victims compared to those with Black (22%) or Hispanic (25%) victims.

Figure 6. Predicted Probability of the Death Notice by Defendant Race

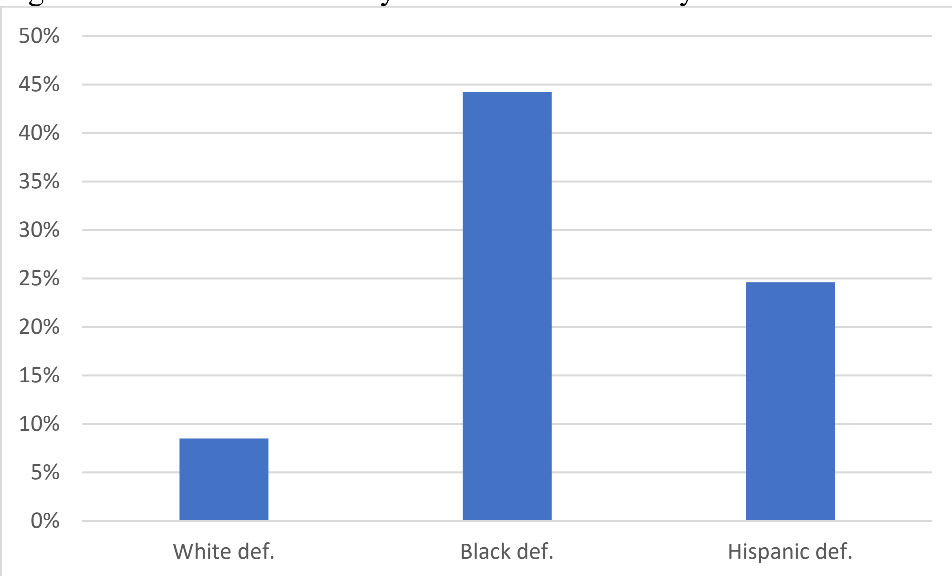
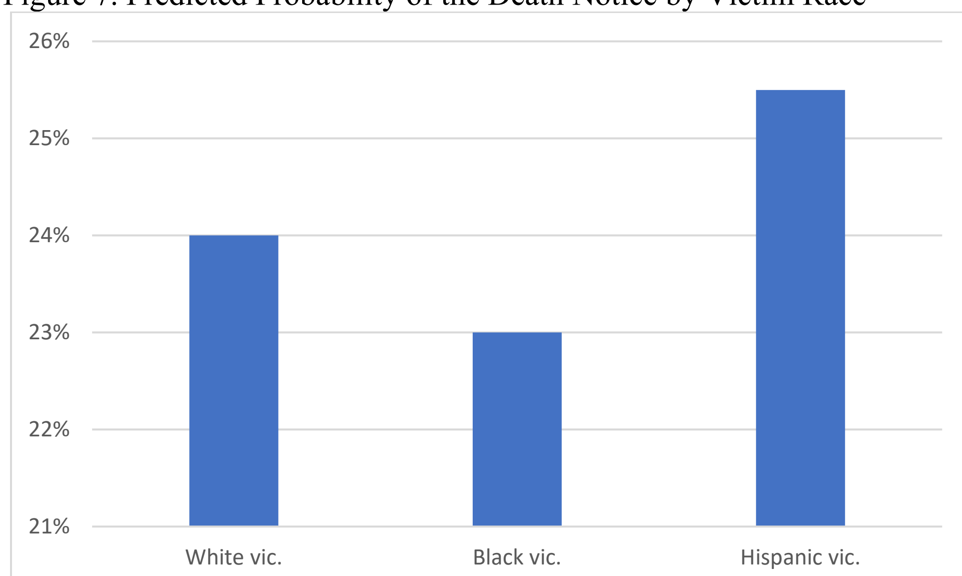


Figure 7. Predicted Probability of the Death Notice by Victim Race



39. Finally, victim and defendant racial disparities are more similar in terms of death sentencing. Figure 8 shows that Black (8%) or Hispanic (6%) defendants are more likely to result in a death sentence than White defendants, whereas the opposite is true for victim race. Figure 9 shows that cases with White (7%) victims are more likely to result in a death sentence than cases with a Black (3%) or Hispanic (2%) victim.

Figure 8. Predicted Probability of the Death Sentence by Defendant Race

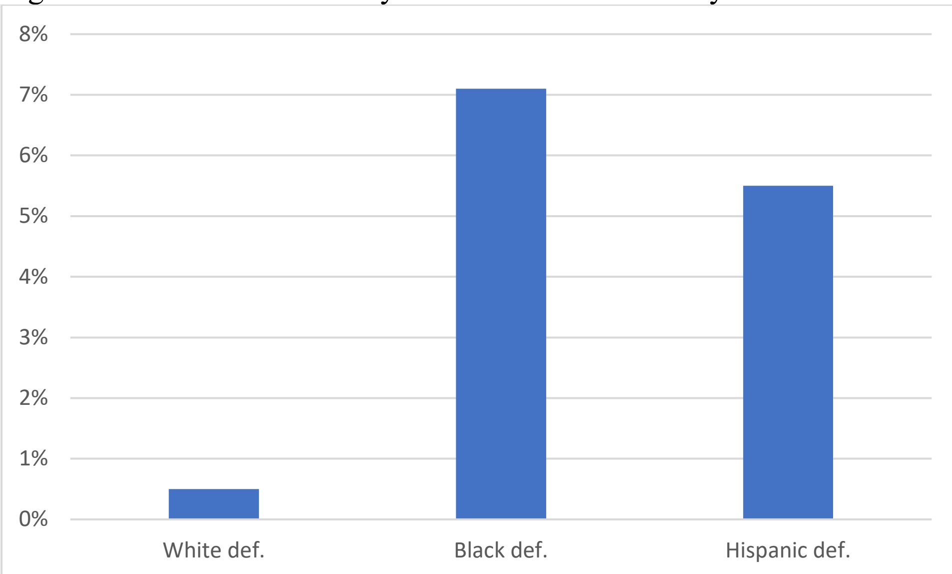
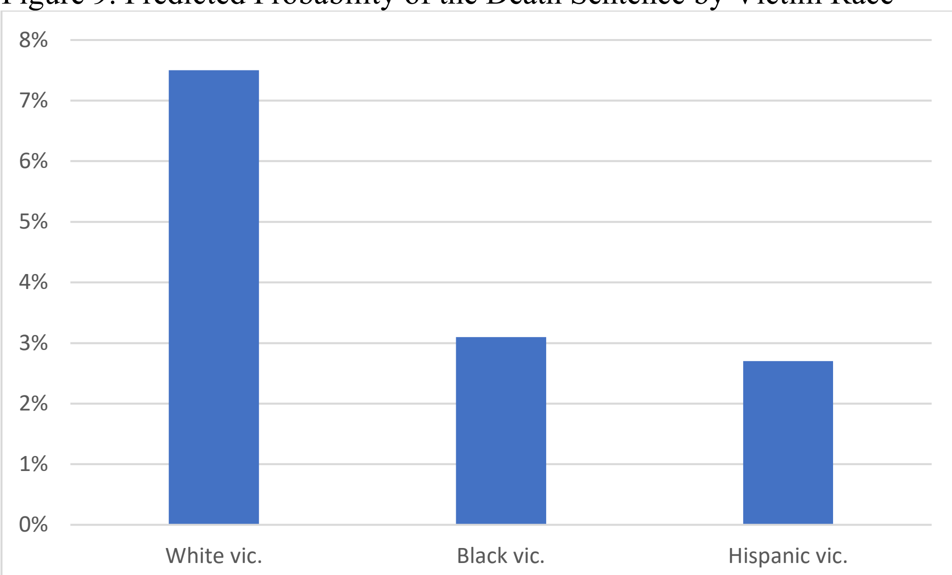


Figure 9. Predicted Probability of the Death Sentence by Victim Race

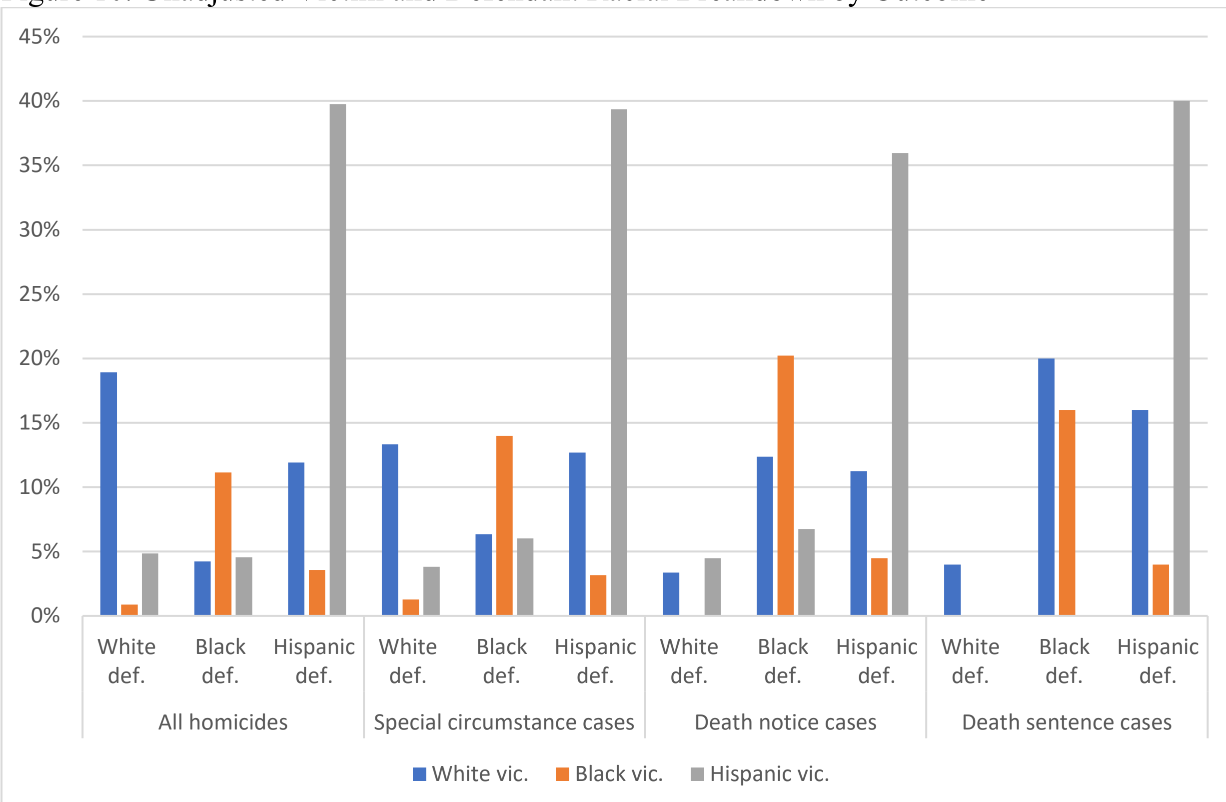


Interactional Effects of Victim and Defendant Race Dyads:

40. I also examined interaction effects for victim and defendant racial dyads. In particular, I examined White vs. minority (i.e., Black and Hispanic) racial breakdowns due to the small number of certain victim-by-defendant racial combinations. For example, there were no cases with a White defendant and a Black/Hispanic victim that received a death sentence. This is mainly a function of racial disparities in death notice filing, particularly for cases with a Black

victim. For example, Figure 10 below notes no death notice cases involving a White defendant and Black victim, making it impossible for such a case to result in a death sentence. Similarly, only 2% of death notice cases involved a White defendant and Hispanic victim, making it possible, but very unlikely, that such a case would result in a death sentence.

Figure 10. Unadjusted Victim and Defendant Racial Breakdown by Outcome



41. Given that there were no death sentences among some of these racial dyads, in Table 3, I divided the sample racially into White vs. minority (i.e., Black and Hispanic) groups to better highlight patterns in the data. Compared to cases with a White victim and a White defendant, cases with a White victim and a minority defendant are 1.38 times more likely to result in special circumstance, cases with a minority victim and a White defendant are 1.38 times more likely to result in a special circumstance, and cases with a minority victim and a minority defendant are 1.41 times more likely to result in a special circumstance. Compared to cases with a White victim and a White defendant, cases with a White victim and a minority defendant are 9.41 times more likely to result in a death notice, cases with a minority victim and a White defendant are 12.59 times more likely to result in a death notice, and cases with a minority victim and a minority

defendant are 10.65 times more likely to result in a death notice. Compared to cases with a White victim and a White defendant, cases with a White victim and a minority defendant are 6.87 times more likely to result in a death notice, and cases with a minority victim and a minority defendant are 2.31 times more likely to result in a death notice. Although most of these disparities are not statistically significant at the 0.1 p-value level, aside from the death notice models, they still point to large inequalities that are practically significant. In particular, the death notice models highlight large racial disparities, but the small number of death sentences for certain racial dyads means it is difficult to detect statistically significant patterns due to the smaller sample size. In fact, there were no cases resulting in a death sentence involving a minority victim and a White defendant, so this relationship could not be estimated in the model. While this means that logistic regression estimates cannot be produced for minority-by-White racial dyads, this finding further points to racial disparities in death sentencing where no death sentence cases during the period of analysis involved a minority victim and a White defendant.

Table 3. Logistic Regressions Predicting Death Penalty Outcomes in Riverside County with Victim-Defendant Racial Interactions.

Model #	(1)	(2)	(3)
Population	All charged murders	Special circumstance murders	
Outcome	Special circumstance	Death notice	Death sentence
	OR(SE)	OR(SE)	OR(SE)
Defendant & victim demographics:			
White victim & minority defendant	1.38 (0.44)	9.41** (9.39)	6.87 (8.69)
Minority victim & White defendant	1.38 (0.67)	12.59** (14.82)	NA
Minority victim & minority defendant	1.41 (0.41)	10.65** (10.34)	2.31 (2.79)
Prior criminal history enhancement	0.82 (0.22)	2.27** (0.84)	5.34** (3.76)
Victim age	1.00 (0.01)	1.01 (0.01)	0.98 (0.01)
Male victim	0.62* (0.17)	0.59 (0.20)	1.30 (0.74)
Case characteristics:			
Multiple victims	1.84** (0.51)	1.75 (0.64)	2.28 (1.21)
Multiple defendants	3.32*** (0.71)	0.75 (0.24)	1.23 (0.67)
log # non-murder charges	2.71*** (0.44)	1.28 (0.27)	1.13 (0.51)
Death-eligible felony	1.89* (0.73)	1.77 (0.83)	1.21 (1.01)
Pending case		1.21 (0.44)	0.50 (0.35)
Weapon: Firearm	1.25 (0.29)	0.94 (0.33)	0.78 (0.55)
Weapon: Knife	0.91 (0.31)	2.25 (1.15)	3.23 (2.43)
Victim-defendant relationship: stranger	2.81** (1.15)	1.28 (0.75)	0.42 (0.38)
Victim-defendant relationship: other	2.08** (0.73)	0.86 (0.46)	0.36 (0.29)
Victim-defendant relationship: unknown	1.38 (0.59)	1.33 (0.79)	0.15* (0.17)
Location: residence	1.70* (0.47)	1.34 (0.54)	1.00 (0.81)
Location: street	1.72* (0.52)	0.90 (0.39)	0.97 (0.72)
Observations	836	313	297

Exponentiated coefficients; Standard errors in parentheses

Notes: Listwise deleted sample. Reference groups = White victim; White defendant; not a death-eligible felony;single victim; single defendant case; other murder weapons; family victim-offender relationship; other incident locations.

Not applicable (NA) = parameter could be not be estimated due to collinearity.

* p < .10, ** p < .05, *** p < .01

42. To help visualize victim and defendant race dyad interactions, I calculated predicted probabilities. Although many of the logistic regression estimates were not statistically significant due to small sample sizes, the predicted probability figures highlight practically significant victim-by-defendant racial disparities at multiple stages. Most notably, Figure 12 and Figure 13 show that minority defendants accused of killing White victims have an increased likelihood of receiving a death notice or a death sentence. These patterns have great practical significance as they underscore large-scale racial disparities in the administration of Riverside County's death penalty system.

Figure 11. Predicted Probability of Special Circumstances by Defendant & Victim Race

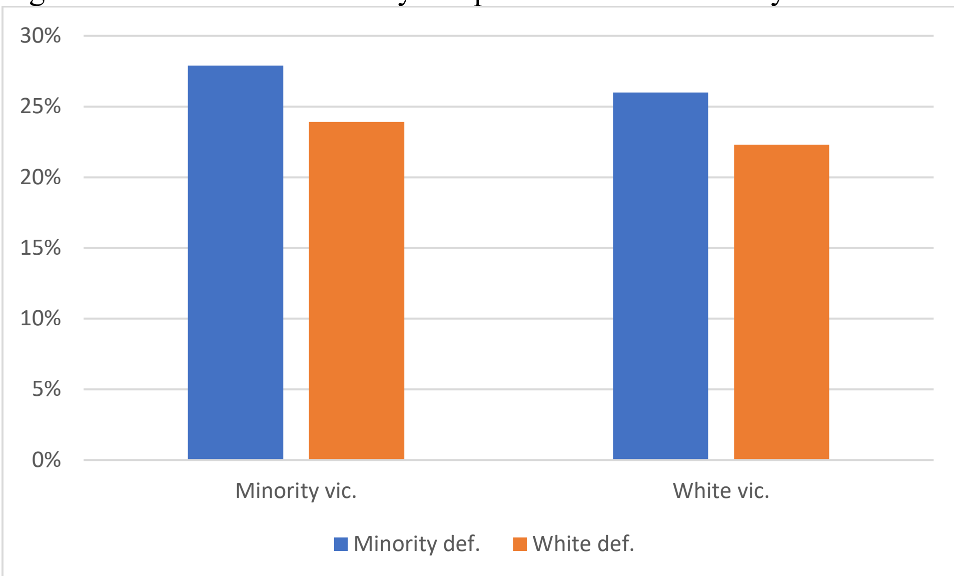


Figure 12. Predicted Probability of the Death Notice by Defendant Race & Victim Race

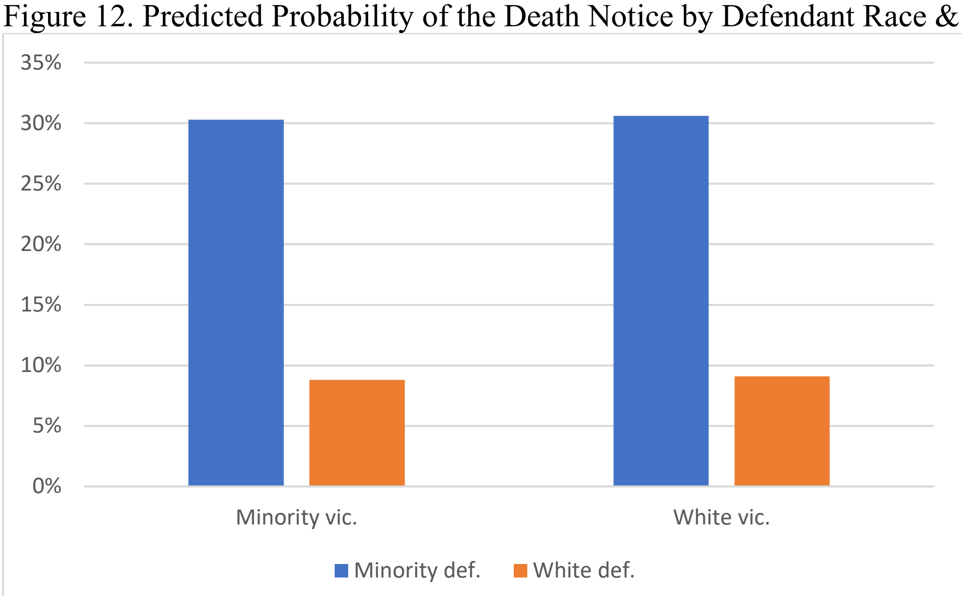
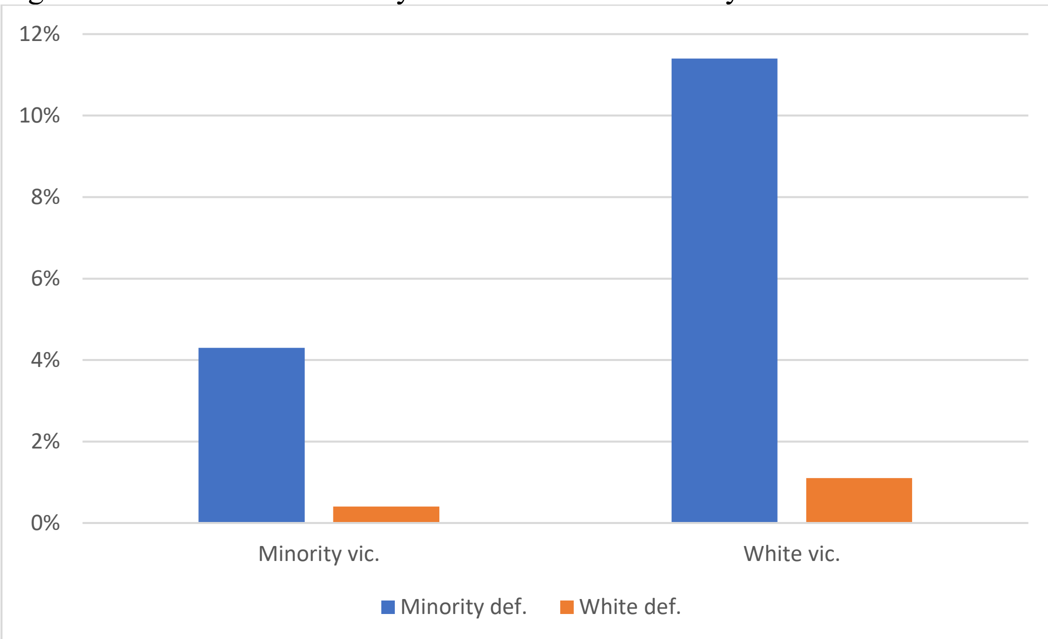


Figure 13. Predicted Probability of the Death Sentence by Defendant Race & Victim Race



Summary of Findings

43. These findings offer evidence of racial disparities in Riverside County death penalty outcomes from 2006 to 2019. Even after controlling for important legally relevant factors like the presence of multiple victims or a felony, logistic regression results indicate that murders with Black and Hispanic defendants are more likely to involve a special circumstance, a death notice, and a death verdict. Moreover, cases with Black victims are less likely to result in a special circumstance, death notice, and death sentence compared to cases with White victims. Finally, these findings are especially pronounced in cases involving White victims and minority defendants, where they are more likely to result in a special circumstance, death notice, and death sentence.

IV. THE SHR STUDY

Data and Methodology

44. To examine whether racial disparities based on victim or suspect[59] exist in Riverside County death sentencing trends across a wider timeframe (1976 through 2018) than that contained in the charging study, I relied on a previously established methodology[60] to examine racial data related to homicides during that period. I used the SHR to gather data on all homicides reported to the police in Riverside County between 1976 and 2018.[61] Next, I obtained death-sentencing data from the Habeas Corpus Resource Center, a state repository statutorily tasked with collecting such data.[62] This dataset contains information on all death sentences rendered in Riverside County from 1976 through 2018.[63]

45. Like the charging study, I used probabilistic matching using the "reclink2" package in Stata to link the SHR and death sentence.[64] Since the SHR does not include the exact homicide date for confidentiality reasons (including the month and year instead), probability matching was required. For matching purposes, I used the following categorical variables to link the two datasets: county, date of homicide (month and year), victim race, multiple homicide victims, felony murder, number of suspects (continuously measured), as well as whether the homicidal circumstances included lewd/lascivious conduct, poison, arson, carjacking, rape, robbery, or gang activity.[65]

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59 I use the term "suspect" rather than "defendant" because the SHR includes all homicides, not just those resulting in an arrest. Thus, suspects in the SHR data are not necessarily defendants in criminal cases.

60 Gross and Mauro, *supra* note 15; Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

61 Each year law enforcement agencies report SHR data to the FBI, which is then made available to the public. SHR data for this project was obtained from the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan (https://www.icpsr.umich.edu/web/pages/).

62 These data were provided to me by lawyers at the California Office of the State Public Defender.

63 Where the death sentence database was missing suspect or case information, supplemental data was gathered from the California Department of Corrections and Rehabilitation's "Condemned Inmate List" (https://www.cdcr.ca.gov/capital-punishment/condemned-inmate-list-secure-request/). When the death sentence database was missing victim race information, lawyers at the California State Public Defender's Office and Habeas Corpus Resource Center used death certificates or conferred with appellate attorneys familiar with the homicide to determine this information.

64 For death penalty studies employing similar techniques, see Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

65 In a "reclink2" algorithm using the default minimum match score of 0.6, I force the county and homicide date (month and year) to match exactly by including them in the "required" subcommand. Moreover, I assigned greater matching weights using the "wmatch" subcommand to victim race, multiple homicide victims, felony murder, number of suspects, lewd/lascivious, poison, and arson, while assigning lesser weight to carjacking, rape, robbery, or gang activity. Per Wasi and Flaaen, a visual inspection of each homicide with matched ties was conducted using Stata's clinical review package "clrevmatch." Wasi and Flaaen, *supra* note 44.

While my “reclink2” algorithm allows for probability matching for most of these characteristics, it required a perfect match for the county and homicide date (month and year).

46. In their California study of death sentencing trends using the SHR, for example, Pierce & Radelet[66] note that:

> Other researchers who have used this matching method have also found minor problems in matching. Samuel Gross and Robert Mauro, for example, note that, “often more than one SHR case would correspond to a given death row case; however, since this matching was done only for the purpose of analyzing data on variable(s) that were reported in both sources, it did not matter whether a particular death row case was identified with a unique FBI/SHR case.”

In this study, I use a similar approach and limited my analysis to only those variables that are present in both the death sentence and SHR datasets. I further excluded all homicides committed by those under age eighteen (as juveniles are no longer eligible for the death penalty)[67] and eliminated from consideration any homicide lacking suspect race information (most commonly those wherein no arrest was ever made).[68] Like prior research, I also limited the SHR sample to homicides involving victims and suspects who are White, Black, and Hispanic.[69] The resulting dataset included 101 homicides that resulted in a death sentence and 2781 homicides that did not result in a death sentence.

Dependent variable:

47. Because the SHR dataset only includes death sentencing data, my analysis examines one binary dependent variable: Whether the jury sentenced the defendant to death (i.e., a death verdict). Cases in which the jury rendered a death verdict were coded as “1.” Cases that did not result in a death verdict were coded as “0.” Thus, the SHR analysis is more limited than the charging study, but it is nevertheless useful in determining whether those trends identified in the charging study might exist over a longer time period.

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66 Pierce and Radelet, *supra* note 11 at 33.

67 Penal Code 190.5 (a).

68 Gross and Mauro, *supra* note 15; Pierce and Radelet, *supra* note 11.

69 Similar to the charging study, multi-victim cases with at least one White victim were coded as “White victim” cases, whereas those with no White victims but at least one Black victim were coded as “Black victim” cases.

Victim and Defendant Race:

48. Like the charging study, victim and suspect race was coded using a series of categorical variables, with other racial groups such as Asians and Native Americans being excluded: 0 = White ("reference" group), 1 = Hispanic, 2 = Black.

Case Characteristics:

49. I also include binary variables measuring whether the homicide incident involved multiple victims or a co-occurring felony,[70] as the co-occurrence of a felony and multiple-murder are among the most commonly alleged special circumstances in California and other jurisdictions.[71] Finally, I control for the decade in which the homicide incident occurred using several binary variables pertaining to the following time periods: 1976-1987, 1988-1994, 1995-2001, 2002-2009, and 2010-2018. These time periods were constructed by evenly dividing the number of homicides in each one. In other words, the periods 1976-1987 and 1988-1994 had roughly the same number of homicides because there were more homicides committed during the 1990s.

Analysis Strategy:

50. To estimate the likelihood of a homicide resulting in a death sentence, I calculated logistic regression models for all homicides occurring in Riverside County from 1976 through 2018. In contrast to the charging study, I do not utilize a two-stage modeling approach since my data is limited to death sentencing decisions, and thus I do not have data on earlier death penalty decisions such as special circumstance and death notice filings.

51. While the charging study utilizes the 0.1 p-value level to evaluate claims of statistical significance due to its small sample size, the SHR study utilizes the 0.05 p-value level

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70 These refer to the presence of a co-occurring felony or multiple murder victims, not necessarily the filing of that special circumstance allegation for those factors under Penal Code § 190.2(a)(17) or § 190.2(a)(3), respectively. Thus, these variables measure whether a felony or multiple murder special circumstance could be alleged based on the case facts, not whether it was alleged.

71 Acker and Lanier, *supra* note 37; Kreitzberg, *supra* note 37; Petersen and Lynch, *supra* note 37; Peterson and Bailey, *supra* note 37; Shatz, *supra* note 37.

given its larger sample size and the fact that 0.05 p-value cut-off levels are commonly used in the social sciences.[72]

Results

Unadjusted Summary Statistics:

52. Table 4 shows "unadjusted" summary statistics. That is, Table 4 lists the raw statistics for various measures without controlling for any other victim, suspect, or homicide characteristics. Compared to the general population of homicides in Riverside County from 1976 to 2018, Table 4 indicates that homicides resulting in a death sentence are more likely to have a White victim and a non-White (Black/Hispanic) suspect. For example, 46% of all Riverside County homicides have a White victim, whereas 53% of Riverside County homicides that result in a death sentence have a White victim.

Table 4. Summary Statistics for Riverside County Homicides in SHR study.

	All homicides	Death sentence	No death sentence
Outcome variables:	%	%	%
Death Sentence (yes/no)	4%	100%	0%
Victim and suspect demographics:			
Black victim	17%	13%	17%
Hispanic victim	37%	26%	37%
White victim	46%	53%	46%
Black suspect	19%	39%	19%
Hispanic suspect	36%	34%	36%
White suspect	44%	28%	45%
Case characteristics:			
Multiple murder - PC190.2(a)(3)	5%	35%	4%
Felony - murder PC190.2(a)(17)	13%	62%	11%
1976-1987	16%	10%	16%
1988-1994	18%	15%	18%
1995-2001	18%	23%	18%
2002-2009	24%	30%	23%
2010-2018	24%	23%	25%
Observations	2882	101	2781

Main Effects of Victim and Suspect Race:

53. Next, I turn to "adjusted" regression estimates in Table 5. These are "adjusted" in the sense that the regression models control for other important legal factors such as the presence

[72] FINLAY AND AGRESTI, *supra* note 25; ACOCK, *supra* note 17.

of multiple victims or a felony. According to the logistic model, homicides involving multiple victims or a felony are more likely to result in a death sentence. These findings are consistent with California's death penalty laws, which consider homicides with multiple victims [PC190.2(a)(3)] or a felony [PC190.2(a)(17)] are more aggravated, and prior research on death penalty outcomes in California.[73]

54. Even after controlling for these important legal factors, however, victim and suspect race shape death penalty outcomes. According to the logistic regression model, homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence, while those with a non-White (Black/Hispanic) suspect are more likely to result in a death sentence. Compared to homicides with a White victim, those with a Black victim are 77% less likely to result in a death sentence, and those with a Hispanic victim are 61% less likely to result in a death sentence. Compared to homicides with a White suspect, those with a Black suspect are 3.96 times more likely to result in a death sentence, and those with a Hispanic suspect are 2.53 more likely to result in a death sentence. These logistic regression results are statistically significant at the 0.01 p-value level (i.e., $p < 0.01$).

55. Next, I calculated predicted probabilities to help visualize the main effects of victim and suspect race/ethnicity. Figure 14, displaying predicted probabilities from the model in Table 5, shows that homicides with White victims are more likely to result in a death sentence, while homicides with White suspects are less likely to result in a death sentence. In contrast, Figure 14 indicates that homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence, while homicides with non-White (Black/Hispanic) suspects are more likely to result in a death sentence. Taken together, these predicted probabilities show an inverse relationship between the victim and suspect race, such that homicides with White victims are more likely to result in a death sentence than homicides with non-White (Black/Hispanic) victims, whereas homicides with non-White (Black/Hispanic) suspects are more likely to result in a death sentence than homicides with White suspects. The inverse relationship between victim and suspect race is consistent with prior research[74] and is suggestive of a victim-by-suspect race interaction, which I explore below.

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73 Petersen, *supra* note 8; Petersen, *supra* note 8; Petersen and Lynch, *supra* note 37; Pierce and Radelet, *supra* note 11; Shatz, *supra* note 37.

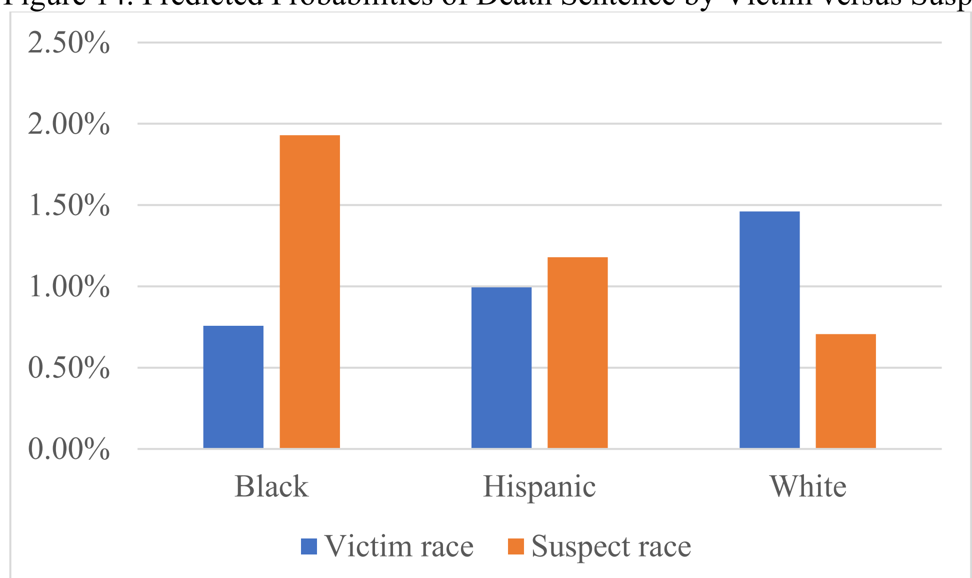
74 Pierce and Radelet, *supra* note 11.

Table 5. Logistic Regression Predicting Victim and Suspect Race Main Effects for Death Sentence in Riverside County for SHR study

Model #	
	OR(SE)
Victim and suspect demographics:	
Black victim	0.23*** (0.09)
Hispanic victim	0.39** (0.12)
Black suspect	3.96*** (1.25)
Hispanic suspect	2.53** (0.81)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	15.90*** (4.44)
Felony - murder PC190.2(a)(17)	13.65*** (3.38)
1988-1994	2.11 (0.98)
1995-2001	2.49* (1.11)
2002-2009	4.48*** (1.96)
2010-2018	3.00* (1.35)
Observations	2882

Exponentiated coefficients (i.e., Odds Ratios/Hazard Ratios); Standard errors in parentheses
Notes: Listwise deleted sample. Reference groups = 1976-1987 offense year; white victim; white suspect
* p < .05, ** p < .01, *** p < .001

Figure 14. Predicted Probabilities of Death Sentence by Victim versus Suspect Race



Interactional Effects of Victim and Suspect Race Dyads:

56. Next, I examined interaction effects for victim and suspect race dyads. Interactional effects outlined in Table 6 indicate that non-White suspects (i.e., Black or Hispanic) who kill White victims are especially likely to result in a death sentence. According to Table 6, compared to

homicides involving a White victim and a White suspect, those with a Black suspect and a White victim are 4.75 times more likely to result in a death sentence. Moreover, compared to homicides involving a White victim and White suspect, those with a Hispanic suspect and a White victim are 2.61 times more likely to result in a death sentence. Thus, the likelihood of a White victim homicide resulting in a death sentence is 4.75 to 2.61 times higher if the suspect is Black or Hispanic (respectively) than if the suspect were White.

57. None of the other victim-by-suspect race interactions are significant statistically significant at the 0.05 p-value level. This, however, does not mean that victim and suspect race is inconsequential in terms of death penalty outcomes; to the contrary, it suggests that many of the main effects for victim and suspect race outlined in Table 5 do not depend on each other. For example, the effect of victim race such that homicides with White victims are more likely to result in the death penalty does not necessarily depend on the suspect's race/ethnicity. The significance of the "White victim & Black suspect" and "White victim & Hispanic suspect" variables simply indicates that homicides where a non-White suspect kills a White victim are especially likely to result in a death sentence.

58. To help visualize victim and suspect race dyad interactions, I calculated predicted probabilities. Figure 15, displaying victim and suspect race interactions in terms of probabilities from the logistic regression in Table 6, indicates that the overall likelihood of a death sentence is very low for all homicides. The predicted probability of a death sentence is so low since the denominator includes all homicides with suspect information, and death sentences are rare. However, when I compare differences in predicted probabilities by victim and suspect race/ethnicity, clear patterns emerge. In particular, Figure 15 indicates that Black or Hispanic suspects who kill White victims are the most likely to receive a death sentence. These findings are consistent with prior research finding that minority suspects who kill White victims are especially disadvantaged in terms of death penalty outcomes.[75]

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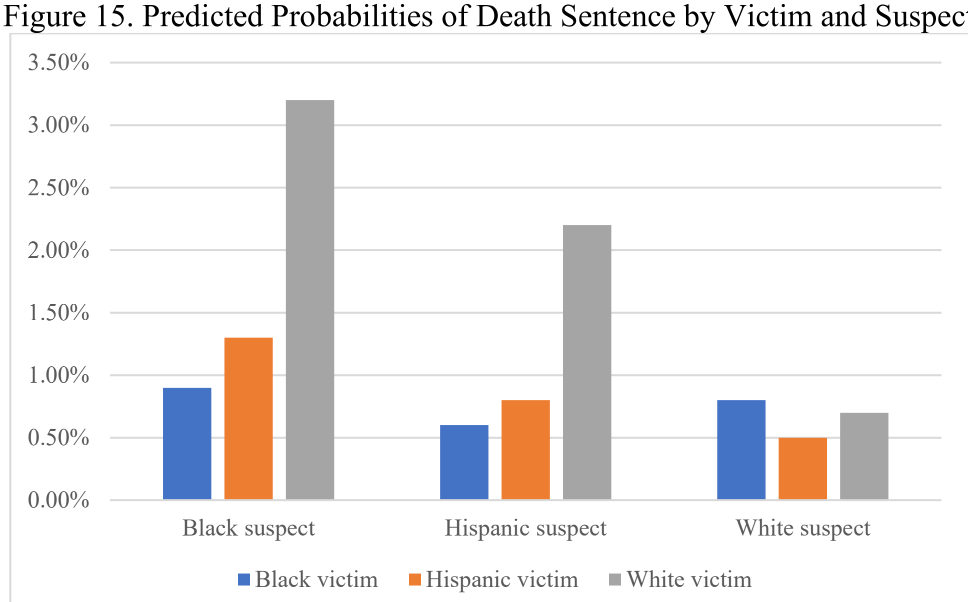
[75] Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND THE DEATH PENALTY OVER TIME (2012).

Table 6. Logistic Regressions Predicting Victim-by-Suspect Race Interactions for Death Sentence in Riverside County in SHR study

	OR(SE)
Victim and suspect demographics:	
White victim & Black suspect	4.75*** (1.76)
White victim & Hispanic suspect	2.61* (1.09)
Black victim & White suspect	0.93 (0.99)
Black victim & Black suspect	0.24 (0.28)
Black victim & Hispanic suspect	0.33 (0.54)
Hispanic victim & White suspect	0.93 (0.60)
Hispanic victim & Black suspect	0.45 (0.39)
Hispanic victim & Hispanic suspect	0.51 (0.39)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	15.45*** (4.62)
Felony - murder PC190.2(a)(17)	17.41*** (4.62)
1988-1994	1.64 (0.80)
1995-2001	2.50* (1.13)
2002-2009	4.05** (1.81)
2010-2018	2.55* (1.18)
Observations	2874

Exponentiated coefficients (i.e., Odds Ratios); Standard errors in parentheses
Notes: Listwise deleted sample. Reference groups = 1976-1987 offense year; white victim & white suspect
* p < .05, ** p < .01, *** p < .001

Figure 15. Predicted Probabilities of Death Sentence by Victim and Suspect Race Interactions



Summary of Findings

59. These findings highlight racial disparities in Riverside County death sentencing trends from 1976 to 2018. Even after controlling for important legally relevant factors like the presence of multiple victims or a felony, regression results indicate that homicides with White victims are more likely to result in a death sentence. The opposite is true for suspect race, where Black or Hispanic suspects are more likely to be sentenced to death. These patterns are especially pronounced in inter-racial homicides involving White victims and non-White suspects. In fact, homicides with a Black or Hispanic suspect and a White victim are more likely to result in a death sentence than any other victim-by-suspect race dyad.

V. CONCLUSIONS

60. Even after controlling for a host of legally legitimate non-racial factors that could explain death penalty decision-making, the charging study finds that cases involving Black or Hispanic defendants are more likely to result in a special circumstance, death notice, and death sentence when compared to similarly situated cases involving White defendants in Riverside County from 2006 through 2019. On the other hand, murder cases with Black or Hispanic victims are less likely to result in a death sentence when compared to similarly situated cases involving White defendants. Mover, White victims killed by minority defendants are more likely to result in a death notice or death sentence. In short, the charging study finds that race plays a major role in explaining death penalty decision-making in Riverside County.

61. Such trends appear to be emblematic of broader racial disparities in Riverside County, spanning more than four decades from at least 1976 through 2018. In particular, the SHR study finds that homicides with Black and Hispanic suspects are more likely to result in a death sentence even when controlling for other non-racial factors when compared to homicides with White suspects. Conversely, homicides with Black or Hispanic victims are less likely to result in a death sentence than those with White victims. Similar to the charging study, results also indicate that homicides involving White victims and minority defendants are more likely to result in a death sentence.

62. While these two studies utilize different data sources covering distinct time periods and analysis techniques, they tell a similar story regarding victim/defendant racial disparities. As a result, the convergence of these findings gives us greater confidence that race plays an important

role in shaping death penalty outcomes in Riverside County. Taken together, these two study results highlight large-scale and widespread racial disparities in Riverside County over several decades, where Black or Hispanic victims and defendants are systematically disadvantaged at multiple death penalty decision-making points. This report offers strong empirical evidence of racial disparities within Riverside County's death penalty system from 1976 through 2019, employing state-of-the-art statistical methodologies and robust datasets capturing multiple features of death penalty decision-making in Riverside County.