EXHIBIT F

Racial Disparities in California Death Sentencing (1987 to 2019)

January 30, 2024

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I. INTRODUCTION

1. This report presents my statistical analysis of death sentencing trends in California from 1987 through 2019 based on information gathered from court records and the California Department of Justice (CDOJ). Using these data, I examine whether there are racial[1] disparities in death sentencing across California counties during this period and whether any observed racial disparities differ by county. To estimate the likelihood of a given homicide resulting in a death sentence, I employed statistical models that allow me to isolate the independent effect of victim/suspect race on death sentencing for homicides with similar characteristics. To assess possible geographic differences in death sentencing trends, I included county-level geographic information for each homicide. This allowed me to account for time-invariant factors that might impact death sentences, such as District Attorney capital charging policies or jury demographics/preferences.

2. Regression results indicate that homicides with White victims or Black suspects are more likely to result in a death sentence. In addition, victim and suspect race interact to influence death sentencing patterns, with Black/Hispanic suspects and White victims being the most likely to result in a death sentence. Finally, geographic analyses reveal considerable uniformity in these racial disparities across California counties, suggesting that these patterns are systemic and not simply isolated to a few counties. Thus, my results underscore widespread racial disparities in California death sentencing trends from 1987 to 2019.

3. Below, I outline how I arrived at these conclusions by discussing the study's methodology and statistical findings. But first, I will briefly introduce some pertinent methodological and conceptual issues.

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[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, my dataset uses 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.

II. ANALYSIS STRATEGY

Population Death Sentencing Data

4. This study examines a *population* of 34,745 homicide incidents that occurred in California from 1987 through 2019. Homicide incident data was combined with a *population* of death verdicts in California from 1987 through 2019 to examine death sentencing trends across all homicides during this period. The fact that this study utilizes population data on homicides and death sentences in California has important methodological implications for interpretations of statistical and practical significance.

5. My analyses focus on death sentences issued by California juries from 1987 through 2019. Because there is no state-wide data on special circumstance allegations and death notice filings, I focus on death sentences. I code death sentences using a binary variable, where the data were coded as "1" if the decision was present and "0" if otherwise.[2] Homicides in which the jury rendered a death sentence were coded as "1." Homicides in which no death sentence was rendered were coded as "0."

Statistical Estimation

6. To estimate the likelihood of a death sentence, I employed logistic regression models. 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/suspect[3] race on death sentences for similarly situated cases.[4]

7. The regression analyses discussed below enabled me to test whether the likelihood of a jury reaching a death sentence varies by race (of both the suspect and the victim),

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[2] "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).

[3] I use the term "suspect" rather than "defendant" because the CDOJ includes all homicides, not just those resulting in prosecution. Thus, suspects in the CDOJ data are not necessarily defendants in criminal cases.

[4] 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 suspect race. Jeffrey Wooldridge, INTRODUCTORY ECONOMETRICS: A MODERN APPROACH (2012).

holding constant a host of non-racial factors that could influence death sentencing trends. This is necessary to ensure that any observed racial disparities are not spurious.[5] To the extent that legally relevant factors correlate with race, my regression analyses account for these factors and isolate the independent effect of race on death sentencing.

8. 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[6], Hispanic[7], or White suspect will receive a death sentence in cases with similar independent variables corresponding to victim/suspect demographics (e.g., age, gender, etc.) and case characteristics (e.g., felony, multiple victims, etc.).

9. In statistical parlance, the dependent variable refers to "the main factor that you're trying to understand or predict,"[8] whereas independent variables are "the factors you suspect have an impact on your dependent variable."[9] For this report, the dependent variable analyzed corresponds to death sentences. In contrast, independent variables refer to victim/suspect demographics and case characteristics. Key independent variables of interest include

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[5] "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.*

[6] 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 (2017); 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).

[7] I use the term "Hispanic" rather than "Latino" or "Latinx" because that is how it appears in the data.

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

[9] *Id.*

victim/suspect race, as prior research has identified these as strong predictors of death penalty outcomes.[10]

10. 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 the jury issued a death sentence or "0" if some other outcome was reached).[11] Consistent with prior empirical research on the death penalty, I used logistic regression models to estimate the likelihood of having a death sentence by race while holding other non-racial predictor 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 death sentence.[12] The unit of analysis is the victim because the CDOJ is a victim-based dataset.[13]

Predicted Probabilities

11. 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 challenging to interpret

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10 BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; Baldus et al., *supra* note 6; Petersen, *supra* note 6; Petersen, *supra* note 6; Baldus, Woodworth, and Weiner, *supra* note 6; 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 BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; Baldus, Woodworth, and Weiner, *supra* note 6; Baldus et al., *supra* note 6; WOOLDRIDGE, *supra* note 4.

12 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-[(β*xi*) X 100]. Baldus et al., *supra* note 6; WOOLDRIDGE, *supra* note 4.

13 By "unit of analysis," I mean that each row in the database corresponds to a homicide victim, regardless of the number of suspects. As such, multi-victim homicides produce separate rows in the dataset. Samuel R. Gross & Robert Mauro, *Patterns of Death: An Analysis of Racial Disparities in Capital Sentencing and Homicide Victimization*, STANFORD LAW REV. 27 (1984); Pierce and Radelet, *supra* note 10; Radelet and Pierce, *supra* note 10.

because there is no inherent scale for odds ratios as they represent nonlinear trends.[14] In contrast, predicted probabilities range from 0% to 100%, making them easier to interpret.[15] The use of predicted probabilities to display logistic regression analyses helps overcome these interpretation difficulties and is common in my own published research[16] and broader social scientific literature.[17] Predicted probabilities are calculated by "plugging in" the group means for non-racial control variables into the model. Thus, predicted probabilities highlight the likelihood of a particular death penalty outcome among an "average" homicide that differs by victim or suspect race.[18] That is, predicted probabilities display the likelihood of a death sentence by victim/suspect race after controlling for (or net of) all the other non-racial variables in the logistic regression model.

Adjusted vs. Unadjusted Results

12. Predicted probabilities described above correspond to "adjusted" statistics in the sense that the logistic regression models "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.

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14 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 6.

15 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).

16 Petersen, *supra* note 6; 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. (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 (2019); Petersen, *supra* note 6.

17 LONG AND FREESE, *supra* note 15. 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.

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Practical vs. Statistical Significance

13. 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.[19] However, the American Statistical 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 a population.[20] As such, my report includes discussions of both statistical *and* practical significance.

14. Focusing on practical significance is important since some counties had few death sentences during the period of analysis, 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,[21] as there is more variability across smaller groups being compared. This means some results may be too small to detect statistically significant relationships, should they exist. However, these smaller sub-populations are not a problem if one is describing the population of interest, as I am doing here, rather than making inferences to other sub-population "realizations."

15. Focusing on practical significance rather than statistical significance simply means that comparisons between races shed light on possible racial disparities for the particular location (California) and timeframe of interest (1987-2019) 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

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19 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 $\beta = 0$ (i.e., "no effect") after taking into account sampling variability in β, this means that there is 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 4; ACOCK, *supra* note 15. In the death penalty context, p-values correspond to the probability that "a [racial] disparity could occur by chance." Baldus et al., *supra* note 6 at 171. In the social sciences, p-values less than 0.05 are typically considered "statistically significant."

20 Ronald L. Wasserstein & Nicole A. Lazar, *The ASA Statement on P-Values: Context, Process, and Purpose*, 70 AM. STAT. 129 (2016).

21 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).

population of homicide court cases from Harris County, Texas. Phillips notes that "ignoring statistical significance in population data is legitimate and appropriate if a researcher is attempting to describe the population rather than draw inferences." [22] In such contexts, he explains, "researchers should focus more on substantive significance and less on statistical significance." [23] Following his advice, I emphasize practical significance.

III. DATA AND METHODOLOGY

Data and Methodology

16. To examine whether racial disparities based on victim or suspect exist in California death sentencing trends (1987 through 2019), I relied on a previously established methodology[24] to examine racial data related to homicides during that period. I used a robust homicide dataset obtained through a special request from the CDOJ tracking all homicides reported to the police in California between 1987 and 2019. In contrast to publicly available homicide data, this CDOJ dataset contains victim names, offense dates, county identifiers, and more detailed information about the crime's circumstances. Next, I obtained death sentencing data from the Habeas Corpus Resource Center (HCRC), a state repository statutorily tasked with collecting such data. This dataset contains information on all death sentences rendered in California from 1987 through 2019, including defendant names, defendant race, victim names, offense dates, and county identifiers.

17. I matched the CDOJ and HCRC databases using the "reclink2" package in Stata, constructing a comprehensive list of all homicides occurring between 1987 and 2019 and whether each homicide resulted in a death sentence.[25] For matching purposes, I used the following variables to link the two datasets: victim name (first, middle, last), offense date (month, day, year), and California county where the crime occurred. Through this process, I was able to match 99% of death-sentenced defendants in the HCRC database to homicide incidents in the CDOJ dataset, with an average match score of 95%. In preparation for the matching process, I excluded homicide victims who were killed outside of the state or the analysis timeframe

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[22] Scott Phillips, *Status Disparities in the Capital of Capital Punishment*, 43 LAW SOC. REV. 807, 821 (2009).

[23] *Id.*

[24] Gross and Mauro, *supra* note 13; Pierce and Radelet, *supra* note 10; Radelet and Pierce, *supra* note 10.

[25] For death penalty studies employing similar techniques, see Pierce and Radelet, *supra* note 10; Radelet and Pierce, *supra* note 10.

(1987-2019).[26] In addition, I removed justifiable homicides by civilians/police and negligent manslaughter incidents (e.g., hunting accidents, gun cleaning, children playing with guns, negligent gun handling, etc.), as they are not eligible for the death penalty.[27] In line with prior studies using a similar matching strategy[28], I eliminated from consideration any homicide lacking suspect race information (most commonly those wherein no arrest was ever made).[29] In addition, I excluded all homicides committed by suspects under the age of eighteen.[30] Like prior research, I also limited the CDOJ data to homicides involving victims and suspects who are White, Black, and Hispanic.[31]

Dependent variable:

18. Because the HCRC dataset only includes death sentencing data, my analysis focuses on whether a homicide incident resulted in a death sentence. Homicides resulting in a death sentence were coded as "1." Homicides that did not result in a death sentence were coded as "0."

Suspect and Victim Demographics:

19. 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.[32] In addition, victim/suspect age were measured in years, while

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26 For example, if a defendant were sentenced to death for a string of murders that occurred between 1984 and 1989, only the murder victims killed from 1987 to 1989 would be included in the dataset. Similarly, only victims killed in California would be included in the dataset if the defendant killed some victims outside of the state.

27 Michael L. Radelet & Glenn L. Pierce, *Choosing Those Who Will Die: Race and the Death Penalty in Florida*, 43 FLA REV 1 (1991).

28 Pierce and Radelet, *supra* note 10 at 33.

29 Gross and Mauro, *supra* note 13; Pierce and Radelet, *supra* note 10.

30 While Penal Code 190.5 (a) making juveniles ineligible for the death penalty was not passed until 1990, I excluded all homicides with juvenile suspects since it can take homicide cases several years to be resolved, especially if a death sentence is rendered. Thus, excluding all cases with juvenile suspects offers a more conservative approach by allowing for this possibility.

31 Gross and Mauro, *supra* note 13; Pierce and Radelet, *supra* note 10.

32 For multi-suspect incidents, the modal (i.e., most common) suspect race was utilized. However, if there was no modal race category because of a tie (i.e., two modal races) and the incident involved at least one Black suspect, the incident was coded as having a Black suspect. This coding scheme reflects the fact that Blackness has been central to social and political concerns about crime and punishment; as such, in terms of suspect racial characteristics, Blackness is most likely to influence case outcomes. Given that such instances were rare (occurring

victim/suspect gender was dichotomously coded (1=male, 0=female).[33] Victim/suspect age was squared (age^2) to capture its potential u-shaped functional form (i.e., homicides with youthful/elderly victims or suspects may receive different treatment than those with middle-aged ones).[34]

Homicide Characteristics:

20. Consistent with other academic models, I controlled for various crime features.[35] Some homicides may be considered more severe than others due to the circumstances surrounding the incident. Thus, it is important to consider these circumstances as they may influence death sentencing. These circumstances included whether the murder was firearm-related, occurred in a public setting (e.g., park, street, etc.), or involved a stranger suspect (i.e., the suspect did not know the victim). In addition, I include the offense year as a predictor to control for annual effects.[36]

21. Importantly, I also include binary variables measuring the presence (1=yes, 0=no) of offense characteristics that could make a crime potentially death-eligible under Penal Code 190.2(a). The CDOJ data includes offense information related to many of the most commonly filed death-eligible offenses in California, including felony-murder (PC 190.2(a)(17)), multiple victims (PC 190.2(a)(3)), drive-by shootings (PC 190.2(a)(21)), and whether the killing was

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in less than 1% of the data), this decision will not likely alter the study's main findings. Katherine Beckett, Kris Nyrop & Lori Pfingst, *Race, Drugs, And Policing: Understanding Disparities In Drug Delivery Arrests*, 44 CRIMINOLOGY 105 (2006); KATHERINE BECKETT, MAKING CRIME PAY: LAW AND ORDER IN CONTEMPORARY AMERICAN POLITICS (1999); KATHERYN RUSSELL-BROWN, THE COLOR OF CRIME: RACIAL HOAXES, WHITE FEAR, BLACK PROTECTIONISM, POLICE HARASSMENT, AND OTHER MACROAGGRESSIONS (1998); Omi Michael & Winant Howard, *Racial Formation in the United States: From the 1960s to the 1990s*, N. Y. CITY ROUTLEDGE (1994).

33 In multi-suspect incidents, the modal (i.e., most common) suspect gender was used for the entire incident. If there was no modal gender because of a tie (i.e., two modal genders) and the incident involved at least one female, the incident was coded as having a female suspect. This coding scheme reflects the fact that crimes involving female suspects are often treated with greater leniency. The mean suspect age was used in multi-suspect incidents. B. Keith Crew, *Sex Differences in Criminal Sentencing: Chivalry or Patriarchy?*, 8 JUSTICE Q. 59 (1991); Cassia Spohn, *Gender and Sentencing of Drug Offenders: Is Chivalry Dead?*, 9 CRIM. JUSTICE POLICY REV. 365 (1999).

34 Phillips, *supra* note 22; Scott Phillips, *Legal Disparities in the Capital of Capital Punishment*, J. CRIM. LAW CRIMINOL. 717 (2009).

35 BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; 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 et al., *supra* note 6.

36 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 (2010).

gang-related (PC 190.2(a)(22)).[37] I coded a case as having a co-occurring death-eligible offense if these factors were present in the CDOJ data, regardless of whether prosecutors eventually filed special circumstances under PC 190.2(a). For example, a homicide was coded as "1" for the felony-murder variable if the homicide involved a robbery, regardless of the eventual outcome. Thus, this variable helps to establish homicides where a death sentence could have been possible, as indicated by the presence of a death-eligible offense characteristics. Given that roughly 70% of death-sentenced homicides in the dataset included one or more special circumstances related to these offense characteristics, these variables capture most of the variability in death-eligibility.

County Characteristics:

22. To assess whether any observed racial disparities in death sentencing vary across California counties, I included several county characteristics. Most notably, I controlled for binary variables for the 9 most populous counties, including Alameda, Contra Costa, Los Angeles, Orange, Riverside, Sacramento, San Bernardino, San Diego, and Santa Clara. In addition, I include a single county indicator variable for the remaining 49 smaller counties, which I label "Smaller counties."[38] Like Ulmer and colleagues, I combined these other 49 counties because they have too few homicides and/or death sentences to examine each county separately.[39] Therefore, for example, separately estimating racial disparities in death sentencing for Alpine County would not be possible because that county did not have any death sentences during this timeframe. Combining the 49 smaller counties into one group labeled "Smaller counties" helps to pool together homicides in these counties, allowing me to retrain homicides

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[37] Prior research suggests that these are among the most frequently filed special circumstances in California. Moreover, death-eligibility under some special circumstances, such as "especially heinous" murders (PC 190.2(a)(15)) or "lying in wait" (PC 190.2(a)(14)) are notoriously difficult to capture based on offense characteristics given their subjective nature. James Acker & Charles Lanier, *Aggravating Circumstances and Capital Punishment Law: Rhetoric or Real Reforms*, 29 CRIM. LAW BULL. 467 (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).

[38] Despite its larger sample size, San Francisco County was included along with other smaller counties in the "smaller counties" group due to its small number of death sentences. For many years now, San Francisco County was sought few, if any, death sentences, making it difficult to estimate as a separate fixed-effect.

[39] Jeffery T. Ulmer, Gary Zajac & John H. Kramer, *Geographic Arbitrariness? County Court Variation in Capital Prosecution and Sentencing in Pennsylvania*, 19 CRIMINOL. PUBLIC POLICY 1073 (2020).

from these counties in my analysis. Importantly, this means my results capture *all* California homicides from 1987 to 2019, not just those from large counties.

In line with prior research examining geographic disparities in California death sentencing,[40] I included county-level U.S. census and crime statistics as control variables. Relying on data from the decennial censuses, I measured the total population size and the percentage of residents in each county who identified as Black or Hispanic. I also included a census measure capturing the percentage of the county's population considered urban, homeowners, and Republican voters in presidential elections.[41] Finally, I controlled for the annual rate of homicide incidents in each county per 1,000 residents based on county-level CDOJ data.[42] Controlling for homicide rates is important because counties with more homicides may have a greater likelihood of issuing death sentences simply because they have a larger number of homicide cases moving through their court system.

Analysis Strategy:

23. To investigate whether any observed racial disparities in death sentences vary across counties, I calculated fixed-effects logistic regression models for *all* homicides occurring in California from 1987 through 2019. By including binary county indicator variables (or "fixed-effects") in the regression model, I can account for time-invariant factors that might impact death sentences, such as District Attorney capital charging policies or jury demographics/preferences. For example, including a binary variable (i.e., fixed-effect) for Riverside County controls for the fact that District Attorneys in the county have more aggressively sought death sentences, and thus, the likelihood of a given homicide from Riverside County resulting in a death sentence is high. To this point, Firebaugh and colleagues[43] note the following about fixed-effects in regression models:

> if the data under consideration are longitudinal, the fixed effects approach can also alleviate the effects of confounding variables without measuring them…The fixed effects

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40 Pierce and Radelet, *supra* note 10.

41 Presidential electin data were obtained from Algara, Carlos; Sharif Amlani, 2021, "Replication Data for: Partisanship & Nationalization in American Elections: Evidence from Presidential, Senatorial, & Gubernatorial Elections in the U.S. Counties, 1872-2020", https://doi.org/10.7910/DVN/DGUMFI, Harvard Dataverse, V1, UNF:6:glfQoiLzpXDGTfErebfBIQ== [fileUNF]

42 https://openjustice.doj.ca.gov/data

43 G Firebaugh, C Warner & M Massoglia, *Fixed Effects, Random Effects, and Hybrid Models for Causal Analysis*, *in* HANDBOOK OF CAUSAL ANALYSIS FOR SOCIAL RESEARCH (2013).

> approach removes the effects of time-invariant causes, whether those causes are measured or not. That is a powerful feature because it means that fixed effects methods can alleviate omitted-variable bias.

Thus, including county fixed-effects allows me to examine whether racial disparities in death sentencing differ by county, net of any unobserved time-invariant county-level factors that might affect death sentencing such as capital charging policies or jury demographics/preferences. For these county fixed-effects, Los Angeles County was used as the reference group since it had the largest number of homicides during the period of analysis.

24. In addition, my regression models utilize clustered standard errors at the incident level via Stata's "vce(cluster DOJ offense #)" command to account for the fact that homicides within a given incident may be correlated.[44] The use of clustered standard errors in fixed-effects longitudinal regression is common in social science studies, as it allows researchers to account for additional unobserved similarities between data points within clusters (or, in this case, homicide incidents).[45] According to Hansen, "The clustering problem is caused by the presence of a common unobserved random shock at the group level that will lead to correlation between all observations within each group."[46] Likewise, Cameron and Miller note, "The key assumption is that the errors are uncorrelated across clusters while errors for individuals belonging to the same cluster may be correlated."[47] In this analysis, homicides are clustered within offenses because the characteristics and outcomes of homicide incidents may be more similar within the incident than between them (e.g., victim/suspect demographics, weapon type, etc.). As such,

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[44] Stata's reference manual notes the following about the "vce(cluster)" command: "vce(cluster clustvar) specifies that the standard errors allow for intragroup correlation, relaxing the usual requirement that the observations be independent. That is, the observations are independent across groups (clusters) but not necessarily within groups. clustvar specifies to which group each observation belongs, for example, vce(cluster personid) in data with repeated observations on individuals. vce(cluster clustvar) affects the standard errors and variance-covariance matrix of the estimators but not the estimated coefficients; see [U] 20.22 Obtaining robust variance estimates." Stata, *Datasets for Stata Base Reference Manual, Release 17*, 17 (2021), https://www.stata.com/manuals/r.pdf.

[45] A. Colin Cameron & Douglas L. Miller, *A Practitioner's Guide to Cluster-Robust Inference*, 50 J. HUM. RESOUR. 317 (2015); WOOLDRIDGE, *supra* note 4; A. COLIN CAMERON & PRAVIN K. TRIVEDI, REGRESSION ANALYSIS OF COUNT DATA (2013); ACOCK, *supra* note 15; LONG AND FREESE, *supra* note 15; FINLAY AND AGRESTI, *supra* note 21; 135 ALAN AGRESTI, AN INTRODUCTION TO CATEGORICAL DATA ANALYSIS (1996).

[46] Christian B. Hansen, *Generalized Least Squares Inference in Panel and Multilevel Models with Serial Correlation and Fixed Effects*, 140 J. ECONOM. 670 (2007).

[47] Cameron and Miller, *supra* note 45.

clustering the standard errors at the incident level helps to control this possibility by relaxing the regression assumption of uncorrelated observations.[48]

25. For several reasons, I use county fixed-effects regression with incident-level clustered standard errors rather than multi-level models with incidents nested in incidents/counties. Foremost, fixed-effects models allow researchers to estimate coefficients for specific geographic units (in this case, counties), whereas multi-level models estimate the effects of variables across geographic units (e.g., counties) but do not provide estimates for each geographic unit.[49] In other words, fixed-effects regressions allow me to assess whether victim/suspect disparities are larger in specific counties, while multi-level models would not.[50] Thus, county fix-effects are ideal for identifying death sentencing "hotspots" relevant to lawmakers and criminal justice officials. Second, the dataset does not meet sample size requirements for multi-level models. Multi-level models require at least 30 level 1 units (victims) in each level 2 (incident) or level 3 (county) unit, with 30 or more groups at level 2 or 3.[51] However, few homicides have more than 3 victims, making multi-level models with victims (level 1) nested in incidents (level 2) inappropriate. Similarly, even though California has 58 counties, the 9 largest counties listed above account for nearly all death sentences in California during this period. Indeed, 19 counties had no death sentences during this time, and 75% of counties had fewer than 10 death sentences. Third, research shows it is unnecessary to cluster standard errors for variables included as fixed effects (i.e., counties),[52] obviating the need to cluster standard errors at the county level. As such, models with county fixed-effects and incident-level standard errors represent the best approach for our research questions.

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48 WOOLDRIDGE, *supra* note 4.

49 *Id.*; Firebaugh, Warner, and Massoglia, *supra* note 43; ROBERT BICKEL, MULTILEVEL ANALYSIS FOR APPLIED RESEARCH: IT'S JUST REGRESSION! (2012); SOPHIA RABE-HESKETH & ANDERS SKRONDAL, MULTILEVEL AND LONGITUDINAL MODELING USING STATA (2008).

50 Since multi-level models allow the intercepts and slopes of variables to vary across geographic units, they do not permit researchers to estimate coefficients for specific geographic units. BICKEL, *supra* note 49; RABE-HESKETH AND SKRONDAL, *supra* note 49.

51 BICKEL, *supra* note 49; RONALD H. HECK & SCOTT L. THOMAS, AN INTRODUCTION TO MULTILEVEL MODELING TECHNIQUES: MLM AND SEM APPROACHES (2020); Joop Hox & Daniel McNeish, *Small Samples in Multilevel Modeling*, SMALL SAMPLE SIZE SOLUT. 215 (2020); Cora JM Maas & Joop J. Hox, *Sufficient Sample Sizes for Multilevel Modeling.*, 1 METHODOL. EUR. J. RES. METHODS BEHAV. SOC. SCI. 86 (2005).

52 According to Abadie and colleagues, "If one includes fixed effects in the regression function to account for the clusters, there is no reason to cluster standard errors, because the fixed effects completely eliminate the within-cluster correlation of the residuals." Alberto Abadie et al., *When Should You Adjust Standard Errors for Clustering?*, 138 Q. J. ECON. 1, 7 (2023); Rustam Ibragimov & Ulrich K. Müller, *Inference with Few Heterogeneous Clusters*, 98 REV. ECON. STAT. 83 (2016).

Results

Unadjusted Summary Statistics:

26. Table 1 shows "unadjusted" summary statistics. That is, Table 1 lists the raw statistics for various measures without controlling for any other variables. Compared to the general population of homicides in California from 1987 to 2019, Table 1 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, 31% of all California homicides have a White victim, whereas 49% of California homicides that result in a death sentence have a White victim. In contrast, 32% of California homicides involve a Black suspect, but 36% of homicides that result in a death sentence involve a Black suspect.

Table 1. Unadjusted Statistics for California Homicides (1987-2019)

	All homicides %	Death sentence %	No death sentence %
Dependent variable:			
Death sentence	2%	100%	0%
Victim and suspect demographics:			
White victim	31%	49%	30%
Hispanic victim	41%	28%	42%
Black victim	28%	23%	28%
Male victim	75%	57%	76%
Victim age	32.5	32.37	32.5
White suspect	26%	33%	26%
Hispanic suspect	42%	31%	43%
Black suspect	32%	36%	32%
Male suspect	90%	92%	90%
Suspect age	31	28.98	31.04
Case characteristics:			
Felony murder	13%	61%	12%
Multiple victims	9%	63%	8%
Drive-by shooting	1%	2%	1%
Gang killing	16%	12%	16%
Firearm	18%	19%	18%
Killed in public place	47%	44%	47%
stranger killing	27%	40%	27%
Offense year	1999.51	1996.64	1999.56
County characteristics:			
% Black population	6.70%	5.94%	6.71%
% Hispanic population	31.31%	28.58%	31.36%
% urban	94.32%	92.93%	94.35%
% owner occupied	54.99%	57.54%	54.94%
% Republican vote	40.18%	43.08%	40.12%
total population	4286224.89	3384304.89	4303069.12
Alameda County	4%	6%	4%
Contra Costa County	3%	3%	2%
Los Angeles County	40%	29%	40%
Orange County	4%	5%	4%
Riverside County	5%	13%	5%
Sacramento County	4%	5%	4%
San Bernardino County	7%	7%	7%
San Diego County	5%	5%	5%
Santa Clara County	2%	2%	2%
Smaller counties	25%	25%	25%
Observations	34745	637	34108

27. Figure 1 maps the death sentencing rate for California counties per 1,000 homicide incidents. Death sentencing rates were calculated by dividing the total number of death sentences in each county from 1987 to 2019 by the total number of homicides in the same county during that period, multiplied by 1,000 (i.e., [death sentences/homicides] X 1,000). The color shading shows the death sentencing rates broken down by standard deviations, with the most death sentence prone counties shaded in green. However, because many counties have had few, if any, death sentences, Figure 2 graphs death sentencing rates for the largest California counties. Most notably, Figure 2 shows that Riverside County's death sentencing rate is nearly double (59 death sentences per 1,000 homicides), its next highest competitor of Orange County (30 death sentences per 1,000 homicides). Although there are other interesting death sentencing patterns, they are overshadowed by Riverside County's elevated death sentencing rate, which lengthens the y-axis considerably, given its strikingly high death sentencing rate. For example, Los Angeles has the lowest death sentencing rate even though it is the largest county in the state and sends the largest number of inmates to death row in raw numbers.

Figure 1. Map of Death Sentencing Rates in California Counties

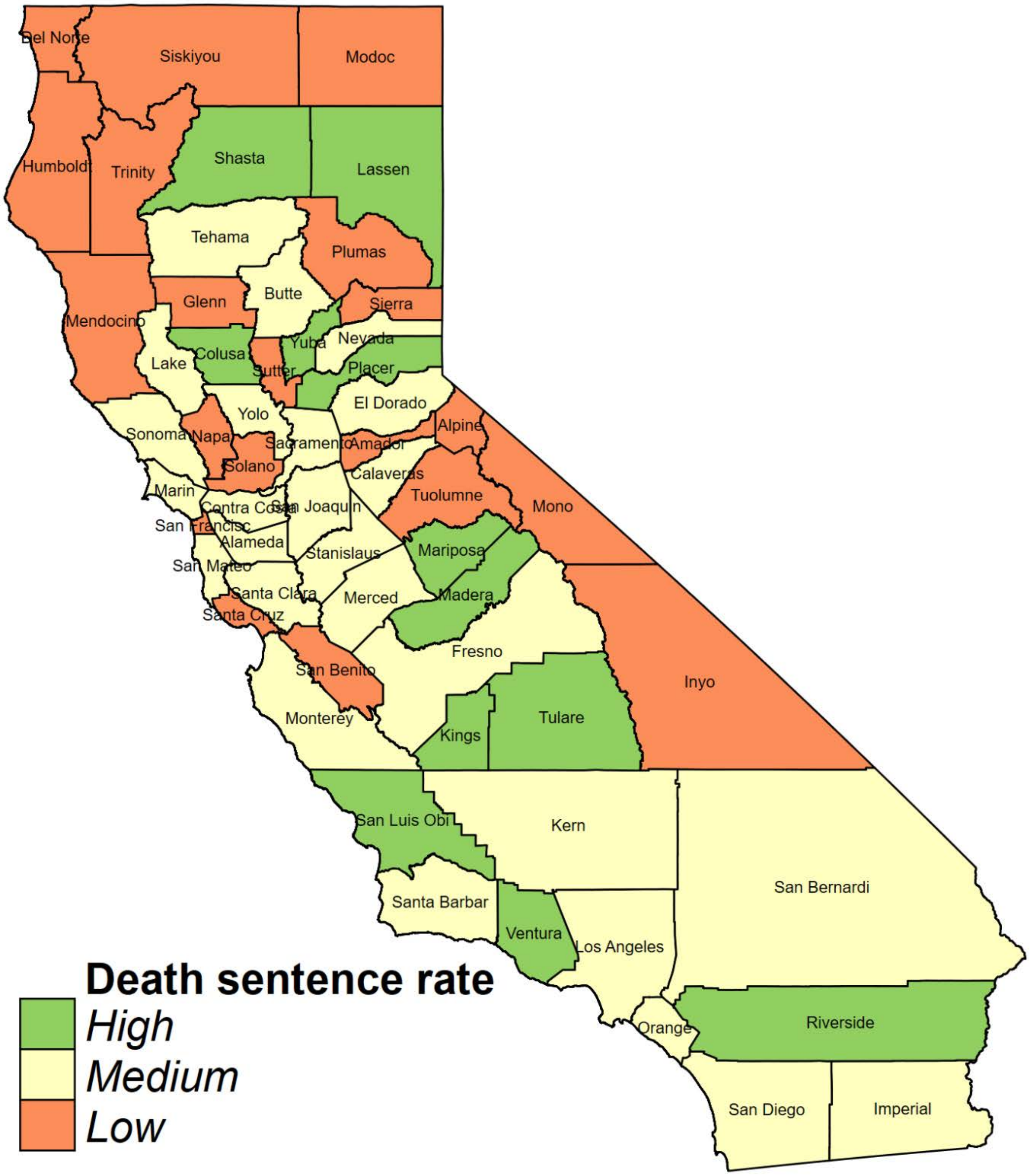
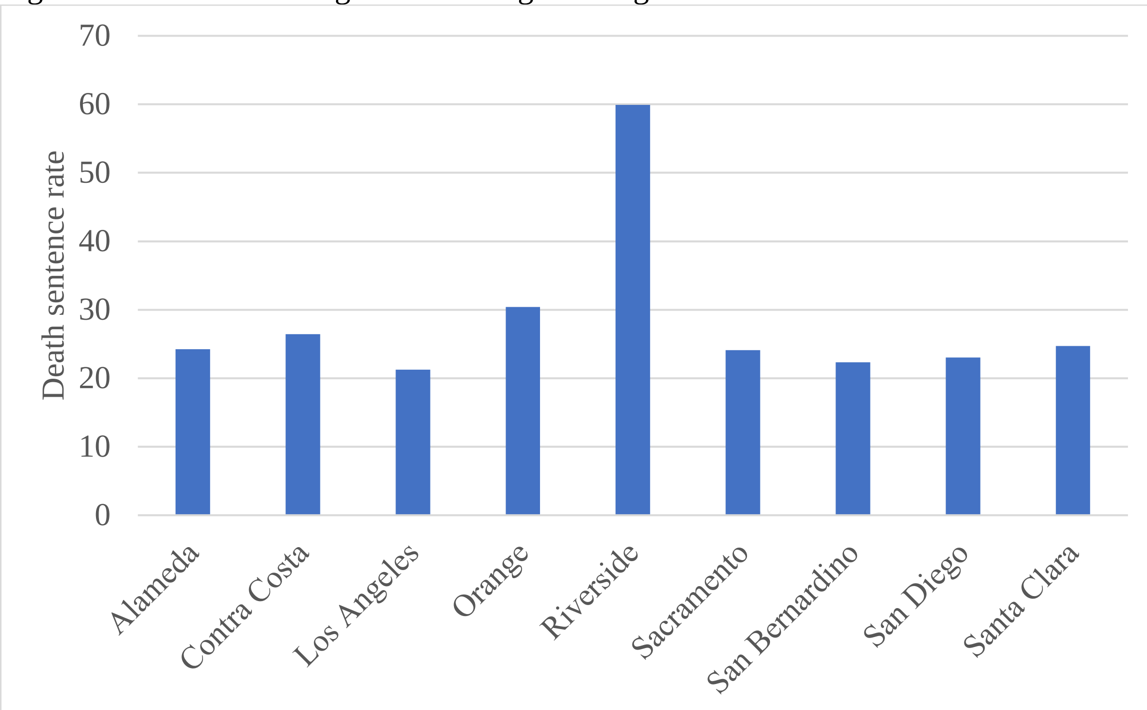


Figure 2. Death Sentencing Rates Among the Largest California Counties



Adjusted Racial Disparities:

28. 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 the logistic model, homicides involving death-eligible offenses (e.g., multiple murder, felony-murder, drive-by-shooting, gang killing) more likely to result in a death sentence. These findings are consistent with California's death penalty laws that consider homicides to be more aggravated, and prior research examining death penalty outcomes in California.[53]

29. Even after controlling for these important legal factors, however, victim and suspect race shape death sentences. 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 53% less likely to result in a death

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53 Petersen, *supra* note 6; Petersen, *supra* note 6; Petersen and Lynch, *supra* note 37; Pierce and Radelet, *supra* note 10; Shatz, *supra* note 37.

sentence, and those with a Hispanic victim are 36% less likely to result in a death sentence. Compared to homicides with a White suspect, those with a Black suspect are 1.49 times more likely to result in a death sentence, and those with a Hispanic suspect are 1.22 more likely to result in a death sentence.

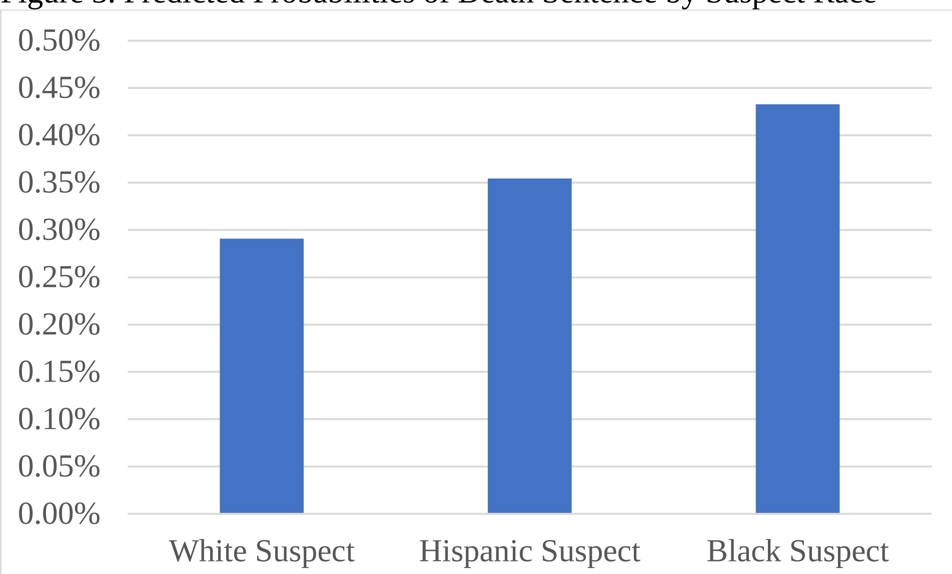
Table 2. Regressions Predicting Death Sentencing Outcomes in California (1987-2019).

	OR(SE)
Victim and suspect demographics:	
White victim	Reference
Hispanic victim	0.47*** (0.08)
Black victim	0.64* (0.12)
Male victim	0.45*** (0.05)
Victim age	0.99 (0.01)
Victim age (squared)	1.00 (0.00)
White suspect	Reference
Hispanic suspect	1.22 (0.24)
Black suspect	1.49* (0.30)
Male suspect	1.11 (0.26)
Suspect age	1.06 (0.04)
Suspect age (squared)	1.00 (0.00)
Case characteristics:	
Felony murder	15.00*** (2.26)
Multiple victims	22.08*** (2.63)
Drive-by shooting	5.74*** (2.09)
Gang killing	2.83*** (0.59)
Firearm	1.60** (0.23)
Killed in a public place	1.18 (0.16)
stranger killing	1.31* (0.17)
Offense year	0.89*** (0.01)
County characteristics:	
% Black population	1.02 (0.02)
% Hispanic population	1.04*** (0.01)
% urban	0.99 (0.01)
% owner occupied	1.06** (0.02)
% Republican vote	1.00 (0.01)
total population	1.00 (0.00)
Annual homicide rate	0.49*** (0.09)
Alameda County	14.12 (22.47)
Contra Costa County	7.20 (12.34)
Los Angeles County	Reference
Orange County	3.76 (4.98)
Riverside County	8.10 (12.83)
Sacramento County	10.62 (16.99)
San Bernardino County	3.55 (5.47)
San Diego County	6.20 (8.05)
Santa Clara County	2.80 (4.55)
Smaller counties	6.15 (10.57)
Observations	34745

Exponentiated coefficients; Standard errors in parentheses
Notes: Listwise deleted sample. Reference groups = white victim; white suspect
* p < .05, ** p < .01, *** p < .001

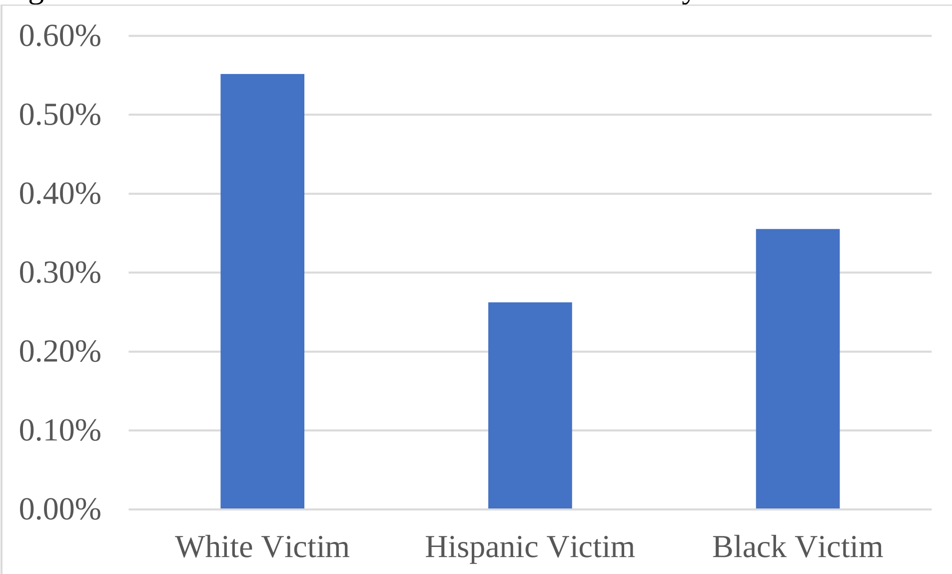
30. Next, I calculated predicted probabilities to help visualize the effects of victim and suspect race/ethnicity from the regression model in Table 2. Figure 3 shows that homicides with White victims are more likely to result in a death sentence, while homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence. In contrast, Figure 3 indicates that homicides with White suspects 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[54] and suggests a victim-by-suspect race interaction, which I explore below.

Figure 3. Predicted Probabilities of Death Sentence by Suspect Race



54 Pierce and Radelet, *supra* note 10.

Figure 4. Predicted Probabilities of Death Sentence by Victim Race



31. Since prior research on the death penalty in California[55] and elsewhere[56] points to the influence of victim-by-suspect racial groupings on case outcomes, next I examined the effects of victim-by-suspect racial dyads. Here, I investigated whether victim and suspect race variables work together to shape death sentences. Table 3 indicates that non-White suspects (Black/Hispanic) who kill White victims are especially likely to result in a death sentence. According to Table 3, compared to homicides involving a White victim and a White suspect, those with a Black suspect and a White victim are 1.46 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 1.18 times more likely to result in a death sentence, Thus, the likelihood of a White victim homicide resulting in a death sentence is 1.46 to 1.18 times higher if the suspect is Black or Hispanic (respectively) than if the suspect were White.

32. In addition, homicides with White suspects and minority victims (Black/Hispanic) are less likely to result in a death sentence than those with White suspects and White victims. Likewise, homicides with minority suspects (Black/Hispanic) and minority victims (Black/Hispanic) are less likely to result in a death sentence than those with White suspects and

55 Petersen, *supra* note 6; Petersen, *supra* note 6.

56 Baldus et al., *supra* note 6; 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).

White victims. For example, homicides with a Hispanic suspect and Hispanic victim are 46% less likely to result in a death sentence than with White suspects and White victims.

Table 3. Regressions Predicting Death Sentencing Outcomes in California by Suspect and Victim Racial Dyads (1987-2019).

	OR(SE)
Victim and suspect demographics:	
White suspect & White victim	Reference
White suspect & Black victim	0.96 (0.45)
White suspect & Hispanic victim	0.53 (0.19)
Black suspect & White victim	1.46 (0.31)
Black suspect & Black victim	0.91 (0.23)
Black suspect & Hispanic victim	0.80 (0.24)
Hispanic suspect & White victim	1.18 (0.28)
Hispanic suspect & Black victim	0.86 (0.38)
Hispanic suspect & Hispanic victim	0.54** (0.11)
Male suspect	1.13 (0.27)
Suspect age	1.06 (0.04)
Suspect age (squared)	1.00 (0.00)
Male victim	0.45*** (0.05)
Victim age	0.99 (0.01)
Victim age (squared)	1.00 (0.00)
Case characteristics:	
Firearm	1.60** (0.23)
Killed in a public place	1.17 (0.16)
stranger killing	1.30* (0.17)
Offense year	0.89*** (0.01)
Felony murder	14.84*** (2.24)
Multiple victims	22.05*** (2.63)
Drive-by shooting	5.75*** (2.09)
Gang killing	2.87*** (0.60)
County characteristics:	
% Black population	1.02 (0.02)
% Hispanic population	1.04*** (0.01)
% urban	0.99 (0.01)
% owner occupied	1.06** (0.02)
% Republican vote	1.00 (0.01)
total population	1.00 (0.00)
Annual homicide rate	0.49*** (0.09)
Alameda County	14.12 (22.54)
Contra Costa County	7.13 (12.27)
Los Angeles County	Reference
Orange County	3.75 (4.97)
Riverside County	7.92 (12.60)
Sacramento County	10.54 (16.92)
San Bernardino County	3.46 (5.35)
San Diego County	6.17 (8.03)
Santa Clara County	2.78 (4.52)
Smaller counties	6.08 (10.49)
Observations	34745

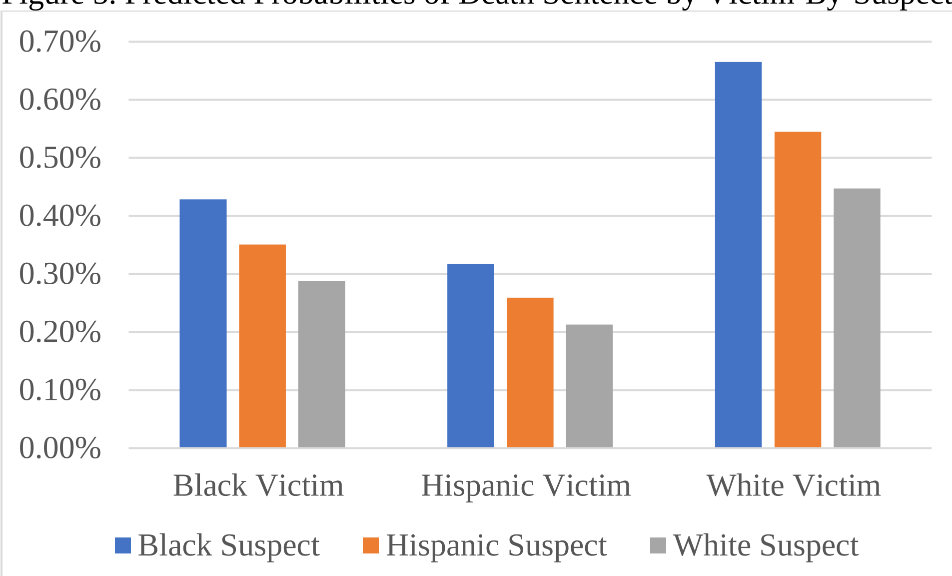
Exponentiated coefficients; Standard errors in parentheses

Notes: Listwise deleted sample. Reference groups = white victim; white suspect

* p < .05, ** p < .01, *** p < .001

33. To help visualize victim-by-suspect racial dyads, I calculated predicted probabilities. Figure 5, displaying victim-by-suspect racial dyads in terms of probabilities from the logistic regression in Table 3, 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, clear patterns emerge when I compare differences in predicted probabilities by victim and suspect race. In particular, Figure 5 shows 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 sentences.[57]

Figure 5. Predicted Probabilities of Death Sentence by Victim-By-Suspect Racial Dyads

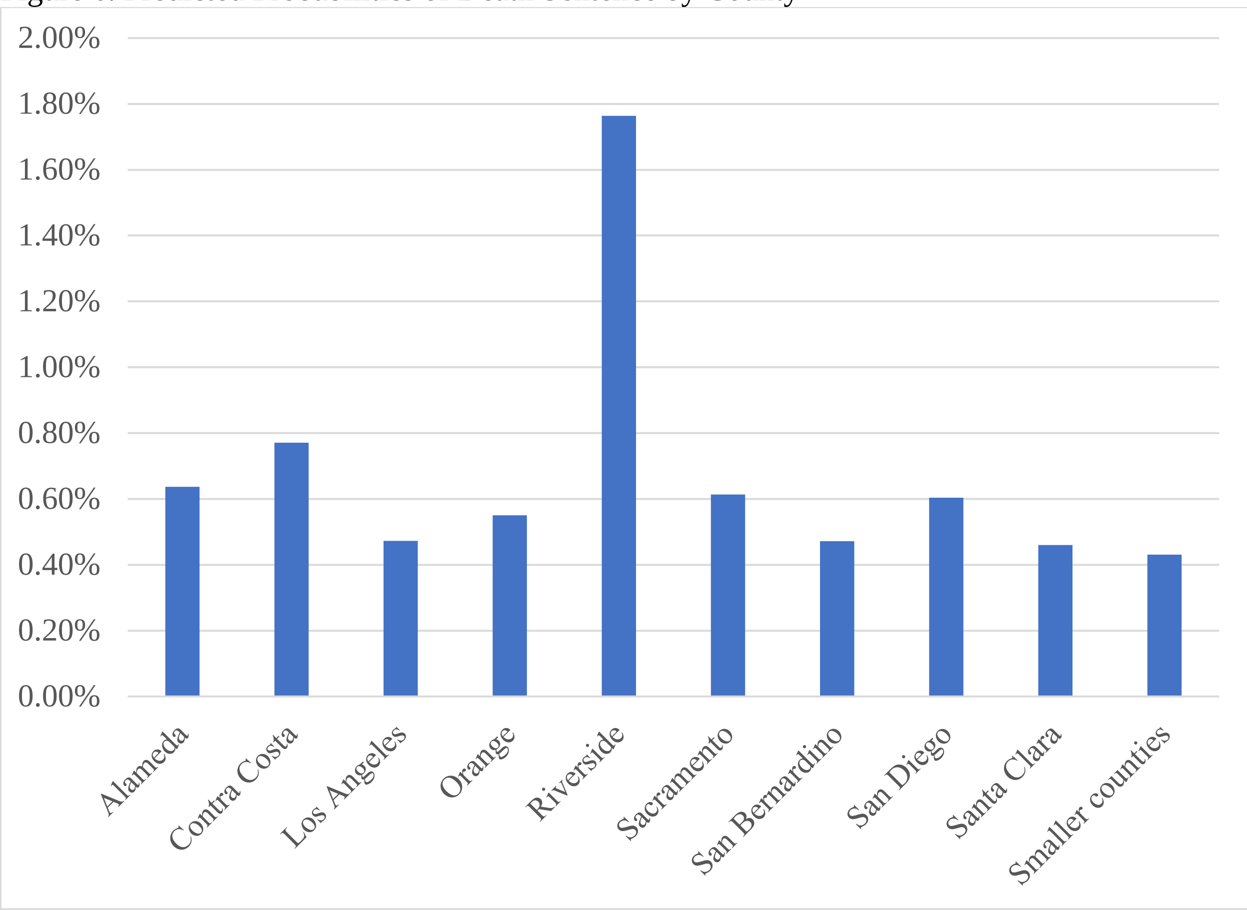


[57] Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND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

Do Racial Disparities Vary Across California Counties?

34. To examine whether the identified patterns of racial inequality vary across California counties, I focus on county fixed-effects and victim-by-suspect race variables. But before delving into the issue, it is important to establish general county trends in death sentencing. To do so, I plotted the predicted probability of a homicide resulting in a death sentence by county fixed-effects from the logistic regression model in Table 3. According to Figure 6, homicides occurring in Riverside County have the highest likelihood of a death sentence, net of other variables.

Figure 6. Predicted Probabilities of Death Sentence by County



35. Figure 7 and Figure 8 also examine county differences in the likelihood of a death sentence but add victim-by-suspect race into the picture. Two especially noteworthy findings can be gleaned from these figures. First, homicides with non-White (Black/Hispanic) suspects are more likely to result in a death sentence, while homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence. Second, these findings are remarkably consistent across counties. While the size of these victim-by-suspect racial disparities differs somewhat across counties, the overall trends noted above are very consistent. The findings reveal a three-tiered suspect/victim racial hierarchy in death sentencing that is present across all California counties from 1987 to 2019. In Figure 7, homicides involving Black suspects are the most likely to result in a death sentence, followed by homicides with Hispanic and White suspects (respectively). In contrast, Figure 8 shows a reversed three-tiered racial hierarchy where homicides involving White victims are the most likely to result in a death sentence, followed by homicides with Hispanic and Black victims (respectively). When viewed together, Figure *7* and Figure 8 illustrate a remarkably consistent three-tiered suspect/victim racial hierarchy in death sentencing across California counties.

Figure 7. Predicted Probabilities of Death Sentence by County and Suspect Race

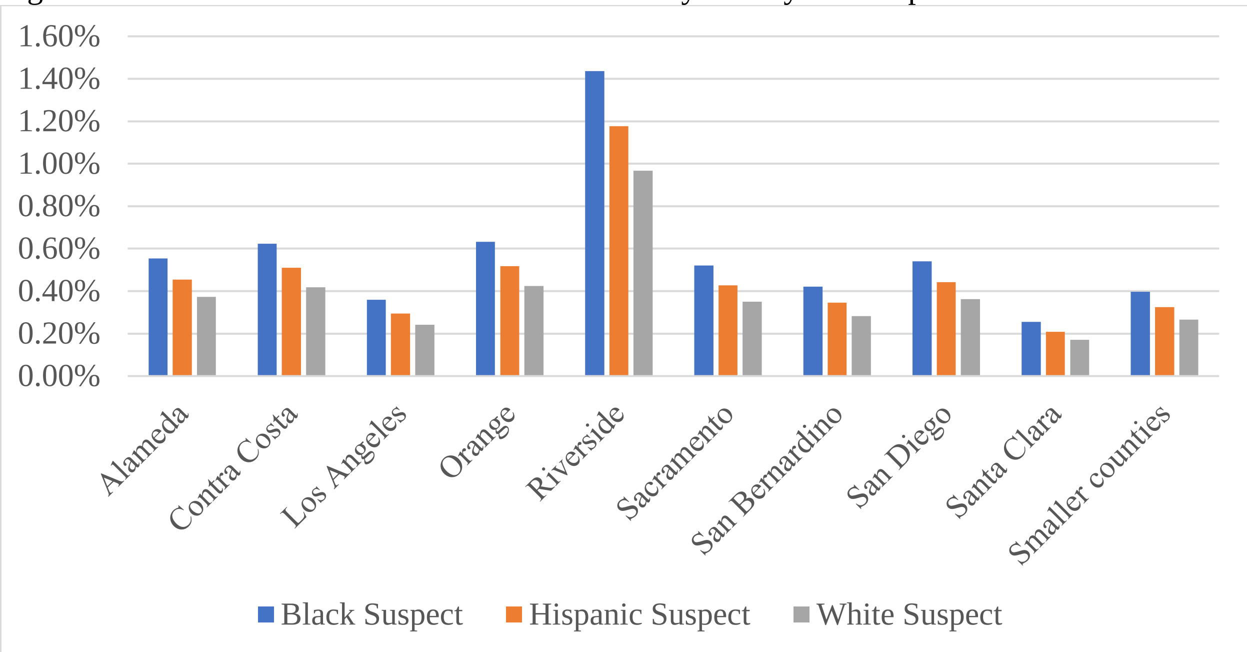
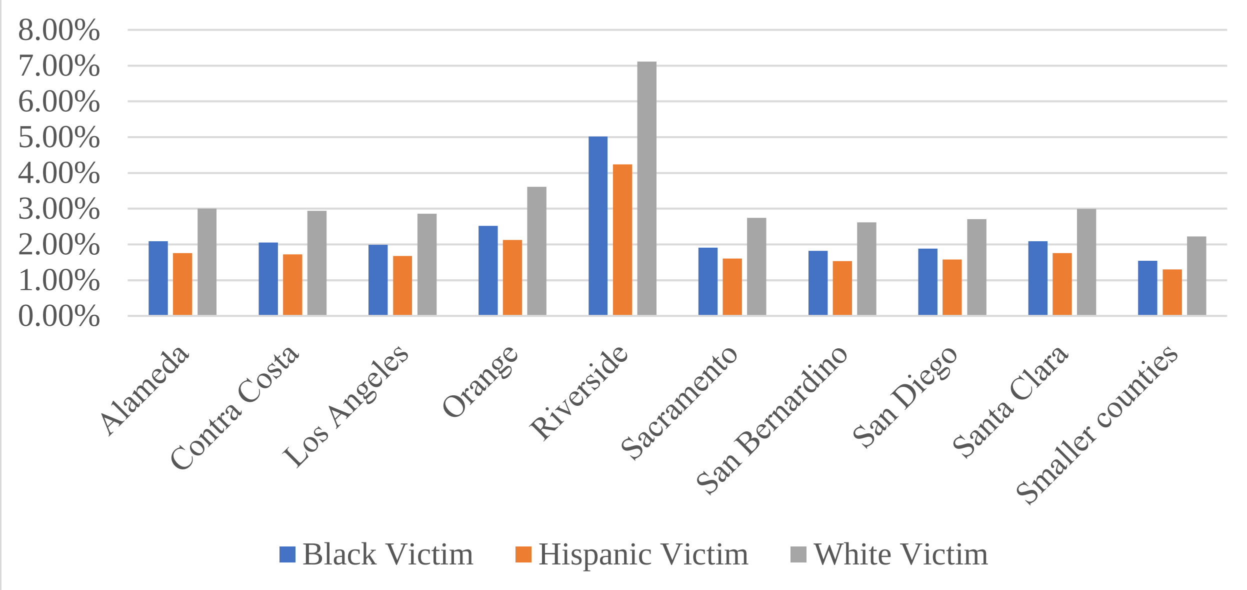
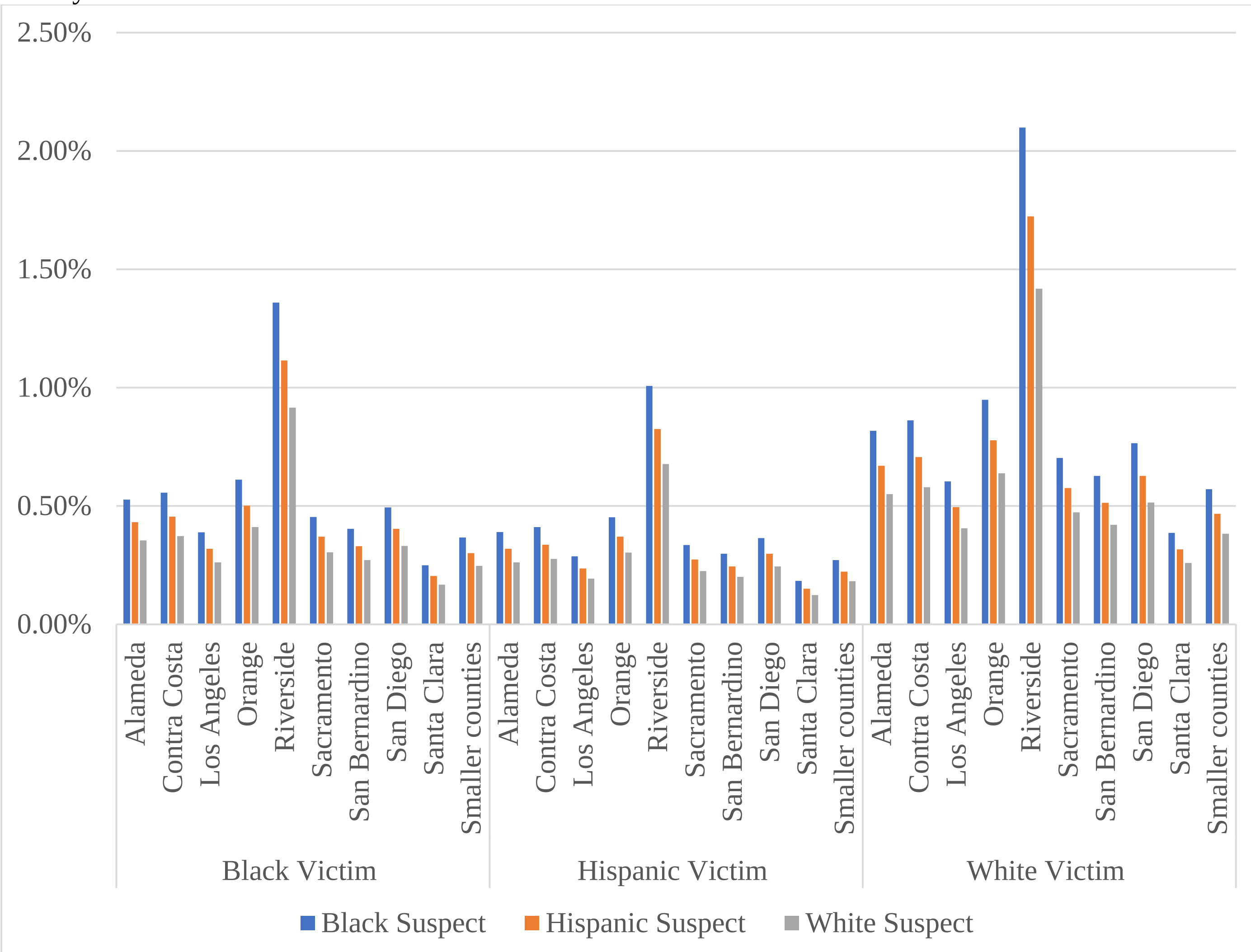


Figure 8. Predicted Probabilities of Death Sentence by County and Victim Race



36. To understand whether death sentencing disparities based on victim-suspect race dyads differ across counties, I calculated predicted probabilities. Like the victim-by-suspect dyads previously discussed, Figure 9 shows that homicides involving Black suspects and White victims are most likely to result in a death sentence. While there are certainly differences in the magnitude of victim-suspect racial disparities, the overall trends are remarkably consistent across California counties. In every county, homicides with Black suspects and White victims are the most likely to result in a death sentence, while homicides with Black suspects and Black victims are the least likely to result in a death sentence. Like the separate victim and suspect findings noted above, Figure 9 illustrates a remarkably consistent trend in terms of victim-suspect racial disparities across California counties from 1987 to 2019.

Figure 9. Predicted Probabilities of Death Sentence by Victim-By-Suspect Racial Dyads and County

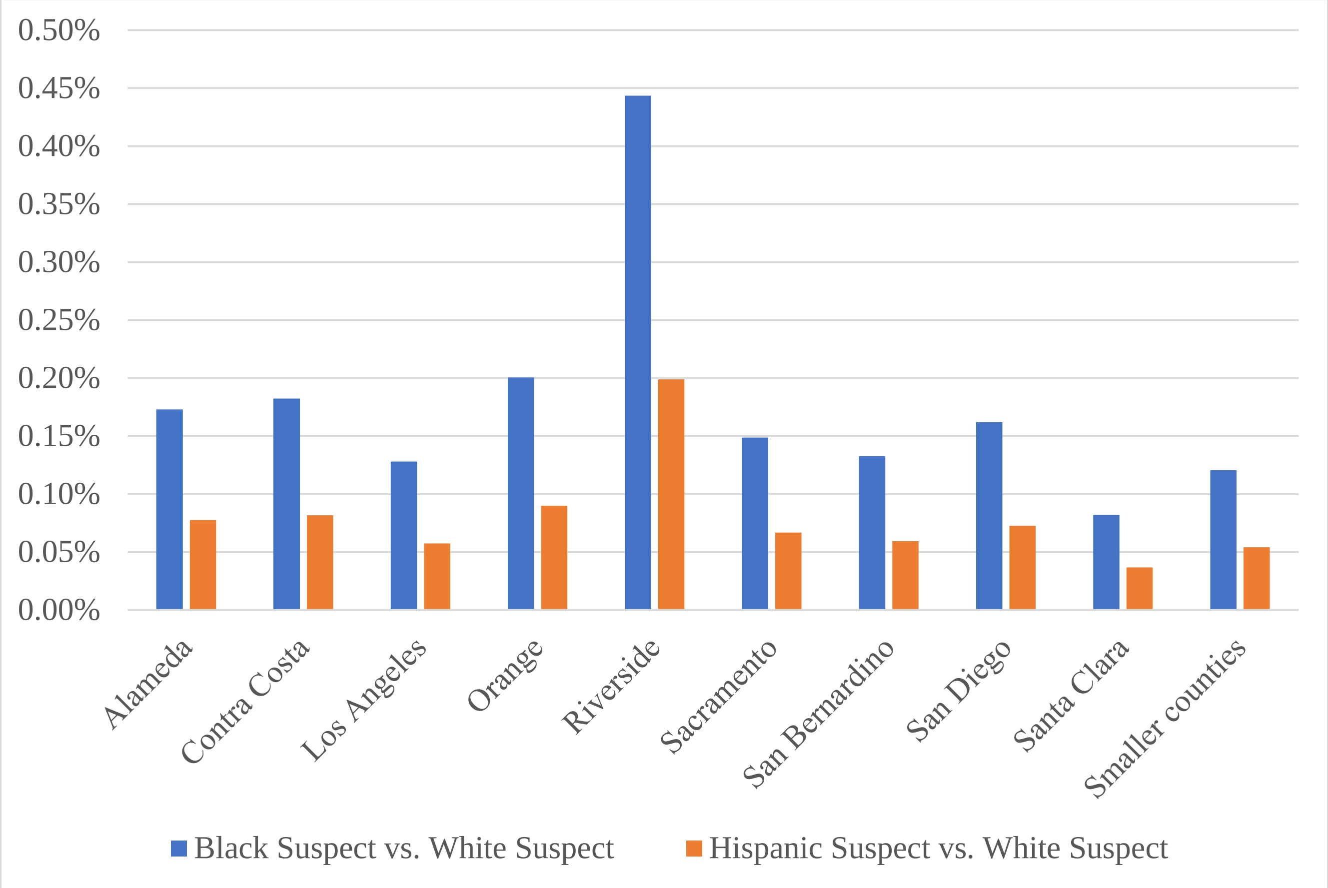


37. Figure 10 further probes spatial-racial disparities by displaying differences in the predicted probability of a death sentence for homicides with White victims by suspect race and county. Since homicides with White victims and Black/Hispanic suspects are the most likely to result in a death sentence, Figure 10 compares the predicted probabilities of homicides with White victims and Black/Hispanic suspects versus homicides with White victims and White suspects by county. For example, the blue bars compare differences in the predicted probability of a death sentence for homicides with White victims and Black suspects to homicides with White victims and White suspects. Likewise, the orange bars compare differences in the

predicted probability of a death sentence for homicides with White victims and Hispanic suspects to homicides with White victims and White suspects.

38. These comparisons allow us to assess whether death sentencing rates for homicides with White victims vary by suspect race and county. Figure 10 highlights variability in spatial-racial disparities, with inequalities being largest in places with the highest death sentencing rates overall, including Riverside, Orange, Alameda, Sacramento, Contra Costa, and San Diego counties. Conversely, spatial-racial disparities are smaller in counties with lower death sentencing rates, such as Los Angeles. Riverside County's trends are particularly noteworthy, as its racial disparities double that of other death penalty-prone counties. For example, differences in the predicted probability of a death sentence for homicides with White victims and Black versus White suspects in Riverside are more than twice as large as those in Orange County (0.44%/0.20%=2.21). Similarly, differences in the predicted probability of a death sentence for homicides with White victims and Hispanic versus White suspects in Riverside are more than twice as large as those in Orange County (0.20%/0.09%=2.22). Thus, while homicides with White victims and Black suspects are the most likely to result in death sentences in Riverside and other counties, the magnitude of spatial-racial disparities for homicides involving White victims and Hispanic suspects is fairly similar. Even though the actual percentage differences outlined here are small given the rarity of death sentences, the magnitude of spatial-racial disparities across counties is compelling and clearly points to several racialized death sentencing "hotspots," especially Riverside County.

Figure 10. Differences in Predicted Probabilities of Death Sentence for White Victim Incidents by Suspect Race and County



IV. CONCLUSIONS

39. These findings highlight victim-by-suspect racial disparities in California death sentencing trends from 1987 to 2019. 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 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. 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.

40. County fixed-effects highlight considerable uniformity in racial disparities across California counties. While the exact size of the racial inequality differs across counties, the overall pattern is remarkably consistent. This suggests that racial disparities in California death

sentencing cannot be attributed to a few problematic counties. Instead, the findings reveal consistent and systematic racial disparities in death sentencing across California counties. While *Gregg* sought to mitigate inequalities in death sentencing, this report offers strong empirical evidence of racial disparities in California death sentencing from 1987 to 2019, employing state-of-the-art statistical methodologies and a robust dataset spanning several decades.