EXHIBIT E

Racial Disparities in California Death Sentencing During the Post-*Gregg* Period, 1979 to 2018

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I. INTRODUCTION

1. This report presents my statistical analysis of death sentencing trends in California in the post-*Gregg* period (1979 through 2018) based on information gathered from court records and the Supplemental Homicide Report (SHR).[1] Using these data, I examine whether there are racial[2] 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, which 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 involving 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 result underscore wide-spread racial disparities in California death sentencing trends in the post-*Gregg* period.

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

II. ANALYSIS STRATEGY

Population Death Sentencing Data

1 I start the analysis period in 1979 since California's death penalty was not re-instated until November 1978, after the passage of Proposition 7.

2 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.

4. This study examines a *population* of 55,922 homicide incidents that occurred in California from 1979 through 2018. Homicide incident data was combined with a *population* of death verdicts in California from 1979 through 2018 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 1979 through 2018. Because there is no state-wide data on special circumstance allegations and death notice filings,[3] 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.[4] Homicides in which the jury rendered a death sentence were coded as "1." Homicides in which a 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[5] race on death sentences for similarly situated cases.[6]

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), holding constant a host of non-racial factors that could influence death sentencing trends. This is necessary

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[3] 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.

[4] "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).

[5] 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.

[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 suspect race.

to ensure that any observed racial disparities are not spurious.[7] To the extent that legally relevant factors (e.g., number of victims, presence of a co-occurring felony) 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, Hispanic, or White[8] 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,"[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 variable analyzed corresponds to death sentences. In contrast, independent variables refer to victim/suspect demographics and case characteristics. Key independent variables of interest

[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.*

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

[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.*

include victim/suspect race, as prior research has identified these are strong predictors of death penalty outcomes.[11]

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).[12] 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 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 death sentence.[13] The unit of analysis is the homicide incident because the SHR is an incident-based dataset.[14]

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 difficult to interpret

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[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 8; 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).

[12] BALDUS, WOODWORTH, AND PULASKI, *supra* note 8; Baldus, Woodworth, and Weiner, *supra* note 8; 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 65% higher for homicides with white victims than for those with black victims [1-($\beta_{0.35}$ X 100) = 65%] 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 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 (1984); Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

because there is no inherent scale for odds ratios as they represent nonlinear trends.[15] In contrast, predicted probabilities range from 0% to 100%, making them easier to interpret.[16] 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[17] as well as the broader social scientific literature.[18] 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 suspect race. 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. For example, the predicted probability of a Black suspect receiving a death sentence in an "average" homicide is 0.63% according to Figure 2, net of other victim and suspect demographics, case characteristics, and other 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

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15 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 8.

16 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).

17 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. (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 8.

18 LONG AND FREESE, *supra* note 16. 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.

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.

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 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 that 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 simply 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 time periods of interest (1979-2018), and cannot necessarily be generalized to

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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 6; ACOCK, *supra* note 16. 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."

[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).

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." [22] In such contexts, he explains, "researchers should focus more on substantive significance and less on statistical significance." [23] Following his advice, I focus more on practical significance, although I do highlight statistically significant relationships as well.

III. DATA AND METHODOLOGY

Data and Methodology

16. To examine whether racial disparities based on victim or suspect exist in California death sentencing trends in the post-*Gregg* period (1979 through 2018), I relied on a previously established methodology[24] 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 California between 1979 and 2018.[25] Next, I obtained death sentencing data from the Habeas Corpus Resource Center, a state repository statutorily tasked with collecting such data.[26] This dataset contains information on all death sentences rendered in California from 1979 through 2018.[27]

17. I conducted probabilistic matching using the "reclink2" package in Stata to link the SHR and death sentence datasets.[28] Since the SHR does not include the exact homicide date for confidentiality reasons (including the month and year instead), probability matching was required.

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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 14; Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.
25 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/).
26 These data were provided to me by lawyers at the California Office of the State Public Defender.
27 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.
28 For death penalty studies employing similar techniques, see Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

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.[29] 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).

18. In their California study of death sentencing trends using the SHR, for example, Pierce & Radelet[30] 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."

19. 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)[31] and eliminated from consideration any homicide lacking suspect race information (most commonly those wherein no arrest was ever made).[32] Like prior research, I also limited the SHR data to homicides involving victims and suspects who are White, Black, and Hispanic.[33]

Dependent variable:

20. Because the Habeas Corpus Resource Center dataset only includes death sentencing data, my analysis focuses on whether a homicide incident resulted in a death sentence. Homicides

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[29] 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." Nada Wasi & Aaron Flaaen, *Record linkage using Stata: Preprocessing, linking, and reviewing utilities*, 15 STATA J. 672 (2015).

[30] Pierce and Radelet, *supra* note 11 at 33.

[31] Penal Code 190.5 (a).

[32] Gross and Mauro, *supra* note 14; Pierce and Radelet, *supra* note 11.

[33] 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.

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 Race:

21. 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.

Homicide Characteristics:

22. I also include binary variables measuring whether the homicide incident involved multiple victims or a co-occurring felony,[34] as the co-occurrence of a felony and multiple murder are among the most commonly alleged special circumstances in California and other jurisdictions.[35] In addition, I control for the time period in which the homicide incident occurred using several binary variables pertaining to the following time periods: 1979-1989, 1990-1999, 2000-2009, and 2010-2018.[36]

County Characteristics:

23. 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 capturing the county in which the homicide occurred for the 10 most populous counties, including Alameda, Contra Costa, Los Angeles, Orange, Riverside, Sacramento, San Bernardino,

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[34] 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.

[35] 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).

[36] Supplementary analyses focusing on homicides from 2000 to 2018, when death sentences were on the decline, yield substantively similar results to those presented below. Thus, even in a period with lower death sentencing rates, racial and geographic disparities persist in death sentencing trends.

San Diego, San Francisco, and Santa Clara. In addition, I include a single county indicator variable for the other remaining 48 smaller counties, which I label "Smaller counties." I combined these other 48 counties because they have too few homicides and/or death sentences to examine each county separately. Therefore, separately estimating racial disparities in death sentencing for Alpine County would not be possible. Combining the 48 smaller counties into one group labeled "Smaller counties" helps to pool together homicides in these counties, allowing me to retrain homicides from these counties in my analysis. Importantly, this means my results capture *all* California homicides in the post-*Gregg* era, not just those from large counties.

24. In line with prior research examining geographic disparities in California death sentencing,[37] I included county-level U.S census and crime statistics as control variables. Relying on data from the decennial censuses, I measured 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. Finally, I controlled for the annual homicide rate of each county per 1,000 residents. To construct annual homicide rates, I aggregated homicides listed in the SHR to the county level and then standardized that by each county's population. 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. Therefore, adjusting for homicide rates allows me to assess geographic patterns of death sentencing, net of the fact that some counties may have more homicides than others.

Analysis Strategy:

25. 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 1979 through 2018. 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 San Francisco County controls for the

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

fact that District Attorneys in the county have adopted policies over the last several decades not to seek the death penalty, and thus the likelihood of a given homicide from San Francisco County resulting in a death sentence low. To this point, Firebaugh and colleagues[38] 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 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.

26. In addition, my regression models utilize clustered standard errors via Stata's "vce(cluster county)" command to account for the fact that homicides within a given county may be correlated.[39] 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, counties).[40] 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."[41] Likewise, Cameron and Miller note that "The key assumption is that the errors are uncorrelated across

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[38] 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).

[39] 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.

[40] A. Colin Cameron & Douglas L. Miller, *A practitioner's guide to cluster-robust inference*, 50 J. HUM. RESOUR. 317 (2015); WOOLDRIDGE, *supra* note 6; A. COLIN CAMERON & PRAVIN K. TRIVEDI, REGRESSION ANALYSIS OF COUNT DATA (2013); ACOCK, *supra* note 16; LONG AND FREESE, *supra* note 16; FINLAY AND AGRESTI, *supra* note 21; 135 ALAN AGRESTI, AN INTRODUCTION TO CATEGORICAL DATA ANALYSIS (1996).

[41] Christian B. Hansen, *Generalized least squares inference in panel and multilevel models with serial correlation and fixed effects*, 140 J. ECONOM. 670 (2007).

clusters while errors for individuals belonging to the same cluster may be correlated."[42] In this analysis, homicides are clustered within counties because the characteristics and outcomes of homicide incidents may be more similar within the same county than between counties (e.g., victim/suspect demographics, District Attorney charging policies, jury demographics/preferences, etc.). As such, clustering the standard errors at the county level helps to control this possibility by relaxing the regression assumption of uncorrelated observations.[43]

Results

Unadjusted Summary Statistics:

27. Table 1 shows "unadjusted" summary statistics. That is, Table 1 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 California from 1979 to 2018, 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, 35% of all California homicides have a White victim, whereas 54% of California homicides that result in a death sentence have a White victim. In contrast, 31% of California homicides involve a Black suspect, but 37% of homicides that result in a death sentence involve a Black suspect.

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[42] Cameron and Miller, *supra* note 40.

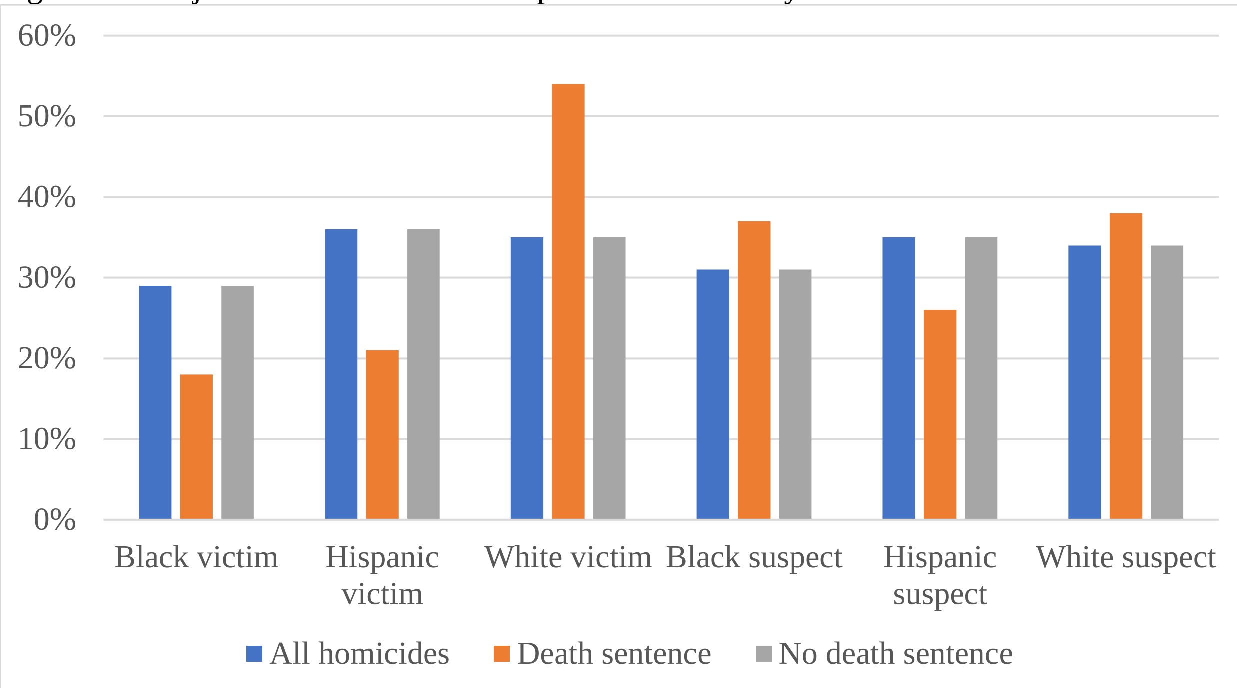
[43] WOOLDRIDGE, *supra* note 6.

Table 1. Unadjusted Statistics for California Homicides (1979-2018)

	All homicides	Death sentence	No death sentence
Victim and suspect demographics:			
Black victim	29%	18%	29%
Hispanic victim	36%	21%	36%
White victim	35%	54%	35%
Black suspect	31%	37%	31%
Hispanic suspect	35%	26%	35%
White suspect	34%	38%	34%
Case characteristics:			
Multiple murder - PC190.2(a)(3)	4%	43%	4%
Felony - murder PC190.2(a)(17)	14%	63%	13%
1980-1989	35%	39%	35%
1990-1999	30%	33%	30%
2000-2009	20%	25%	20%
2010-2018	15%	3%	15%
% Black population	5%	4%	5%
% Hispanic population	29%	27%	29%
% urban	95%	94%	95%
Annual homicide rate	1.21	1.14	1.22
Alameda County	4%	4%	4%
Contra Costa County	2%	2%	2%
Los Angeles County	42%	31%	42%
Orange County	3%	5%	3%
Riverside County	4%	11%	4%
Sacramento County	3%	3%	3%
San Bernardino County	5%	5%	5%
San Diego County	4%	4%	4%
San Francisco County	2%	0%	2%
Santa Clara County	2%	1%	2%
Smaller counties	30%	33%	30%
Observations	55922	808	55114

28. Figure 1 shows the unadjusted breakdowns for suspect/victim race. It is particularly noteworthy is the fact that homicides involving White victims are overrepresented among those resulting in a death sentence, as compared to all homicides. Conversely, Black suspects are overrepresented in homicides resulting in a death sentence relative to all homicides.

Figure 1. Unadjusted Breakdowns for Suspect/Victim Race by Death Sentence



Adjusted Racial Disparities:

29. 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 multiple victims, or a felony are more likely to result in a death sentence. These findings are consistent with California's death penalty laws that consider homicides with multiple victims [PC190.2(a)(3)] or a felony [PC190.2(a)(17)] to be more aggravated, and prior research examining death penalty outcomes in California.[44]

30. 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 66% less likely to result in a death sentence, and those with a Hispanic victim are 66% less likely to result in a death sentence. Compared to

[44] Petersen, *supra* note 8; Petersen, *supra* note 8; Petersen and Lynch, *supra* note 35; Pierce and Radelet, *supra* note 11; Shatz, *supra* note 35.

homicides with a White suspect, those with a Black suspect are 2.17 times more likely to result in a death sentence, and those with a Hispanic suspect are 1.52 more likely to result in a death sentence. The effect for Hispanic suspects is significant at the 0.05 p-value, meaning that there is less than a 5% chance of obtaining this result by random chance.[45] All of the other results are statistically significant at the 0.01 p-value level (i.e., $p < 0.01$), meaning that there is less than a 1% chance of obtaining these results by random chance.[46]

45 FINLAY AND AGRESTI, *supra* note 21; BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.
46 FINLAY AND AGRESTI, *supra* note 21; BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.

Table 2. Regressions Predicting Death Sentencing Outcomes in California (1979-2018).

	OR(SE)
Victim and suspect demographics:	
Black victim	0.34*** (0.03)
Hispanic victim	0.34*** (0.08)
Black suspect	2.17*** (0.34)
Hispanic suspect	1.52* (0.26)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	23.21*** (6.45)
Felony - murder PC190.2(a)(17)	11.45*** (1.35)
1990-1999	1.19 (0.40)
2000-2009	0.91 (0.28)
2010-2018	0.09*** (0.05)
County characteristics:	
% Black population	0.98 (0.04)
% Hispanic population	1.02* (0.01)
% urban	1.01 (0.01)
Annual homicide rate	0.50*** (0.08)
Alameda County	2.22* (0.69)
Contra Costa County	1.43 (0.44)
Orange County	1.40 (0.42)
Riverside County	3.71*** (0.59)
Sacramento County	1.42 (0.42)
San Bernardino County	1.16 (0.15)
San Diego County	1.10 (0.25)
San Francisco County	0.12*** (0.03)
Santa Clara County	0.72 (0.20)
Smaller counties	1.11 (0.26)
Observations	55922

Exponentiated coefficients; Standard errors in parentheses

Notes: Listwise deleted sample. Reference groups = 1979-1989 offense year; white victim; white suspect; Los Angeles County

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

31. Next, I calculated predicted probabilities to help visualize the effects of victim and suspect race/ethnicity from the regression model in Table 2. Figure 2 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[47] and suggests a victim-by-suspect race interaction, which I explore below.

Figure 2. Predicted Probabilities of Death Sentence by Suspect Race

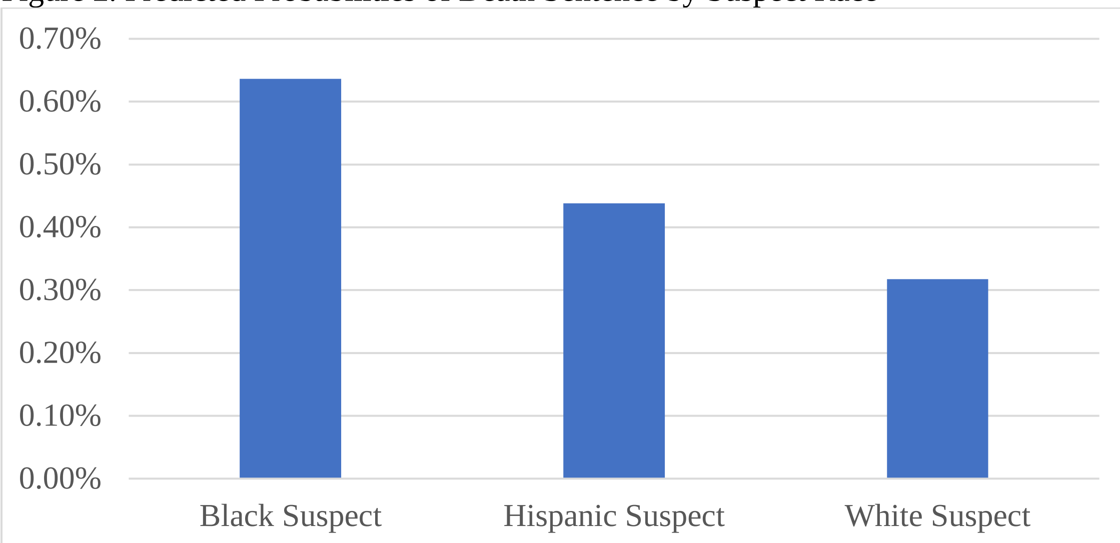
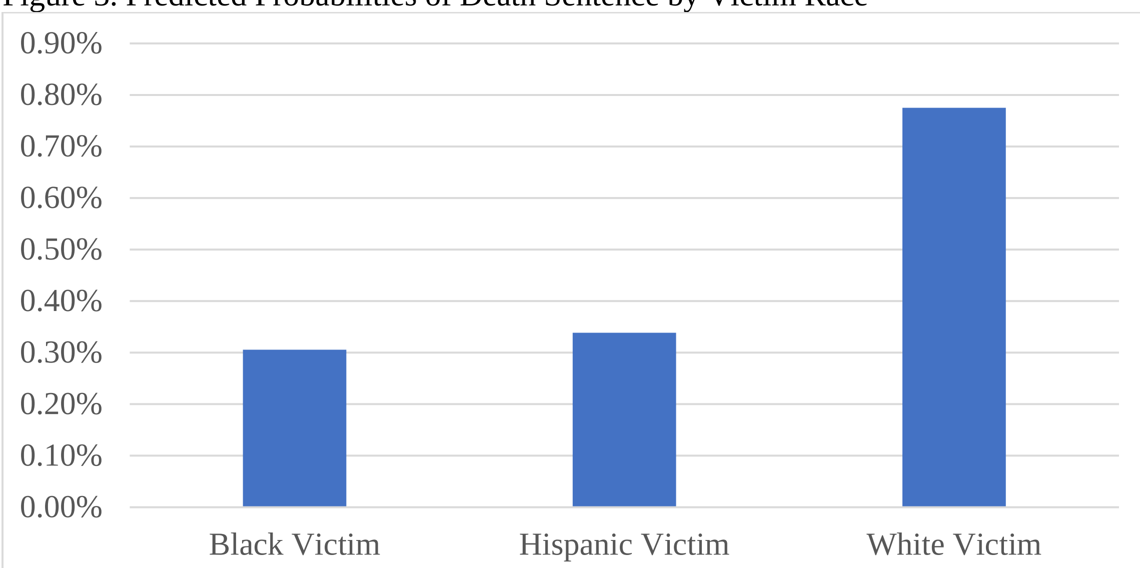


Figure 3. Predicted Probabilities of Death Sentence by Victim Race



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47 Pierce and Radelet, *supra* note 11.

32. Since prior research on the death penalty in California[48] and elsewhere[49] 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 1.79 times more likely to result in a death sentence. This relationship is significant at the 0.001 p-value level. Moreover, compared to homicides involving a White victim and White suspect, those with a Hispanic suspect and a White victim are 1.08 times more likely to result in a death sentence, although the effect is not statistically significant at the 0.05 p-value level. Thus, the likelihood of a White victim homicide resulting in a death sentence is 1.79 to 1.08 times higher if the suspect is Black or Hispanic (respectively) than if the suspect were White.

33. 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 White victims.

[48] Petersen, *supra* note 8; Petersen, *supra* note 8.

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

Table 3. Regressions Predicting Death Sentencing Outcomes in California by Suspect and Victim Racial Dyads (1979-2018).

	OR(SE)
Victim and suspect demographics:	
White suspect & Black victim	0.38** (0.12)
White suspect & Hispanic victim	0.48** (0.13)
Black suspect & White victim	1.79*** (0.27)
Black suspect & Black victim	0.64*** (0.05)
Black suspect & Hispanic victim	0.58* (0.13)
Hispanic suspect & White victim	1.08 (0.20)
Hispanic suspect & Black victim	0.60 (0.19)
Hispanic suspect & Hispanic victim	0.45*** (0.08)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	22.92*** (6.29)
Felony - murder PC190.2(a)(17)	11.76*** (1.34)
1990-1999	1.23 (0.41)
2000-2009	0.94 (0.30)
2010-2018	0.09*** (0.05)
County characteristics:	
% Black population	0.98 (0.04)
% Hispanic population	1.02* (0.01)
% urban	1.01 (0.01)
Annual homicide rate	0.51*** (0.08)
Alameda County	2.27** (0.69)
Contra Costa County	1.45 (0.45)
Orange County	1.41 (0.42)
Riverside County	3.67*** (0.58)
Sacramento County	1.41 (0.42)
San Bernardino County	1.13 (0.15)
San Diego County	1.09 (0.25)
San Francisco County	0.12*** (0.03)
Santa Clara County	0.73 (0.20)
Smaller counties	1.10 (0.26)
Observations	55922

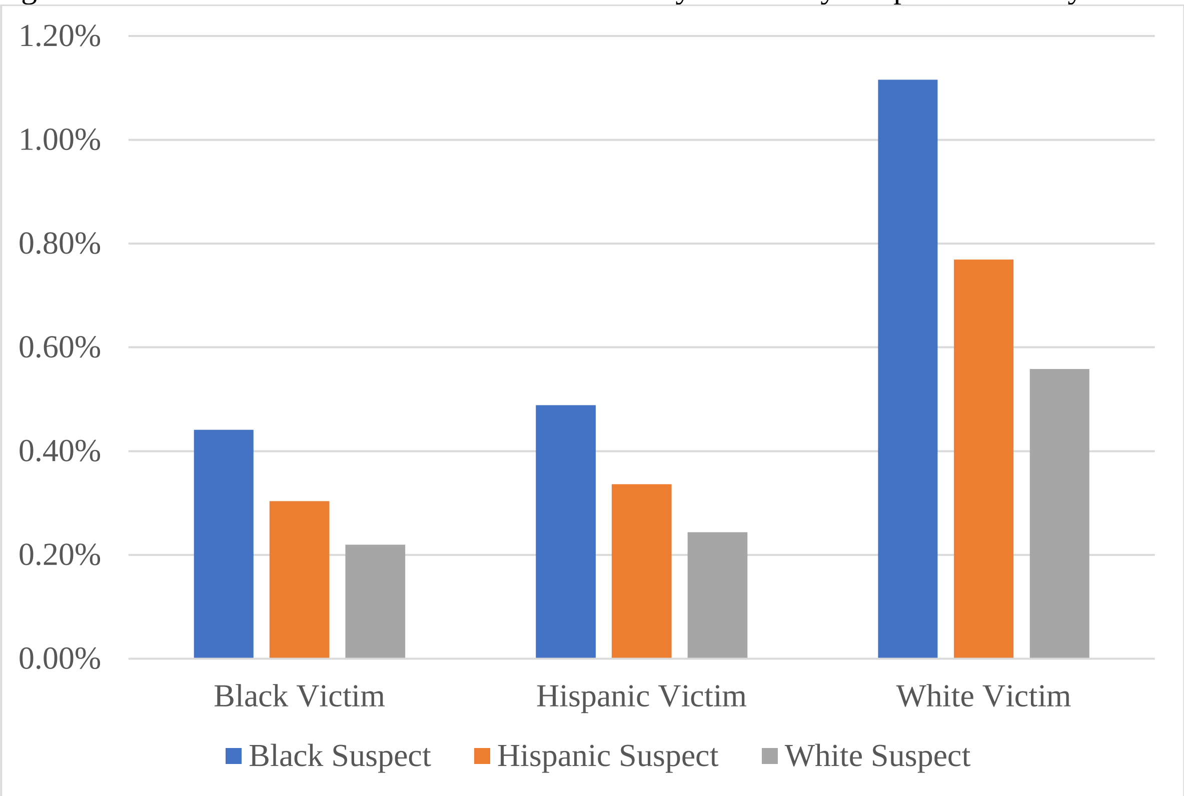
Exponentiated coefficients; Standard errors in parentheses

Notes: Listwise deleted sample. Reference groups = 1979-1989 offense year; white victim & white suspect; Los Angeles County

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

34. To help visualize victim-by-suspect racial dyads, I calculated predicted probabilities. Figure 4, 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, when I compare differences in predicted probabilities by victim and suspect race, clear patterns emerge. In particular, Figure 4 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.[50]

Figure 4. Predicted Probabilities of Death Sentence by Victim-By-Suspect Racial Dyads

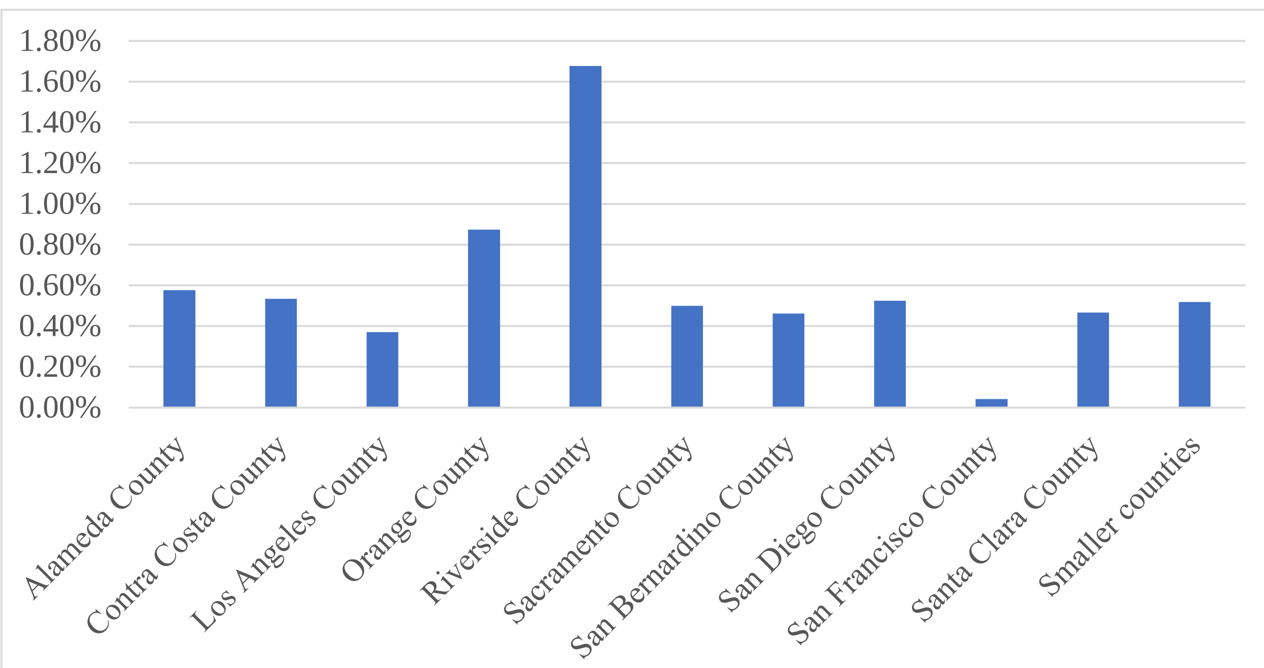


50 Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND THE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

Do Racial Disparities Vary Across California Counties?

35. 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 5, homicides occurring in Riverside and Orange counties have the highest likelihood of a death sentence, net of other variables. Even though Riverside County and Orange County combined had only 3,773 homicides from 1979 through 2018, compared to 23,338 in Los Angeles County and 2,985 in San Bernardino County—homicides in Riverside and Orange counties were substantially more likely to result in a death sentence. In fact, the probability of a given homicide resulting in a death sentence is 4.5 times greater in Riverside County than in Los Angeles County (1.68% vs. 0.37%) and 2.3 times greater in Orange County than in Los Angeles County (0.87% vs. 0.37%).

Figure 5. Predicted Probabilities of Death Sentence by County



36. Figure 6 and Figure 7 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 1979 to 2018. In Figure 6, 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 7 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 6 and Figure 7 illustrate a remarkably consistent three-tiered suspect/victim racial hierarchy in death sentencing across California counties in the post-*Gregg* period.

Figure 6. Predicted Probabilities of Death Sentence by County and Suspect Race

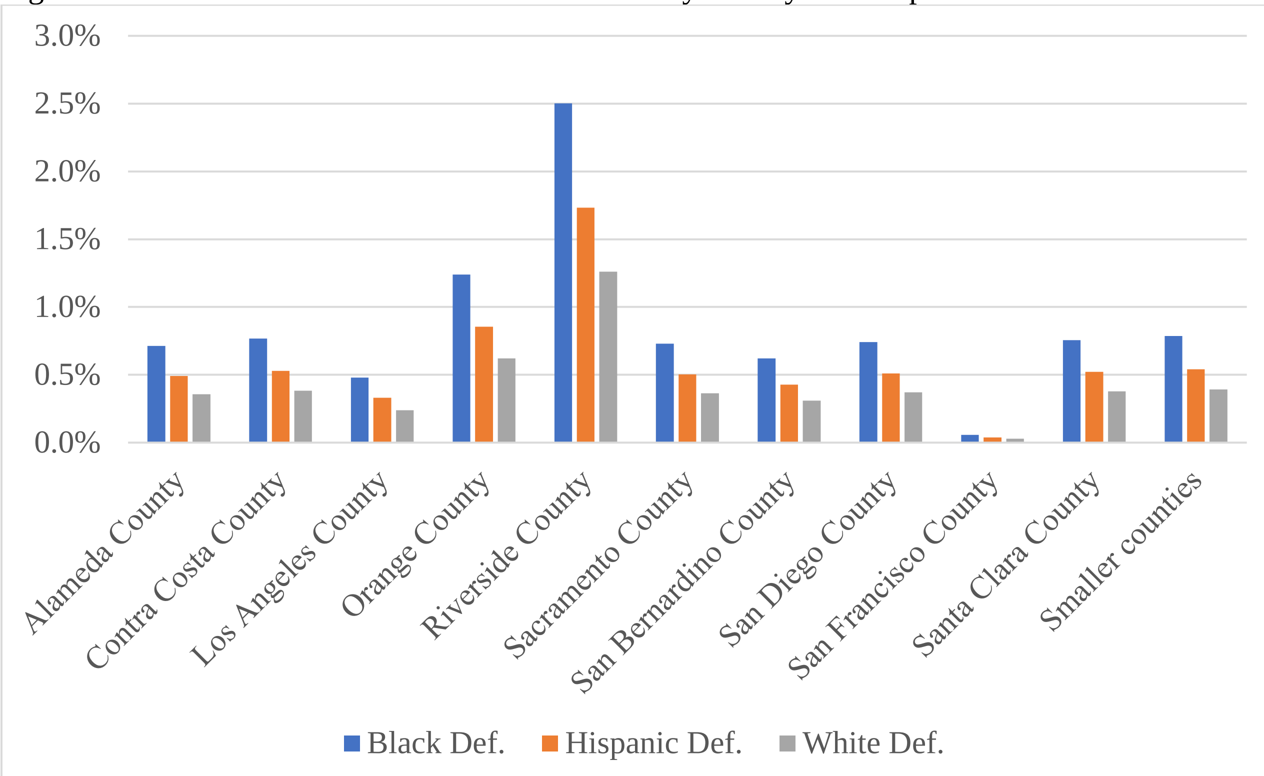
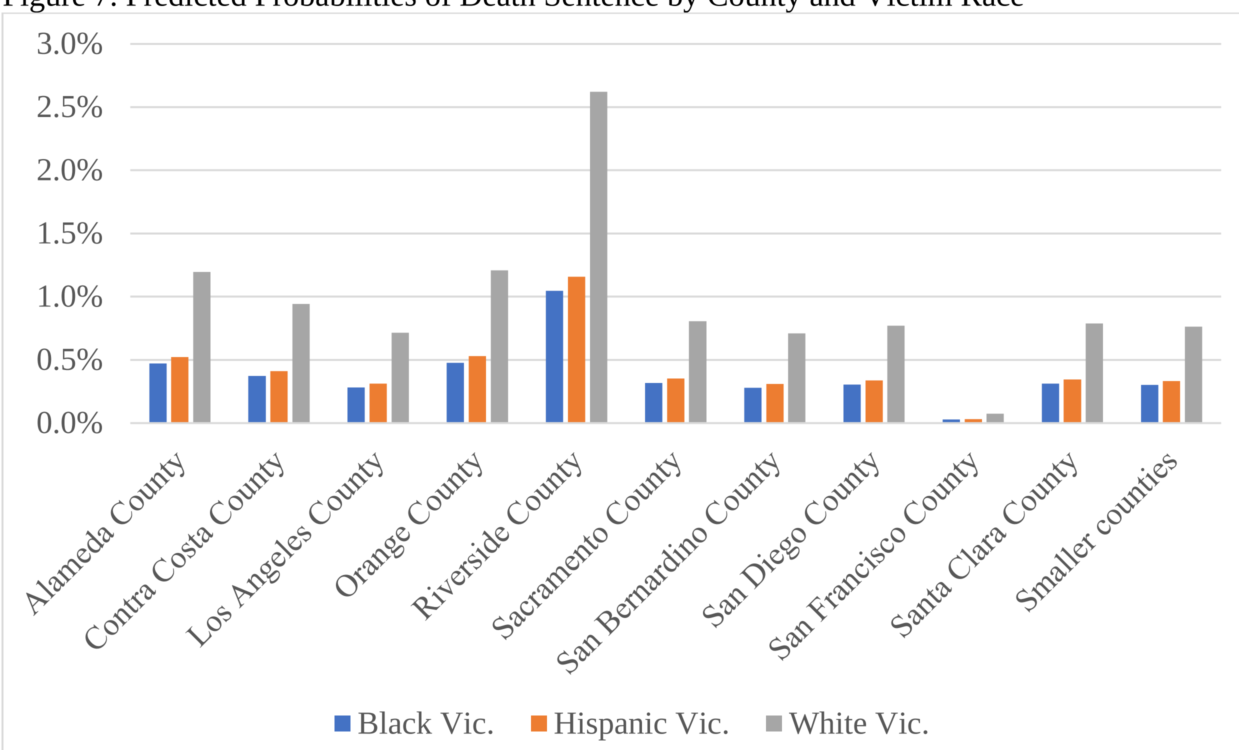
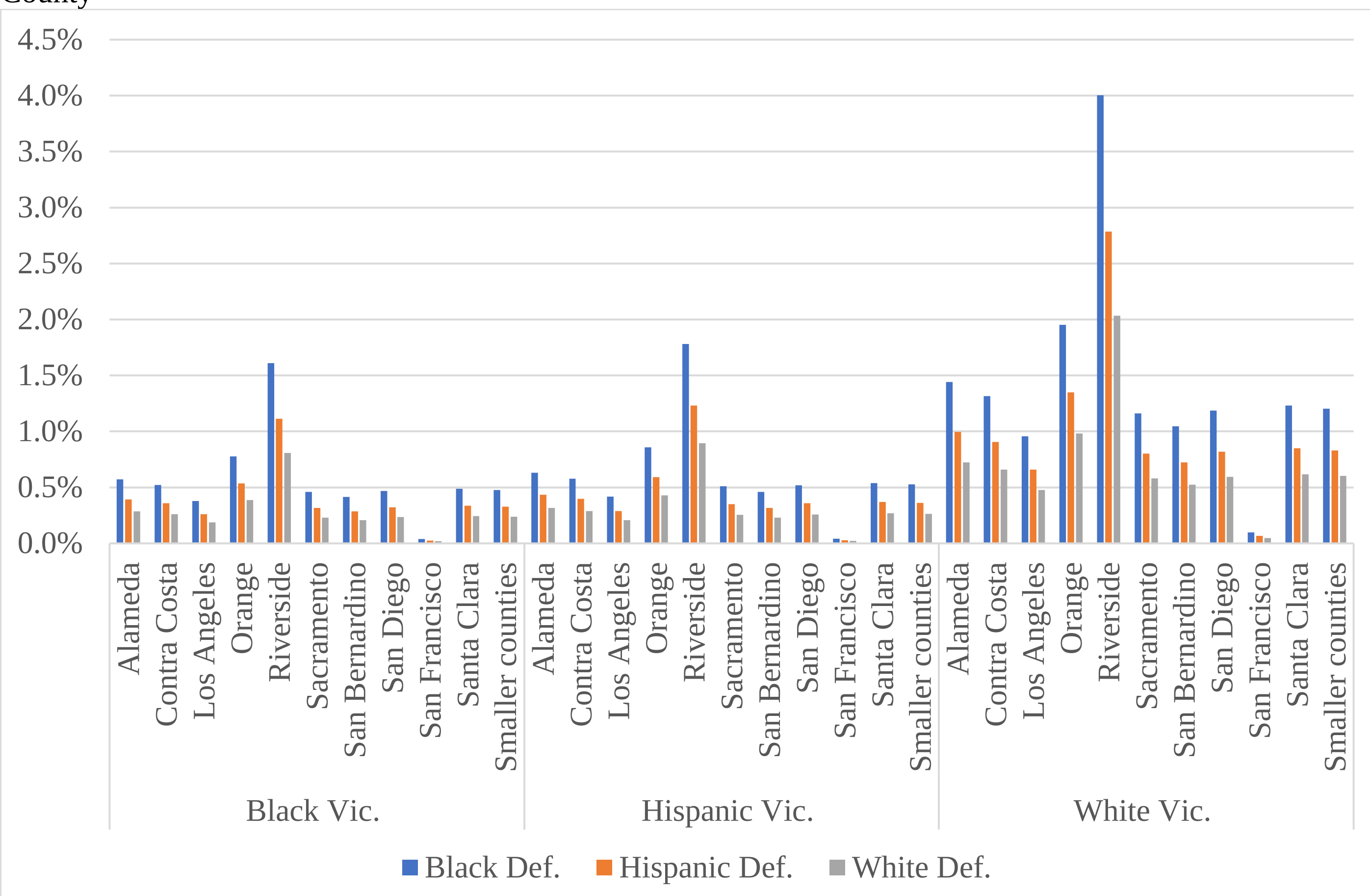


Figure 7. Predicted Probabilities of Death Sentence by County and Victim Race



37. 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 8 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 8 illustrates a remarkably consistent trend in terms of victim-suspect racial disparities across California counties from 1979 to 2018.

Figure 8. Predicted Probabilities of Death Sentence by Victim-By-Suspect Racial Dyads and County



IV. CONCLUSIONS

38. These findings highlight victim-by-suspect racial disparities in California death sentencing trends from 1979 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 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.

39. County fixed-effects highlight considerable uniformity in racial disparities across California counties. While the exact size of the racial disparities 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 during the post-*Gregg* era, employing state-of-the-art statistical methodologies and a robust dataset spanning four decades.