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). Using these data, I examine whether there are racial
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

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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, 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. 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 race on death sentences for similarly situated cases.

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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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. 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 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,” whereas independent variables are the “the factors you suspect have an impact on your dependent variable.” 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

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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.


10 Id.
include victim/suspect race, as prior research has identified these as 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


12 Balduc, 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-[(βi) 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-(β0.35 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.\textsuperscript{15} In contrast, predicted probabilities range from 0% to 100%, making them easier to interpret.\textsuperscript{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\textsuperscript{17} as well as the broader social scientific literature.\textsuperscript{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.

\textbf{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

\textsuperscript{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, \textit{supra} note 8.


\textsuperscript{18} LONG AND FRESEE, \textit{supra} note 16. In this leading book on categorical data analysis, including logistic regression, Sociology Professors Scott Long and Jeremy 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” \textit{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” \textit{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. 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. 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, 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 ($\beta$) for group 1 and group 2 based on the amount of variability in $\beta$ from sample to sample. If $\beta$ significantly differs from the null hypothesis value of $\beta = 0$ (i.e., “no effect”) after taking into account sampling variability in $\beta$, 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.”


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.” In such contexts, he explains, “researchers should focus more on substantive significance and less on statistical significance.” 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-\textit{Gregg} period (1979 through 2018), I relied on a previously established methodology\textsuperscript{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.\textsuperscript{25} Next, I obtained death sentencing data from the Habeas Corpus Resource Center, a state repository statutorily tasked with collecting such data.\textsuperscript{26} This dataset contains information on all death sentences rendered in California from 1979 through 2018.\textsuperscript{27}

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

\textsuperscript{22} Scott Phillips, \textit{Status disparities in the capital of capital punishment}, 43 LAW SOC. REV. 807, 821 (2009).
\textsuperscript{23} \textit{Id}.
\textsuperscript{24} Gross and Mauro, \textit{supra} note 14; Pierce and Radelet, \textit{supra} note 11; Radelet and Pierce, \textit{supra} note 11.
\textsuperscript{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/).
\textsuperscript{26} These data were provided to me by lawyers at the California Office of the State Public Defender.
\textsuperscript{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.cdc.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.
\textsuperscript{28} For death penalty studies employing similar techniques, see Pierce and Radelet, \textit{supra} note 11; Radelet and Pierce, \textit{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. 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 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) and eliminated from consideration any homicide lacking suspect race information (most commonly those wherein no arrest was ever made). Like prior research, I also limited the SHR data to homicides involving victims and suspects who are White, Black, and Hispanic.

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

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, as the co-occurrence of a felony and multiple murder are among the most commonly alleged special circumstances in California and other jurisdictions. 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.

**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.


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-\textit{Gregg} era, not just those from large counties.

24. In line with prior research examining geographic disparities in California death sentencing,\textsuperscript{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.

\textit{Analysis Strategy:}

25. To investigate whether any observed racial disparities in death sentences vary across counties, I calculated fixed-effects logistic regression models for \textit{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

\textsuperscript{37} Pierce and Radelet, \textit{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 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. 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). 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.” Likewise, Cameron and Miller note that “The key assumption is that the errors are uncorrelated across...
clusters while errors for individuals belonging to the same cluster may be correlated.\textsuperscript{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.\textsuperscript{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.

\textsuperscript{42} Cameron and Miller, *supra* note 40.

\textsuperscript{43} Wooldridge, *supra* note 6.
Table 1. Unadjusted Statistics for California Homicides (1979-2018)

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

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.\footnote{FINLAY AND AGRESTI, supra note 21; BALDUS, WOODWORTH, AND PULASKI, supra note 8.} 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.\footnote{FINLAY AND AGRESTI, supra note 21; BALDUS, WOODWORTH, AND PULASKI, supra note 8.}
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\footnote{Pierce and Radelet, supra note 11.} and suggests a victim-by-suspect race interaction, which I explore below.

Figure 2. Predicted Probabilities of Death Sentence by Suspect Race

![Bar chart showing predicted probabilities of death sentence by suspect race.](chart1)

Figure 3. Predicted Probabilities of Death Sentence by Victim Race

![Bar chart showing predicted probabilities of death sentence by victim race.](chart2)
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.


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<tr>
<th>Demographics/Case Characteristics</th>
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<tr>
<td>Victim and suspect demographics:</td>
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<td>White suspect &amp; Hispanic victim</td>
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<td>Hispanic suspect &amp; Black victim</td>
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<tr>
<td>Felony - murder PC190.2(a)(17)</td>
<td>11.76*** (1.34)</td>
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<tr>
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<td>2000-2009</td>
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<td>2010-2018</td>
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<td>County characteristics:</td>
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<td>% Black population</td>
<td>0.98 (0.04)</td>
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<td>% Hispanic population</td>
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<td>Annual homicide rate</td>
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<td>Observations</td>
<td>55922</td>
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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

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
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

![Graph showing predicted probabilities of death sentence by victim-by-suspect racial dyads and county, with Alameda, Contra Costa, Los Angeles, Orange, Riverside, Sacramento, San Bernardino, San Diego, San Francisco, Santa Clara, and smaller counties highlighted. The graph indicates that homicides involving Black suspects and White victims are most likely to result in a death sentence, while those involving Black suspects and Black victims are least likely.]
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.