Case No. __________

IN THE SUPREME COURT OF THE STATE OF CALIFORNIA

OFFICE OF THE STATE PUBLIC DEFENDER, EVA PATERSON, LATINOJUSTICE PRLDEF, ELLA BAKER CENTER FOR HUMAN RIGHTS, and WITNESS TO INNOCENCE,

Petitioners,

v.

ROB BONTA,
California Attorney General, in his official capacity,

Respondent.

EXHIBITS TO PETITION FOR WRIT OF MANDATE

File 1

First of two (1 of 2) exhibit files in electronically filed document supporting Petition for Writ of Mandate.

Total number of pages in document: 517

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OFFICE OF THE STATE PUBLIC DEFENDER, EVA PATERSON, LATINOJUSTICE PRLDEF, ELLA BAKER CENTER FOR HUMAN RIGHTS, and WITNESS TO INNOCENCE

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EXHIBIT A

THE INFLUENCE OF THE RACE OF DEFENDANT AND THE RACE OF VICTIM ON CAPITAL CHARGING AND SENTENCING IN CALIFORNIA

Catherine M. Grosso, Jeffrey Fagan, and Michael Laurence*

ABSTRACT

California's capital punishment statute is the nation's most expansive. Through its lengthy array of statutory eligibility categories, it permits virtually unlimited discretion for charging and sentencing decisions. The California Racial Justice Act of 2020 recognized racial and ethnic discrimination as a basis for relief in capital cases, expressly permitting several types of statistical evidence to be introduced. This statewide study of the influence of race and ethnicity on the application of capital punishment contributes to this evidence. We draw on data from over 27,000 murder and manslaughter convictions in California state courts between 1978 and 2002. Using multiple methods, we found significant racial and ethnic disparities in charging and sentencing decisions. Controlling for defendant culpability and specific statutory aggravators, we show that Black and Latinx defendants and all defendants convicted of killing at least one white victim are substantially more likely to be sentenced to death. We further examined the role that race and ethnicity have in decision-making at various points in the criminal justice system. We found that prosecutors were significantly more likely to seek death against defendants who kill white victims, and that juries were significantly more likely to sentence those defendants to death. The magnitude of these effects is substantially higher than in prior studies in other states and in single-jurisdiction research. The results show an entrenched pattern of racial disparities in charging and sentencing that privileges white victim cases, as well as patterns of racial disparities in who is charged and sentenced to death in California courts that are the natural result of California's capacious statutory definition of death eligibility. This pattern of racial preferences illustrates the social costs of California's failure to follow the Court's directive in *Furman v Georgia* to narrow the application of capital punishment over 50 years ago.

* Catherine M. Grosso is a professor at Michigan State University College of Law. Jeffrey Fagan is the Isidor and Seville Sulzbacher Professor of Law at Columbia Law School and Professor of Epidemiology at the Mailman School of Public Health, Columbia University. Fagan's research was made possible in part by The Madsen Family Faculty Research Fund at Columbia Law School. Michael Laurence previously was the Executive Director of the Habeas Corpus Resource Center and counsel of record in the federal habeas corpus case challenging the California death penalty statute based on a previous analysis of the data presented here.

David C. Baldus (1935-2011), George Woodworth, and Richard Newell designed the study and created the database analyzed here. Their work provides the foundation for these findings. Any errors remain with the authors.

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I. INTRODUCTION

For the past fifty years, capital punishment in California has served as a perennial legal and political issue. In February 1972, the California Supreme Court in *People v. Anderson*[1] invalidated the state's capital punishment statute, presaging the United States Supreme Court decision in *Furman v. Georgia*, five months later.[2] The legislative reactions to those decisions were swift and predicable, with California adopting first an unconstitutional mandatory death penalty statute[3] and then a relatively narrow replacement in 1977.[4] In 1978, California voters a passed a ballot measure that substantially expanded the reach of the state's capital punishment statute. The ballot measure promised the execution of every convicted murderer."[5] That 1978 death penalty statute has been frequently amended to add additional death-eligible murders, leading to a statute unique in the United States in its expansive eligibility.[6] As a result, California houses the largest death row nationally, with more than 660 individuals facing a death penalty; its population is more than twice the size of the next largest.[7]

Given its unique and expansive statutory framework, the California statute and its application presents a critical area for study. The central role of statistical analysis in research on the statute was heightened with the adoption of the California Racial Justice Act in 2020, which recognized racial and ethnic discrimination as the basis for relief and expressly permitted

1 6 Cal. 3d 628 (1972).

2 408 U.S. 238 (1972).

3 1973 Cal. Stat. c. 719, §§ 1- 5 (S.B. 450)), invalidated by *Rockwell v. Superior Court*, 18 Cal. 3d 420 (1976).

4 1977 Cal. Stat. c. 316, §9 (S.B. 155), effective August 11, 1977.

5. California Voters Pamphlet, General Election, Nov. 7, 1978, at 32-46.

6 *See infra* Section II.

7 Death Penalty Information Center, Facts About the Death Penalty (Updated Feb. 14, 2024), https://dpic-cdn.org/production/documents/pdf/FactSheet.pdf.

"statistical evidence" such as that presented in this Article.[8] Under the provisions of the statute, a criminal defendant may establish a violation by "statistical evidence, aggregate data, expert testimony, and the sworn testimony of witnesses."[9]

The California Legislature found that the Racial Justice Act's remedy for racial disparities in charging, convicting, and sentencing was necessary because "[e]ven when racism clearly infects a criminal proceeding, under current legal precedent, proof of purposeful discrimination is often required, but nearly impossible to establish."[10] The Racial Justice Act became retroactive for capital defendants beginning on January 1, 2023.[11] Notably, approximately 75 percent of persons on California's on death row as of January 2024 committed their offenses between 1978 and 2002, the period of this study.[12]

The California death penalty scheme has been subjected to substantial empirical analysis since *Furman v. Georgia*.[13] The most comprehensive of these earlier analyses has produced two published empirical studies using data drawn from over 27,000 murder and manslaughter convictions between 1978 and 2002.[14] The first study, designed by the late Professor David Baldus, examined the breadth of California's capital punishment statute and found that the death-

[8] Cal. Penal Code § 745(a) (West 2024).

[9] Cal. Penal Code § 745(c)(1) (West 2024).

[10] Cal. Penal Code § 745(a)(2(c) (West 2024).

[11] Cal. Penal Code § 745(j)(2) (West 2024).

[12] California Department of Corrections and Rehabilitation, Condemned Inmate List (Updated Jan. 11, 2024), available at https://www.cdcr.ca.gov/capital-punishment/condemned-inmate-list-secure-request/.

[13] 408 U.S. 238 (1972) (invalidating then-existing death sentencing statutes).

[14] Catherine M. Grosso, Jeffrey Fagan, Michael Laurence, David Baldus, George Woodworth, & Richard Newell, *Death by Stereotype: Race, Ethnicity, and California's Failure to Implement Furman's Narrowing Requirement*, 66 UCLA L. REV. 1394, 1406 (2019) ("Grosso"); David Baldus, George Woodworth, Catherine Grosso, Michael Laurence, Jeffrey Fagan, & Richard Newell, *Furman at 45: Constitutional Challenges from California's Failure to (Again) Narrow Death Eligibility*, 16 J. EMP. LEGAL STUD. 693 (2019) ("Baldus").

eligibility rate among California homicide cases was the highest in the nation. Indeed, 95% of all first-degree murder convictions and 60% of all first-degree murder, second-degree murder, and voluntary manslaughter convictions were death eligible under California's 2008 capital punishment statute.[15] Equally important under the *Furman* jurisprudence, only a fraction of those eligible for a death sentence were actually sentenced to death: Only 4.3 percent of the defendants who committed a factually eligible capital murder were sentenced to death.[16]

In the second study, we examined the racial and ethnic dimensions of California's expansive capital punishment statute. We found that individual special circumstances[17]—the factors that are required to impose a death sentence—apply to defendants disparately by race and ethnicity.[18] The racial and ethnic disparities were particularly apparent with respect to two special circumstances—(1) murders committed by drive-by shootings and (2) murders committed by an active gang participant in furtherance of the activities of a criminal street gang[19]—which were added to the California Penal Code despite expressed concerns about the racial effects of the amendments.[20] As a result of our analysis, we concluded that California's capital punishment "statute appears to codify rather than ameliorate the harmful racial stereotypes that are endemic to our criminal justice system."[21]

15 Baldus, *supra* note 14, at 713 & Table 2; *see also id*. at 722 Figure 1 (comparing California's death-eligibility rate to the rest of the country). The California's death penalty statutes have undergone significant expansion since 1977. *See, e.g.*, *id*. at 701-04. The law in existence in 2008 was selected as the appropriate law to determine eligibility because it contained most of the expansive provisions and was in effect at the time that the comprehensive coding was conducted.

16 *Id*. at 724 fig.2.

17 Cal. Penal Code § 190.2 (West 2024).

18 Grosso, *supra* note 14, at 1433-40.

19 Cal. Penal Code § 190.2(a)(21), (22) (West 2024).

20 *See* Grosso, *supra* note 14, at 1405-07.

21 Grosso, *supra* note 14, at 1441

This third study provides the results of a comprehensive analysis of the influence of race and ethnicity in capital charging and sentencing decisions.[22] We begin by exploring the potential sources of racial discrimination in California's criminal justice system. We then provide details about our data and methods and report our findings organized according to charging and sentencing outcomes after analyzing the progression of cases from eligibility to death sentence. We first report results of the racial disparities in the overall risk of receiving a death sentence among the universe of death-eligible cases. We then focus on two decisions in the progression of cases toward their final outcome: (1) the decision by prosecutors to charge special circumstances, and (2) the decision by juries to impose a death sentence. We also test for differences by race and ethnicity in the dropout or survival of cases through each stage of case processing.

Each analysis tested for differences in decision-making by both defendant and victim race. Consistent with an extensive and robust literature on racial disparities in charging and sentencing, we analyzed models for (1) Black and Latinx defendants, (2) white victims,[23] (3) murders of white victims by Black and Latinx defendants, and (4) multiple combinations of the race of the defendant and the race of the victim.[24] For each round of analysis (overall risk of death, charging, and sentencing), we report the unadjusted differences and then the differences controlling for

22 We previously presented the results of our initial analysis on this issue in a March 22, 2021 letter to the California Committee on the Revision of the Penal Code. *See* http://www.clrc.ca.gov/CRPC/Pub/Memos/CRPC21-04s2.pdf (Exhibit J in the Additional Written Materials).

23 In this study, as in our earlier work, we defined white victim to include the presence of at least one white victim in the case. This follows the standard approach in this kind of study. *See* DAVID BALDUS, GEORGE WOODWORTH, NEIL ALAN WEINER, DAVID ZUCKERMAN & CATHERINE M. GROSSO, *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 Acker eds. 2009).

24 We conducted additional analysis combining Black, Latinx, and Native American defendants into a single variable. The results of this analysis found consistent racial and ethnic disparities.

statistically and theoretically significant special circumstances that determine death eligibility, and then for the factors that relate to defendant culpability for the crime. Although we analyzed the significance for race of defendant and race of victim individually and in multiple combinations, we limit this report to those racial disparities that we identified as statistically significant for each outcome.

As more fully presented in Section IV below, we found significant racial and ethnic disparities in the application of California's capital punishment scheme. Converting the parameters to odds ratios, we show that Black defendants faced significantly higher odds, between 4.6 and 8.7 times higher than similarly situated defendants, of being sentenced to death overall.[25] Latinx defendants faced significantly higher odds, between 3.2 and 6.2 times higher than similarly situated defendants. Similarly, persons convicted of killing at least one white victim faced 2.8 and 8.8 higher odds of being sentenced to death than defendants who kill non-white victims. Black defendants who kill at least one white victim faced 3.2 and 4.4 greater odds of being sentenced to death than white defendants who kill at least one white victim. Latinx defendants faced similarly even higher disparities, with an odds ratio between 3.4 and 8.0 higher than white defendants who kill at least one white victim.

We found differences by race and ethnicity in charging decisions and sentencing decisions. Although we did not find that race of the defendant has a role in charging decisions, prosecutors were significantly more likely to charge special circumstances (1.6 and 2.3 greater odds), in cases in which at least one of the victims was white.

[25] We report the odds ratio from two logistic regression models for each outcome as explained below. In short, one odds ratio comes from a model that controls for individual special circumstances and the other comes from the model that controls for the defendant culpability scale. *See infra* Section IV.

Juries were significantly more likely to return death sentences for Black defendants (between 4.4 and 5.7 times greater odds) and Latinx defendants (between 3.7 and 5.0 greater odds). Similarly, juries were significantly more likely to return death sentence for Black defendants convicted of killing at least one white victim (between 2.3 and 3.1 greater odds) and Latinx defendants convicted of killing at least one white victim (between 4.1 and 5.9 odds) than for white defendants killing at least one white victim.[26] Although other studies of the administration of capital punishment in California have found similar racial effects, the magnitude of the racial effects are startling, particularly with respect to Black and Latinx defendants.[27]

In Section II, we suggest a context in which to place our findings by briefly reviewing research on the dynamics that contribute to produce racial disparities in California death sentences. The broad scope of discretion, the complexity of the charging and sentencing processes, the number of decision makers, and the deep and persistent history of explicit and implicit race discrimination in the administration of justice in the United States each have a role in producing disparate outcomes. Section III presents the study methods including details about the sample,

[26] Using the combined variable of Black, Latinx, and Native American defendants found strikingly similar effects. Minority defendants faced significantly higher odds, between 4.3 and 4.8 times higher than non-minority defendants, of being sentenced to death. Similarly, all persons convicted of killing white victims faced 2.5 and 4.0 higher odds of being sentenced to death than defendants who kill non-white victims. Minority defendants who kill white victims faced 3.2 and 4.4 greater odds of being sentenced to death. Race and ethnicity similarly affected charging decisions. Prosecutors were significantly more likely to charge special circumstances, which is necessary for a capital sentence (1.6 and 2.3 greater odds), in cases in which at least one of the victims was white. And juries were significantly more likely to return death sentences for minority defendants overall (between 3.9 and 5.4 times greater odds) and minority defendants who have been convicted of killing white victims (between 3.1 and 3.5 greater odds).

[27] *See, e.g.*, Steven F. Shatz, Glenn L. Pierce & Michael L. Radelet, *Race, Ethnicity, and the Death Penalty in San Diego County: The Predictable Consequences of Excessive Discretion*, 51 COLUM. HUM. RTS. L. REV. 1070 (2020); Nick Petersen, *Cumulative Racial and Ethnic Inequalities in Potentially Capital Cases: A Multistage Analysis of Pretrial Disparities*, 45 CRIM. JUST. REV. 225 (2020); Nick Petersen, *Examining the Sources of Racial Bias in Potentially Capital Cases: A Case Study of Police and Prosecutorial Discretion*, 7 RACE & JUST. 7 (2016); Glenn L. Pierce & Michael L. Radelet, *The Impact of Legally Inappropriate Factors on Death Sentencing for California Homicides, 1990-1999*, 46 SANTA CLARA L. REV. 1 (2005).

data sources, race coding, and our analysis. Section IV presents the findings in four parts. Part A documents the findings with respect the overall risk in receiving a death sentence. Part B turns to findings with respect to prosecutorial decisions to charge special circumstances. Part C presents the findings with respect to jury decision making at penalty trials. Part D documents the influence of race and ethnicity of defendant and victim as cases progress or drop out from charging to sentencing. Section V concludes and summarizes the findings.

II. THE PROCESSES THAT PRODUCE RACIAL DISPARITIES IN CALIFORNIA DEATH SENTENCES

Legal scholars and social scientists have documented actors and processes that contribute to racial disparities in capital punishment, and in the processing of California death penalty cases, in particular.[28] For example, Scott Phillips and Mark Cooney[29] applied the classic sociological theory of Donald Black on the social geometry of law[30] to describe the social and political spaces where decisions—both charging and sentencing—in capital punishment are made. Rather than being arbitrary and random, as the *Furman* majority claimed, *Geometrical Justice* suggests that death sentences reflect the ordering of social status of defendants and their victims that intersects with the details of cases to shape the decisions that privilege some races and genders—those in higher status positions of society—in the allocation of justice. The disparities that we identify in the administration of capital punishment reflect those processes. They provide an important

28 *See, e.g.,* Grosso, *supra* note 14.

29 SCOTT PHILIPS & MARK COONEY, GEOMETRICAL JUSTICE: THE DEATH PENALTY IN AMERICA (2022) (applying Donald Black's foundational theories of the social behavior of the law to identify sources and meanings of racial disparities in capital punishment).

30 Donald Black, *Pure Sociology and the Geometry of Discovery*, 31 CONTEMP. SOC. 668 (2002). Donald Black, *Legal Relativity*, 3 ENCYCLOPEDIA OF LAW AND SOCIETY: AMERICAN AND GLOBAL PERSPECTIVES 1292 (2007); Donald Black, *Violent Structures*, in VIOLENCE: FROM THEORY TO RESEARCH 145 (Margaret A. Zahn, Henry H. Brownstein & Shelly L. Jackson. eds. 2004).

framework to test and explain the racial disparities in capital punishment that have persisted across time and social space for decades. Prior research has demonstrated the importance of criminal legal institutions and institutional actors in perpetuating racial disparities.[31] Examining the causes of racial disparities in a capital sentencing system begins with the statutory provisions that permit the imposition of a death sentence. Here, we briefly present an overview of the core processes that have been shown to produce racial and ethnic disparities in the administration of capital punishment.[32]

In *Furman v. Georgia*, the U.S. Supreme Court held that the death penalty statutes in effect in 1972 violated the Eighth and Fourteenth Amendments' proscriptions against cruel and unusual punishments.[33] Although the five-justice majority of the Court issued a one-paragraph per curium opinion without explaining its collective reasoning, the nine separate opinions in *Furman* and subsequent decisions have clarified that the Eighth Amendment demands that state legislatures establish standards and criteria to regulate capital sentencing systems to minimize the risk of unconstitutional arbitrary and capricious sentences.[34]

Four years after *Furman*, the U.S. Supreme Court reviewed newly enacted state death penalty statutes that attempted to cure their predecessors' constitutional defects.[35] In *Gregg v. Georgia*, the Supreme Court reiterated the constitutional rule that legislatures must guard against capricious and arbitrary death sentencing by providing a "meaningful basis for distinguishing the

31 Matt Barno & Mona Lynch, *Selecting Charges*, *in* THE OXFORD HANDBOOK OF PROSECUTORS AND PROSECUTION 35, (Ronald F. Wright, Kay L. Levine & Russel Gold eds. 2021).

32 Our more detailed review of the structure and interplay of these processes in the production of racial disparities in criminal justice is in progress.

33. 408 U.S. 238, 239 (1972) (per curiam).

34 *See, e.g.,* Gregg v. Georgia, 428 U.S. 153, 189 (1976) (plurality opinion).

35. Gregg, 428 U.S. 153; Jurek v. Texas, 428 U.S. 262 (1976); Proffitt v. Florida, 428 U.S. 242 (1976).

few cases in which [the death penalty] is imposed from the many cases in which it is not."[36] The Supreme Court relies on the Eighth Amendment's narrowing principle to assure that the selection of defendants actually sentenced to death is regulated by legislatively prescribed criteria of sufficient specificity to guard against arbitrariness and capriciousness.[37]

California, like several other states,[38] has chosen to implement the narrowing requirement by broadly defining capital offenses and then requiring the trier of fact to find at least one statutory aggravating factor that defines the defendant's crime as capital-eligible.[39] The California death penalty statute defines death eligibility as the commission of a first-degree murder with the

36. Gregg, 428 U.S. at 188 (plurality opinion) (quoting Furman, 408 U.S. at 313 (White, J., concurring)).

37 *See* Chelsea Creo Sharon, *The "Most Deserving" of Death: The Narrowing Requirement and the Proliferation of Aggravating Factors in Capital Sentencing Statutes*, 46 HARV. C.R.-C.L. L. REV. 223, 247 (2011).

38 *See, e.g.*, Ariz. Rev. Stat. Ann. § 13-751 (2024); Fla. Stat. § 921.141 (2024); Ga. Code Ann. § 17-10-30 (2024).

39. *See*, *e.g.*, Cal. Penal Code §§ 189, 190.2 (West 2024) (requiring a finding of the presence of an enumerated "special circumstance" before a defendant is subject to a capital sentence). California uses the term special circumstances to define death eligibility; other states use the terms "aggravating factors" or "aggravating circumstances" for statutory provisions that define death eligibility. As the California Supreme Court held in *People v. Bacigalupo*, under the California death penalty law, "the section 190.2 'special circumstances' perform the same constitutionally required 'narrowing' function as the 'aggravating circumstances' or 'aggravating factors' that some of the other states use in their capital sentencing statutes." 862 P.2d 808, 813 (Cal. 1993); *see also id.* at 820 (emphasizing that the section 190.3 aggravating factors used in the selection phase of the California death penalty scheme "do not perform a 'narrowing' function"); People v. Visciotti, 825 P.2d 388, 537 (Cal. 1992) (rejecting that under Furman, 408 U.S. 238 (1972), and Maynard v. Cartwright, 486 U.S. 356 (1988), the aggravating factors in section 190.3 must limit "open-ended discretion" in the selection phase of the California death penalty scheme because it is instead the special circumstances in section 190.2 that function "to channel jury discretion by narrowing the class of defendants who are eligible for the death penalty"); People v. Cornwell, 117 P.3d 622, 657 (Cal. 2005) ("The state death penalty scheme meets Eighth Amendment requirements through its listing of special circumstances; the aggravating and mitigating circumstances referred to in section 190.3 do not and need not perform a narrowing function.").

presence of one or more enumerated special circumstances.[40] Nearly every state follows that design, consistent with *Gregg*'s scheme of guided discretion.[41]

The breadth of the California's death-penalty statute, with thirty-two special circumstances,[42] invariably invests substantial discretion in prosecutors, jurors, and judges, which permits decision-making influenced by racial considerations. In the empirical literature on charging and sentencing death-eligible cases, this breadth of discretion has been associated with the persistence of racial bias.[43] Sherod Thaxton argues that the narrowing of discretion afforded under capital statutes may be "the most consistently advocated legal reform."[44] These advocates adopted the guided discretion approach of the widely adopted capital statute recommended by the American Law Institute in 1962[45] and subsequently withdrawn in 2009 partly on the basis that the section had "not withstood the tests of time and experience."[46] The widespread adoption of

40. Cal. Penal Code §§ 189, 190.2 (West 2024).

41 *See, e.g.*, Ga. Code § 17-10-30 (2024).

42. Cal. Penal Code § 190.2 (West 2024). The special circumstances are enumerated in twenty-two paragraphs, one of which, paragraph 17, contains twelve subparagraphs each defining an independent basis for death eligibility. *Id.* Although Penal Code section 190.2 contains thirty-three special circumstances, the California Supreme Court invalidated section 190.2(a)(14) as unconstitutional. People v. Superior Court (In re Engert), 647 P.2d 76 (Cal. 1982).

43 *See, e.g.*, Grosso, *supra* note 14, at 1441; Angela J. Davis, *In Search of Racial Justice: The Role of the Prosecutor*, 16 N.Y.U. J. LEGIS. & PUB. POL'Y 821 (2013) ("As the most powerful officials in the criminal justice system, their discretionary decisions-especially their charging and plea-bargaining decisions-play a very significant role in creating and maintaining the racial disparities in the criminal justice system."); Jonathan Simon & Christine Spaulding, *Token of Our Esteem: Aggravating Factors in the Era of Deregulated Death Penalties*, in THE KILLING STATE: CAPITAL PUNISHMENT IN LAW, POLITICS AND CULTURE 81 (Austin Sarat, ed. 1999).

44 Sherod Thaxton, *Shrinking the Accountability Deficit in Capital Charging*, *in* THE OXFORD HANDBOOK OF PROSECUTORS AND PROSECUTION 559, 566 (Ronald F. Wright, Kay L. Levine & Russel Gold eds., 2021) (reviewing external reforms proposed in the literature).

45 *Report of the Council to the Membership of the American Law Institute on the Matter of the Death Penalty* 1 (American Law Institute, Philadelphia, PA), April 15, 2009, https://www.ali.org/media/filer_public/3f/ae/3fae71f1-0b2b-4591-ae5c-5870ce5975c6/capital_punishment_web.pdf

46 *Id*. at 4.

guided-discretion statutes has not produced clear evidence of a benefit with respect to eliminating or significantly mitigating the influence of race in the administration of capital punishment.[47]

Other research also suggests that the broad exercise of discretion may contribute to the racial disparities observed and experienced in the administration of the criminal laws in general and of capital punishment in particular. Under institutional theories of racism, "biased action is most likely to occur in circumstances where institutional actors have the most decision-making authority and the least oversight."[48] The biases producing disparities need not be overt or driven by animosity, although they might be.[49]

Empirical research on prosecutorial charging decisions has been impeded by the extent of discretion and the opacity of the decision making.[50] Death penalty studies provide a substantial exception to this limitation, as scholars have conducted capital punishment charging studies in many of the jurisdictions that retain a death penalty.[51] In 2004, Baldus and Woodworth observed,

47 Thaxton, *supra* note 44, at 566-67 (reviewing and collecting research reaching this conclusion.).

48 *Id*. at 45 (internal quotations omitted).

49 Nicole Gonzales Van Cleve provided an excellent example of this in her case study of prosecutions in Cook County, Illinois (Chicago). Prosecutors applied well-rehearsed and ostensibly race-neutral categories to cases without acknowledging the "ubiquity of race and racism" prevalent in the court system. The lack of oversight allowed categories to remain unexamined and the disparities to continue uninterrupted or perhaps magnified by generation. NICOLE GONZALEZ VAN CLEVE, CROOK COUNTY: RACISM AND INJUSTICE IN AMERICA'S LARGEST CRIMINAL COURT 78-82 (2016); *see also* Anna VanCleave, *The Illusion of Heightened Standards in Capital Cases*, 2023 U. ILL. L. REV. 1289, 1298, 1309 (2023).

50 *See generally* Marc L. Miller & Ronald F. Wright, *The Black Box*, 94 IOWA L. REV. 125 (2008) (describing the inner workings of prosecutors' offices as "the black box").

51 *See, e.g.,* David C. Baldus & George Woodworth, *Race Discrimination and the Legitimacy of Capital Punishment: Reflections on the Interaction of Fact and Perception*, 53 DEPAUL L. REV. 1411, 1426 (2004) (reviewing the literature since the 1980s); *see also* Catherine M. Grosso, Barbara O'Brien, Abijah Taylor & George Woodworth, *Race Discrimination and the Death Penalty: An Empirical and Legal Overview, in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT (CHARLES S. LANIER, ROBERT BOHM & JAMES ACKER eds.) (Durham, N.C.: Carolina Acad. Press 3d ed., 2014) (updating the literature review and providing annotations) ("Grosso et al."); Barbara O'Brien, Catherine M. Grosso, George Woodworth & Abijah Taylor, *Untangling the Role of Race in Capital Charging and Sentencing in North Carolina, 1990-2009*, 94 N.C. L. REV. 1623 (2013) (reporting findings of race of victim discrimination); Jeffrey

"The literature is clear that when race-of-victim disparities exist, the most common source is prosecutorial charging decisions."[52] Subsequent research confirms this observation,[53] as several rigorous studies also have identified race of defendant disparities.[54]

In part, the discriminatory patterns observed in charging decisions may reflect bias earlier in the criminal justice process. Research has shown that homicide clearance rates may carry an undetected and unstated bias and that this, in turn, introduces bias in the construction of the pool of cases referred to prosecutors. Racial or ethnic disparities in clearance rates, either in victim or suspect race, will introduce a selection bias in the supply of cases eligible for capital prosecution.[55] This bias introduces a risk that disparities observed in charging or sentencing may reflect antecedent racial biases in the relative effectiveness of police efforts to solve or "clear" capital-eligible homicides.[56]

Fagan, Garth Davies & Raymond Paternoster, *Getting to Death: Race and the Paths of Capital Cases After* Furman, 107 CORNELL L. REV. 1565 (reporting findings of race of discrimination in a dataset of 2,328 first-degree murder convictions in Georgia from 1995-2004). *See also supra* note 27 and related text (discussing and citing charging and sentencing studies in California).

52 Baldus & Woodworth, *supra* note 51, at 1426.

53 *See generally* Grosso et al., *supra* note 51.

54 *See* David C. Baldus, Catherine M. Grosso, George Woodworth, & Richard Newell, *Racial Discrimination in the Administration of the Death Penalty: The Experience of the United States Armed Forces (1984–2005)*, 101 J. CRIM. L. & CRIMINOLOGY 1227, 1270 tbl.4 (2012) (After controlling for non-racial case characteristics, minority-accused cases remained 11% more likely to receive a death sentence than white-accused cases (OR 5.2, p = .15)); Scott Phillips, *Racial Disparities in the Capital of Capital Punishment*, 45 HOUSTON L. REV. 807, 832 tbl.5 (2008) (finding race of defendant disparities in controlled analyses of both charging (OR 1.75) and sentencing decisions (OR 1.49)); David C. Baldus, George Woodworth, David Zuckerman, Neil Alan Weiner, and Barbara Broffitt, *Racial Discrimination and the Death Penalty in the Post-Furman Era: An Empirical and Legal Overview, With Recent Finding from Philadelphia*, 83 CORNELL L. REV. 1683, 1758-61 (1998) (finding significant and substantial black-defendant effects in jury weighing decisions (OR 9.3) and in the overall death sentencing decisions among all death-eligible cases (OR 3.1)).

55 Jeffrey A. Fagan & Amanda Geller, *Police, Race, and the Production of Capital Homicides*, 23 BERKELEY J. CRIM. L. 261 (2018).

56 *Id*. at 297 (showing that racial disparities originate and accumulate beginning with clearance patterns and through prosecutors' bias in charging decisions); *see also* Philip J. Cook & Ashley Mancik, *The Sixty-Year Trajectory of Homicide Clearance Rates: Toward a Better Understanding of the Great*

The literature also documents the role that prosecutors, defense counsel, juries, and judges have in contributing to racial disparities in California death sentencing. As a general matter, explicit biases of any of these actors may explain some of the observed disparities in California death sentences.[57] Lawyers in death penalty cases have routinely challenged "a host of local practices and allegedly racists state actors,"[58] but the overwhelming majority of these explicit racist behaviors have gone undocumented, unchallenged, or unchallengeable.[59] The California Legislature noted, "Existing precedent has provided no recourse for a defendant whose own attorney harbors racial animus towards the defendant's racial group, or toward the defendant, even where the attorney routinely used racist language and 'harbor[ed] deep and utter contempt' for the

Decline, 7 ANN. REV. CRIMINOLOGY (forthcoming Jan. 2024), available at https://doi.org/10.1146/annurev-criminol-022422-122744 (reviewing research on homicide clearance rates and reporting similar findings through 2023).

We are constrained in this analysis by the absence of counterfactuals to better estimate the clearance rates in the study sample. In response, we follow the logic and conclusions of Johann Gaebler and colleagues. Johann Gaebler, William Cai, Guillaume Basse, Ravi Shroff, Sharad Goel & Jennifer Hill, *A Causal Framework for Observational Studies of Discrimination*, 9 STAT. & PUB. POL'Y 26 (2022), DOI: 10.1080/2330443X.2021.2024778. By carefully defining the estimator as a two dimensional event – victim and defendant characteristics, as well as characteristics of the murder and its location — we can bound our estimates of racial disparities in charging and sentencing based on two features of our design: control for the selection of cases from the eligible pool of cases, and a robust weighting procedure by event location to account for the distribution across counties based on the features of those counties. *See, e.g.*, Andrew Gelman, Jeffrey Fagan & Alex Kiss, *An Analysis of the New York City Police Department's "Stop-and-Frisk" Policy in the Context of Claims of Racial Bias*, 102 J. AM. STAT. ASS'N 813 (2007).

57 Sheri Johnson, John Blume, and Patrick Wilson reviewed the modern racial epithet cases, i.e., those reported in the first decade of the twenty-first century, and documented "the continued presence of race-based animosity" expressed by judges, jurors, prosecutors, and defense counsel. Sheri Lynn Johnson, John H. Blume & Patrick M. Wilson, *Racial Epithets in the Criminal Process*, 2011 MICH. ST. L. REV. 755, 768-70 (2011); *see also* Paul Messick, *Represented by a Racist: Why Courts Rarely Grant Relief to Clients of Racist Lawyers*, 109 CAL. L. REV. 1231 (2021) (discussing *Ellis v. Harrison,* 947 F.3d 555, 556 (9th Cir. 2020)).

58 *See* Robert L. Tsai, *After* McCleskey, 96 SO. CAL. L. REV. [page 5] (2023) (forthcoming)

59 *See generally* Sheri Lynn Johnson, *supra* note 57 (documenting repeated resistance to providing meaningful relief in modern racial epithet cases).

defendant's racial group."[60] Similarly, "Existing precedent tolerates the use of racially incendiary or racially coded language, images, and racial stereotypes in criminal trials."[61]

To remedy this situation, the California Legislature enacted the Racial Justice Act, which, as noted above, provides an express cause of action if a judge or an attorney "exhibited bias or animus towards the defendant because of the defendant's race, ethnicity, or national origin"[62] or "used racially discriminatory language about the defendant's race, ethnicity, or national origin, or otherwise exhibited bias or animus towards the defendant because of the defendant's race, ethnicity, or national origin, whether or not purposeful."[63] California did not enact the Racial Justice Act, however, until after the period of this study.

Jury selection and jury decision-making may also contribute to the racial disparities observed in the administration of the death penalty in California.[64] Race has long been used—explicitly and implicitly—to exclude citizens from jury participation.[65] Early state laws in this country strictly limited jury participation to white male property owners.[66] The exclusion of Black citizens from juries through the middle of the last century was "near absolute."[67] This pattern

60 Cal. Assemb. Bill No. 2542 (2019-2020 Reg. Sess.) § 2(d) (internal citations omitted).

61 Cal. Assemb. Bill No. 2542 (2019-2020 Reg. Sess.) § 2(e).

62 Cal. Penal Code § 745 (a)(1) (West 2024).

63 Cal. Penal Code § 745 (a)(2) (West 2024).

64. A more complete review of research on the impact of race on jury selection can be found in Catherine M. Grosso & Barbara O'Brien, *Race and Jury Selection*, in RESEARCH HANDBOOK IN LAW AND PSYCHOLOGY (forthcoming 2023).

65. *See generally* James Forman, Jr., *Juries and Race in the Nineteenth Century*, 113 YALE L.J., 895 (2004).

66. Alexis Hoag, *An Unbroken Thread: African American Exclusion from Jury Service, Past and Present*, 81 LA. L. REV. 55, 57-58 (2020) (reviewing state laws in the 1700s and 1800s).

67. *Id*. at 56.

replicated itself in California.[68] Decades later, racism—explicit, implicit, and structural—continues to produce disparities in how jurisdictions summon potential jurors, whom the court excuses for cause or hardship, and how lawyers exercise their peremptory strikes.[69] In many places, including California, juries remain predominantly white even though the communities in which they sit are not.[70]

Scholars have documented the importance of heterogeneity in juries on both punitiveness and the quality of deliberation. Diversity enhances the quality of deliberation.[71] Conversely, juries lacking in diversity have been found to be more punitive.[72] Two meta-analyses of noncapital juror decision making found mock jurors are more likely to reach guilty verdicts in cases with other-race defendants.[73]

68. *See generally* ELISABETH SEMEL ET AL., WHITEWASHING THE JURY BOX: HOW CALIFORNIA PERPETUATES THE DISCRIMINATORY EXCLUSION OF BLACK AND LATINX JURORS (June 2020), https://doi.org/10.15779/J26054 (last visited Jan. 22, 2024) (hereafter WHITEWASHING THE JURY BOX); *see also id*. at 3 (collecting cases including *People v. Hines*, 12 Cal. 2d 535, 537 (1939), where an all-White jury convicted a Black defendant of shooting and killing a Black man, and California Supreme Court noted that despite constituting 8% of the population, "no negro had ever been placed on the venires or called for jury service in criminal cases in Merced county").

69. *See generally* Shari Seidman Diamond & Mary R. Rose, *The Contemporary American Jury*, 14 ANN. REV. LAW & SOC. SCI. 239 (2018) (collecting and reviewing research on discrimination and jury selection).

70. *See*, *e.g.*, WHITEWASHING THE JURY BOX, *supra* note 68, at 13 (summarizing empirical findings of exclusionary behavior in California) & note 52 (collecting cases comparing California's population demographics to jury demographics in various state jurisdictions).

71. Samuel R. Sommers, *On Racial Diversity and Group Decision Making: Identifying Multiple Effects of Racial Composition on Jury Deliberations*, 90 J. PERSONALITY & SOC. PSYCHOL. 597 (2006); Thomas Framptom & Brandon Charles Osowski, *The End of* Batson*: Rule Making, Race and Criminal Procedure Reform*, 124 COLUM. L. REV. 1 (2024)

72. *See generally* Jennifer S. Hunt, *Race, Ethnicity, and Culture in Jury Decision Making*, 11 ANN. REV. L. & SOC. SCI. 269 (2015) (reviewing the literature).

73. *Id*. at 271 (reviewing Tara L. Mitchell, Ryann M. Haw, Jeffrey E. Pfeifer & Christian A. Meissner, *Racial Bias in Mock Juror Decision-Making: A Meta-Analytic Review of Defendant Treatment*, 29 LAW & HUM. BEHAV. 621 (2005)); *see also* Shamena Anwar, Patrick Bayer & Randi Hjalmarsson, *Unequal Jury Representation and Its Consequences*, 4 AM. ECON. REV.: INSIGHTS 159, 160 (2022); Mona Lynch & Emily V. Shaw, *Downstream Effects of Frayed Relations: Juror Race, Judgment, and Perceptions of Police*, RACE & JUST. (2023).

Judges and judicial decision-making also may contribute to racial disparities in California death sentences. Two review chapters collect much of the extensive research on judicial biases. Allison Harris and Maya Sen reviewed research on the ways that judicial backgrounds influence the risk of judicial bias and concluded that "judges' personal backgrounds, professional experiences, life experiences, and partisan and ideological loyalties might impact their decision making,"[74] but that the strongest effects arise from ideology and partisanship rather than race.[75] Overall, however, the research suggests that "the composition of the judiciary as a whole . . . greatly informs the overall kinds of decisions that judges will yield."[76] California judges between 1978 and 2002 remained overwhelmingly white and male.[77] Judges are also influenced by implicit biases in ways that may produce racial disparities.[78]

III. METHODS

Full details on the development and coding of the database used in this study are provided in our earlier publications, but we repeat the key details here for convenience and provide new information concerning additional race and ethnicity coding completed for this study.

[74] Allison P. Harris & Maya Sen, *Bias and Judging*, 22 ANN. REV. POL. SCI. 241, 242 (2019).

[75] *Id*.

[76] *Id*. at 255.

[77] News Release, California Courts Newsroom, Survey Results: California Bench Continue to Grow More Diverse (Mar. 1, 2023), https://newsroom.courts.ca.gov/news/survey-results-california-bench-continues-grow-more-diverse (reporting that as late as 2006 California judges and justices were 70% white).

[78] *See* Andrew J. Wistrich & Jeffrey J. Rachlinski, *Implicit Bias in Judicial Decision Making: How It Affects Judgment and What Judges Can Do About It, in* ENHANCING JUSTICE: REDUCING BIAS 87, 99-104 (Sarah E. Redfield ed., 2017) (concluding based on multijurisdictional study involving 133 judges that judges hold implicit racial biases that can influence their judgement in criminal cases, but that this influence can be mitigated at times).

A. The Universe and Sample of Cases

For this study, we examined a universe of 27,453 defendants convicted of first-degree murder, second-degree murder, and voluntary manslaughter, with an offense date between January 1, 1978, and June 30, 2002. These records were drawn from a database produced by the California Department of Corrections and Rehabilitation. From this universe, we derived a stratified sample of 6.9 percent (1,900/27,453).

We stratified the sample on three dimensions to produce a more representative sample of the cases than would have been produced by a random sampling method.[79] The first dimension, the crime of conviction, provides proportionate representation for the first-degree, second-degree, and voluntary manslaughter conviction cases. The second dimension is the population density of the county of prosecution. For the third dimension, we stratified the sample based on the four time periods in the evolution of the California capital punishment statute that were relevant to our analysis. The result was a random sample of cases consisting of forty-eight strata: three offense categories by four county population density categories by four time periods. For each stratum, we weighted the cases in the sample based on the ratio of the number of cases in the universe and the sample.

We estimated the power of the sample of 27,453 cases using G*Power 3.1.9.6, a widely used open-source application.[80] The power of a statistical test is the probability that a null hypothesis (of no difference between groups) will be rejected when it is false. In other words,

[79] Our previous publications contain more extensive descriptions of the stratification process. Baldus, *supra* note 14, at 707-08; Grosso, *supra* note 14, at 1418-20.

[80] Hyun Kang, *Sample Size Determination and Power Analysis Using the G*Power Software*, 18 J. EDUC. EVAL. HEALTH PROF. 17 (2021); Franz Faul, Edgar Erdfelder, Axel Buchner, & Albert-Georg Lang, *Statistical Power Analyses Using G*Power 3.1: Tests for Correlation and Regression Analyses*, 41 BEHAV. RES. METHODS 1149 (2009).

power is the probability that a result is "correct."[81] Power is a function of (a) the sample size, (b) the significance level, and (c) the anticipated effect size (the difference between groups). There is no absolute standard on a minimum power, but convention suggests that a minimum power level should be .80.[82]

For this analysis, we estimated the power of the sample cases with an effect size of .10, based on the difference in the rate of charging for minority defendant death-eligible cases (.25) compared to the charging rate (.35) of all other death-eligible cases.[83] We tested for power using a significance level of .05 and a two-tailed test based on a linear regression model. Results show that with these parameters, we obtain a minimum power estimate of .95.

B. Data Sources and Coding Process

The primary source of information on each case was the probation report prepared by the county probation officer with jurisdiction over the case.[84] Our previous publications present the coding process and the methodology used to determine factual eligibility in detail.[85] In some cases, the probation report did not provide sufficient information to complete the data coding process,

81 Jacob Cohen, *Statistical Power Analysis*, 1 CURRENT DIRECTIONS PSYCHOL. SCI. 98 (1992); Jacob Cohen, *A Power Primer*, 112 PSYCHOL. BULL. 155 (1992).

82 Cohen, *Statistical Power Analysis*, *supra* note 81, at 100 (proposing that "as a convention that in the absence of any other basis for setting the value for desired power, .80 be used"). While most people might think that "more is better" for sample size, that actually is not the case. There is an optimal sample size given the parameters of the planned study design and sample, and there are reductions to power for sample sizes that for samples that are substantially greater or smaller than that optimal rate. *Id.* at 99 ("Statistical power analysis exploits the mathematical relationship among these four variables in statistical inference: power, alpha, N, and ES. The relationship is such that when any three of them are fixed, the fourth is determined.").

83 *See infra* Table 2.

84 California law requires the preparation of a probation report for each homicide to assess the appropriateness of probation as a sentencing alternative in the case. CAL. PENAL CODE § 1203 (West 2024). These reports, routinely relied on by California courts, are subject to examination and correction by both the prosecuting authorities and defendants. CAL. PENAL CODE § 1203.01 (West 2024).

85 Baldus, *supra* note 14, at 710-13; Grosso, *supra* note 14, at 1421-23.

and we obtained additional official judicial records to cure the data insufficiency.[86] From the information in the probation reports, we assessed each defendant's liability for first-degree murder and the factual presence of each special circumstance under pre-*Furman* Georgia law, post-*Furman* California law in effect between December 1983 and October 1987 (known as the "*Carlos* Window"), and 2008 California law.[87] This analysis evaluates the influence of race of defendant and race of victim under the law in effect in California as of January 1, 2008.

C. Coding Defendant and Victim Race and Ethnicity

Limited and missing information for race or ethnicity presented a significant issue in this study. The original sources used to code this database did not consistently report race or ethnicity of the defendants or the name, race, or ethnicity of the victims. The initial coding process identified race or ethnicity for 81 percent of defendants (1,546/1,900), but only 33 percent of victim race or ethnicity (630/1,900). For this study, we resolved the missing race information by conducting additional data collection.

We obtained the race or ethnicity of every defendant in the study via California Public Records Act requests to the California Department of Corrections and Rehabilitation.

To complete missing race information for victims, we first needed to learn their names. In an earlier study, we identified missing victim names in all but 129 cases.[88] In June 2020, research

86 A complete description of the data insufficiency issue and the process by which it was cured is detailed in our first publication. Baldus, *supra* note 14, at 709.

87 The "*Carlos* Window" refers to the law in effect following the California Supreme Court's ruling in *Carlos v. Superior Court* that temporarily narrowed the application of capital punishment. 672 P.2d 862 (Cal. 1983). In *Carlos*, the court held that the felony-murder special circumstances required the state to prove that a defendant possessed the intent to kill during the commission of the felony. The *Carlos* ruling, however, applies only to murders committed between December 12, 1983, the date on which *Carlos* was decided, and October 13, 1987, the date on which the California Supreme Court overruled *Carlos* in People v. Anderson, 742 P.2d 1306 (Cal. 1987).

88. Grosso, *supra* note 14, at 1423-25 (explaining the process and noting that we identified missing victim names in all but 129 cases in 2018).

assistants at Michigan State University requested court documents that typically include the victim names.[89] This process yielded the missing victim names for all but ten cases. We then obtained permission through the Committee for the Protection of Human Subjects at the California Health and Human Services Agency to review the Death Statistical Master File (DSMF) for each year of the study (1978-2002). These files provided for each decedent variables including the first, middle, and last names; year, month, and day of death; sex; race; ethnicity; and age. We identified the missing race and ethnicity for the victims in the study by locating their entries in these files.

We successfully identified names and race information for all but 105 victims, 5.5 percent of the cases. Although the rate of missing data is low, we included those cases in the analyses by coding missing victim race information as "non-white" for purpose of race of victim analysis. Accordingly, our estimates of the racial influences on case decisions and outcomes are conservative with respect to estimating racial disparities.

D. Analysis

We analyzed the influence of race in California's capital punishment scheme using three sets of models. We first analyzed the racial disparities in death sentencing compared to racial characteristics in death-eligible cases using simple bivariate analyses. As this approach does not account for the influence of additional variables on case outcomes, we then estimated a series of logistic regressions to test for disparities for each decision stage controlling for offense, defendant, and case characteristics.[90] The regression model takes the form of:

$$\pi_i = Pr(Yi=1|Xi=xi) = \frac{\exp(\beta 0+\beta 1xi)}{1+\exp(\beta 0+\beta 1xi)}$$

89 The Michigan State research assistants were Shawn Fagan and Emma Thronson.

90 *See* DAVID W. HOSMER JR., STANLEY LEMESHOW, & RODNEY X. STURDIVANT, APPLIED LOGISTIC REGRESSION (2nd ed. 2000).

Where Y is the outcome of interest (0 or 1), π is the probability that an individual i will be in the category of interest, $\beta 0$ is the intercept, and βx represents the concurrent effects of a set of explanatory variables or predictors of that outcome.

The analysis first examined race and ethnicity alone as predictors. To identify a subset of special circumstances as predictors, we analyzed each statutory special circumstance in isolation and in discrete combinations to identify the statutory provisions that were robust predictors of the totality of charged circumstances. Accordingly, the models presented for each outcome include control variables found in combination to be theoretically and substantively important to the outcome. [91] For each predictor, in each model, we report the odds ratio, standard error, the two-tailed significance, and confidence intervals for each predictor for each outcome.[92] For each

[91] For each logistical regression model reported, we included codes for every statutory special circumstance that consistently and reliability predicted whether a case would advance to the outcome under analysis. We included the special circumstances as individual variables and in combination with others and removed special circumstance variables from the model in reverse order of statistical significance. That is, we started by removing those that were least likely to contribute to the outcome. These typically have odds close to 1.00. We continued removing special circumstance variables in this manner until the model includes only those at least marginally important to the outcome under analysis. This follows the methodology in previous charging and sentencing studies. *See, e.g.*, Barbara O'Brien, Catherine M. Grosso, George Woodworth & Abijah Taylor, *Untangling the Role of Race in Capital Charging and Sentencing in North Carolina, 1990-2009*, 94 N.C. L. REV. 1997 (2016); David C. Baldus, George Woodworth, Catherine M. Grosso, & Richard Newell, *Racial Discrimination in the Administration of the Death Penalty: The Experience of the United States Armed Forces (1984-2005),* 101 J. CRIM. L. & CRIMINOLOGY 1227 (2011). *See generally* David Baldus, George Woodworth, Neil Alan Weiner, David Zuckerman, & Catherine M. Grosso, *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 Acker eds. 2009).

[92] Odds ratios indicate the relative change in the outcome for each unit increase in the predictor. An odds ratio of 1.0 for a particular predictor indicates that that predictor neither increases nor decreases the likelihood of an outcome; whereas an odds ratio of 2.0 indicates that the presence of the predictor is twice as likely to result in an outcome. An odds ratio of .50 indicates that the outcome is 50% less likely to occur in the presence of the predictor. *See* J. Martin Bland & Douglas G. Altman, *The Odds Ratio*, 320 BRIT. MED. J. 1468 (2000).

predictor, in each model, we report the odds ratio, standard error of the predictor, the probability level, and the 95% confidence intervals for the predicted outcome. [93]

For each outcome and defendant-victim racial and ethnic group, we conducted alternative regression analyses using a six-level, race-purged culpability scale to control for the underlying facts in each case. This scale seeks to specify for each case, a race-purged numerical prediction of the relative risk that the defendant would have been sentenced to death.

David C. Baldus and George Woodworth created the defendant culpability scale in a multistep process. The process purges race from the prediction so that the predictor is not correlated with the race and ethnic predictors. The scaling process began by producing a culpability index with a logistic model that used the Mantel-Haenzel method in SAS to produce a predicted probability of a death sentence for each case.[94] This model included variables for the fact of four special circumstances being found or present—Cal. Penal Code § 190.2(3) (multiple victims), § 190.2(5) (for the purpose of avoiding arrest), § 190.2(10) (witness victim), and § 190.2(16) (victim bias as motive for murder). It also included variables for the number of special circumstances in the case, whether the crime included kidnapping the victim, whether the defendant did not factually cause the victim's death, the presence of co-perpetrators, and a scale for the age of the defendant. The cases were ranked according to those predictions and divided into a six-level culpability scale. They then estimated the racial disparity within each cell and combined those disparities to compute a weighted average of the disparities across all of the cells. This was used to purge the race effects from the index. The resulting index estimated the

[93] Each case in the study was analyzed to determine whether a statutory special circumstance could have been charged and found to be true by the jury. Our previous publications explained the methodology used to make these determinations. Grosso, *supra* note 14, at 1421-23; Baldus, *supra* note 14, at 710-13.

[94] *See* Nathan Mantel & William Haenszel, *Statistical Aspects of the Analysis of Data from Retrospective Studies of Disease*, 22 J. NAT'L CANCER INST. 719 (1959) (establishing this method).

culpability level of each case in the study. We refer to this index as the "defendant culpability scale."

We included a pair of logistic regression models for each outcome in the findings below. The first model controls for individual special circumstances, as described above, and the second controls for the defendant culpability scale. We include both models because they control for difference in the cases using marginally different information. The consistency of findings across both models adds to our confidence in the observed disparities.

The first and last set of regressions examine racial disparities in death sentencing. To control for the selection of cases from the full sample that are eligible for death, we also include a control for prosecutorial decision making in the overall death sentencing model. Receiving a death sentence depends, overall or at a penalty trial, on the prosecutorial decision to charge one or more death-eligible special circumstance. Accordingly, we controlled for prosecutorial selection in determining the overall probability of receiving a death sentence. We used the logistic regression model of the prosecutorial selection of cases as death-eligible based on filing special circumstances presented in Table 12-A below to estimate a linear predicted value, or probability of selection in Stata. This procedure generated a single parameter, ranging from 0.0 to 1.0, for the probability that the prosecutor would have charged special circumstances in the case, based on the combination of case characteristics including race and ethnicity of defendant and victim.[95] We used an inverse weighting procedure to estimate and apply the selection parameter to adjust for

95 The Appendix contains details concerning the construction of this parameter.

selection decisions.[96] We then included this variable in the overall death sentencing and jury death sentencing models.[97]

The third analysis modelled the progression of cases from eligibility through sentencing using ordered probit analyses. Unlike analyses of decisions at each stage, these analyzes estimated the odds by race or ethnicity of a case proceeding through each successive stage from prosecutorial selection (i.e., special circumstance charging) to death sentencing. Next, we used an ordered probit regression to identify factors that predict which cases pass through all decision points to receive a death sentence.[98] Ordered probit regression models explain variation in an ordered categorical dependent variable with more than two outcomes as a function of one or more independent variables. In this case, let:

$$\mathrm{Y}^* = b'\mathbf{X}_\iota + e_i$$

where Y* is the underlying latent variable (selection parameter) that indexes the level of participation of the defendant in a capital prosecution, X_i is a vector of parameters to be estimated including case characteristics and mediating case factors, and e_i is the error term.

We established a 3-stage ordinal scale marking of 0-3, where the scale score represents the stage of adjudication and sentencing that where each case is reaches. The latent variable is a

96 *See* Heejung Bang & James M. Robins, *Doubly Robust Estimation in Missing Data and Causal Inference Models*, 61 Biometrics 962 (2005); *see also* Alka Indurkhya, Nandita Mitra & Deborah Schrag, *Using Propensity Scores to Estimate the Cost-Effectiveness of Medical Therapies*, 25 STAT. MED. 1561 (2006); Greg Ridgeway & John M. MacDonald, *A Method for Internal Benchmarking of Criminal Justice System Performance*, 60 CRIME & DELINQ. 145 (2014).

97 See the Appendix for the estimation procedure for the selection parameter.

98 *See, e.g.*, Maiyaki A. Damisa & Margaretha Yohanna, *Role of Rural Women in Farm Management Decision Making Process: Ordered Probit Analysis*, 3 WORLD J. AGRIC. SCI. 543 (2007) (employing a probit model to analyze parameters of the hierarchical work choices in the socio-economic lives of rural women); *see also* Christopher Winship & Robert D. Mare, *Regression Models with Ordinal Variables*, 49 AMER. SOC. REV. 512 (1984) (resolving issues of scale and ordinality in ranked variables and developing an analytic model to estimate ordinal regressions in a common framework with other forms of regression).

set of ordinal (or ordered) categories, which could be coded as 0, 1, 2, 3, , k. In this analysis, we use three categories. The response of category k is thus observed when the underlying continuous response falls in the k-th interval.[99] In this design, a death-eligible case in which the prosecutor declined to file a special circumstance has a value of 1 on the scale. A case in which the prosecutor filed at least one special circumstance has a value of 2, and case that received a death sentence has a value of 3. We used ordered probit regressions controlling for the presence of the special circumstances that are most predictive of a death sentence, and, separately, for the defendant culpability scale, to test the effects of race in determining on the final stage that of decision making in each case reaches.

The results are reported as regression coefficients, where each race coefficient identifies the effects of victim or defendant race on determining the stage of final disposition or conclusion of the case. As before, we conducted separate analyses, by (1) defendant race (Black or Latinx defendants compared to all others), (2) white victim cases compared to all others, (3) murders of

[99] In the ordered probit model described in the text, the response of category k is thus observed when the underlying continuous response falls in the *k*-th interval as:

$$Y^* = 0 \text{ if } Y^* \leq \delta_0$$
$$Y^* = 1 \text{ if } \delta_0 \leq Y^* \leq \delta_1$$
$$Y^* = 2 \text{ if } \delta_1 \leq Y^* \leq \delta_2$$
$$Y^* = 3 \text{ if } \delta_2 \leq Y^* \leq \delta_3$$
$$Y^* = 4 \text{ if } \delta_3 \leq Y^* \leq \delta_4$$

Where δ (i=0,1,2,3) are the unobservable threshold parameters that will be estimated together with other parameters in the model. The probabilities for each of the observed ordinal response will be given as:

$$\text{Prob}(Y = 0) = P(Y^* \leq 0) = P(\beta' X_i + \varepsilon_i \leq 0) = \phi(-\beta' X)$$
$$\text{Prob}(Y = 1) = \phi(\delta_1 - \beta' X) - \phi(-\beta' X)$$
$$\text{Prob}(Y = 2) = \phi(\delta_2 - \beta' X) - \phi(\delta_1 - \beta' X)$$
$$\text{Prob}(Y = 3) = \phi(\delta_3 - \beta' X) - \phi(\delta_2 - \beta' X)$$
$$\text{Prob}(Y = 4) = 1 - \phi(\delta_3 - \beta' X)$$

Where $0 < \delta_1 < \delta_2 < ... < \delta_{k-1}$ is the cumulative normal distribution function such that the sum total of the above probabilities is equal to one.

white victims by Black or Latinx defendants, and (4) multiple combinations of the race of the defendant and the race of the victim. As with the logistic regression analyses, we estimated separate models controlling for the presence of the special circumstances that are most predictive of a death sentence and for the defendant culpability scale.[100]

IV. RESULTS

This section presents the results of analyses to identify the influence of race and ethnicity on the overall risk of receiving each of three decisions: a death sentence, the prosecutorial decision to charge a case with special circumstances, and the jury decision to impose a death sentence. The first part presents unadjusted findings in simple bivariate analyses, and the second presents the results of logistic regression analyses. The final section models the progression of cases from eligibility through sentencing using ordered probit regressions.

The methods described above produced a stratified random sample of cases. Table 1 presents the final sample and estimated universe, by conviction and by sentence outcome. Each row of information includes the number of cases in the 1,900-case sample and in the 27,453-case estimated universe. Row 1 reports that the sample includes 61 death-sentenced cases, 193 cases resulting in life without parole (LWOP), and 1,646 cases resulting in a sentence less than LWOP. Rows 2-4 report the distribution of these sentencing outcomes by conviction. Column F reports that 764 of the cases in the sample resulted in a first-degree murder conviction, 491 in a second-degree murder conviction, and 645 in a voluntary manslaughter conviction.

[100] All models were estimated using SVY procedures in Stata 17.0. https://www.stata.com/

TABLE 1. Description of the Sample by Sentence Outcome

	A	B	C Death		D LWOP		E Term of Years		F Total
1.	**Total**	*Sample*	3%	61	10%	193	87%	1,646	1,900
		Weighted	3%	705	9%	2,364	89%	24,384	27,453
2.	**First-degree murder conviction**	*Sample*	8%	61	25%	193	67%	510	764
		Weighted	8%	705	27%	2,364	65%	5,642	8,711
3.	**Second-degree murder conviction**	*Sample*	-	0	-	0	100%	491	491
		Weighted	-	0	-	0	100%	7,900	7,900
4.	**Voluntary manslaughter conviction**	*Sample*	-	0	-	0	100%	645	645
		Weighted	-	0	-	0	100%	10,842	10,842

Table 2 presents the study sample and weighted universe by conviction (in columns) and race and ethnicity (in rows). Column B presents the sample overall, with Columns C-E showing the distribution among first- and second-degree murder and voluntary manslaughter cases, by race and ethnicity. The rows are sorted by the size of the racial or ethnic population in the study. The vast majority (95%) of the defendants across all cases are Black, white, or Latinx.

TABLE 2. Description of the Sample by Race or Ethnicity of Defendant and Conviction, by size

	A **Race of Defendant**	B **Total**		C **First-Degree Murder**		D **Second-Degree Murder**		E **Voluntary Manslaughter**	
		sample	*weighted*	*sample*	*weighted*	*sample*	*weighted*	*sample*	*weighted*
1.	**White**	678	7,435	285	2,418	197	2,284	196	2,644
		36%	27%	38%	27%	39%	29%	30%	24%
2.	**Black**	586	9,638	245	3,327	127	2,403	214	3,835
		31%	35%	33%	35%	25%	30%	33%	35%
3.	**Latinx**	542	9,075	174	2,279	154	2,790	214	3,938
		28%	33%	23%	33%	31%	35%	33%	36%
4.	**Asian American**	31	437	10	99	13	211	8	127
		2%	2%	1%	2%	3%	3%	1%	1%
5.	**Other**	25	321	9	85	9	107	7	129
		1%	1%	1%	1%	2%	1%	1%	1%
6.	**Pacific Islander**	19	391	9	224	5	85	5	82
		1%	1%	1%	1%	1%	1%	1%	1%
7.	**Native American**	19	156	9	52	1	12	9	85
		1%	1%	1%	1%	<1%	<1%	1%	1%
8.	**Total**	1,900	27,453	741	8,483	506	7,900	653	10,842

The analysis present below analyzes the disparities for Black and Latinx defendants as separate variables. We conducted the primary analysis including all cases in the study, including the small numbers of Asian American, Pacific Islander, Native American, and other defendants. We replicated this analysis excluding these defendants and report any instances in which we found significant differences in the results in the notes. We also analyze disparities with respect to the presence of white victims in the cases. Following practice in earlier studies, this variable is coded one if there is at least one white victim in the case.

A. Racial Disparities Observed in the Overall Risk of Receiving a Death Sentence

In the first step of our study, we analyzed whether race or ethnicity had a role in determining which defendants received a death sentence from the universe of death-eligible cases. This analysis considered the aggregate effects of prosecutorial and jury decision-making.

1. Unadjusted Findings

We first compared racial characteristics among death-eligible case to cases in which a death sentence was imposed. Table 3 examines the characteristics of the cases that were death eligible, cases in which the prosecutors charged specials circumstances, and cases in which the juries imposed death sentences. Table 3, Column A shows that Black defendants comprised 51% (357/703), and Column B reports that Latinx defendants comprised 28% (200/703) of the cases resulting in a death sentence (Row 3). These numbers compare to 37% (Black defendants) (6,037/16,385) and 32% (5,328/16,385) (Latinx defendants) of the death eligible cases (Row 1).

TABLE 3. Percent of Population of Cases with Minority Defendants, White Victims, and Minority Defendants/White Victim Cases in Each Category of Analysis

sample n (weighted n)	A **Black Defendants**	B **Latinx Defendants**	C **White Victim**	D **Black Defendant/ White Victim**	E **Latinx Defendant/ White Victim**
1. Death Eligible Cases	37%	32%	34%	8%	5%
n = 1,226 (16,385)	6,037	5,328	5,617	1,288	901
2. Cases in which Prosecutor Charged Special Circumstance	36%	25%	46%	12%	8%
n = 347 (4,609)	1,678	1,167	2,124	544	361
3. Cases in which Death Sentenced Imposed	51%	28%	52%	15%	19%
n = 60 (703)	357	200	368	106	133

Tables 4-A and 4-B show the rate of selection of cases in each subgroup and case outcome.[101] The increase in representation of Black defendants among death sentenced cases reflected in Table 3 arises from the increased rate at which Black defendant cases resulted in a death sentence as reported in Table 4-A, Row 1, Column A. Six percent of Black defendant cases resulted in a death sentence (357/6,037) compared to 3% of all other cases (346/10,348). This is a ratio of 2.0 to 1. The disparity is not statistically significant.[102]

[101] Separate chi-square tests were conducted for each cell in the table.

[102] All reports of statistical significance are based on a two-tailed chi-square test.

TABLE 4-A. Rate of Selection of Cases in Each Subgroup for Outcome by Black Defendants, Latinx Defendants, and White Victims, in Each Category of Analysis

		A Black Defendants		B Latinx Defendants		C White Victim	
	sample n (weighted n)	**Black Defendants**	**Other Defendants**	**Latinx Defendants**	**Other Defendants**	**White Victim**	**No-White Victim**
1.	**Death Sentence Imposed in Death-Eligible Case**	6% 357/6,037	3% 346/10,348	4% 200/5,328	5% 503/11,057	7% 371/5,623	3% 332/10,762
	n = 1,226 (16,385)	*p* = .15		*p* = n.s.		*p* = .06	
2.	**Prosecutor Charged Defendant with at Least One Special Circumstance**	28% 1,678/6,037	28% 2,931/10,348	22% 1,167/5,328	31% 3,441/11,057	38% 2,124/5,617	23% 2,485/10,767
	n = 1,226 (16,385)	*p* = n.s.		*p* < .03		*p* < .001	
3.	**Jury Imposed Death Sentence on Defendant**	21% 357/1,678	12% 346/2,931	17% 200/1,167	15% 503/3,441	17% 371/2,124	13% 335/2,485
	n = 347 (4,609)	*p* < .12		*p* = n.s.		*p* = n.s.	

TABLE 4-B. Rate of Selection of Cases in Each Subgroup for Outcome by Black Defendants, Latinx Defendants, and Minority Defendants/White Victim Cases in Each Category of Analysis

		A Black Defendant/ White Victim		B Latinx Defendant/ White Victim	
	sample n (weighted n)	**BD/WV**	**Other**	**LD/WV**	**Other**
1.	**Death Sentence Imposed in Death-Eligible Case** n = 1,226 (16,385)	8% 106/1,288 $p = .16$	4% 596/15,096	15% 133/906 $p < .01$	4% 570/15,478
2.	**Prosecutor Charged Defendant with at Least One Special Circumstance** n = 1,226 (16,385)	42% 545/1,288 $p < .04$	27% 4,065/15,096	44% 362/906 $p = .14$	27% 4,247/15,478
3.	**Jury Imposed Death Sentence on Defendant** n = 347 (4,609)	19% 106/545 p = n.s.	15% 596/4,063	37% 133/362 $p < .03$	13% 570/4,247

Returning to Table 3, Column C, white victim cases comprised 52% of the cases resulting in a death sentence (368/703), compared to 34% of the death eligible cases overall (5,617/16,385). This is a 153% increase in representation (52%/34%). Again, the increase in representation is consistent with the increased rate at which death-eligible cases with at least one white victim resulted in a death sentence as reported in Table 4-A, Row 1, Column C. Seven percent of white victim death-eligible cases resulted in a death sentence (371/5,623) compared to 3% of all other death-eligible cases (332/10,762). White victim death-eligible cases were more than twice as likely to result in a death sentence as all other death-eligible cases. This disparity is marginally significant ($p = .06$).

Turning to Table 3, Columns D and E, Black and Latinx defendants who killed at least one white victim in death-eligible cases faced larger unadjusted disparities in overall death sentencing. Black defendant/white victim cases comprised only 8% of death-eligible cases overall (1,288/16,385), but their presence almost doubled to 15% of death sentenced cases (106/703).

Latinx defendant/white victim cases comprised only 5% of death-eligible cases overall (901/16,385), but their presence almost quadrupled to 19% of death sentenced cases (133/703).

In Table 4-B, Row 1, Column A reports that Black defendant/white victim cases resulted in a death sentence at two times the rate of all other cases (8%, 106/1,288 vs. 4%, 596/15,096), this large disparity does not achieve statistical significance. Column B presented the disparities for Latinx defendant/white victim cases. While there are fewer Latinx defendant/white victim cases, the disparity in the rate at which they receive a death sentence is even larger than for Black defendant/white victim cases—15% (133/906) compared to 4% (570/15,478). This large disparity, a relative risk ratio of 3.75, is statistically significant ($p < .01$).

2. Disparities Estimated in Regression Analysis

We used logistic regressions to model each decision. Logistic regression allowed us to see the unique effect of race or ethnicity, controlling for case characteristics that might influence decision making.[103]

Tables 5-A, Model 1 reports that Black defendants were 8.7 times more likely to receive a death sentence compared with all other defendants even after controlling for the presence of at least one white victim in the case and for statutory special circumstances and the importance of prosecutor decisions on the outcome.[104] This large disparity is statistically significant ($p < .01$). This model also reports that Latinx defendants were 6.2 times more likely to receive a death

103 All models control for the influence of legal chances during the *Carlos* Window, and the selection effects of prosecutor decisions to charge special circumstances (when appropriate). This includes Tables 5-A, 5-B, 6, 7-A, 7-B, 13, 14-A, 14-B, 15, 16-A, 16-B, 17, 18, 19, 20, and 21. *See supra* text accompanying notes 95 and 96 for a detailed discussion.

104 For this portion of our analysis – considering all decisions in the death sentencing process – the special circumstances that are most predictive of a death sentence in our model were Cal. Penal Code § 190.2(a)(3) (multiple victims), Cal. Penal Code § 190.2(a)(17)(A) (robbery felony murder), and Cal. Penal Code § 190.2(a)(17)(C-F, K) (sex crimes felony murders). *See supra* note 91.

sentence compared with all other defendants even after controlling for the presence of at least one white victim in the case and for statutory special circumstances and the importance of prosecutor decisions on the outcome. This large disparity is statistically significant ($p < .05$). Finally, the white victim variable is large and statistically significant ($p < .05$). Table 5-B replicates Model 1, providing complete results.

Table 6 includes the same race variable as Table 5-B, Model 1, but controls using the defendant culpability scale, rather than the most predictive special circumstances. The odds ratio faced by Black defendants fell to 4.6, but remains statistically significant ($p < .002$). The odds ratio faced by Latinx defendants fell to 3.2, but remains statistically significant ($p < .044$). The odds ratio for a death sentence in white victim cases also fell to 2.8 and remains statistically significant ($p < .033$). This increases confidence in the disparities reported in Tables 5-A, Model 1, and 5-B and suggests that both cases with Black and Latinx defendants and those with white victims faced significantly greater risks of receiving a death sentence overall when compared with all other cases in the study.

Table 5-A includes four additional models presenting alternate race or ethnicity variables. We decomposed the race and ethnicity effects to better identify their unique contributions to decision making comparing each racial or ethnic victim and defendant group to Whites. In Model 2 (which omits the Latinx defendant variable), the Black defendant disparity remains large (2.8) and statistically significant ($p < .01$) as does the white victim variable (5.3, $p < .05$). In Model 3 (which omits the Black defendant variable), the Latinx defendant loses power and significance when include in the model without Black defendant but the white victim variable maintains power and significance (3.5, $p < .05$). In Model 4 (which omits race of the defendant variables), the white victim variable is large and significant with the other race variables (3.3, $p < .05$). When the Black

defendant and Latinx defendant variables are included in Model 5 without controlling for the influence of the presence of at least one white victim in the case, disparities persist but the p-value exceeds the level of statistical significance.

Table 5-A. Logistic Regression of Death Sentence on Defendant and Victim Race, Controlling for Statistically Significant Special Circumstances Found or Present (n = 1,226)

Models	Model 1		Model 2		Model 3		Model 4		Model 5	
	OR	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Black Defendant	8.74***	5.57	2.80**	1.40					3.06*	1.97
Latinx Defendant	6.20**	3.99			1.46	0.77			2.64	1.62
White Victim	8.76**	5.98	5.27**	3.77	3.47**	2.19	3.29**	2.04		
Multiple Victims Special Circ.	1186.63**	2676.65	549.83**	1378.11	265.30**	519.80	261.06**	543.05	27.90**	33.70
Robbery Special Circ.	41.08**	64.58	36.70**	63.81	29.07**	40.26	29.62**	43.40	5.30*	5.08
Sex Crime Felony Special Circ.	628.74**	1170.04	381.77**	740.70	233.01***	383.66	232.56***	393.16	48.87***	60.67
_cons	<0.002**	<0.01	<0.01***	0.003	<0.01***	<0.01	0.01***	0.01	0.01***	0.00

n (universe) = 16,385

Significance: *** *p* <= .01, ** *p* <= .05, * *p* <= .10

Table 5-B. Logistic Regression of Death Sentence on Defendant and Victim Race, Controlling for Statistically Significant Special Circumstances Found or Present (n = 1,226)[105]

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% conf. interval]
Black Defendant	8.74	5.57	3.40	0.001	2.50-30.53
Latinx Defendant	6.20	3.99	2.83	0.005	1.75-21.94
White Victim	8.76	5.98	3.18	0.002	2.30-33.43
Multiple Victims Special Circumstance[106]	1186.63	2676.65	3.14	0.002	14.20-99156.76
Robbery Felony Special Circumstance[107]	41.08	64.58	2.36	0.018	1.88-897.36
Sex Crime Felony Special Circumstances[108]	628.74	1170.04	3.46	0.001	16.32-24216.95
_cons	<0.01	0.01	-7.98	0.001	<0.001-0.01

n (universe) = 16,385

Although the results suggest that white-victim cases were more likely to be sentenced to death, there is a substantial likelihood that a Black or Latinx defendant also will be more likely sentenced to death among this sample of death-eligible cases. In other words, both victim race and defendant race contributed to the likelihood of a case resulting in a death sentence, both separately and jointly.

105 Neither the size or the statistically significance of any variable in the model changes when the defendants who are not white, Black or Latinx are excluded from the analysis in Table 5-B (n = 15,677).

106 Cal. Penal Code § 190.2(a)(3).

107 Cal. Penal Code § 190.2(a)(17)(A).

108 Cal. Penal Code § 190.2(a)(17)(C-F, K).

Table 6. Logistic Regression of Death Sentence on Defendant and Victim Race, Controlling for Defendant Culpability Scale (n = 1,226)[109]

	Odds Ratio	Lin. Std. Err.	t	P>t	[95% conf. interval]
Black Defendant	4.63	2.32	3.05	0.002	1.73-12.39
Latinx Defendant	3.18	1.82	2.02	0.044	1.03-9.79
White Victim	2.76	1.31	2.14	0.033	1.09-6.99
Defendant Culpability Scale	1.67	0.28	3.13	0.002	1.21-2.31
_cons	<0.01	0.001	-8.83	0.001	0.00-0.00

n (universe) = 16,385

Table 7-A and Table 7-B test for differences among the outcomes for cases with at least one white victim. The models contrast white defendant/white victim cases with Black defendant/white victim cases and Latinx defendant/white victim cases. Table 7-A includes individual special circumstances and Table 7-B includes the defendant culpability scale. This analysis limits the data to Black, Latinx, and white defendants. In Table 7-A, Black defendant/white victim cases face 5.32 higher odds of receiving a death sentence overall than white defendant/white victim cases ($p < .01$). Latinx defendant/white victim cases face even higher odds of a death sentence, 7.99 ($p < .01$). The magnitude of these disparities decline when we controlled for the defendant culpability scale in Table 7-B. Black defendant/white victim cases odds ratio is 2.57 and only marginally significant ($p < .10$). Latinx defendant/white victim cases face an odds ratio of 3.38. That disparity achieves statistical significance ($p < .05$). These findings reveal that Black and Latinx defendants who kill at least one white victim face a higher risk of receiving a death sentence than white defendants with at least one white victim.

109 The race disparities fall slightly but remain large and the Latinx Defendant variable falls out of statistical significance when the defendants who are not Black, Latinx, or white are removed from the analysis (n = 15,677).

Table 7-A. Logistic Regression of Death Sentence Contrasting Black and Latinx Defendant cases with at least One White Victim with White Defendant cases with at least One White Victim, Controlling for Statistically Significant Special Circumstances Found or Present (n = 1,171)

A	B	C
	Odds Ratio	Lin. Std. Err.
Black Defendant/ White Victim	5.32***	3.33
Latinx Defendant/ White Victim	7.99***	5.58
Multiple Victims Special Circumstance	296.62***	498.24
Robbery Special Circumstance	17.78**	21.83
Sex Crime Felony Special Circumstances	194.47***	296.51
_cons	0.01	0.00

n (universe) = 15,677
Significance: *** $p <= .01$, ** $p <= .05$, * $p <= .10$

Table 7-B. Logistic Regression of Death Sentence Contrasting Black and Latinx Defendant cases with at least One White Victim with White Defendant cases with at least One White Victim, Controlling for Defendant Culpability Scale (n = 1,171)

A	B	C
	Odds Ratio	Lin. Std. Err.
Black Defendant/ White Victim	2.57*	1.44
Latinx Defendant/ White Victim	3.38**	2.13
Defendant Culpability Scale	1.66***	0.27
_cons	0.01***	0.01

n (universe) = 15,677
Significance: *** $p <= .01$, ** $p <= .05$, * $p <= .10$

B. Racial Disparities Observed in Prosecutorial Decisions to Charge a Case with Special Circumstances

In the first section, we considered only whether cases resulted in a death sentence, rather than the decision making throughout the process. This section examines the influence of race on the prosecutors' decisions to charge special circumstances, the first step in the adjudication process leading to a death sentence.

1. Unadjusted Disparities

As with our previous analysis of the imposition of death sentencing in the aggregate, we initially examined prosecutorial decisions to charge special circumstances without controlling for any specific characteristics of the cases. We first examined the racial composition of the cases in which the prosecutor charged one or more special circumstances. As reported in Table 3, Row 2, Column A, Black defendants comprised 36% of the cases in which prosecutors charged special circumstances compared to 37% of the death-eligible cases. Latinx defendants comprised 25% of the cases in which prosecutors charged special circumstances compared to 32% of the death-eligible cases.

We next examined the rate at which prosecutors charged Black and Latinx defendants in death-eligible cases with at least one special circumstance. Table 4, Row 2, Column A, documents that prosecutors charged one or more special circumstance in 28% of Black defendant death-eligible cases (1,678/6037) compared to 28% of all other death-eligible cases (2,931/10,348), or at the same rate for both categories. Prosecutors charged one or more special circumstance in 22% of Latinx defendant death-eligible cases (1,167/5,328) compared to 31% of all other death-eligible cases (3,441/11,057). This negative 9-point difference in the charging rate is a statistically significant difference ($p < .03$). Although this unadjusted comparison suggests that prosecutors were not influenced in a discriminatory way by the race of the defendant in their charging decisions, the race of the victim in cases involving Black and Latinx defendants had a significant effect on charging decisions.

In contrast, Table 3, Row 2, Column C, reports that cases involving at least one white victim comprised 46% of the death-eligible cases where prosecutors charged special circumstance (2,124/4,609), compared to a 34% presence in the death-eligible cases overall (5,617/16,385). This is a 10-point increase in representation. As Table 4-A, Row 2, Column C, reports, prosecutors filed special circumstances in 38% of cases involving at least one white victim (2,124/5,617), compared to 23% of all other cases (2,485/10,767). This is relative ratio over 1.5 (38%/23%) in the rate of filing special circumstances. This disparity is statistically significant ($p < .001$).

Charging decisions involving cases with a Black or Latinx defendant and at least one white victim reflected similar disparities. Table 3, Row 2, Column D reports that prosecutors charged special circumstances in 12% of Black defendant/white victim cases (544/4,609) compared to 8% of the death-eligible cases overall (1,288/16,385). This is a 4-point increase in their representation. Prosecutors charged special circumstances in 8% of Latinx defendant/white victim cases (361/4,609) compared to 5% of the death-eligible cases overall (901/16,385), a 3-point increase in representation.

Table 4-B, Row 2, Column A and B, report the relative rate at which prosecutors charged Black defendant/white victim case and Latinx defendant/white victim cases with one or more special circumstances. Prosecutors charged Black defendant/white victim cases with special circumstances in 42% of the cases (545/1,288) compared to 27% of all other cases (4,065/15,096), a relative risk of 1.6 ($p < .04$). Latinx defendant/white victim cases have a similar risk ratio, but the disparity is not statistically significant. Prosecutors charged Latinx defendant/white victim

cases with at least one special circumstances in 44% of the cases (362/906) compared to 27% of all other cases (4,247/15,478).

2. Disparities Estimated in Regression Analysis

Logistic regressions on charging decisions show that prosecutors charged one or more special circumstance allegations in cases involving at least one white victim at a significantly higher rate than all other death-eligible cases.[110] Tables 12-A, Model 1, and 12-B report that death-eligible cases involving at least one white victim were 1.6 times more likely to have one or more special circumstances charged than all other cases. This disparity is statistically significant ($p < .04$).

Table 13 replicates the analysis in Table 12-A, Model 1 and 12-B but controls for defendant culpability scale rather than individual special circumstances. In the second model, defendants charged with killing at least one white victim were 2.3 times more likely to be charged with one or more special circumstance. This disparity is statistically significant ($p < .001$).

Table 12-A, Models 2 and 3, report that while prosecutors were significantly less like to charge one or more special circumstances in cases with Black or Latinx defendants with odds ratios of 0.77 and 0.79, respectively, neither disparity achieves statistical significance. The disparities are consistent with the unadjusted disparities discussed above. As the overwhelming majority of cases involve defendants of the same race as the victim, the downward charging of Black defendant cases contributes to increased population of white victim cases across stages. Model 4 includes

[110] As noted above, the special circumstances variables included in the logistic regression model in Tables 12-A and 12-B reflect those identified as statistically important to prosecutorial decision making. *See supra* note 91. For this portion of our analysis, the special circumstances that are most predictive of the filing of a special circumstance in our model were Cal. Penal Code § 190.2(a)(3) (multiple victims); Cal. Penal Code § 190.2(a)(17)(A) and (G) (robbery and burglary felony murder); Cal. Penal Code § 190.2(a)(17)(B) (kidnapping felony murder) and Cal. Penal Code § 190.2(a)(17)(C-F, K) (sex crimes felony murders).

all three race variables which remain consistent with respect to magnitude and direction, but do not achieve statistical significance.

Table 12-A. Logistic Regression of Prosecutor Decisions to Charge One or More Special Circumstances in White Victim Cases, Controlling for Special Circumstances Found or Present (n = 1,226)[111]

	Model 1		Model 2		Model 3		Model 4	
	OR	**SE**	**OR**	**SE**	**OR**	**SE**	**OR**	**SE**
Black Defendant			0.77	0.18			0.72	0.22
Latinx Defendant					0.79	0.20	0.72	0.24
White Victim	1.607**	0.378					1.38	0.39
Multiple Victims Special Circumstance	9.885***	3.786	9.96***	3.90	9.79***	3.78	9.50***	3.67
Robbery & Burglary Special Circumstance	5.642***	1.370	6.37***	1.52	5.89***	1.42	5.88***	1.43
Kidnapping Special Circumstance	2.848*	1.562	2.67*	1.48	2.99**	1.58	2.63*	1.41
Sex Crime Felony Special Circumstance	5.145**	2.980	5.61**	3.16	5.57**	3.08	5.23**	2.95
_cons	0.063	0.014	0.08***	0.02	0.08***	0.02	0.08***	0.03

n (universe) = 16,385
Significance: *** *p* <= .01, ** *p* <= .05, * *p* <= .10

[111] Removing defendants who are not Black, Latinx, or white brings the white victim variable into statistical significance in Model 4 (OR 1.630, SE 0.471), but does not affect the individual race of defendant variables.

Table 12-B. Logistic Regression of Prosecutor Decisions to Charge One or More Special Circumstances in White Victim Cases, Controlling for Special Circumstances Found or Present (n = 1,226)

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% Conf. Interval]	
White Victim	1.61	0.38	2.02	0.044	1.01	2.55
Multiple Victims Special Circumstance	9.88	3.79	5.98	0.001	4.66	20.96
Robbery & Burglary Special Circumstances	5.64	1.37	7.13	0.001	3.50	9.08
Felony Kidnapping Special Circumstance	2.85	1.56	1.91	0.057	0.97	8.36
Felony Sex Crimes Special Circumstances	5.15	2.98	2.83	0.005	1.65	16.03
_cons	0.06	0.01	-12.55	0.001	0.04	0.10

n (universe) = 16,385

Table 13. Logistic Regression of Prosecutor Decisions to Charge One or More Special Circumstances in White Victim Cases, Controlling for Defendant Culpability Scale (n = 1,226)

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% Conf. Interval]
White Victim	2.27	0.48	3.90	0.001	1.502-3.425
Defendant Culpability Scale	1.58	0.13	5.68	0.001	1.351-1.857
_cons	0.05	0.02	-8.82	0.001	0.0276-0.102

n (universe) = 16,385

We replicated the analysis in the previous section that contrasted white defendant/white victim cases with Black defendant/white victim cases and Latinx defendant/white victim cases in analysis of the relative risk of receiving a death sentence. We did not find disparities among white victim cases with respect to the prosecutorial charging decisions.

The findings in this section demonstrate that prosecutors in this study brought special circumstance charges against cases with at least one white victim significantly higher than all other cases, even after controlling for difference in the cases. As a result, prosecutorial charging decisions substantially increased the presence of cases with at least one white victim in the cases presented to the jury. As noted in Table 3, white victim cases represented 34% of the death eligible cases overall. In contrast, they represent 46% of the cases presented to the jury to death sentencing.

C. Racial Disparities Observed in Jury Sentencing Decisions Among Cases in Which Prosecutors Charged One or More Special Circumstances

This section focused separately on jury penalty trial decisions. As such, it analyzes the extent to which race or ethnicity influenced juries' decisions to impose death sentences in those cases in which the prosecutor charged one or more special circumstance and which were not resolved in plea negotiations before reaching the jury.

1. Unadjusted Disparities

Table 3, Row 3, Column A reports that Black defendant cases constitute 51% (357/703) of the cases in which a jury imposed a death sentence, 14 points above the 37% representation rate of Black defendant death-eligible cases overall (6,037/16,385). As Table 4-A, Row 3, Column A depicts, juries sentenced 21% of the cases with Black defendants to death (357/1,678) compared to 12% of all other cases (346/2,931). This is a 9-point disparity (21%–12%). Black defendants faced a 1.7 times higher relative risk (21%/12%). This disparity is not statistically significant ($p < .12$).

Latinx defendants' presence among cases in which the jury imposed a death sentence, presented in Table 3, Row 3, Column B, declined 4 points from 32% among all death eligible cases (5,328/16,385) to 28% of death sentenced cases (200/703). Table 4-A, Line 3, Column B depicts that juries sentenced 17% of the Latinx defendants to death (200/1,167) compared to 15% of all other cases (503/3,441), or at a 1.2 times higher relative risk. This disparity is not statistically significant.

Recall that white victim cases increased from 34% of death eligible cases (5,617/16,385) to 46% of cases in which the prosecutor charged special circumstances (2,124/4,609). This increase continues in the population of death sentenced cases where white victim cases increased to 52% of death sentenced cases (368/703). This is an 18-point increase in representation.

Table 4-A, Line 3, Column C reports that juries sentenced 17% of white victim cases to death (368/2,124) compared to 13% of all other cases (335/2,485). This 4-point disparity, relative risk of 1.3, was not statistically significant.

Black and Latinx defendants convicted of killing at least one white victim compose a substantially higher portion of the death sentence cases than they did of death eligible cases overall. Black defendant/white victim cases increase from 8% (1,288/16,385) to 15% (106/703), almost doubling in presence. Latinx defendant/white victim cases increase from 5% in the death eligible cases overall (901/16,385) to 19% of the death sentenced cases (133/703), almost four times the initial presence.

Table 4-B, Row 3, Column A, reports that Black defendants who killed at least one white victim faced a higher rate of death sentencing, 19% (106/545), compared to all others 15% (596/4,063), but this disparity is smaller and did not reach statistical significance (n.s.). In Column B, Latinx defendants convicted of killing at least one white victim faced an even higher risk of being sentenced to death at the penalty trial than all other defendants. Compare 37% (133/362) to 13% (570/4,247), a ratio of 2.8 ($p < .03$).

The rate of death sentencing shows the greatest disparity in the treatment of Latinx defendant/white victim cases, followed by minority defendant cases overall, and then by white victim cases.

2. Disparities Estimated in Regression Analysis

The unadjusted disparities reported above came into clearer focus in controlled analysis. As reported in Table 14-A, Model 1, Black defendants faced significantly higher odds of receiving a death sentence, 5.7, and Latinx defendants face significantly higher odds of 5.0 of receiving a death sentence, compared to all other defendants even after controlling other factors in the case.[112] These disparities are statistically significant (p < .01). This finding is presented more completely in Table 14-B. The analysis presented in Table 15 introduces the defendant culpability scales rather than individual special circumstances. The disparities continue to appear in this model where Black defendants face an odds ratio of 4.38 (p < .01) and Latinx defendants face an odds ratio of 3.7 (p < .03) compared to all other cases even after controlling with defendant culpability scale.

Table 14-A, Model 2, adds the white victim variable to the model. In this model, the Black defendant disparity increases to an odds ratio of 7.6 and Latinx defendant disparity increases to an odds ratio of 6.3 (p < .01) and the variable reporting the importance of the presence of at least one white victim show a higher odds ratio (1.9), but is not statistically significant. Models 3, 4, and 5 introduce the race variables individually where they show lower odds ratios and are not statistically significant. Collectively, these models suggest that Black and Latinx defendant cases together face the highest risk of death sentencing.

[112] As noted above, the special circumstances variables included in each logistic regression reflect those identified as statistically important to jury decision making. *See supra* note 91. We found that juries considered some factors more important in sentencing than prosecutors did in charging. For this portion of our analysis, the special circumstances that are most predictive of a death sentence in our model were Cal. Penal Code § 190.2(a)(3) (multiple victims) and Cal. Penal Code § 190.2(a)(17)(C-F, K) (sex crimes felony murders).

Table 14-A. Logistic Regression of Jury Decision to Impose a Death Sentence, Controlling for Race of Defendant and Special Circumstances Found or Present (n = 347)[113]

	Model 1		Model 2		Model 3		Model 4		Model 5	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Black Defendant	5.68***	3.34	7.62***	4.69	2.44*	1.18				
Latinx Defendant	5.04***	3.12	6.35***	4.33			1.71	0.88		
White Victim			1.88	1.01					0.99	0.49
Multiple Victims Special Circumstance	4.39***	2.42	4.81***	2.82	3.68**	2.09	3.42**	1.94	3.32**	1.91
Sex Crime Felony Special Circumstance	13.44***	8.95	12.36***	8.74	11.33***	7.91	10.62***	7.55	10.42***	7.49
_cons	0.04***	0.02	0.02***	0.02	0.09***	0.04	0.12***	0.06	0.14***	0.07

n (universe) = 4,609
Significance: *** $p <= .01$, ** $p <= .05$, * $p <= .10$

113 A model introducing only Black defendant and white victim does not differ with respect to magnitude or statistical significance of the race variables. In a model introducing only Hispanic defendant and white victim, the Latinx victim variable loses power and significance (OR 1.72, SE 0.94, p = 0.320). Removal of defendants who are not Black, Latinx, or white did not change the model with respect to magnitude or significance of the race variables.

Table 14-B. Logistic Regression of Jury Decision to Impose a Death Sentence, Controlling for Race of Defendant and Special Circumstances Found or Present (n = 347)

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% Conf.	Interval]
Black Defendant	5.68	3.34	2.96	0.003	1.79	18.06
Latinx Defendant	5.04	3.12	2.61	0.009	1.49	17.04
Multiple Victims Special Circumstance[114]	4.39	2.42	2.69	0.008	1.48	12.96
Felony Sex Crimes Special Circumstances[115]	13.44	8.95	3.90	0.001	3.62	49.84
_cons	0.04	0.02	-5.62	0.001	0.01	0.12

n (universe) = 4,609

Table 15. Logistic Regression of Jury Decision to Impose a Death Sentence, Controlling for Defendant Culpability Scale (n = 347)

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% Conf.	Interval]
Black Defendant	4.38	2.46	2.63	0.009	1.45	13.22
Latinx Defendant	3.73	2.21	2.22	0.027	1.16	11.96
Defendant Culpability Scale	1.79	0.25	4.20	0.001	1.36	2.36
_cons	0.02	0.01	-5.78	0.001	0.00	0.07

n = 4,609

Table 16-A and Table 16-B test for difference among the jury sentencing outcomes for case with at least one white victim. The models contrast white defendant/white victim cases with Black defendant/white victim cases and Latinx defendant/white victim cases. As above, Table 16-A includes individual special circumstances and Table 16-B includes the defendant culpability scale. This analysis limits the data to Black, Latinx, and white defendants.

The analysis in Table 16-A reports that Black defendant/white victim cases face 3.1 ($p < .10$) higher odds of being sentence to death by the jury than white defendant/white victim cases, and that Latinx defendant/white victim cases face 5.9 higher odds ($p < .05$) than white

[114] Cal. Penal Code § 190.2(a)(3).

[115] Cal. Penal Code § 190.2(a)(17)(C-F, K).

defendant/white victim cases when controlling for individual special circumstances. In Table 16-B, when controlling for the defendant culpability scale, the Black defendant/white victim cases continue to face large disparities, but these disparities are not statistically significant. The Latinx defendant/white victim odds ratio falls slightly to 4.1, and remains statistically significant ($p < .01$).

Tables 17 and 18 present complete model information for the Latinx defendant/white victim disparity, controlling first for individual special circumstances, and then for the defendant culpability scale. Latinx defendant/white victim cases an odds ratio disparity of at least 4.0 compared in both models.

This analysis suggests that Latinx defendant who kill at least one white victim face higher odds receiving a death sentence from the jury than all other cases. This supplements the contrast analysis in Table 16-A and 16-B and reaching the same findings.

Table 16-A. Logistic Regression of Jury Decision to Impose a Death Sentence, Contrasting Black and Latinx Defendant cases with at least One White Victim with White Defendant cases with at least One White Victim, Controlling for Statistically Significant Special Circumstances Found or Present (n = 329)

	Odds Ratio	Std. Err.
Black Defendant/ White Victim	3.11*	2.04
Latinx Defendant/ White Victim	5.94**	4.36
Multiple Victims Special Circumstance	10.07***	7.50
Sex Crime Felony Special Circumstance	16.07***	14.22
After *Carlos* Window	0.47	0.30
_cons	0.16***	0.10

n (universe) = 4,304
Significance: *** $p <= .01$, ** $p <= .05$, * $p <= .10$

Table 16-B. Logistic Regression of Jury Decision to Impose a Death Sentence, Contrasting Black and Latinx Defendant cases with at least One White Victim with White Defendant cases with at least One White Victim, Controlling Defendant Culpability Scale (n = 329)

	Odds Ratio	Std. Err.
Black Defendant/ White Victim	2.35	1.45
Latinx Defendant/ White Victim	4.09**	2.92
Defendant Culpability Scale	1.73***	0.27
After *Carlos* Window	0.27**	0.15
_cons	0.03***	0.02

n (universe) = 4,304
Significance: *** $p <= .01$, ** $p <= .05$, * $p <= .10$

Table 17. Logistic Regression of Jury Decision to Impose a Death Sentence, Controlling for Latinx Defendant/White Victim and Special Circumstances Found or Present (n = 347)

	Odds Ratio	Lin. Std. Err.	t	P>t	[95% Conf. Interval]	
Latinx Def./White Victim	4.01	3.13	1.78	0.076	0.86	18.63
Multiple Victims Special Circumstance	3.61	2.03	2.28	0.023	1.19	10.94
Felony Sex Crimes Special Circumstances	9.13	6.93	2.91	0.004	2.05	40.64
_cons	0.13	0.05	-4.78	0.001	0.05	0.29

n (universe) = 4,609

Table 18. Logistic Regression of Jury Decision to Impose a Death Sentence, Controlling for Minority Defendant/White Victim and Defendant Culpability Scale (n = 347)

	Odds Ratio	Lin. Std. Err.	T	P>t	[95% Conf. Interval]	
Latinx Def./White Victim	4.17	3.02	1.97	0.049	1.00	17.32
Defendant Culpability Scale	1.66	0.23	3.65	0.001	1.26	2.17
_cons	0.05	0.03	-4.76	0.001	0.02	0.18

n (universe) = 4,609

D. Ordered Probit Analysis of Progression of Cases from Charging to Sentencing

As with the previous analyses, the analysis of the progression of cases from charging to sentencing was modeled in three phases: defendant and victim race alone, defendant and victim race controlling for special circumstances, and defendant and victim race controlling for defendant culpability. The goal of these analyses is to determine if there were differences by defendant and victim race cases in which cases survived each stage of case processing and ultimately resulted in a death sentence. In this section, the results are shown as regression coefficients, meaning that they show the difference in the probability of reaching each stage in the adjudication and sentencing process for a particular race or ethnicity model compared to all others. A positive coefficient shows that a case with the specified race or ethnicities was resolved at a later stage of the adjudicative process. A negative coefficient should be interpreted in the opposite way.

Table 19. Ordered Probit Regression of Progression to Death Sentence by Defendant and Victim Race and Ethnicity in Death-Eligible Cases (n = 1226)

Victim-Defendant	Model 1			Model 2			Model 3			Model 4		
Models by Race	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**
Black Defendant	-0.124	0.132	0.350									
Latinx Defendant	-0.329	0.132	0.013									
White Victim				0.429	0.115	0.000						
Black Defendant							0.064	0.144	0.657			
Latinx Defendant							-0.127	0.153	0.408			
White Victim							0.415	0.133	0.002			
Black Def./ White Vic.										0.426	0.190	0.025
Latinx Def./ White Vic.										0.453	0.250	0.070

n =1,226 death-eligible cases sampled from 48 County Year Strata

This first set of ordered probit regressions in Table 19 presents baseline results with only defendant and victim race entered as predictors and with no controls for case characteristics. All four models show significant differences in the stage at which each case was ultimately resolved. Model 1 shows that Black and Latinx defendants were less likely to reach later stages of case processing than all other defendant cases. Model 2 shows that white victim cases had a significantly higher likelihood to reach and be resolved at later stages including a guilt or penalty phase trial or imposition of a death sentence than cases with no white victims. Model 3 included the predictors for Black and Latinx defendants and the predictor for white victims simultaneously, and shows again that Black defendant cases were slightly more likely to proceed further into the death penalty process than non-minority defendant cases, although the result is not statistically significant, Latinx defendants remain less likely to proceed further, although also not statistically significant, and, again, that white victim cases were more likely than cases with no white victims to proceed deeper into the process. Model 3 suggests that even after controlling for both race of defendant and race of victim, the results in Models 1 and 2 persist, although the results for Black and Latinx defendants does not reach statistical significance.

The fourth model introduces only the predictors identifying the specific subset of cross-racial murders where Black or Latinx defendants killed at least one white victim and shows the oft-cited result that minority defendants who kill white victims were more likely to proceed deeper into the death penalty process than cases with all other defendant/victim combinations. Both predictors show that Black and Latinx defendants who kill at least one white victim are more likely to proceed farther into the process. This is likely to mean that a death sentence is the result.

Table 20 shows the results of the same analyses with controls for three special circumstances that we found to be most predictive of a death sentence as shown in Tables 5-A and 5-B: Cal. Penal Code § 190.2(a)(3) (multiple victims); Cal. Penal Code § 190.2(a)(17)(A) (robbery felony murder); and Cal. Penal Code § 190.2(a)(17)(C-F, K) (sex crimes felony murders). The pattern of results is the same for all models in Table 20. Models 1 and 3 again report that Black and Latinx defendant cases were less likely to reach and be resolved at later stages. Neither finding is statistically significant. In contrast, white victim cases in Models 2 and 3 produce positive coefficients, suggesting that these cases were more likely to reach and be resolved at later stages. In this analysis, however, only the white victim cases in Model 2 reach statistical significance. In Model 3 of Table 20, white victim cases have higher scale scores than other cases. Model 4 in

Table 20 also shows the same results seen in Table 20, but the results are not significant, a more tempered conclusion than in the previous model.

Comparing Tables 19 and 20, we see that the conditioning effects of the special circumstances—which are positive and significant in each model—exerted a measurable and strong influence on the patterns of racial disparities in the progression of death-eligible cases from charging to death sentencing.

Table 20. Ordered Probit Regression of Progression to Death Sentence by Defendant and Victim Race and Ethnicity and Special Circumstance in Death-Eligible Cases (n = 1226)

	Model 1			Model 2			Model 3			Model 4		
	B	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**
Black Defendant	-0.137	0.140	-0.980									
Latinx Defendant	-0.134	0.147	-0.910									
White Victim				0.240	0.124	0.054						
Black Defendant							-0.036	0.155	0.815			
Latinx Defendant							-0.033	0.167	0.845			
White Victim							0.225	0.144	0.118			
Black Defendant -White Victim										0.278	0.206	0.178
Latinx Defendant - White Victim										0.294	0.260	0.258
Multiple Victims Special Circ.	1.305	0.184	0.000	1.307	0.181	0.000	1.307	0.182	0.000	1.320	0.184	0.000
Robbery Special Circumstance	1.112	0.122	0.000	1.063	0.126	0.000	1.066	0.124	0.000	1.074	0.125	0.000
Felony Sex Crimes Special Circumstances	0.680	0.308	0.028	0.672	0.306	0.028	0.671	0.308	0.030	0.701	0.302	0.021

Notes. N=1,226 death-eligible cases sampled from 48 County Year Strata.

Table 21 repeats the analysis of Table 20, but controls with the defendant culpability scale rather than individual special circumstances. The results are also the same with the important exception that cross-racial cases now have significantly higher scale scores. The Black defendant/white victim cases have a higher regression coefficient (.573) and is statistically significant ($p < .01$). The Latinx defendant/white victim cases have a higher regression coefficient (.380), but not statistical significance. As in Table 20, the addition of conditioning variables—in this case, the defendant culpability scale presented in earlier sections—has a substantial effect on the progression of cases from charging to sentencing in every model.

Table 21. Ordered Probit Regression of Progression to Death Sentence by Defendant and Victim Race and Ethnicity and Defendant Culpability (n = 1226)

	Model 1			Model 2			Model 3			Model 4		
	B	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**	**B**	**SE**	**p>t**
Black Defendant	-0.109	0.133	0.414									
Latinx Defendant	-0.353	0.138	0.011									
White Victim				0.469	0.118	0.000						
Black Defendant							0.098	0.145	0.499			
Latinx Defendant							-0.133	0.155	0.392			
White Victim							0.462	0.134	0.001			
Black Defendant -White Victim										0.573	0.194	0.003
Latinx Defendant - White Victim										0.380	0.246	0.123
Defendant Culpability Scale	0.278	0.043	0.000	0.284	0.042	0.000	0.287	0.043	0.000	0.279	0.043	0.000

Notes. N=1,226 death-eligible cases sampled from 48 County Year Strata

As explained above, in these analyses, a set of cases with a negative regression coefficient for their scale score were more likely to leave the stream of cases resulting in death sentencing at an earlier stage, either by pleading to a lesser charge or accepting a plea agreement at a stage prior to the penalty trial, or by having charges withdrawn by the prosecution or dismissed by the court. A positive regression coefficient for the scale score could indicate that a case was more likely to move through each decision point, especially to a trial, which may end in mercy or a death sentence. The positive regression coefficients reported in this section for white victim cases and

Black defendant/white victim cases in Models 2, 3, and 4 suggest that race matters. This finding persists even after including the specified special circumstances or the defendant culpability scale. This suggests that the fact that a case included at least one white victim or the fact that a case involved a Black defendant and at least one white victim remains important, along with other features of the case, in determining its outcome, up to and including a death sentence.[116] Race mattered, in other words, in important and consistent ways.

The negative covariates in Models 1 and 3 for Black and Latinx defendants in all four tables reflect the persistent effects of prosecutors favoring white victims and disfavoring minority victims, a finding that is consistent with our analysis in Sections IV.A., IV.B, and IV.C., above. As explained in Sections IV.A and IV.C., the race of the defendant significantly influenced who was sentenced to death among those who are death eligible and who juries selected from cases in which prosecutors filed special circumstances. Our findings in Section IV, which examines prosecutorial decisions, did not find defendant race effects in charging special circumstances, but found that race of the victim significantly affected charging decisions. The results in Table 19-21 underscore the magnitude by which prosecutors favored white victim cases and discounted minority victim cases in charging decisions, one of the earliest stages. This results in heightened charging decisions for both white and minority defendants who killed white victims. This makes even more salient the minority defendant disparities documented in jury decision making and reported in Section IV, Part C.

[116] Scott Phillips & Justin F. Marceau, *Whom the State Kills*, 55 HARV. C.R.-C.L. L. REV. 585, 606 (2020) (showing that in Georgia, for example, defendants convicted of murdering white victims were 17 times more likely to be executed than defendants convicted of murdering Black victims).

V. CONCLUSIONS

Using varied models and approaches, we consistently find that the race of the defendant and the race of the victim considerations significantly influenced capital sentencing in California. The findings are consistent with the empirical and doctrinal research surveyed in Section II documenting the ways that the underlying processes organizing and enabling capital punishment produce and replicate these racial disparities.

First, we observed significant disparities by victim and defendant race in who received a death sentence among those cases that were death eligible. With respect to overall death sentencing, using logistic regression analyses that controlled for case characteristics, we found that combined Black defendants faced between 4.6 and 8.7 times higher odds and Latinx defendants faced between 3.2 and 6.2 time higher odds of being sentenced to death, even after controlling for relevant difference in the cases. Similarly, persons convicted of killing at least one white victim faced between 2.8 and 8.8 higher odds of being sentence to death than defendants who kill non-white victims.

Black defendants who were accused of killing at least one white victim faced between 3.2 and 4.4 times the odds of being sentenced to death higher than white defendants accused of killing at least one white victim. Latinx defendants who were accused of killing at least one white victim faced even higher odds of being sentenced to death than white defendants who killed at least one white victim, odds ratios between 3.4 and 8.0.

Second, our analysis found racial and ethnic disparity in prosecutors' decisions to charge a case with special circumstances based on the race of the victim. Defendants accused of killing at least one white victim faced between 1.6 and 2.3 times the odds of being charged with special circumstances higher than those faced by defendants accused of killing non-white victims.

Finally, racial disparities persist when the case proceeds to trial after the prosecutor filed special circumstances in the case and the jury was asked whether to impose a death sentence. Black defendants and Latinx defendants faced significantly higher odds of receiving a death sentence in the penalty trial. Black defendants faced between 4.4 and 5.7 higher odds and Latinx defendants faced between 3.7 and 5.0 higher odds.

Analysis of jury decisions also reveals disparate outcomes for Black defendants convicted of killing at least one white victim (between 4.4 and 5.7 higher odds ratios) and for Latinx defendants with a least one white victim (between 4.1 and 5.9 higher odds ratios).

These finding were replicated by the oprobit analysis in the final section of analysis show which cases are more likely to proceed to a death sentence.

The importance of these findings is underscored by the race effects that were apparent in imposition of death sentences by capital punishment statutes outlawed by *Furman v. Georgia*. Although controlled studies of pre-*Furman* capital charging and sentencing outcomes are limited, Professor David Baldus and his colleagues found "strong race-of-defendant and race-of-victim effects among defendants convicted of murder" in Georgia.[117] In contrast, a detailed study of pre-*Furman* California penalty trials in murder cases showed no race effects during the 1960s."[118] And, although many studies conducted post-*Furman* have found race-of-the-victim effects in the administration of capital punishment, virtually none have found race-of-the-defendant effects present in modern-day California.

[117] Catherine M. Grosso, Barbara O'Brien, Abijah Taylor, & George Woodworth, *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, in AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT 536 (Charles S. Lanier, Robert Bohm, & James Acker eds. 3d ed. 2014) (citing DAVID BALDUS, GEORGE WOODWORTH, & CHARLES PULASKI, JR., EQUAL JUSTICE AND THE DEATH PENALTY 248-53 (1990)).

[118] *Id*.

These results, confirmed through multiple statistical approaches, unmistakably demonstrate that race has infected the California capital sentencing process. Our findings are confirmed whether the analysis focuses on who among the death-eligible were sentenced to death or on decisions made by prosecutors or juries. Moreover, they are consistent with studies in California and other states showing similar disparities by defendant or victim race or ethnicity.

When combined with our two previous studies, these findings demonstrate that California's death penalty scheme suffers from the arbitrariness and racial discrimination condemned in *Furman*. With the most expansive death penalty statute in the country, California provides prosecutors with almost unlimited discretion in determining which defendants to charge with capital crimes, but also produces a small fraction of death sentences from that large universe. Compounding this situation is that California has adopted several qualifying special circumstances that ensure that minority defendants will be disproportionately eligible for capital prosecutions. Our current analysis demonstrates that, in practice, racial factors have infected California capital sentencing: whether sentencing is considered in the aggregate or as decisions made by prosecutors or juries, racial considerations determine who is subject to the ultimate punishment in California.

APPENDIX

A. Controlling for Non-Random Assignment

Our analyses in Section IV.A. examining racial and ethnic disparities in death sentencing are based on logistic regressions comparing 60 persons receiving a death sentence among the 1,226 death-eligible persons in the full sample. The findings presented in Section IV.B, and IV.C. examined the decisions of prosecutors and juries. This kind of overarching analysis provides one window on the impact of race in the California death penalty system. It is important in this analysis to account for the case selection by prosecutors in this overall analysis.

Since not everyone in the pool of death-eligible persons were selected for possible capital prosecution, we adjusted the regressions using a weighting procedure to account for such selection. This procedure is widely used in studies of policy or treatment interventions to reduce selection bias in the estimates of outcomes.

The procedure we used required three steps. First, we estimated a logistic regression to identify the parameters of selection for capital prosecution. In California, prosecutors identified these persons by charging one or more special circumstances in the case. We reported the results of this analysis of the decision to file special circumstances in Tables 12-A and 12-B.

The second step used the logistic regression model from the first step (reported in Tables 12-A and 12-B) to generate for each case a predicted probability of selection. This propensity score is the estimated probability *p* of membership in each of the outcome groups that account for confounding variables between the outcome of interest (charging special circumstances) and the selection of persons for that group. The prediction parameter is a linear probability of the prosecutor charging special circumstances in each case.[119]

[119] David W. Hosmer, Jr., Stanley A. Lemeshow, & R. X. Sturdivant, Applied Logistic Regression (2nd ed. 2013). Paul R. Rosenbaum, & Donald B. Rubin, "*The Central Role of the Propensity*

The third step computed the weighted probability of selection into each outcome or group.[120] Again following Bang and Robins,[121] we defined the propensity score as PS=1/(p(x), where x is the "treatment" for cases in the "treatment" group of defendants selected for capital prosecution (by charging special circumstances). We then decomposed the propensity score to properly weight each of the groups and used the inverse probability of selection. Accordingly, we use the inverse of the propensity score: IPTW=1/(1-p(x)).[122]

We computed these transformations for each group, with the cases selected for prosecution as the 'treatment' group and the non-selected as the 'untreated' group. Each case was weighted according to its group membership. The variable expressing the selection effects of the decision to charge special circumstances on death sentencing (*pseekdeath*) was included in the tables showing the results of analysis as stated above.

Score in Observational Studies for Causal Effects," 70 BIOMETRIKA 41 (1983).

120 *See* Heejung Bang, *supra* note 96; *see also* Alka Indurkhya, *supra* note 96.

121 Bang, *supra* note 96.

122 Bang, *supra* note 96, at 965; *see also* Ridgeway, *supra* note 96; Indurkhya, *supra* note 96, at 1570.

B. Selection Rates by Special Circumstance.

Selection Rates for Found or Presence and Counts by Special Circumstance, for sample and estimated (weighted) universe with statistical significance shown for disparity in outcome between selection (for special circumstances or for death) and not (n = 1,226)[123]

				Part 1 Selection Rates & Counts for the Prosecutorial Decision to File Special Circ.				Part 2 Selection Rates & Counts for Death Sentencing			
A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
Special Circ ¶ # in Penal Code 190.2	**Special Circumstance Brief Name**	**sample n**	**weighted n**	**sample pseek**	**weighted pseek**	**sample n**	**weighted n**	**sample death_08**	**weighted death_08**	**sample n**	**weighted n**
1	**For Financial Gain**	92	929	38%**	37%	35	343	4%	5%	4	48
2	**Previous Murder**	17	156	35%	13%*	6	20	18%***	6%	3	9
3	**Multiple Murder**	128	1,616	66%***	69%***	84	1,119	19%***	19%***	25	308
10	**Witness Victim**	21	152	43%	64%***	9	98	5%	15%	1	23
15	**Lying in Wait**	601	8,063	(17%***)	(16%***)	102	1,308	(1%***)	(1%***)	5	57
17a	**Robbery Felony**	429	5,301	44%***	49%***	189	2,601	8%***	7%*	36	354
17g	**Burglary Felony**	168	2,063	51%***	57%***	85	1,179	10%***	7%	17	155
17ag	**Robbery or Burglary Felony**	456	5,639	45%***	49%***	203	2,743	8%***	6%*	38	361
17b	**Kidnapping Felony**	51	659	55%***	63%***	28	418	10%*	5%	5	30
17cd	**Rape or Sodomy Felony**	56	638	61%***	60%***	34	381	14%***	24%***	8	151
17e	**Child Sex Assault Felony**	12	168	75%***	88%***	9	149	42%***	83%***	5	140
17f	**Child Sex Oral Assault Felony**	9	106	78%***	94%***	7	100	11%	40%***	1	42

[123] Special Circumstances with two or fewer cases in the study are not included. Special Circumstances 4 to 9, 11 to 14, 16, 17i, and 20.

				Part 1 Selection Rates & Counts for the Prosecutorial Decision to File Special Circ.				Part 2 Selection Rates & Counts for Death Sentencing			
A Special Circ ¶ # in Penal Code 190.2	**B** Special Circumstance Brief Name	**C** sample n	**D** weighted n	**E** sample pseek	**F** weighted pseek	**G** sample n	**H** weighted n	**I** sample death_08	**J** weighted death_08	**K** sample n	**L** weighted n
17h	**Arson Felony**	10	83	40%	47%	4	39	10%	2%	1	2
17j	**Mayhem Felony**	8	67	(12%)	(4%***)	1	3	0	0	0	0
17k	**Rape by Instrument Felony**	8	95	62%**	75%**	5	71	13%	63%***	1	60
17c-f,k	**Sex Crimes Felony**	67	825	61%***	64%***	41	563	18%***	35%***	12	288
17l	**Carjacking**	17	225	35%	68%***	6	150	0	0	0	0
18	**Torture**	199	2,334	28%	28%	56	656	6%	8%*	11	191
19	**Poison**	5	118	40%	83%***	2	98	40%***	83%***	2	98
21	**Drive By**	61	1,203	(12%***)	(18%***)	7	211	0	0	0	0
22	**Defendant in Street Gang**	129	3,097	(12%***)	(13%***)	16	404	(1%**)	(1%***)	1	4

Significance: *** *p* <= .01, ** *p* <= .05, * *p* <= .10

EXHIBIT B

31 March 2024

Catherine M. Grosso
Professor of Law, Michigan State University
grosso@law.msu.edu

Dear Professor Grosso,

We are delighted to conditionally accept your excellent paper, "The Influence of the Race of Defendant and the Race of Victim on Capital Charging and Sentencing in California," for publication in the *Journal of Empirical Legal Studies*.

Below you will find editor comments that in our estimation provide substantive ways to improve the paper. This conditional acceptance is subject to receiving a revised version that addresses the comments or explains why a comment need not be addressed. We hope you find these comments helpful.

In keeping with our editorial timeline, we request receipt of your revised paper (and revision memo) on or before **May 27, 2024.**

Our thanks for submitting this scholarship to *JELS*. We look forward to working with you toward publication.

Best Regards,

Dawn M. Chutkow

Dawn M. Chutkow
Executive Editor
Journal of Empirical Legal Studies

Comments

1) The paper is still considerably longer than usual for an empirical journal. We appreciate the various alternate specifications, but we suggest that you make a careful reconsideration of the results' presentation and, where you feel appropriate, move some of the text and related analyses into the Appendix. We will publish this with the article, but prefer the primary text be streamlined.

2) Tables and figures should be consecutively numbered

Editors' Formatting Comments

1. Please provide the revised manuscript in Word.

2. In your response email or letter, provide a preferred mailing address and email contact for all authors.

3. An unnumbered * footnote should be included on the title page that provides the corresponding author's title, institutional affiliation, mailing address, and email address, and the title and institutional affiliation of the co-author. As a matter of *JELS* editorial board policy, we strongly recommend that this footnote contain the following statement: "Data necessary to replicate the results of this article are available upon request from the corresponding author."

4. Our publisher (Wiley) now requires APA citation style with in-text citation and a reference section at the end of the paper. Please confirm that the in-text citations and reference section conform.

5. Eliminate the table of contents.

EXHIBIT C

UCI University of California, Irvine

Criminology, Law and Society
School of Social Ecology
2340 Social Ecology II
Irvine, CA 92697-7080

www.uci.edu

June 20, 2023

Review of **REPORT ON THE INFLUENCE OF THE RACE OF DEFENDANT AND THE RACE OF VICTIM ON CAPITAL CHARGING AND SENTENCING IN CALIFORNIA BETWEEN JANUARY 1, 1978, AND JUNE 30, 2002** by Catherine M. Grosso, Jeffrey Fagan, and Michael Laurence

The authors of this report asked me to review the above-titled report to assess its scientific validity and substantive conclusions, which I agreed to do. This study follows in a long line of research that examines outcomes in potential and actual capital cases to determine whether the race of defendants and/or victims is associated with decisions by prosecutors to seek the death penalty and by juries to impose a death sentence. That body of research has been conducted in numerous jurisdictions including, among others, California, Colorado, Connecticut, Florida, Georgia, Nebraska, New Jersey, North Carolina, Pennsylvania, South Carolina, and Washington. The bulk of these studies have been conducted since the U.S. Supreme Court's decision in *Gregg v. Georgia* (1976), which approved several models of death sentencing structures that were supposed to cure the constitutional deficiencies identified in *Furman v. Georgia* (1972), including the risk of racially discriminatory sentence outcomes.

This body of research has consistently found a race of victim effect, such that white victim cases are more likely to end in death sentences, after controlling for relevant case factors. The evidence regarding race-of-defendant effects is more equivocal, with some studies finding that African American (or more generally, minority) defendants are more likely to be sentenced to death than white defendants. An interaction effect has also been found in some studies, such that African American (or minority) defendants with white victims are significantly more likely to receive a death sentence relative to all others.

The study reported here similarly uses case outcome data to examine racial disparities in death sentences. It also advances this line of research by examining the entire pool of convicted homicide cases as a starting point. Given the important role that prosecutorial decision-making in charging plays in the documented race-based outcomes (particularly regarding victim race), this is a critical advancement. It is especially so in California, which has among the broadest eligibility of all death penalty statutes in the U.S., as the report authors as well as previous scholars have clearly documented. Given the previously-published finding that 95% of all convicted first degree murder cases and 60% of all convicted first-degree, second degree and manslaughter cases have elements that would qualify for at least one special circumstance allegation, using a pool of all convicted homicide cases allows the researchers to empirically assess the key decision as to whether the case is charged with first degree and special circumstances, the necessary first step for a California homicide case to become death eligible.

Given the design choice to begin with the pool of all homicide convictions between 1978 and 2002, the researchers then needed to sample from the population of cases (which totaled more than 27,000) in order to feasibly code the cases with sufficient rigor and detail. The researchers employed a sophisticated systematic sampling plan to ensure a representative sample of the population of cases. The sample was stratified to ensure that the subset of 1900 selected cases was representative on actual conviction type (1st degree, 2nd degree, manslaughter); county population features; and time period. This sampling plan is consistent with scientific standards for sampling, and represents among the most rigorous approaches to sampling that is used by social scientists to ensure representation. The researchers also used an appropriate power analysis to determine a sample size that would allow them to uncover race effects, should they exist. The final sample of 1900 cases thus allows the researchers to use multivariate analytic techniques that control for multiple legal variables with a high degree of statistical power (.95, well above the recommended minimum of .80).

The coding scheme used by the researchers was also appropriate for the data and analytic plan, and is consistent with well-established coding procedures used by social scientists in these kinds of analyses. Especially impressive was the effort made to obtain full and accurate race data for victims and defendants in the sample. In the end, they had no missing data for defendant race, and their percentage of missing data for victim race is both very low (5.5%) and seemingly random, so poses little risk for being able to draw conclusions from the analyses. Nonetheless, the researchers opted for a strategy of replacing missing data that makes for an even more stringent (or conservative) test of their hypotheses, which was to code those cases as non-white victims.

The researchers use several statistical modeling techniques that are well-justified by the specific research hypotheses posed. Their initial models do not include any control variables, so demonstrate associations between the race variables and the case outcome variables without regard to legally-relevant case factors. The next set of logistic regression models include appropriate controls for case factors, first using statistically meaningful special circumstances, and second using a researcher-derived culpability scale. The final set of models allows the researchers to examine the progression of case decision-making. The design choices are parsimonious while capturing the important influences on case outcomes, and are consistent with the larger body of research in this area. In sum, this is a very well-designed study, using state-of-the-art research methods. The design is also well-informed by the researchers' collective knowledge and expertise in the substantive area of study (racial disparities in capital punishment and on the particular features of California's capital punishment legal structure), so the decisions on the coding scheme, inclusion of control variables, etc. are grounded in an outstanding real-world understanding of how homicide cases, including capital cases, proceed in California.

In regard to the findings, the analyses indicate that, after controlling for case factors, minority (African American, Latinx, and Native American) defendants are substantially and significantly more likely to be sentenced to death relative to white defendants overall, as well as in cases with minority defendants and one of more white victims. Cases with white victims overall are also significantly more likely to receive death, relative to those with no white victims. The third set of analyses was able to disaggregate the stages that contributed to these defendant and victim race effects. Consistent with a robust body of previous research, these analyses find that prosecutors' decisions to charge special circumstances was significantly associated with victim race, in that they were much more likely to allege them in eligible cases involving white victims. Prosecutors were less likely, however, to allege special circumstances in minority defendant cases.

Conversely, capital juries were substantially and significantly more likely to sentence minority defendants to death, relative to others, while race of victim was not significantly associated with death sentence imposition by juries. This finding comports with other research of case outcome data, as well as controlled experimental research with mock jurors, that indicates significant defendant race effects, disadvantaging minority defendants, in capital jury decision-making.

In conclusion, the findings reported in this report indicate substantial and robust race effects across the different analyses. The study is able to pinpoint at which discretionary stage race appears to be inappropriately influencing decision-making, and the findings are consistent with existing research findings from other jurisdictions and using different research methodologies and analytic techniques. Given the methodological rigor of the study, coupled with the convergence with existing research, these findings can be viewed as scientifically valid and reliable.

Mona Lynch

Mona Lynch
Chancellor's Professor, Criminology, Law & Society and School of Law (by courtesy)
University of California, Irvine

EXHIBIT D

University of Colorado at Boulder

Department of Sociology

159 Ketchum Hall
327 UCB
Boulder, Colorado 80309-0327

Michael L. Radelet
Professor Emeritus
Radelet@Colorado.edu

Please use this address/phone:
3755 Smuggler Place
Boulder CO 80305
(303) 886-6401 (cell)

May 12, 2023

TO: Professor Catherine Grosso
FROM: Glenn L. Pierce
Michael L. Radelet

At your request, we have independently reviewed the report coauthored by Catherine M. Grosso, Jeffrey Fagan, & Michael Laurence, *Report on the Influence of the Race of Defendant and the Race of the Victim on Capital Charging and Sentencing in California Between January 1, 1978, and June 30, 2002* (unpublished draft, May 2023). We have carefully examined the (hereinafter "GF&L") study, and reviewed the credentials of the three authors. We took special care to attempt to identify any flaws, holes, exaggerations, inappropriate statistical analyses, or statements in the paper that are not fully supported by the data.

After multiple readings of the report by each of us, we conclude that you and your colleagues have produced a remarkable study that meets the highest standards of legal and empirical research. We believe that it is the single most important study that has examined the death penalty in California using data collected after the California Supreme Court invalidated the state's death sentencing statute in 1972.[1]

The paper builds on two previous articles published (with others) by these three authors that utilize data collected on 27,000 murder and manslaughter convictions in California between 1978 and 2002. These two papers have been widely cited, and - as far as we know - no authorities (including those who support the death penalty) have criticized the methodology or statistics or data upon which their findings are based.

In this third paper in their research program, GF&L show that homicide cases with at least one white victim and/or with minority defendants are treated more harshly than similar homicides that involve minority victims and white defendants. Among key findings in the new study, GF&L document that California has the highest rate in the U.S. of eligibility for the death penalty among defendants convicted of first- or second-degree murder and voluntary homicide convictions, although fewer than five percent are actually sentenced to death. Findings of "Special circumstances" – necessary to impose a death sentence – are significantly more likely to be found for black and LatinX defendants compared to others.

[1] *California v. Anderson*, 493 P.2d 880, 6 Cal. 3d 628 (1972).

GF&L use counterfactual reasoning and analytic methods to conclude that decisions are racial disparate by controlling for defendant culpability and other salient features of each case. The data and coding are clearly explained and even a reader with no training in statistics should be able to understand how the data were collected and analyzed. They focus on two distinct stages of case processing, with different legal actors reaching those decisions, to show the inevitability of racially disparate decisions among similarly situated populations. They observe these disparities in both charging decisions by prosecutors and sentencing decisions by juries, independent bodies whose decisions instantiate the racial inequalities in the California capital punishment system. GF&L show that homicide cases with at least one white victim and/or with minority defendants are treated more harshly than similar homicides that involve minority victims and white defendants. Many of the findings are reported as odds ratios,[2] an appropriate and widely used statistic among social scientists and epidemiologists in this type of quantitative study, well suited to intuitively show the extent of the racial and ethnic disparities in capital punishment case processing.

We cannot find any flaws in the design and execution of this study that would undermine any of the findings in this extraordinary study. Please reach out to either of us for additional information on our review of the GF&L study and its implications for racial equality and fairness in the administration of capital punishment in California.

Yours sincerely,

Michael L. Radelet

Michel Radelet
Radelet@colorado.edu
https://www.colorado.edu/sociology/our-people/michael-radelet

Glenn L. Pierce

Glenn Pierce
GPierce@Northeastern.edu
https://cssh.northeastern.edu/faculty/glenn-pierce/

Professors Pierce and Radelet have co-authored 15 papers on race and death sentencing in edited books, Sociology journals, law reviews, and numerous additional papers in scholarly outlets alone or with other coauthors. Included is a statewide study of race and death sentencing commissioned by Gov. George Ryan in Illinois that contributed to his decision to commute 160 death sentences in 2003, and the first post-*Furman* statewide study of race and death sentencing in California.[3]

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[2] These are straight-forward means of expressing the odds of certain findings and are taught in most undergraduate statistics courses in American universities.

[3] *The Impact of Legally Inappropriate Factors on Death Sentencing for California Homicides*, 46 SANTA CLARA LAW REVIEW 1-47 (1999).

EXHIBIT E

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

October 30, 2022

Nick Petersen, Ph.D.
Associate Professor of Sociology & Criminology
Secondary appointment in Law School
University of Miami
Coral Gables, Florida, United States
npetersen@miami.edu
(305) 284-6169

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

[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

[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

[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

[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 β = 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.

[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

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,

[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

[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.

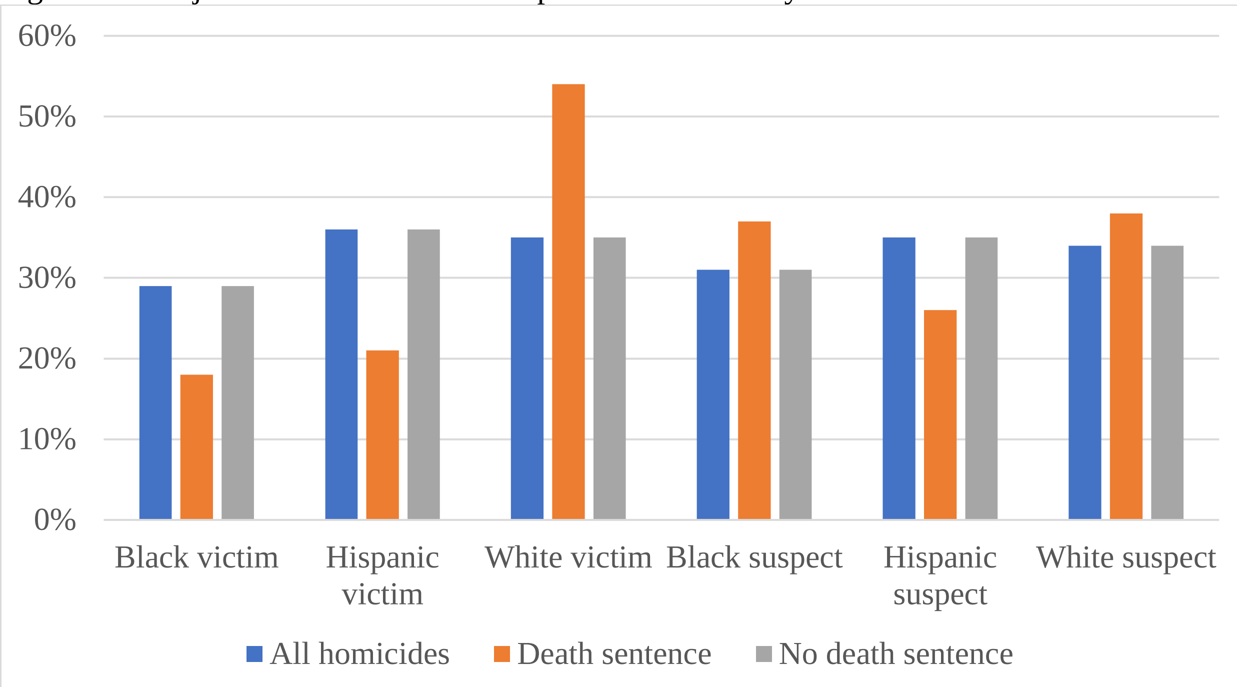
[42] Cameron and Miller, *supra* note 40.
[43] WOOLDRIDGE, *supra* note 6.

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

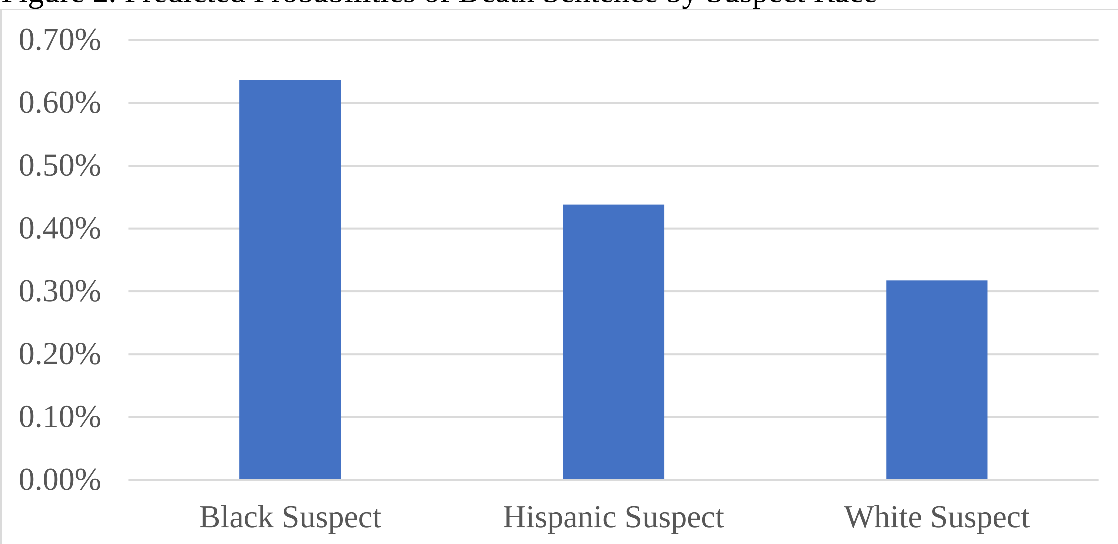
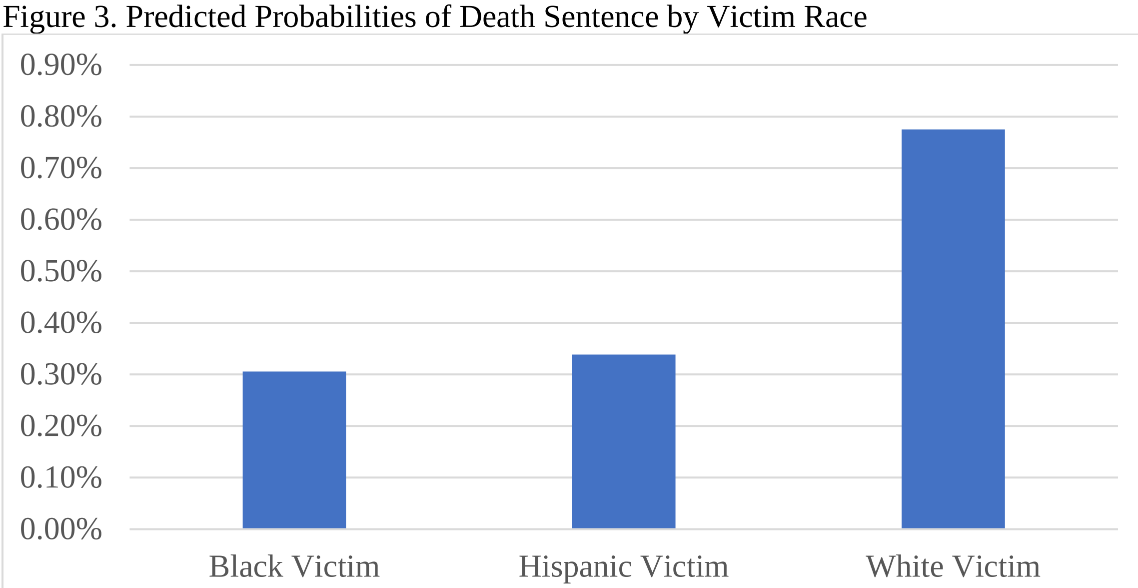


Figure 3. Predicted Probabilities of Death Sentence by Victim Race



[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

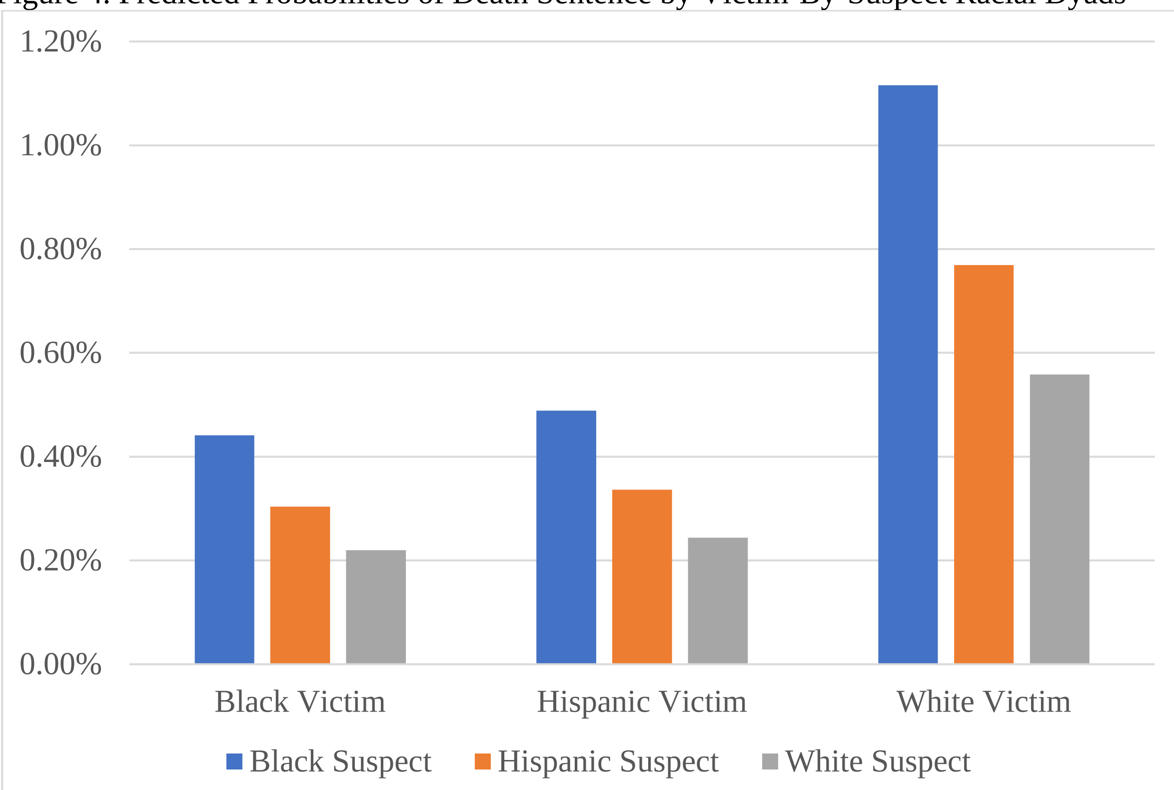
Exponentiated coefficients; Standard errors in parentheses

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

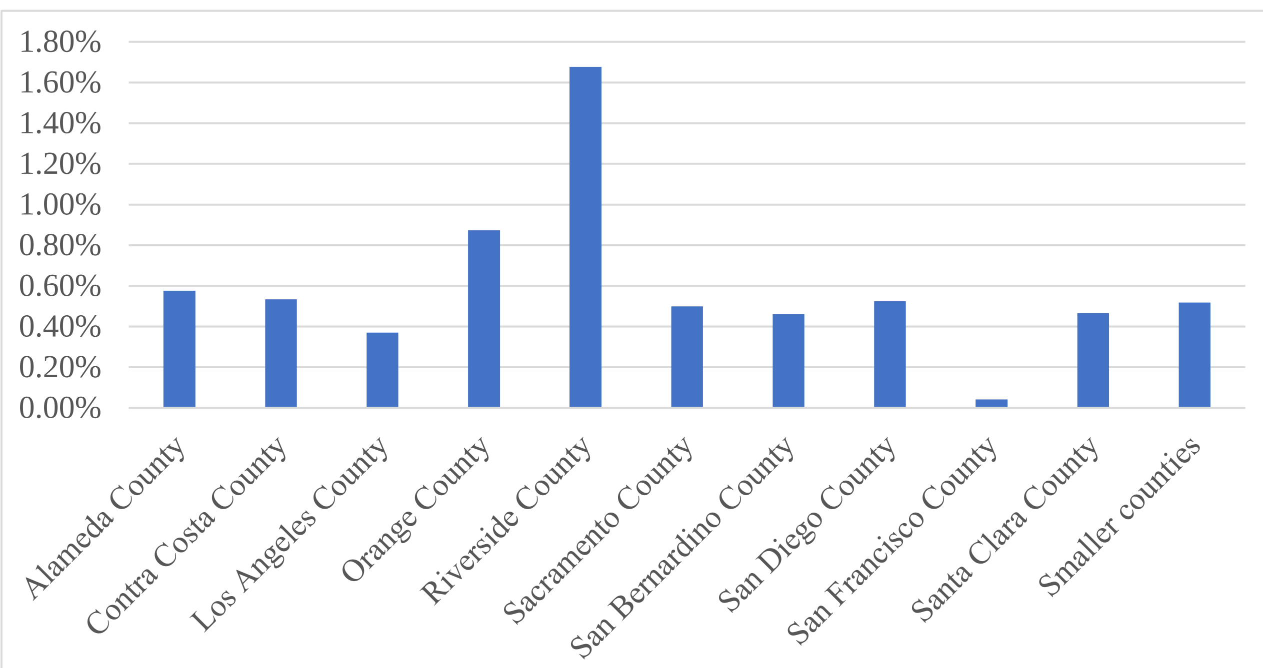


[50] Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview, in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND THE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

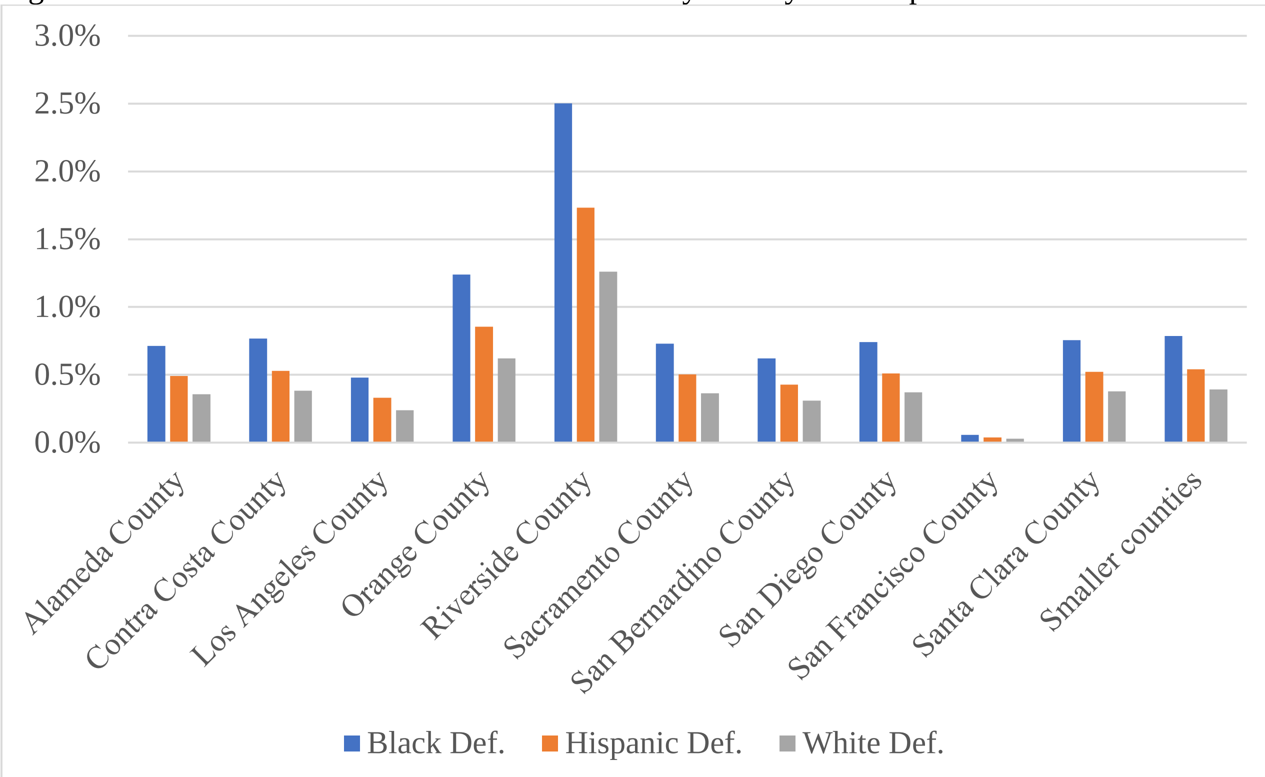
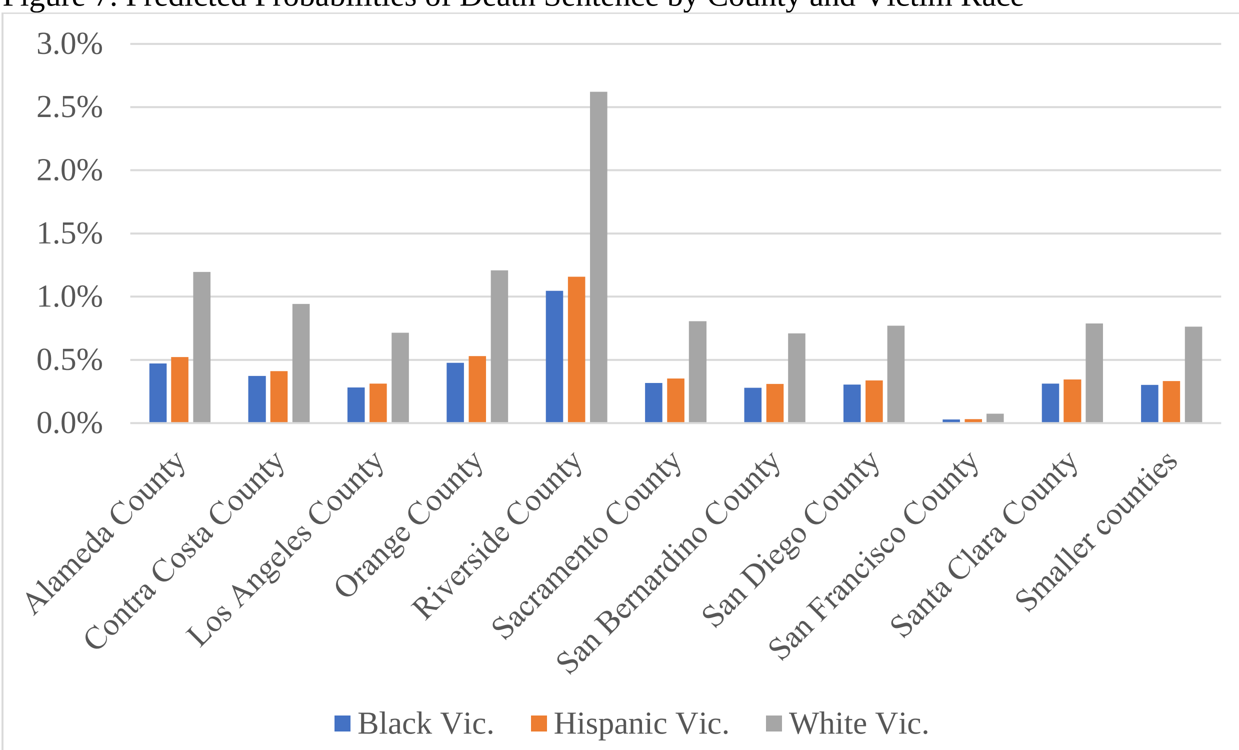
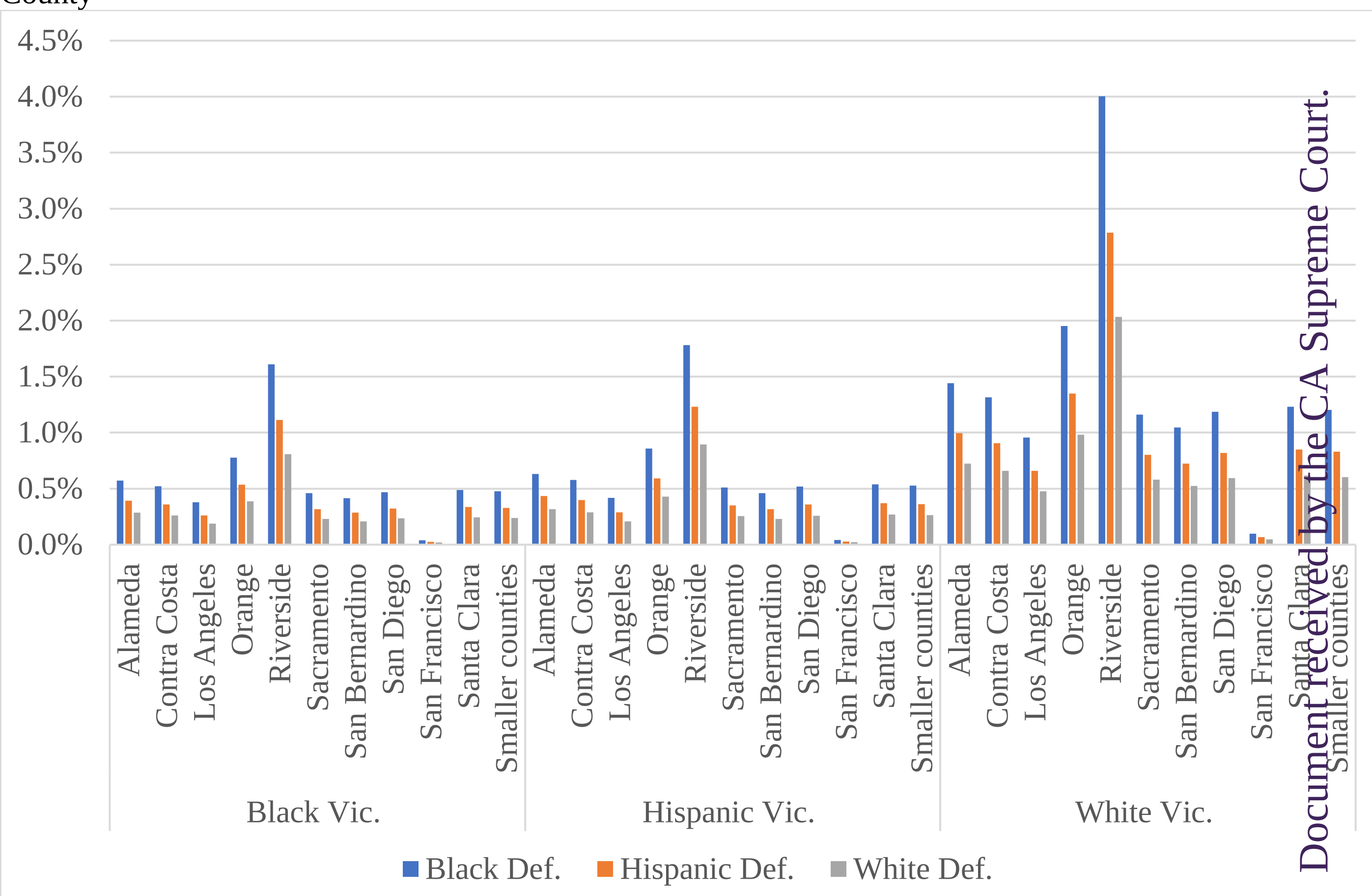


Figure 7. Predicted Probabilities of Death Sentence by County and Victim Race



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.

EXHIBIT F

Racial Disparities in California Death Sentencing (1987 to 2019)

January 30, 2024

Nick Petersen, Ph.D.
Associate Professor of Sociology & Criminology
Secondary appointment in Law School
University of Miami
Coral Gables, Florida, United States
npetersen@miami.edu
(305) 284-6169

I. INTRODUCTION

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

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

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

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

II. ANALYSIS STRATEGY

Population Death Sentencing Data

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

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

Statistical Estimation

6. To estimate the likelihood of a death sentence, I employed logistic regression models. I use regression models to analyze these data because they are the "most widely used vehicle for empirical analysis in economics and other social sciences," and they allow me to isolate the independent effect of victim/suspect[3] race on death sentences for similarly situated cases.[4]

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

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

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

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

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

8. Regression models control for numerous non-racial factors (independent variables) that could impact death penalty decision-making (the dependent variable). In this context, the phrases "controlling for" or "holding constant" non-racial factors mean that the regression models compare the likelihood of a death penalty decision for two similarly situated defendants except for race. For example, with such an analysis, one can compare the likelihood that a Black[6], Hispanic[7], or White suspect will receive a death sentence in cases with similar independent variables corresponding to victim/suspect demographics (e.g., age, gender, etc.) and case characteristics (e.g., felony, multiple victims, etc.).

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

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

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

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

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

[9] *Id.*

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

10. Logistic regression is the specific type of regression used in both studies, as it is appropriate for binary dependent variables like those I used. It estimates the likelihood of a factor being "present" versus "absent" based on a series of predictors, where "presence" is coded as "1" and "absence" is coded as "0" (e.g., "1" if the jury issued a death sentence or "0" if some other outcome was reached).[11] Consistent with prior empirical research on the death penalty, I used logistic regression models to estimate the likelihood of having a death sentence by race while holding other non-racial predictor variables constant, as described below. Logistic regressions are displayed as odds ratios where values larger than 1 indicate an increased likelihood of a case resulting in a particular death penalty outcome, whereas odds ratios less than 1 indicate a decreased likelihood of a homicide resulting in a death sentence.[12] The unit of analysis is the victim because the CDOJ is a victim-based dataset.[13]

Predicted Probabilities

11. Results from logistic regression models are displayed as predicted probabilities to help visualize the relevant statistical comparisons and to improve the interpretability of my findings. Logistic regression models generate odds ratios, which can be challenging to interpret

[10] BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; Baldus et al., *supra* note 6; Petersen, *supra* note 6; Petersen, *supra* note 6; Baldus, Woodworth, and Weiner, *supra* note 6; Glenn Pierce & Michael Radelet, *Impact of Legally Inappropriate Factors on Death Sentencing for California Homicides, 1990-1999, The*, 46 ST. CLARA REV 1 (2005); Michael L. Radelet & Glenn L. Pierce, *Race and Death Sentencing in North Carolina, 1980-2007*, 89 NCL REV 2119 (2010).

[11] BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; Baldus, Woodworth, and Weiner, *supra* note 6; Baldus et al., *supra* note 6; WOOLDRIDGE, *supra* note 4.

[12] For the purposes of this document, logistic regression estimates are discussed as percentage changes in terms of odds ratios, with 1 corresponding to equal odds (i.e., "no effect"). Binary variables estimated in a logistic equation can be interpreted as a percentage change in the odds/hazard using the following formula: 1-[(β*xi*) X 100]. Baldus et al., *supra* note 6; WOOLDRIDGE, *supra* note 4.

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

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

Adjusted vs. Unadjusted Results

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

14 In a logistic regression model, odds (O) and probabilities (P) have the following relationship: Odds = P/1-P and Probability = O/1+O. Baldus, Woodworth, and Weiner, *supra* note 6.

15 J. SCOTT LONG & JEREMY FREESE, REGRESSION MODELS FOR CATEGORICAL DEPENDENT VARIABLES USING STATA (Third Edition ed. 2014), https://www.stata.com/bookstore/regression-models-categorical-dependent-variables/ (last visited Nov 14, 2020); ALAN C. ACOCK, A GENTLE INTRODUCTION TO STATA (3rd ed. 2013).

16 Petersen, *supra* note 6; Marisa Omori & Nick Petersen, *Institutionalizing Inequality in the Courts: Decomposing Racial and Ethnic Inequality in Detention, Conviction and Sentencing*, CRIMINOLOGY (2020); Nick Petersen, *Low-Level, but High Speed?: Assessing Pretrial Detention Effects on the Timing and Content of Misdemeanor versus Felony Guilty Pleas*, JUSTICE Q. (2019); Brandon P. Martinez, Nick Petersen & Marisa Omori, *Time, Money, and Punishment: Institutional Racial-Ethnic Inequalities in Pretrial Detention and Case Outcomes*, CRIME DELINQUENCY 0011128719881600 (2019); George Wilson et al., *Particularism and Racial Mobility into Privileged Occupations*, 78 SOC. SCI. RES. 82 (2019); Petersen, *supra* note 6.

17 LONG AND FREESE, *supra* note 15. In this leading book on categorical data analysis, including logistic regression, Sociology Professors Scott Long and Jeremey Freese spend considerable time discussing the importance of predicted probabilities for making results more interpretable. In particular, they note: "Models for categorical outcomes are nonlinear, and this nonlinearity is the fundamental challenge that must be addressed for effective interpretation. Most simply, this means that you cannot effectively represent your model by presenting a list of estimated parameters. Instead, we believe the most effective way to interpret your models is by first fitting the model and then computing and estimating postestimation predictions [i.e., predicted probabilities] for the outcomes" *Id.* at p. 133. They go on to note that: "The primary methods for interpretation presented in this book are based on predictions from the model. The model is fit and the estimated parameters are used to make predictions at values of the independent variable that are (hopefully) useful for understanding the implications of the nonlinear model" *Id.* at p. 136.

18

Practical vs. Statistical Significance

13. Many scientific studies rely on statistical significance when discussing results from sample data. Statistical significance permits the researcher to extrapolate the results from their data analysis to locations and time frames beyond their dataset.[19] However, the American Statistical Association (ASA) has sought to move away from focusing solely on statistical significance in recent years, noting that practical significance is also an essential consideration in any scientific study, particularly when researchers are analyzing a population.[20] As such, my report includes discussions of both statistical *and* practical significance.

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

15. Focusing on practical significance rather than statistical significance simply means that comparisons between races shed light on possible racial disparities for the particular location (California) and timeframe of interest (1987-2019) and cannot necessarily be generalized to other possible historical/future "realizations" of the population. This approach is consistent with Professor Scott Phillips' analysis of death-penalty decision-making among a full

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 β = 0 (i.e., "no effect") after taking into account sampling variability in β, this means that there is a statistically significant difference that cannot be explained by random sampling variability as measured by sampling variability. In this regard, the major advantage of statistical significance is that it allows researchers to make inferences about a population based on sample data since the sampling variability is factored into the equation. WOOLDRIDGE, *supra* note 4; ACOCK, *supra* note 15. In the death penalty context, p-values correspond to the probability that "a [racial] disparity could occur by chance." Baldus et al., *supra* note 6 at 171. In the social sciences, p-values less than 0.05 are typically considered "statistically significant."

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

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

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

III. DATA AND METHODOLOGY

Data and Methodology

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

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

22 Scott Phillips, *Status Disparities in the Capital of Capital Punishment*, 43 LAW SOC. REV. 807, 821 (2009).
23 *Id.*
24 Gross and Mauro, *supra* note 13; Pierce and Radelet, *supra* note 10; Radelet and Pierce, *supra* note 10.
25 For death penalty studies employing similar techniques, see Pierce and Radelet, *supra* note 10; Radelet and Pierce, *supra* note 10.

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

Dependent variable:

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

Suspect and Victim Demographics:

19. Victim and suspect race was coded using a series of categorical variables, with other racial groups such as Asians and Native Americans being excluded: 0 = White ("reference" group), 1 = Hispanic, 2 = Black.[32] In addition, victim/suspect age were measured in years, while

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

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

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

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

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

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

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

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

Homicide Characteristics:

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

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

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

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

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

35 BALDUS, WOODWORTH, AND PULASKI, *supra* note 6; David Baldus & George Woodworth, *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2003); Baldus et al., *supra* note 6.

36 Xia Wang & Daniel P. Mears, *Examining the Direct and Interactive Effects of Changes in Racial and Ethnic Threat on Sentencing Decisions*, J. RES. CRIME DELINQUENCY (2010); Xia Wang & Daniel P. Mears, *A Multilevel Test of Minority Threat Effects on Sentencing*, 26 J. QUANT. CRIMINOL. 191 (2010).

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

County Characteristics:

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

[37] Prior research suggests that these are among the most frequently filed special circumstances in California. Moreover, death-eligibility under some special circumstances, such as "especially heinous" murders (PC 190.2(a)(15)) or "lying in wait" (PC 190.2(a)(14)) are notoriously difficult to capture based on offense characteristics given their subjective nature. James Acker & Charles Lanier, *Aggravating Circumstances and Capital Punishment Law: Rhetoric or Real Reforms*, 29 CRIM. LAW BULL. 467 (1993); Ellen Kreitzberg, *A Review of Special Circumstances in California Death Penalty Cases*, (2008), http://www.ccfaj.org/documents/ reports/dp/ expert/Kreitzberg.pdf; Nick Petersen & Mona Lynch, *Prosecutorial Discretion, Hidden Costs, and the Death Penalty: The Case of Los Angeles County*, 102 J. CRIM. LAW CRIMINOL. 1233 (2013); Ruth D. Peterson & William C. Bailey, *Felony Murder and Capital Punishment: An Examination of the Deterrence Question*, 29 CRIMINOLOGY 367 (1991); Steven F. Shatz, *Eighth Amendment, the Death Penalty, and Ordinary Robbery-Burglary Murderers: A California Case Study, The*, 59 FLA REV 719 (2007).

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

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

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

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

Analysis Strategy:

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

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

40 Pierce and Radelet, *supra* note 10.

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

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

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

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

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

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

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

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

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

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

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

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

48 WOOLDRIDGE, *supra* note 4.

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

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

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

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

Results

Unadjusted Summary Statistics:

26. Table 1 shows "unadjusted" summary statistics. That is, Table 1 lists the raw statistics for various measures without controlling for any other variables. Compared to the general population of homicides in California from 1987 to 2019, Table 1 indicates that homicides resulting in a death sentence are more likely to have a White victim and a non-White (Black/Hispanic) suspect. For example, 31% of all California homicides have a White victim, whereas 49% of California homicides that result in a death sentence have a White victim. In contrast, 32% of California homicides involve a Black suspect, but 36% of homicides that result in a death sentence involve a Black suspect.

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

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

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

Figure 1. Map of Death Sentencing Rates in California Counties

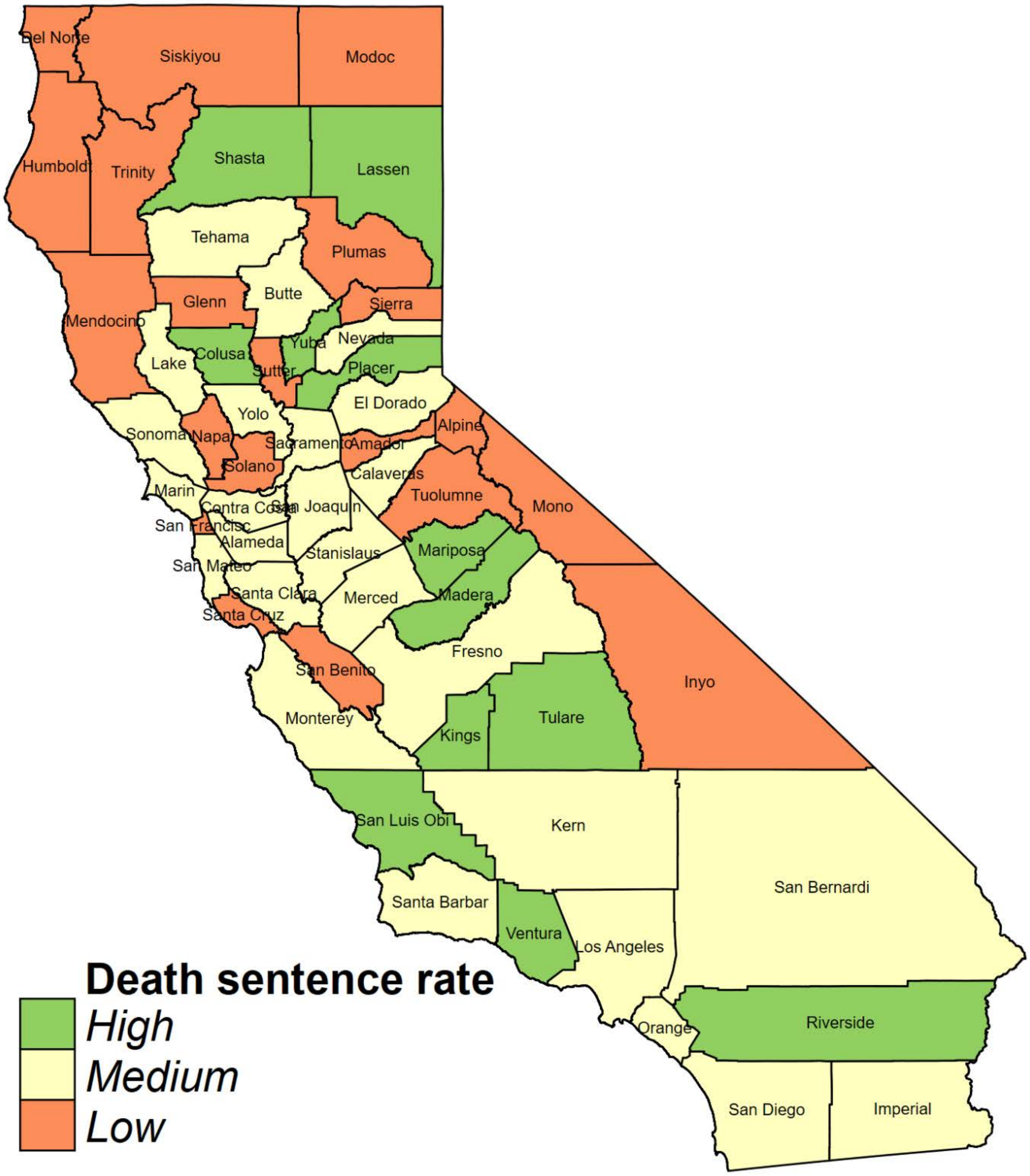
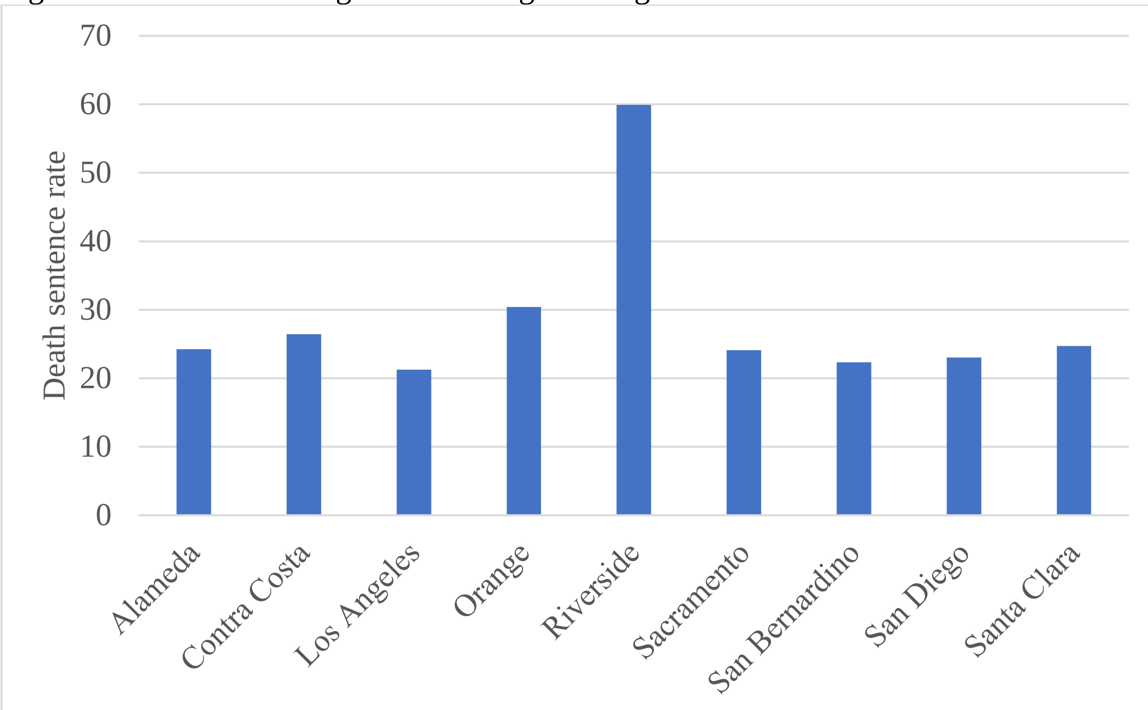


Figure 2. Death Sentencing Rates Among the Largest California Counties



Adjusted Racial Disparities:

28. Next, I turn to "adjusted" regression estimates in Table 2. These are "adjusted" in the sense that the regression models control for other important legal factors such as the presence of multiple victims or a felony. According to the logistic model, homicides involving death-eligible offenses (e.g., multiple murder, felony-murder, drive-by-shooting, gang killing) more likely to result in a death sentence. These findings are consistent with California's death penalty laws that consider homicides to be more aggravated, and prior research examining death penalty outcomes in California.[53]

29. Even after controlling for these important legal factors, however, victim and suspect race shape death sentences. According to the logistic regression model, homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence, while those with a non-White (Black/Hispanic) suspect are more likely to result in a death sentence. Compared to homicides with a White victim, those with a Black victim are 53% less likely to result in a death

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

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

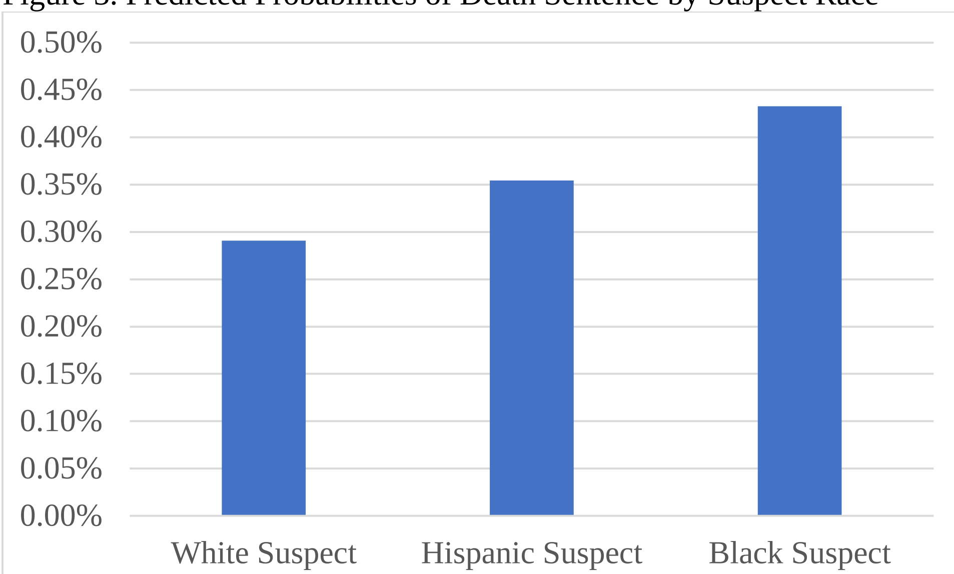
Table 2. Regressions Predicting Death Sentencing Outcomes in California (1987-2019).

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

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

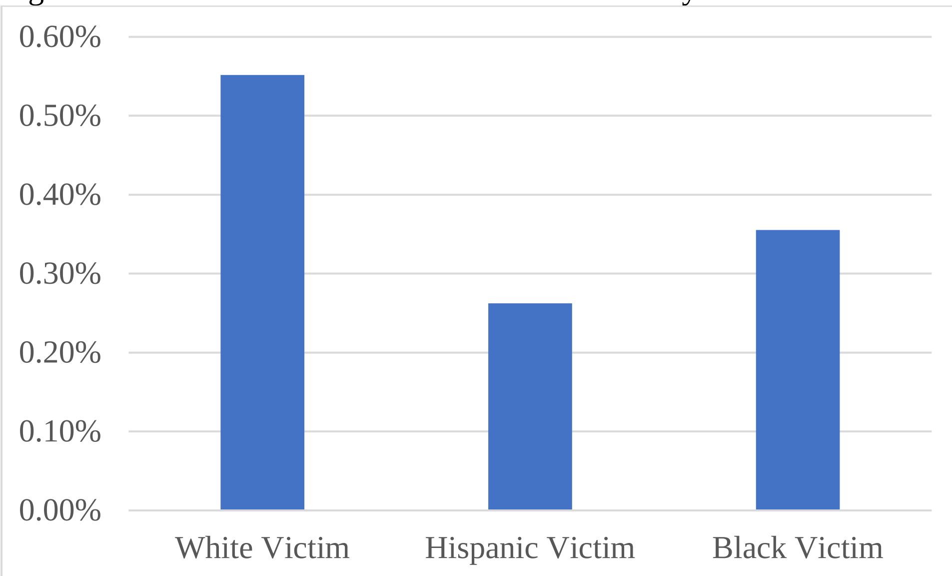
30. Next, I calculated predicted probabilities to help visualize the effects of victim and suspect race/ethnicity from the regression model in Table 2. Figure 3 shows that homicides with White victims are more likely to result in a death sentence, while homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence. In contrast, Figure 3 indicates that homicides with White suspects are less likely to result in a death sentence, while homicides with non-White (Black/Hispanic) suspects are more likely to result in a death sentence. Taken together, these predicted probabilities show an inverse relationship between the victim and suspect race, such that homicides with White victims are more likely to result in a death sentence than homicides with non-White (Black/Hispanic) victims, whereas homicides with non-White (Black/Hispanic) suspects are more likely to result in a death sentence than homicides with White suspects. The inverse relationship between victim and suspect race is consistent with prior research[54] and suggests a victim-by-suspect race interaction, which I explore below.

Figure 3. Predicted Probabilities of Death Sentence by Suspect Race



[54] Pierce and Radelet, *supra* note 10.

Figure 4. Predicted Probabilities of Death Sentence by Victim Race



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

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

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

56 Baldus et al., *supra* note 6; David Baldus & George Woodworth, *Race Discrimination and the Legitamacy of Capital Punishment: Reflections on the Interaction of Fact and Perception*, 53 DEPAUL REV 1411 (2003).

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

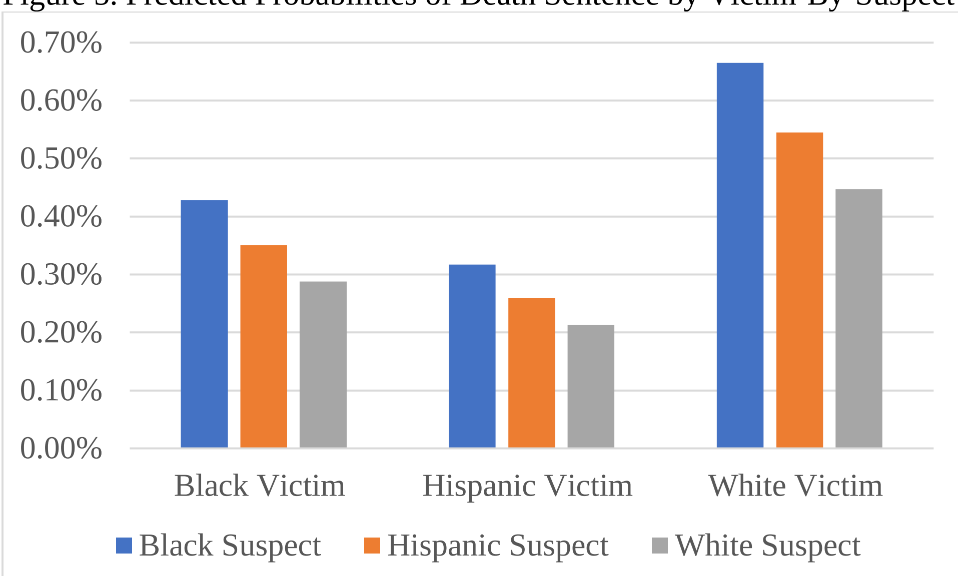
Table 3. Regressions Predicting Death Sentencing Outcomes in California by Suspect and Victim Racial Dyads (1987-2019).

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

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

33. To help visualize victim-by-suspect racial dyads, I calculated predicted probabilities. Figure 5, displaying victim-by-suspect racial dyads in terms of probabilities from the logistic regression in Table 3, indicates that the overall likelihood of a death sentence is very low for all homicides. The predicted probability of a death sentence is so low since the denominator includes all homicides with suspect information, and death sentences are rare. However, clear patterns emerge when I compare differences in predicted probabilities by victim and suspect race. In particular, Figure 5 shows that Black or Hispanic suspects who kill White victims are the most likely to receive a death sentence. These findings are consistent with prior research finding that minority suspects who kill White victims are especially disadvantaged in terms of death sentences.[57]

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

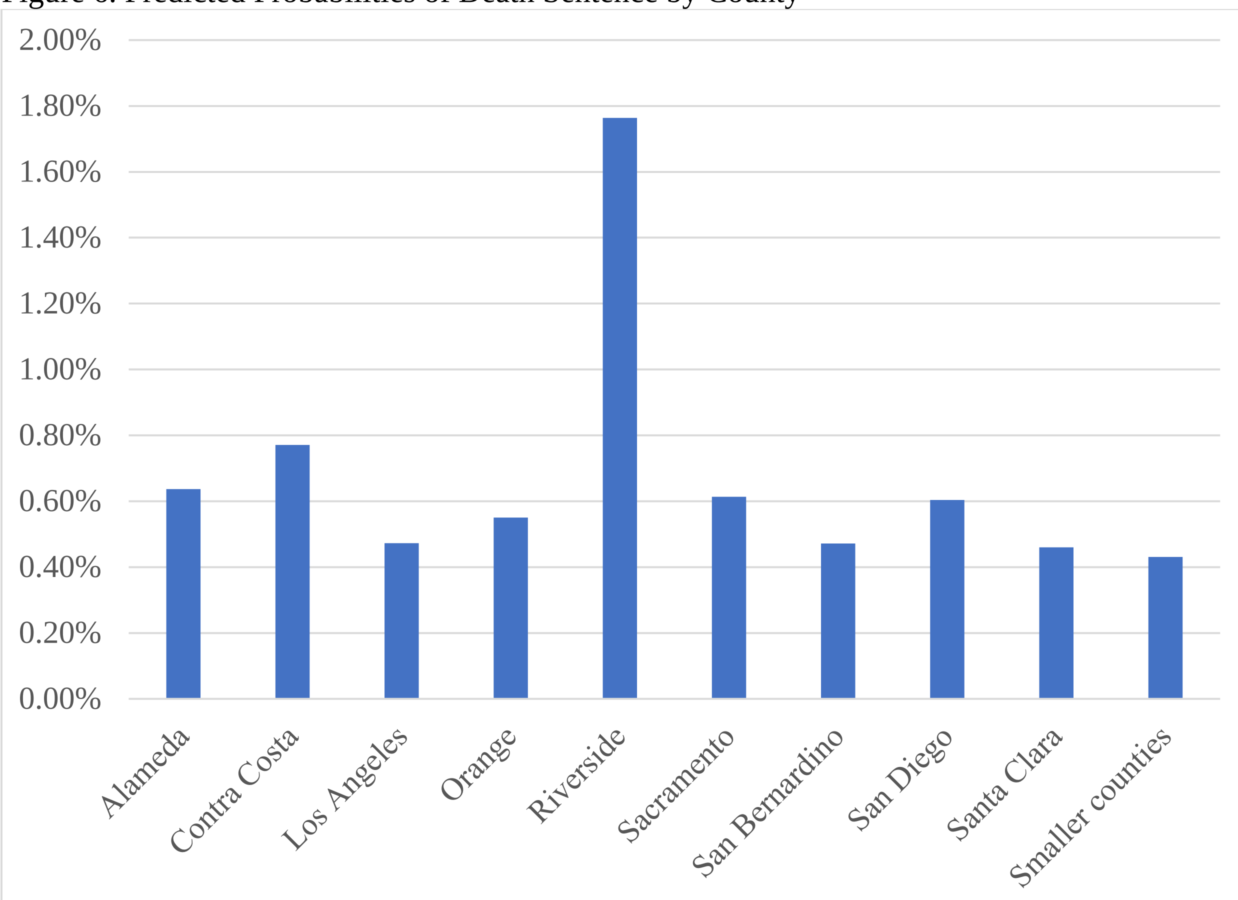


[57] Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND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

Do Racial Disparities Vary Across California Counties?

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

Figure 6. Predicted Probabilities of Death Sentence by County



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

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

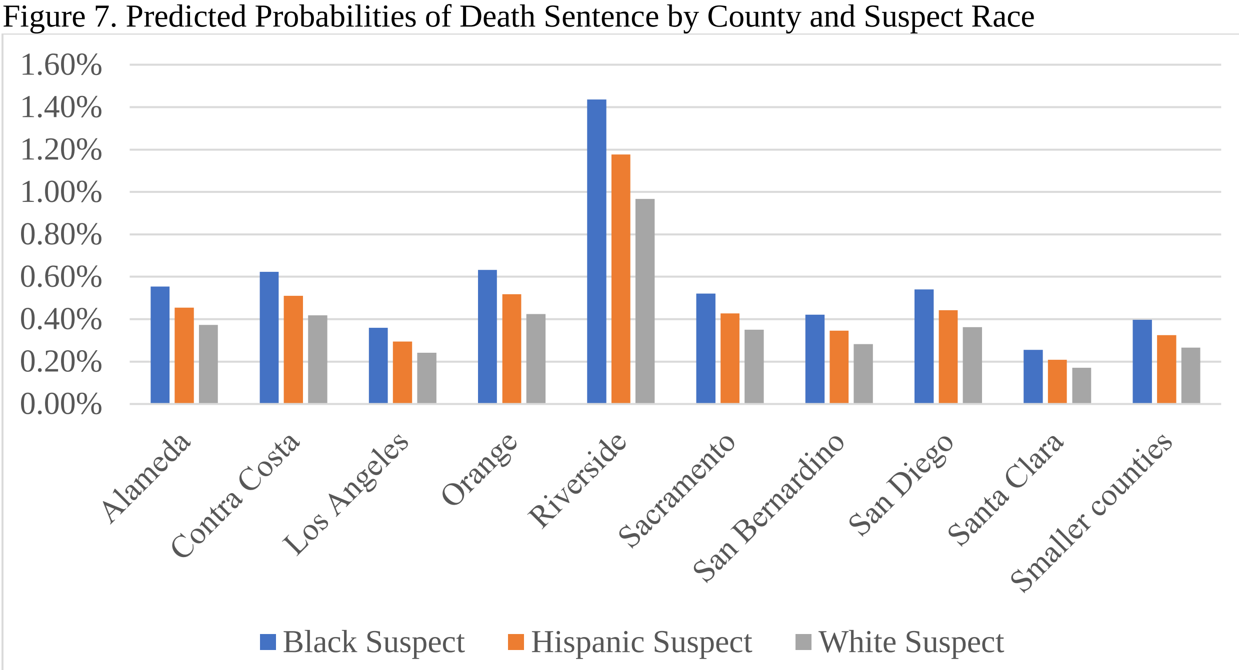
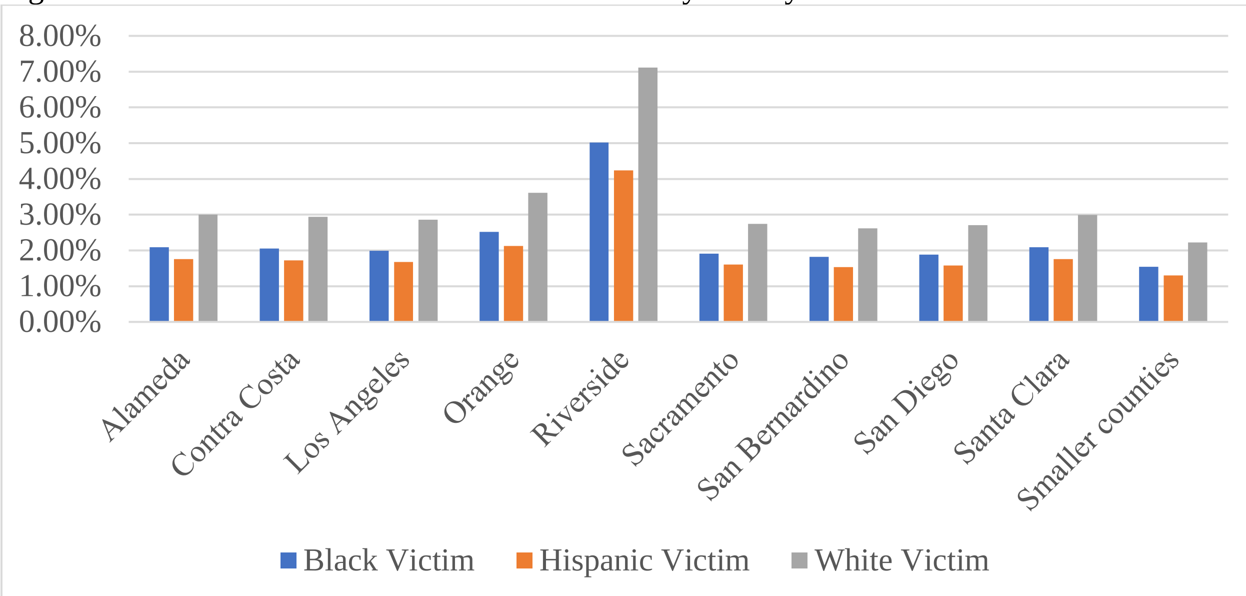
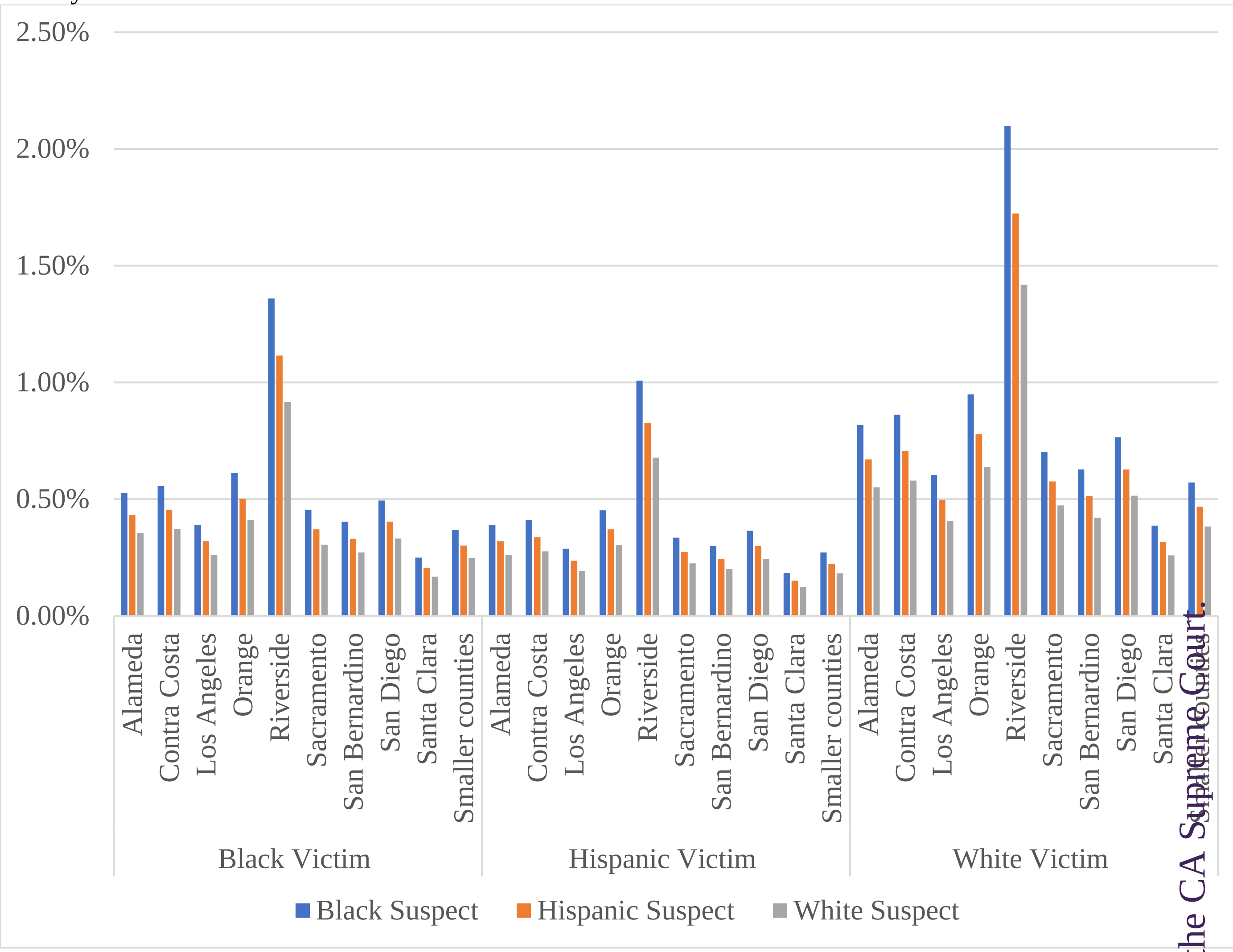


Figure 8. Predicted Probabilities of Death Sentence by County and Victim Race



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

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

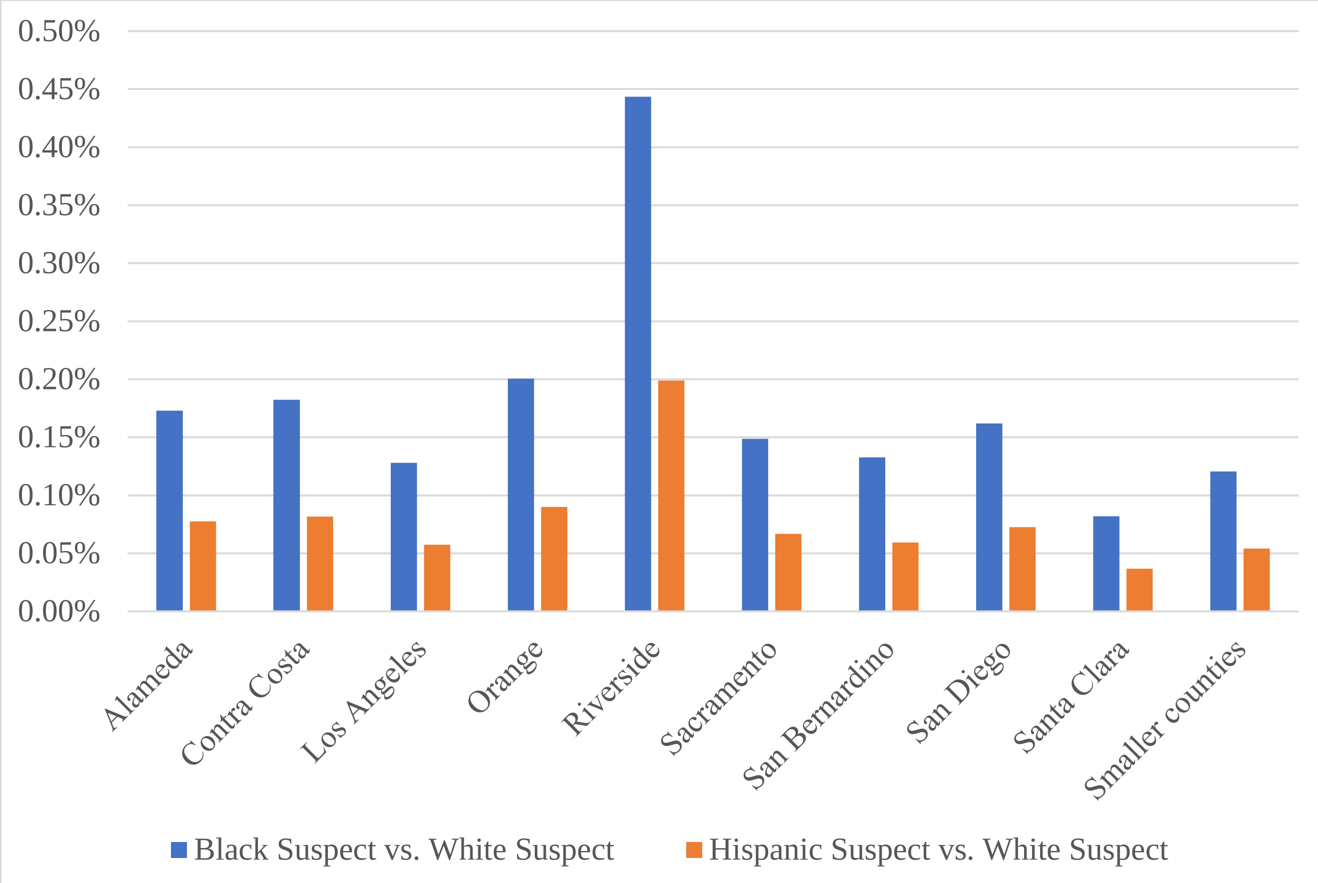


37. Figure 10 further probes spatial-racial disparities by displaying differences in the predicted probability of a death sentence for homicides with White victims by suspect race and county. Since homicides with White victims and Black/Hispanic suspects are the most likely to result in a death sentence,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

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

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

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



IV. CONCLUSIONS

39. These findings highlight victim-by-suspect racial disparities in California death sentencing trends from 1987 to 2019. Even after controlling for important legally relevant factors like the presence of multiple victims or a felony, regression results indicate that homicides with White victims are more likely to result in a death sentence. The opposite is true for suspect race, where Black suspects are more likely to be sentenced to death. These patterns are especially pronounced in inter-racial homicides involving White victims and non-White suspects. Homicides with a Black or Hispanic suspect and a White victim are more likely to result in a death sentence than any other victim-by-suspect race dyad.

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

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

EXHIBIT G

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Glenn L. Pierce

Michael L. Radelet

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THE IMPACT OF LEGALLY INAPPROPRIATE FACTORS ON DEATH SENTENCING FOR CALIFORNIA HOMICIDES, 1990–1999

Glenn L. Pierce*

Michael L. Radelet**

This study examines the racial, ethnic, and geographical variations present in the imposition of the death penalty in California. In doing so, it analyzes all reported homicides committed in California during the 1990s, comparing those that resulted in a death sentence with those that did not.

I. OVERVIEW

A. *The Death Penalty in California, 1972-2003*

In February 1972, the California Supreme Court emptied

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* Principal Research Scientist, Institute for Race and Justice and College of Criminal Justice, Northeastern University, Boston, Massachusetts; B.A., Bates College; M.A., Northeastern University; Ph.D., Northeastern University.

** Professor and Chair, Department of Sociology, University of Colorado, Boulder, Colorado; B.A., Michigan State University; M.A., Eastern Michigan University; Ph.D., Purdue University.

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that state's death row when it decided *People v. Anderson*.[1] The court based its decision on the State Constitution's ban on cruel or unusual punishments. The ban automatically commuted the sentences of all 107 inmates then on California's death row to life imprisonment.[2] Four months later, the United States Supreme Court's landmark death penalty ruling in *Furman v. Georgia*[3] emptied all other death rows in the United States.

Many California voters were not pleased with the effect of *People v. Anderson*. In November 1972, they passed Proposition 17, a ballot initiative that amended the California Constitution specifically to allow for the death penalty.[4] The California legislature responded to this initiative in 1973 by enacting a statute making the death penalty mandatory upon conviction of first-degree murder with a finding of at least one of ten statutorily defined "special circumstances."[5] However,

1. 493 P.2d 880 (Cal. 1972), *cert. denied*, 406 U.S. 958 (1972).

2. See Jonathan R. Sorenson, James W. Marquart & Madhava R. Bodapati, *Research Note: Two Decades After* People v. Anderson, 24 LOY. L.A. L. REV. 45 (1990), for research on the effects of *People v. Anderson*.

3. 408 U.S. 238 (1972). *Furman* was announced on June 29, 1972. *Id.*

4. This initiative declared that the death penalty was not "the infliction of cruel or unusual punishments within the meaning of Article I, Section 6 [of the California Constitution]." CAL. CONST. art. I, § 27. For more information on the history of the death penalty in California after 1972, see Steven F. Shatz & Nina Rivkind, *The California Death Penalty Scheme: Requiem for* Furman?, 72 N.Y.U. L. REV. 1283, 1306-17 (1997); John W. Poulos, *The Lucas Court and the Penalty Phase of the Capital Trial: The Original Understanding*, 27 SAN DIEGO L. REV. 521, 527-42 (1990).

5. *See* 1973 Cal. Stat. 719, §§ 1-5 (current version at CAL. PENAL CODE § 190.2 (Deering 2005)). In California, prosecutors make this decision by charging "special circumstances," which, if found at the sentencing phase of the trial, make the homicide a death-eligible case. *Id.* The initial list of special circumstances is found in 1973 Cal. Stat. 719, §§ 1-5. The California Supreme Court has ruled that the special circumstances "perform the same constitutionally required 'narrowing' function as the 'aggravating circumstances' or 'aggravating factors' that some of the other states use in their capital sentencing statutes." People v. Bacigalupo, 862 P.2d 808, 813 (Cal. 1993).

However, "special circumstances" are not the same as "aggravating factors." As Shatz and Rivkind explain, "California's special circumstances operate at the guilt phase to define the class of death-eligible first degree murderers .... They should not be confused with California's 'aggravating circumstances,' which operate at the penalty phase to help the jury select the penalty." *See* Shatz & Rivkind, *supra* note 4, at 1291 n.39 (citation omitted). Examples of "special circumstances" in the 1973 statute include whether the victim was a police officer, whether the murder was committed to eliminate a witness, and whether the murder was accompanied by one of a specified list of when the U.S. Supreme Court approved several new death penalty statutes in 1976,[6] it also invalidated the mandatory death penalty statutes of North Carolina[7] and Louisiana.[8] As a result of the later decisions, in late 1976 the California Supreme Court invalidated California's mandatory death penalty law.[9]

The California legislature responded by passing a new death penalty statute in 1977 that gave jurors the discretion to decide whether defendants should be sentenced to death.[10] Like its predecessor, the 1977 statute required a conviction of first-degree murder with the presence of special circumstances for the imposition of a death sentence. However, the 1977 statute increased the number of special circumstances that could be used to justify a death sentence from ten to twelve.

The death penalty in California was further expanded the next year when, on November 7, 1978, California voters passed Proposition 7.[11] Named after the California Senator who was its author and chief supporter, John V. Briggs, the Initiative superseded the 1977 law. It added fourteen new special circumstances, and broadened some of the older ones to allow prosecutors much more latitude in pursuing the death penalty.[12] Since then, several more special circumstances have been added, bringing the total to twenty-five, or a total of thirty-six when various subsections are also included.[13] The definition of first-degree murder has also

accompanying felonies. *See id.* at 1307-08 n.141. "Aggravating circumstances" include the circumstances of the crime, writ large. *See* CAL. PENAL CODE §190.3 (Deering 2005); Robert M. Sanger, *Comparison of the Illinois Commission Report on Capital Punishment with the Capital Punishment System in California*, 44 SANTA CLARA L. REV. 101, 109-19 (2003) (arguing that aggravating circumstances "have been interpreted so broadly that prosecutors can argue practically any case warrants the death penalty").

6. *See* Gregg v. Georgia, 428 U.S. 153 (1976) and accompanying cases.

7. *See* Woodson v. North Carolina, 428 U.S. 280 (1976).

8. *See* Roberts v. Louisiana, 428 U.S. 325 (1976).

9. Rockwell v. Superior Court, 556 P.2d 1101, 1116 (Cal. 1976).

10. 1977 Cal. Stat. 316, § 9; *see* Shatz & Rivkind, *supra* note 4, at 1308 & n.144.

11. Initiative Measure Proposition 7 (approved Nov. 7, 1978) (codified at CAL. PENAL CODE §§ 190, 190.1-.5 (Deering 2005)).

12. *See* Shatz & Rivkind, *supra* note 4, at 1311 & n.155. The Briggs Initiative broadened several special circumstances so that some non-intentional murders were eligible for the death penalty, as were accomplices. *Id.* at 1313.

13. "There are twenty-five special circumstances under the current

been broadened, further expanding the potential applicability of the death penalty in California.[14]

B. Demographics and Homicides in California

California's population is among the most ethnically and racially diverse in the United States. Table 1a shows that the Hispanic population[15] of the state increased from approximately one-fourth of the total state population in 1990[16] to just under one-third by 2000.[17] When race alone is measured (regardless of ethnicity), the African American population was 6.7% in 2000, with whites constituting 59.5% of the population, and Asians and others constituting approximately 33.8%.[18]

Table 1a

Hispanic Population—California, 1990 and 2000 (total population in parentheses)

	1990	**2000**
Hispanic	25.8% (7,688,000)	32.4% (10,967,000)
Non-Hispanic	74.2% (22,072,000)	67.6% (22,905,000)
Total Population	29,760,000	33,872,000

California statutes, many with subsections, rendering over thirty-six actual circumstances in which capital punishment may be sought." Sanger, *supra* note 5, at 108-09.

14. This was done in several ways, including expanding the felonies that can be used to find felony murder, expanding the means of murder to include, for example, discharging a firearm from a motor vehicle, and by limiting diminished capacity defenses. *See* Shatz & Rivkind, *supra* note 4, at 1314-15.

15. Hispanic refers to a person of Mexican, Puerto Rican, Cuban, Central or South American, or other Spanish culture or origin, regardless of race.

16. *See infra* tbl.1a; U.S. BUREAU OF THE CENSUS, STATISTICAL ABSTRACT OF THE UNITED STATES: 1992, at 24-25 (112th edition 1992).

17. *See infra* tbl.1a; U.S. BUREAU OF THE CENSUS, STATISTICAL ABSTRACT OF THE UNITED STATES: 2002, at 26-28 (122nd edition 2002) [hereinafter 2002 STATISTICAL ABSTRACT].

18. *See infra* tbl.1b; 2002 STATISTICAL ABSTRACT, *supra* note 17, at 27.

Table 1b
Racial Breakdown—California, 1990 and 2000 (in thousands)

	1990	2000
White	69.0% (20,524,000)	59.5% (20,170,000)
African American	7.4% (2,209,000)	6.7% (2,264,000)
Asian & Other	23.6% (7,027,000)	33.8% (11,438,000)
Total Population	29,760,000	33,872,000

California has the unfortunate distinction of leading the United States in the number of homicides perpetrated.[19] In 2001, there were 2206 homicides and non-negligent manslaughters in California, followed by 1332 in Texas, 986 in Illinois, 960 in New York, and 874 in Florida.[20] With 653 homicides in 2002, Los Angeles recorded more homicides than any city in the country.[21]

California health statistics reveal that the risk of homicide victimization varies significantly by gender, race, and ethnicity. They show that between 1980 and 1997, males were approximately four times more likely than females to fall victim to homicide.[22] From 1985 through 1997, there was an annual average of 1285 Hispanic homicide victims, 1007 African American homicide victims, 946 white homicide victims, and 184 homicide victims of Asian or "other" races.[23] During that thirteen-year period, there were 44,483 homicide victims counted by the California Department of Health Services, of whom 37.6% (16,704) were Hispanic, 29.4% (13,090) were African American, 27.6% (12,293) were white,

19. *See* FED. BUREAU OF INVESTIGATION, UNIFORM CRIME REPORTS, CRIME IN THE UNITED STATES—2001, at 66-75 tbl.4 (2001), http://www.fbi.gov/ucr/01cius.htm (last visited Oct. 5, 2005).

20. *Id.*

21. Richard Winton, *Crime Edges Up in State*, L.A. TIMES, Apr. 28, 2003, at B7. Los Angeles's homicide rate rose 11.1% during 2002. *Id.*

22. CAL. CTR. FOR HEALTH STATISTICS, HOMICIDE DEATHS, CALIFORNIA, 1980-1997, at 1 (1999), http://www.dhs.ca.gov/hisp/chs/OHIR/reports/leadingcause/homicide1980.pdf (last visited Oct. 5, 2005).

23. *See id.* at 6 tbl.2.

and 5.4% (2396) were Asian/other.[24]

By a wide margin, African Americans have the highest crude homicide death rate per 100,000 population.[25] They averaged 47.4 deaths per year, 1985-1997. Crude annual death rates during this period averaged 16.0 for Hispanic victims, 6.1 for Asian/other victims, and 5.6 for white victims.[26] The victimization rate for African Americans in California is high, but not unusual. National estimates from the National Crime Victimization Survey in 2000 show that African Americans reported 34.1 instances of victimization from violent crime[27] per 1000 population, compared to 27.9 for Hispanics, 26.5 for whites, and 8.4 for Asians.[28]

C. *Post-*Furman *Death Sentencing and Executions in California*

As of July 1, 2005, California had the largest death row population in the United States, with 648 inmates under sentences of death.[29] The race/ethnic composition of this population is presented in Table 2. Note from Table 1b that the 2000 California population was 6.7% African American; in contrast, the racial makeup of California's death row in July 2005 was 36% African American.[30] This raises the obvious question of whether death sentencing rates for African Americans are disproportionate to the rate of involvement of African Americans in capital offenses.

24. *Id.* at 6.
25. *Id.*
26. *Id.*
27. The survey includes as violent crime rape/sexual assault, robbery, aggravated assault, and simple assault. CALLIE MARIE RENNISON, HISPANIC VICTIMS OF VIOLENT CRIME, 1993-2000, at 1 (2002), http://www.ojp.usdoj.gov/bjs/pub/pdf/hvvc00.pdf (last visited Oct. 5, 2005).
28. *Id.* at 2 tbl.1.
29. NAACP LEGAL DEFENSE AND EDUCATIONAL FUND, INC., DEATH ROW U.S.A. 29-30 (2005), http://www.naacpldf.org/content/pdf/pubs/drusa/DRUSA_Summer_2005.pdf (last visited Oct. 5, 2005). The latest data published by the California Department of Corrections shows 630 people on death row as of Jan. 28, 2004. *See* CAL. DEP'T OF CORR., CONDEMNED INMATE SUMMARY LIST, http://www.corr.ca.gov/CommunicationsOffice/CapitalPunishment/PDF/Summary.pdf (Oct. 20, 2005) [hereinafter CONDEMNED INMATE SUMMARY LIST].
30. *See infra* tbl.2.

Table 2

Racial Breakdown of California Death Row Inmates, July 1, 2005 (N = 648)[31]

Race	Number	Proportion
White	253	.39
African American	233	.36
Hispanic	128	.20
Asian	20	.03
Native American	14	.02

Between 1972 and November 1, 2005, there were eleven prisoners executed in California.[32] The names of those executed, the date of execution, the number of victims they were convicted of murdering, and the race of the defendant and his victim(s) is displayed in Table 3.

Table 3

Executions in California, 1972 to Sept. 15, 2005 (N = 11)

Date	Name	Defendant Race/Ethnicity & Victim Race/Ethnicity*
04-21-92	Robert Harris	W-2W
08-24-93	David Mason**	W-5W
02-23-96	William Bonin	W-4W
05-03-96	Keith Williams	W-3L
07-14-98	Thomas Thompson	W-W
02-09-99	Jaturun Siripongs***	A-2A
05-04-99	Manny Babbitt	B-W
03-15-00	Darrell Keith Rich	N-2W
03-27-01	Robert Massie**	W-W
01-29-02	Stephen Anderson	W-W
01-19-05	Donald Beardslee	W-2W

* W = White; L = Hispanic; A = Asian; B = African American; N = Native American

** Consensual

*** Foreign National

31. NAACP LEGAL DEFENSE AND EDUCATIONAL FUND, INC., *supra* note 29, at 29.

32. *See* Death Penalty Information Center, http://www.deathpenaltyinfo.org (follow "Execution Database" hyperlink and search for California executions) (last visited Oct. 5, 2005).

	White Victim	Asian Victim	Hispanic Victim
White Defendant	7	-	1
African American Defendant	1	-	-
Native American Defendant	1	-	-
Asian Defendant	-	1	-

The table shows there were seven white defendants executed, one African American, one Hispanic, one Asian, and one Native American.[33] Of the eleven, nine were convicted of killing non-Hispanic whites, one was convicted of killing an Asian, and one was convicted of killing a Hispanic.[34] Seven (63.6%) of those executed were convicted of multiple murders.[35] Two (18%) dropped their appeals and asked to be executed.[36] Seven white inmates, one African American inmate, and one Native American inmate were executed for killing whites.[37] One white inmate was executed for killing three Hispanics, and one Asian was executed for killing two other Asians.[38] Despite the California Health Department data indicating that just 27.6% of the murder victims in the state are white,[39] 82% (9) of those executed were put to death for killing whites.[40] While one cannot generalize from eleven cases, the pattern raises the question of whether a victim's race is inappropriately associated with decisions to impose the death penalty in California.

We now turn our attention to a review of previous research that has investigated patterns in death sentencing in California.

33. *See supra* tbl.3.
34. *Id.*
35. *Id.*
36. *See* Death Penalty Information Center, *supra* note 32.
37. *See* NAACP LEGAL DEFENSE AND EDUCATIONAL FUND, INC., *supra* note 29, at 10.
38. *Id.*
39. *See* CAL. CTR. FOR HEALTH STATISTICS, *supra* note 22, at 6 tbl.2.
40. *See supra* tbl.3.

D. Research on Race, Arbitrariness, and Death Sentencing in California

The possibility of racial bias in California death sentencing has attracted the attention of several researchers over the past four decades. However, only one major study was conducted on pre-*Furman* jury decisions in California capital cases.[41] The study examined 238 cases between 1958 and 1966 in which California juries decided whether to impose death on defendants convicted of first-degree murder. The death penalty was actually imposed in 103 of the cases. The study found that the defendant's race was uncorrelated with whether or not the death penalty was imposed, but that the economic status of the defendant was strongly associated with death sentencing; "blue-collar" defendants were much more likely to be sentenced to death than those from "white-collar" backgrounds.[42]

Other research projects have focused on the question of whether death sentencing is either predictable or arbitrary, although few researchers have examined the possibility that race may affect decisions in the processing of California homicide cases under the death penalty statute now in force. Only one research project has focused specifically on the possible impact of race.[43]

Stephen P. Klein and John E. Rolph, researchers at the Rand Corporation, prepared that study for the California Attorney General and the Los Angeles County District Attorney.[44] Their work, however, did not examine prosecutorial decisions. Instead, it examined 496 cases in which the prosecutors had charged special circumstances and the defendants had been convicted of first-degree murder.[45]

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41. Special Issue, *A Study of the California Penalty Jury in First-Degree-Murder Cases*, 21 STAN. L. REV. 1297 (1969).

42. *Id.*

43. Stephen P. Klein & John E. Rolph, *Relationship of Offender and Victim Race to Death Penalty Sentences in California*, 32 JURIMETRICS J. 33 (1991).

44. *Id.*

45. *Id.* Because prosecutors make a range of discretionary decisions before conviction, the Klein and Rolph study is vulnerable to criticism of sample selection bias. For example, their methodology is unable to detect any racial or ethnic disparities that may result when prosecutors decide not to seek the death penalty for those accused of the murders of African American victims less frequently than for those accused of the murders of whites. Such disparities also go undetected when, having charged one or more special circumstances that make the defendant eligible for the death penalty, prosecutors later

Thus, Klein and Rolph's research focused only on penalty trial sentencing decisions, almost all of which are made by juries.[46] The study began with homicides committed on August 10, 1977 (the date that California's death penalty statute took effect).[47] Only defendants under a sentence of death or life without parole on March 1, 1984, were included in the sample.[48] In the end, 352 inmates (71%) were sentenced to life without parole, and 144 (29%) were sent to death row.[49]

Klein and Rolph's analysis divided the cases into white and non-white victims and defendants, omitting further racial/ethic distinctions.[50] Initially they found a small race-of-victim difference. Thirty-two percent of defendants with white victims were sentenced to death, compared to 23% of those with non-white victims.[51]

The authors then constructed a statistical model that utilized several factors to predict whether the defendants would be sentenced to life without parole or to death.[52] The model correctly predicted the sentence in 81% of the cases in the sample.[53] Because 71% of defendants in the sample were sentenced to life without parole,[54] however, the model increased predictability only slightly.[55] Of the 144 defendants sentenced to death, the authors' model predicted a death sentence in less than half (70) of the cases.[56] Upon statistically controlling for legally relevant variables,[57] the authors concluded that neither the victim's nor the

negotiate a plea agreement and thereby remove the death penalty as a possible sentence.

46. *Id.* at 34.

47. *Id.* at 45.

48. *Id.*

49. *See* Klein & Rolph, *supra* note 43, at 41 tbl.2.

50. *Id.* at 37.

51. *Id.*

52. For a list of factors utilized, see *id.* at 47-48 app. b.

53. *Id.* at 41 tbl.2.

54. *See* Klein & Rolph, *supra* note 43, at 41 tbl.2. This table reports that 352 people (330 plus 22) in the sample of 496, or 71%, were sentenced to life without the possibility of parole. *Id.*

55. *Id.* at 41.

56. The authors' model predicted a death sentence in 70 out of 144 cases in which the death penalty was actually imposed. *Id.* at 41 tbl.2 (1991).

57. For example, Klein and Rolph included measures of the offender's prior criminal record, the offender-victim relationship, and whether or not the murder involved torture. *Id.* at 47-48.

defendant's race had any impact on death sentencing.[58]

A study by Richard Berk, Robert Weiss, and Jack Boger examined 363 homicides (excluding vehicular homicides) from San Francisco County that occurred between 1978-1988.[59] This study focused on identifying the cases in which prosecutors were most likely to seek the death penalty (that is, cases in which special circumstances were charged).[60] The researchers were more interested in the consistency (or inconsistency) of prosecutorial decisions than in race.[61] While no attempt was made to identify which cases were the most aggravated, its data revealed that special circumstances were charged in 27 of the 363 cases (7.4%).[62] After statistically controlling for the victim's sex, the defendant's prior criminal record (number of prior serious felonies and number of prior homicides), the number of victims, and the victim-defendant relationship, the authors found that the odds of being charged with special circumstances were 4.8 times higher for white defendants than defendants of other races, and 3.66 times higher for those who killed women rather than men.[63] Overall, the study concluded that there is systematic capriciousness in the prosecutors' charging decisions.[64]

Raymond Paternoster challenged this conclusion, arguing that the Berk, Weiss, and Boger data showed a "rough consistency" in the processing of homicide defendants.[65] He noted that more culpable defendants generally have increased

58. *Id.* at 44. This conclusion has been criticized. David Baldus and his colleagues argued that Klein and Rolph may have overlooked a statistically significant race-of-victim disparity because they used a statistical method ("CART") that could not capture the full effects of race. *See* David C. Baldus, George Woodworth, David Zuckerman, Neil Alan Weiner & Barbara Broffitt, *Racial Discrimination and the Death Penalty in the Post-*Furman *Era: An Empirical and Legal Overview, with Recent Finds From Philadelphia*, 83 CORNELL L. REV. 1638, 1665-66 n.80 (1998) (criticizing the statistical analysis used in the Klein and Rolph study).

59. Richard A. Berk, Robert Weiss & Jack Boger, *Chance and the Death Penalty*, 27 LAW & SOC'Y REV. 89, 100-08 (1993).

60. *Id.* at 100.

61. *See id.* at 91-92.

62. *Id.* at 100.

63. *Id.* at 101-02. Because of the diversity of victims' races in the sample, the authors were unable to isolate effects for victims' races. *Id.* at 102 n.4.

64. *See* Berk et al., *supra* note 59, at 106-08.

65. Raymond Paternoster, *Assessing Capriciousness in Capital Cases*, 27 LAW & SOC'Y REV. 111, 113-14 (1993).

odds of being charged with special circumstances[66] and concluded that

> [t]here are apparent and meaningful distinctions between those who are more likely to be charged with a capital offense and those who are less likely to be so charged. The capital charging system at work in San Francisco does not operate like a pure or traditionally conceived lottery but instead *tends* to produce just results in the sense of treating different cases differently and like cases comparably.[67]

Instead of substantial capriciousness, Paternoster argued that the unexplained variance in charging decisions could be a product of variables not measured by the researchers.[68] In response, Berk, Weiss, and Boger rejected this hypothesis, pointing out that Paternoster had no evidence to support the hunch that unmeasured variables could explain the disparities.[69] In the end, the authors suggested that their disagreement boils down to a question of what sorts of capriciousness are acceptable.[70]

In a later paper, Robert Weiss, Richard Berk, and Catherine Lee extended their analysis by examining data on 427 San Francisco homicides during the period between 1986 through 1993.[71] They concluded that about two-thirds of the variation in charging could be explained; the remaining one-third was random or capricious.[72]

II. METHODOLOGY AND DATA SOURCES

To examine the possible relationship between racial and ethnic traits and the imposition of the death penalty in California, we examined the characteristics of all those sentenced to death in the state before March 15, 2003, for

66. *Id.* at 119.
67. *Id.* (emphasis added).
68. *Id.* at 113-14.
69. Richard A. Berk, Robert Weiss & Jack Boger, *Rejoinder*, 27 LAW & SOC'Y REV. 125, 126 (1993).
70. *See id.* at 125-27.
71. Robert E. Weiss, Richard A. Berk & Cathrine Y. Lee, *Assessing the Capriciousness of Death Penalty Charging*, 30 LAW & SOC'Y REV. 607, 607-08 (1996).
72. *See id.* at 621. They found further evidence that "if the victim is white or Asian (compared to African American or Latino), the odds of a capital charge are about four times larger." *Id.* at 619.

homicides that occurred between January 1, 1990, and December 31, 1999. We selected the decade of the 1990s so we could examine the most recent patterns of death penalty sentencing in California. The 1990s were also chosen because we assumed that trials for virtually all identified offenders in the decade had concluded by the time our data were collected.[73] We believe that any unconsidered death penalty cases for murders committed during the 1990s will not affect our ultimate conclusions.[74]

A. *Death Penalty Data Set*

Because no public agency in California collects detailed information on who is sentenced to death, the first challenge of this research project was to construct a Death Penalty Data Set. We began with a small data base compiled by the California Department of Corrections.[75] This source gave basic information about every inmate currently on death row, including name, age, sex, race/ethnicity, date of sentence, date of offense, and county of commitment.[76] We also obtained information from a private data base maintained by the California Appellate Project in San Francisco.[77] Their files were used to supplement and check the reliability of the Department of Corrections list, and allowed us to include cases where defendants had been sentenced to death for murders during the 1990s but were, for whatever reason, no longer on death row.[78] The California Appellate Project's files

73. It is likely, of course, that a small number of homicide prosecutions for murders committed in the 1990s were not completed as of March 15, 2003, as on that date some defendants may still have been awaiting capital trials, and some offenders might not even have been identified or arrested yet.

74. That is, there is no reason to believe that any death sentences that may result from 1990-1999 murders that were unresolved or pending prosecution as of March 15, 2003, are correlated with the defendants' or victims' race/ethnicity.

75. *See* CAL. DEP'T OF CORR., DEATH ROW TRACKING SYSTEM: CONDEMNED INMATE LIST, http://www.cdc.state.ca.us/CommunicationsOffice/CapitalPunishment/PDF/InmateSecured.pdf (Oct. 20, 2005) [hereinafter CONDEMNED INMATE LIST].

76. *Id.*

77. The California Appellate Project is a non-profit law office established by the State Bar of California that primarily assists private attorneys appointed in death penalty appeals and state habeas proceedings. *See* Welcome to California Appellate Project of San Francisco, http://www.capsf.org/Welcome5.html (follow "About CAP" hyperlink) (last visited Oct. 4, 2005).

78. The California Department of Corrections supplies information only for inmates currently on death row. We obtained information on former death row

also allowed us to determine the number of victims per defendant and whether the homicides that sent the defendants to death row were accompanied by additional felonies.[79]

Where discrepancies were found, we resolved them through newspaper searches or phone interviews with attorneys involved in the case. While the California Department of Corrections gives information on the race/ethnicity of all death row inmates, it does not provide data on the race/ethnicity of the victim(s) whom the death row inmate was convicted of killing.[80] In some cases, we found a picture of the victim or a newspaper article that clearly identified the victim's race and ethnicity. For other death row inmates, we obtained the information from attorneys familiar with the case. In 187 cases, we purchased a copy of the victim's or victims' death certificate(s), allowing us to determine race/ethnicity directly from that source.

Using this methodology, we were able to identify 302 individuals sentenced to death in California for homicides that occurred in the 1990s. To measure race and ethnicity, we first determined whether or not the defendant was Hispanic, and, if not, whether his or her race was white, African American, or other. For our analysis of racial and ethnic variations in the imposition of the death penalty, we eliminated thirty-nine cases where a person was sentenced to death for multiple murders that took the lives of victims from different races or ethnic groups. Consequently, our study focuses on 263 death penalty cases. For our examination of geographic variations in the imposition of the death penalty, all 302 death sentences were included in the analysis.

B. *Homicide Data*

We gathered information on all California homicides that occurred between 1990 and 1999 from two sources: the Federal Bureau of Investigation's (FBI) Supplementary

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inmates from the California Appellate Project. This group of former inmates includes individuals who died after being sentenced to death (regardless of the cause of death) and those who had their convictions or sentences reversed and were not subsequently re-sentenced to death. *See id.*

79. For example, robbery, rape, etc.

80. *See* CONDEMNED INMATE LIST, *supra* note 75.

Homicide Reports (SHR)[81] and homicide data from death certificates collected by the Office of Vital Records, a subdivision of the California Department of Health Statistics.[82] Each data set includes a slightly different set of homicide cases and variables. Data were obtained from the two sources to cross check the consistency of race and ethnicity information.

1. *Supplementary Homicide Reports*

Supplementary Homicide Reports are compiled from local police departments throughout the United States that report data on homicides either through their state crime reporting programs or directly to the FBI for inclusion in the FBI's Uniform Crime Reports.[83] While the Reports do not list the defendants' or victims' names, they do include the following information: the month, year, and county of the homicide, the age, gender, race, and ethnicity of the suspects and victims, the victim-defendant relationship, the weapon used, and information on circumstances surrounding a victim's death, which includes whether a homicide was accompanied by additional felonies (e.g., robbery or rape).[84] Local law enforcement agencies usually report these data long before the defendant has been convicted, so offender data are for "suspects," not convicted offenders.[85]

The FBI defines murder and non-negligent manslaughter[86] as:

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81. The Supplementary Homicide Report is a reporting form for police departments, provided by the FBI's Uniform Crime Reporting Program,, "designed to collect additional details regarding the murder victim and offender, their relationship to one another, the weapon used, and the circumstances in each criminal homicide." FED. BUREAU OF INVESTIGATION, UNIFORM CRIME REPORTING HANDBOOK 104 (2004), http://www.fbi.gov/ucr/handbook/ucrhandbook04.pdf [hereinafter UNIFORM CRIME REPORTING HANDBOOK].

82. *See* CAL. CTR. FOR HEALTH STATISTICS, CAL. DEP'T OF HEALTH SERVS., ORGANIZATION, http://www.dhs.ca.gov/hisp/chs/default.htm (last visited Oct. 4, 2005).

83. *See* NAT'L ARCHIVE OF CRIMINAL JUSTICE DATA, LEARN MORE ABOUT THE SUPPLEMENTARY HOMICIDE REPORTS, http://www.icpsr.umich.edu/NACJD/SDA/shr7699d.html (last visited Oct. 4, 2005).

84. UNIFORM CRIME REPORTING HANDBOOK, *supra* note 81, at 104-07.

85. *See id.*

86. FED. BUREAU OF INVESTIGATION, CRIME IN THE UNITED STATES 2003: OFFENSES IN UNIFORM CRIME REPORTING, § VII, app. II, at 497 (2004),

> [t]he willful (non-negligent) killing of one human being by another. (Deaths caused by negligence, attempts to kill, assaults to kill, suicides, and accidental deaths are excluded. The Program classifies justifiable homicides separately and limits the definition to: (1) the killing of a felon by a law enforcement officer in the line of duty; or (2) the killing of a felon, during the commission of a felony, by a private citizen.)[87]

As the Bureau of Justice Statistics notes, "The classification of this offense is based solely on police investigation as opposed to thedetermination of a court, medical examiner, coroner, jury, or other judicial body."[88]

2. *Office of Vital Statistics*

Vital Statistics mortality data are also collected nationally as part of a mandatory reporting program.[89] As described by the National Center for Health Statistics:

> [i]n the United States, state laws require death certificates to be completed for all deaths, and federal law mandates national collection and publication of deaths and other vital statistics data. The National Vital Statistics System is the result of the cooperation between CDC and the states to provide access to statistical information from death certificates. Mortality data are used to monitor the underlying and contributing causes of death for persons dying in the United States and to determine life expectancy.[90]

Thus, because state law mandates their collection, Vital Statistics data are an excellent source of information for

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available at http://www.fbi.gov/ucr/cius_03/pdf/03sec7.pdf (last visited Nov. 1, 2005).

87. BUREAU OF JUSTICE STATISTICS, U.S. DEP'T OF JUSTICE, HOMICIDE TRENDS IN THE U.S.: ADDITIONAL INFORMATION ABOUT THE DATA, http://www.ojp.usdoj.gov/bjs/homicide/addinfo.htm (last visited Oct. 4, 2005).

88. FED. BUREAU OF INVESTIGATION, UNIFORM CRIME REPORTS, CRIME IN THE UNITED STATES—2004, http://www.fbi.gov/ucr/cius_04/offenses_reported/violent_crime/murder.html (last visited Nov. 1, 2005).

89. *See generally* NAT'L CTR. FOR HEALTH STATISTICS, CTRS. FOR DISEASE CONTROL & PREVENTION, MORTALITY DATA FROM THE NATIONAL VITAL STATISTICS SYSTEM, http://www.cdc.gov/nchs/about/major/dvs/desc.htm (last visited Nov. 1, 2005).

90. CTRS. FOR DISEASE CONTROL & PREVENTION, MORBIDITY AND MORTALITY WEEKLY REPORT: INDICATORS FOR CHRONIC DISEASE SURVEILLANCE (Sept. 10, 2004), http://www.cdc.gov/mmwr/preview/mmwrhtml/rr5311a1.htm.

deaths caused by homicide. They are also a more comprehensive source of data than the inconsistent or incomplete FBI data.

A state's department of public health or equivalent agency typically collects mortality data.[91] In California, the designated agency is the Office of Vital Records, which is part of the California Department of Health Services.[92] The California Department of Public Health defined "homicide" according to the International Classification of Disease's ninth (ICD-9[93]) and tenth (ICD-10[94]) revisions.[95] Under both classification systems, "homicide" includes death from injuries inflicted with intent to injure or kill, by any means,

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91. According to the National Center for Health Statistics:

> The National Vital Statistics System is the oldest and most successful example of inter-governmental data sharing in Public Health and the shared relationships, standards, and procedures form the mechanism by which NCHS collects and disseminates the Nation's official vital statistics. These data are provided through contracts between NCHS and vital registration systems operated in the various jurisdictions legally responsible for the registration of vital events—births, deaths, marriages, divorces, and fetal deaths. In the United States, legal authority for the registration of these events resides individually with the 50 States, 2 cities (Washington, DC, and New York City), and 5 territories (Puerto Rico, the Virgin Islands, Guam, American Samoa, and the Commonwealth of the Northern Mariana Islands). These jurisdictions are responsible for maintaining registries of vital events and for issuing copies of birth, marriage, divorce, and death certificates.

NAT'L CTR. FOR HEALTH STATISTICS, CTRS. FOR DISEASE CONTROL & PREVENTION, NATIONAL VITAL STATISTICS SYSTEM, http://www.cdc.gov/nchs/nvss.htm (last visited Nov. 1, 2005).

92. *See* OFFICE OF VITAL RECORDS, CAL. DEP'T OF HEALTH SERVS., OFFICE OF VITAL RECORDS INDEX PAGE, http://www.dhs.ca.gov/hisp/chs/OVR/default.htm.

93. *See* NAT'L CTR. FOR HEALTH STATISTICS, CTRS. FOR DISEASE CONTROL & PREVENTION, MORTALITY DATA FROM THE NATIONAL VITAL STATISTICS SYSTEM: INTERNATIONAL CLASSIFICATION OF DISEASES, NINTH REVISION (ICD-9), http://www.cdc.gov/nchs/about/major/dvs/icd9des.htm (last visited Oct. 4, 2005).

94. *See* NAT'L CTR. FOR HEALTH STATISTICS, CTRS. FOR DISEASE CONTROL & PREVENTION, MORTALITY DATA FROM THE NATIONAL VITAL STATISTICS SYSTEM: INTERNATIONAL CLASSIFICATION OF DISEASES, TENTH REVISION (ICD-10), http://www.cdc.gov/nchs/about/major/dvs/icd10des.htm (last visited Oct. 27, 2005).

95. OFFICE OF HEALTH INFORMATION AND RESEARCH, CAL. DEP'T OF HEALTH SERVS., DEATH PROFILES BY ZIP CODE, CALIFORNIA: 1989-2003, http://www.dhs.ca.gov/hisp/chs/OHIR/tables/death/zipcode.htm (last visited Oct. 27, 2005). *See also* Robert N. Anderson et al., *Comparability of Cause of Death Between ICD-9 and ICD-10: Preliminary Estimates*, 49 NAT'L VITAL STAT. REP. (No. 2, May 18, 2001), *available at* http://www.cdc.gov/nchs/data/nvsr/nvsr49/nvsr49_02.pdf (describing the differences between ICD-9 and ICD-10).

but excludes injuries due to legal intervention (ICD-9 codes E970-E978) and operations of war (ICD-9 codes E990-E999).[96]

3. *Comparing Definitions of Homicide*

The FBI and International Classification of Disease/National Center for Health Statistics definitions of homicide differ to the degree that the latter excludes deaths due to legal intervention initiated by actions of law enforcement officers, whereas the former excludes justifiable homicides[97] by both law enforcement officers and non-law enforcement civilians (hereinafter "private citizens"). Thus, NCHS include a relatively small number of justifiable homicides by private citizens, whereas FBI statistics exclude such homicides.

The FBI's definition excludes justifiable homicides committed by private citizens, and its data have the key advantage of providing general information on the circumstances surrounding homicides and on the suspected offenders.[98] Because the FBI data give some details about the homicide, they are particularly valuable for estimating the number of defendants who might be the target of death penalty prosecutions. On the other hand, Vital Statistics homicide data provide somewhat more accurate measures of homicides committed because the collection of death certificate information is mandated by law, and detailed procedures governing the collection of data have been in place for over a century.[99] In the end, the availability of data from these two sources allowed us to cross-validate homicide information obtained from each.[100]

To refine the accuracy of the data on estimated numbers of offenders obtained from FBI data, we adjusted the FBI

96. *See* Anderson et al., *supra* note 95; DEP'T OF BIOMEDICAL INFORMATICS, COLUMBIA UNIV., HOMICIDE AND INJURY PURPOSELY INFLICTED BY OTHER PERSONS (E960-E969), http://www.dmi.columbia.edu/hripcsak/icd9/1tabularE960.html. For a list of ICD-9 codes, see EPICENTER, CAL. DEP'T OF HEALTH SERVS., HELP WITH ICD 9 AND 10 CODES, http://www.applications.dhs.ca.gov/epicdata/help/icd.htm#definitions (last visited Oct. 27, 2005).

97. The FBI category of "justifiable homicide" is comparable to the ICD category of "legal intervention."

98. *See supra* notes 79-80 and accompanying text.

99. *See supra* notes 89-90 and accompanying text.

100. *See* discussion *infra* app. a.

data using Vital Statistics data on homicide victims. This procedure allowed us to correct for some small underreporting of homicides in the FBI data, as well as for missing data on race/ethnicity.[101] To weight the FBI data, for each race/ethnicity combination of homicide victims we divided the total number of homicides in the Vital Statistics data with the total number in the FBI data. The weighting procedure is described in detail in Appendix A.

III. RESULTS

A. *Victim Race and Ethnicity Effects*

Vital Statistics data originate from death certificates and, therefore, give information only on victims, not on offenders.[102] As such, they can be used to calculate probabilities of death sentences for different race and ethnic categories of homicide victims. Table 4 presents these probabilities for different categories of race and ethnicity by using 1990-1999 Vital Statistics victim data to show that death sentences in California are rarely given; less than 1% of all homicides result in a death sentence.[103] While the overall number of death sentences is low (302), there are glaring differences in the rate of death sentences across categories of victim race/ethnicity.[104] Defendants convicted of killing non-Hispanic white victims receive the death penalty at a rate of 1.75 per 100 hundred victims,[105] compared to a rate of .47 for defendants convicted of killing non-Hispanic African American victims.[106] Thus, homicides involving non-Hispanic white victims are 3.7 times as likely to result in a death sentence than those with non-Hispanic African American victims.[107] The death sentencing rate for those with Hispanic victims is .369, indicating that white victim homicides are 4.73 times as likely to result in death as Hispanic victim cases.[108]

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101. *See id.*
102. *See* OFFICE OF VITAL RECORDS, *supra* note 92.
103. *See infra* tbl.4.
104. *See id.*
105. *Id.*
106. *Id.*
107. *Id.*
108. *Id.*

Table 4

Death Sentence Rates per 100 Victims and Inter-group Ratios (Vital Statistics Data)

Race/Ethnicity of Victim	Vital Statistics Victims	Defendants Sentenced to Death	Death Sentence Rate Per 100 Victims	Ratio of White Victim/Other Victim Death Sentence Rate
White non-Hispanic	8136	142	1.745	——
African American non-Hispanic	9338	44	.471	3.70
Hispanic	14,089	52	.369	4.73
Other race, non-Hispanic	2037	25	1.227	1.42
Multiple Race/ Ethnicity Incidents		39		
Unknown	314			
TOTAL	33,914	302	.890	

Chi Square = 144.968; df = 3; $p < .001$.
This Chi Square is calculated only for the four categories of race/ethnicity that are identified (i.e., white non-Hispanic, African American non-Hispanic, Hispanic, and other race, non-Hispanic).

We now shift attention to the FBI's Supplementary Homicide Reports' offender data. FBI data list one case per homicide suspect and give us information about the race/ethnicity of both the suspect and the suspect's victim(s).[109] Thus, cases in which a suspect was not identified by the local law enforcement agency are excluded from this analysis. Since the Death Penalty Data Set is offender-based (that is, one case per defendant sentenced to death), the FBI database allows us to compare information collected by law enforcement on all homicide suspects with information on all defendants sentenced to death. Tables 5 and 6 use FBI

109. *See supra* notes 79-80 and accompanying text. Reference materials for each year of the FBI Supplementary Homicide Reports used in this study are available at NAT'L ARCHIVE OF CRIMINAL JUSTICE DATA, INTER-UNIVERSITY CONSORTIUM FOR POLITICAL AND SOC. RESEARCH, UNIFORM CRIME REPORTING PROGRAM RESOURCE GUIDE, http://www.icpsr.umich.edu/NACJD/ucr.html (last visited Oct. 4, 2005).

offender data to calculate the probabilities of receiving a death sentence based on the victim's race/ethnicity. These data have the advantage of collecting, for each homicide incident, information on the race, ethnicity, age, and gender of the suspected offender and the victim(s). A second advantage of the FBI data is that they provide information on some (though not all) of the most important legally relevant factors in death sentencing decisions. Specifically, the data provide information on the number of victims associated with a given homicide incident and on the felony circumstances (e.g., rape or robbery) associated with the homicide.[110] The latter information enables us to develop measures of the potential aggravating circumstances associated with homicide incidents contained in the FBI data.

Table 5

Death Sentence Rates per 100 Offenders and Inter-group Ratios by Race/Ethnicity of the Victim
(SHR Offender Data, Weighted Sample)

Race of Victim	SHR Offenders	Offenders Sentenced to Death	Death Sentence Rate per 100 Offenders	Ratio of White Victim/Other Victim Rate
White non-Hispanic	6775	142	2.096	—
African American non-Hispanic	6484	44	.679	3.09
Hispanic	10,749	52	.484	4.33
Other race, non-Hispanic	1667	25	1.500	1.40
TOTAL	25,675	263		

Chi Square = 119.079; df = 3; $p < .001$.

Tables 5 and 6 present death sentence rates by the race and ethnicity of victims using weighted FBI homicide offender data. Table 5 shows that 2.1% of the offenders suspected of killing non-Hispanic whites were sentenced to death, compared to .68% of those suspected of killing non-Hispanic African American, .48% of those suspected of killing

110. *See infra* tbl.6.

Hispanics, and 1.5% of those suspected of killing non-Hispanics of other races. The last column of Table 5 compares these rates. It shows that the probability of a death sentence for those who kill non-Hispanic whites is 3.09 times higher than those suspected of killing non-Hispanic African Americans and 4.33 times higher than those suspected of killing Hispanics.[111] The Chi Square figure tells us that the probability of obtaining these results by chance is less than one out of 1000.[112] Therefore, the data in Table 5 further support the hypothesis that death sentencing in California is correlated with the race/ethnicity of the homicide victim.

The increased likelihood of being sentenced to death for killing white victims may be explained by the theory that such homicides are more "aggravated" or "deserving of the death penalty" than homicides that victimize Hispanics and non-whites. Table 6 tests this hypothesis. Here we divide the homicides in Table 5 into three categories: those with no aggravating circumstances, those with one aggravating circumstance, and those with two aggravating circumstances.[113] If homicides that victimize whites are indeed more aggravated than other homicides, death sentencing rates will be similar across each category of victim race/ethnicity for each level of aggravation.

As noted, information on two types of aggravating circumstances is available in both the FBI data and the Death Penalty Data Set. The first aggravating circumstance is whether the homicide had an accompanying felony. The second is whether the homicide incident involved more than one victim. If a homicide offender in the FBI data or the Death Penalty Data Set committed a felony along with a homicide *or* was suspected of killing more than one victim, they were coded as having one aggravating circumstance. Likewise, if such a person was suspected of committing a felony along with a homicide *and* there was more than one homicide victim, they were coded as having two aggravating circumstances. Finally, if the offender was involved in neither of the circumstances, he or she was coded as having no aggravating circumstances identified by our measures.

111. *See supra* tbl.5.
112. *Id.*
113. *See infra* tbl.6.

These two circumstances are among the most common types of aggravating circumstances used by prosecutors, jurors, and judges to justify death sentences.[114]

Table 6

Death Sentence Rates per 100 Offenders and Inter-group Ratios by Race/Ethnicity of the Victim, Controlling for Aggravating Circumstances
(SHR Offender Data, Weighted Sample)

Race of Victim	SHR Offenders	Offenders Sentenced to Death	Death Sentence Rate per 100 Offenders	Ratio of White Victim/Other Victim Rate
With No Aggravating Circumstances				
White non-Hispanic	4775	37	.775	——
African American non-Hispanic	4909	5	.102	7.60
Hispanic	8576	6	.070	11.07
Other race, non-Hispanic	1127	5	.444	1.75
TOTAL	19,387	53		
For above data, Chi Square = 63.560; df = 3; p < .001.				
With One Aggravating Circumstance				
White non-Hispanic	1930	88	4.560	——
African American non-Hispanic	1501	30	1.999	2.28
Hispanic	2085	33	1.583	2.88
Other race, non-Hispanic	503	16	3.181	1.43
TOTAL	6019	167		
For above data, Chi Square = 37.433; df = 3; p < .001.				

114. Shatz and Rivkind, for example, argue that the most important special circumstance in California is "felony murder," which they found in 116 of the 157 cases (73.9 percent) in their sample where a death sentence was imposed. *See* Shatz & Rivkind, *supra* note 4, at 1329. In our Illinois research, we found that the number of homicide victims remained one of the strongest predictors of a death sentence, controlling for other legally relevant and legally irrelevant factors. *See* Glenn L. Pierce & Michael L. Radelet, *Race, Region, and Death Sentencing in Illinois, 1988-1997*, 81 OR. L. REV. 39, 95 tbl.31a (2002).

Race of Victim	SHR Offenders	Offenders Sentenced to Death	Death Sentence Rate per 100 Offenders	Ratio of White Victim/Other Victim Rate
With Two Aggravating Circumstances				
White non-Hispanic	70	17	24.286	——
African American non-Hispanic	74	9	12.162	2.00
Hispanic	88	13	14.773	1.64
Other race, non-Hispanic	37	4	10.811	2.25
TOTAL	269	43		
For above data, Chi Square = 5.230; df = 3; p = .156.				

The Chi Square for the 2X2 version of this sub-table with race/ethnicity grouped into two categories (white non-Hispanic and other) is Chi Square = 4.854; df = 1; p = .028.

The results displayed in Table 6 do not support the hypothesis that death sentencing rates in cases involving white victims are higher because such homicides are more aggravated. The table shows that if we compare death sentencing rates for those who kill non-Hispanic whites and non-Hispanic African Americans, strong differences persist even across different levels of aggravation.[115] Where there are no aggravating circumstances in existence, those who kill non-Hispanic whites are 7.6 times as likely to be sentenced to death as those who kill non-Hispanic African Americans.[116] Where there is one aggravating circumstance present, those who kill non-Hispanic whites are 2.28 times as likely to be sentenced to death as those who kill non-Hispanic African Americans.[117] Where two aggravating circumstances exist, the ratio is 2.00.[118] Similar differences are present when death sentencing rates for those who kill non-Hispanic whites are compared to those who kill Hispanics or non-Hispanic victims of "other" races.[119] Thus, among homicides with two

115. *See supra* tbl.6.
116. *Id.*
117. *Id.*
118. *Id.*
119. *Id.*

aggravating circumstances, the death sentencing rate for non-Hispanic whites is 24.29, which is much higher than the rate for all other categories combined (26/199, or 13.07).[120]

Appendix B contains further analysis focusing on the race of the defendant. This analysis shows that overall, non-Hispanic white defendants are more likely than other murder suspects to be sentenced to death.[121] However, because almost all murders done by whites take the lives of white victims, the race-of-defendant effect, which becomes statistically insignificant in the case of African American victims, is reversed in the case of white victims. That is, blacks who kill whites are more likely to be sentenced to death than whites who kill whites.[122] The likelihood of receiving a death sentence remains higher for white defendants only in the case of Hispanic victims, where a relatively small number of white suspects appear more likely to receive a death sentence.[123] In summary, the race of defendant relationship, where white suspects appear to have higher probabilities of receiving the death sentence, essentially disappears when it is examined in conjunction with the race of the victim.

B. *Regional Effects*

We now turn our attention to geographic patterns of death sentencing. According to the California Department of Corrections, on January 28, 2004, ten of California's fifty-eight counties had sixteen or more inmates under a sentence of death.[124] These counties and the number of death row inmates they had sentenced as of that date are listed in Table 7. By far, the county with the highest number of inmates sentenced to death is Los Angeles, with almost four times as many death row inmates as any other county in the state.[125]

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120. This difference is statistically significant at the .05 level.

121. *See infra* app. b, tbl.b-1.

122. *See infra* app. b, tbl.b-2.

123. *See infra* app. b, tbl.b-3.

124. A more current version of this list with data through Oct. 20, 2005, can be found by examining CONDEMNED INMATE SUMMARY LIST, *supra* note 29, and CONDEMNED INMATE LIST, *supra* note 75. Interested readers can obtain the Jan. 28, 2004, list by deleting those sentenced after January 28, 2005, from the current list.

125. *See infra* tbl.7.

Table 7

Top Ten Death-Sentencing Counties
(Measured by Number of Inmates on Death Row, Jan. 28, 2004)[126]

County	Number of Inmates on Death Row: January 28, 2004
1. Los Angeles	194
2. Riverside	54
3. Orange	49
4. Alameda	43
5. Sacramento	34
6. San Bernardino	34
7. San Diego	32
8. Santa Clara	27
9. Kern	23
10. San Mateo	16

Counting the numbers of death row inmates by county does not get us very far, however, as it is quite possible that counties with the most inmates on death row are also the counties that experienced the highest number of homicides during the 1990s. Table 8 compares death sentences to number of homicides, ordering California's fifty-eight counties based on a ratio of death sentences to homicides. In almost half the counties—twenty-eight of the fifty-eight (48.3%)—no death sentences were returned for homicides in the 1990s.[127] However, these twenty-eight counties accounted for just 5% of the homicides in the state. The only county with over 100 homicides and no death sentences was San Francisco.[128]

126. CONDEMNED INMATE SUMMARY LIST, *supra* note 29.

127. *See infra* tbl.8.

128. The current District Attorney in San Francisco, Kamala Harris, who took office in January 2004, has pledged never to seek a death sentence. Harriet Chiang, *D.A. Defends Decision Not To Seek Execution; Her Position Has Been Clear Since Campaign, She Says*, S.F. CHRONICLE, Apr. 25, 2004, at B1. Her predecessor, Terence Hallinan, never sought a death sentence in his eight years in office. Lee Romney & Carl Ingram, *Officer's Murder Divides San Francisco; Atty. Gen. Lockyer May Step In As the D.A. Refuses to Seek Death in the Killing of a Police Officer*, L.A. TIMES, May 8, 2004, at B1. Since 1979, only two defendants have been sentenced to death for murders in San Francisco. *Death Sentence Upheld in San Francisco Robbery, Killing*, METROPOLITAN NEWS-ENTERPRISE (Los Angeles), Dec. 6, 2002, at 3.

Table 8
Homicides and Death Sentences by County of Venue
(Vital Statistics Data)

County	Homicides*	Death Sentences**	Ratio
Solano	220	1	.0045
San Joaquin	643	3	.0047
Los Angeles	16,113	93	.0058
Santa Barbara	152	1	.0066
Contra Costa	846	6	.0071
San Diego	2010	15	.0075
Fresno	993	8	.0081
Merced	119	1	.0084
STATE RATIO	**33,914**	**302**	**.0089**
San Bernardino	2015	20	.0099
Madera	101	1	.0100
Alameda	1773	18	.0102
Butte	95	1	.0105
Tulare	285	3	.0105
Imperial	93	1	.0108
Monterey	325	4	.0123
San Mateo	232	3	.0129
Sacramento	1081	14	.0130
Kern	661	10	.0151
Orange	1433	23	.0161
Santa Clara	653	12	.0184
Stanislaus	317	6	.0189
Sonoma	146	3	.0205
Riverside	1310	32	.0244
Ventura	305	8	.0262
Lake	37	1	.0270
San Luis Obispo	67	2	.0299
Shasta	100	5	.0500
Napa	33	2	.0606
King	62	4	.0645
Colusa	10	1	.1000

County	Homicides*	Death Sentences**	Ratio
Counties with No Death Sentences			
Alpine	1	0	
Amador	7	0	
Calaveras	22	0	
Del Norte	24	0	
El Dorado	55	0	
Glenn	7	0	
Humboldt	78	0	
Inyo	3	0	
Lassen	23	0	
Marin	53	0	
Mariposa	10	0	
Mendocino	59	0	
Modoc	1	0	
Mono	2	0	
Nevada	25	0	
Placer	78	0	
Plumas	14	0	
San Benito	6	0	
San Francisco	910	0	
Santa Cruz	87	0	
Sierra	4	0	
Siskiyou	18	0	
Sutter	29	0	
Tehama	23	0	
Trinity	12	0	
Tuolumne	24	0	
Yolo	58	0	
Yuba	51	0	
Missing	0	0	

* County of occurrence
** County of trial

Comparing ratios of death sentences to total homicides by county can result in misleading conclusions. Because the denominators in such comparisons include all homicides, the ratios do not take into consideration variations in arrest rates across counties.[129] Vital Statistics data tell us about all homicides, regardless of whether or not the offender has been identified. In addition, the analysis of individual counties presented in Table 8 does not examine whether particular county attributes (for example, population density or racial/ethnic characteristics of the county) may account for the substantial variation we observe in county death sentencing rates. To address this issue, we used weighted FBI/SHR offender data (instead of the Vital Statistics victim data used in Table 8) to calculate death sentence rates for each county. As noted above, the FBI/SHR data only include information on offenders who are known to the police, and the police generally identify an offender at the time of—or shortly before—his or her arrest. Because many homicides are never solved by the police, comparing ratios of death sentences to known offenders per county is therefore better than comparing ratios of death sentences to the total number of homicide victims.

To determine whether county attributes help explain the observed geographic variation in death sentence rates, we examined two characteristics of California counties: the urban character of the county and the proportion of the county's non-Hispanic white residents. We focused on urban-rural differences because it has been identified as an important dimension in a number of previous studies of capital punishment.[130] This factor was measured by the county's population density. Given our interest in race, we also included a measure of the county's non-Hispanic white population to see if it had any impact on death sentencing rates. For the purpose of the regional analyses, the FBI offender estimates are tabulated by county of trial, since these locales are where sentencing decisions are made.[131]

129. For example, larger urban counties may have higher proportions of stranger-to-stranger homicides and correspondingly lower arrest rates.

130. *See, e.g.*, William J. Bowers & Glenn L. Pierce, *Arbitrariness and Discrimination Under Post-*Furman *Capital Statutes*, 26 CRIME & DELINQ. 563, 601-07 (1980); Pierce & Radelet, *supra* note 114, at 65 (reporting that in Illinois, the odds of receiving a death sentence in Cook County are 83.6% lower than the odds of receiving a death sentence for a similar homicide in other areas of the state).

131. Other factors that may explain regional variations are not measured, such as the availability of fiscal resources necessary to pursue death sentences, or political differences in prosecutorial affinity for the death penalty.

Table 9 presents a cross-classification of death sentencing rates and the population density of California counties. For this analysis, counties were grouped into three levels of density: those with population densities under 300 inhabitants per square mile, counties with between 300 and 999 inhabitants per square mile, and counties with 1000 or more inhabitants per square mile.[132] Table 9 shows that in counties with a low population density, there are 1.71 death sentences per 100 homicides. Death sentencing rates are lower for counties with a population of between 300 and 999 inhabitants per square mile,[133] and are the lowest for densely populated counties.[134] Thus, death sentencing rates are highest in counties with a low population density and lowest in densely populated counties.

Table 9

Death Sentences and Death Sentence Rate per 100 Offenders by the Population Density of California Counties for 1990 to 1999 (SHR Offender Data, Weighted Sample)

Population Density (pop. per sq. mile)	SHR Offenders	Offenders Sentenced	Rate per 100 Victims
0 – 299	6181	106	1.71
300-999	2450	27	1.10
1000 and over	17,304	169	.98
Total	25,934	302	1.16

Chi Square = 21.660; df = 2; $p < .001$.

Table 10 shows that death sentencing rates are also related to the racial makeup of California counties. This table divides counties into three groups according to the proportion of their population that is non-Hispanic whites. Where this proportion is high (50% and above), death sentencing rates are also the highest (1.75 death sentences per 100 homicides).[135] Where the non-Hispanic white population is lowest (under 40% of the total county

132. *See infra* tbl.9.
133. 1.10 death sentences per 100 victims. *Id.*
134. .98 death sentences per 100 victims. *Id.*
135. *See infra* tbl.10.

population), the death sentencing rate is also the lowest (.77 death sentences per 100 homicides).[136]

Table 10

Death Sentences and Death Sentence Rate per 100 Offenders by the Percent of County Population that is White non-Hispanic in California Counties for 1990 to 1999
(SHR Offender Data, Weighted Sample)

Percent of County Pop. White non-Hispanic	SHR Offenders	Offenders Sentenced	Rate per 100 Victims
Under 40%	13,162	102	.77
40% to 49.9%	5990	81	1.35
50% and over	6782	119	1.75
Total	25,934	302	1.16

Chi Square = 39.71; df = 2; $p < .001$.

Overall, Tables 9 and 10 support the conclusion that *death sentencing in California is highest in counties with a low population density and a high proportion of non-Hispanic white residents.* The more white and more sparsely populated the county, the higher the death sentencing rate.

136. *Id.*

C. *Logistic Regression Analysis*[137]

To examine the combined effects of region, race/ethnicity, and aggravating circumstances on death penalty decisions in California, a multivariate statistical technique was used. For the analysis of dichotomous dependent variables (such as death sentence vs. no death sentence), the appropriate statistical technique is logistic regression analysis. To conduct this analysis, we first merged our two offender data sets: the Death Penalty Data Set and the data on homicide offenders from the FBI/SHR data set. Cases were matched based on the victim's race and ethnicity, aggravating circumstances, urban character of the county of trial (under 300 inhabitants , 300 to 999 inhabitants, and 1000 and over inhabitants per square mile), and the racial and ethnic character of county of trial. Multiple victim homicide incidents with victims of differing races/ethnicities were not included in the analysis. We were unable to match one of the 263 death penalty cases with a corresponding case in the FBI/SHR data set and, consequently, we deleted that case (a homicide with one Hispanic victim).[138] This reduced the

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137. As we have explained elsewhere,

> [l]ogistic regression models estimate the average effect of each independent variable (predictor) on the odds that a convicted felon would receive a sentence of death. An odds ratio is simply the ratio of the probability of a death sentence to the probability of a sentence other than death. Thus, when one's likelihood of receiving a death sentence is .75 (P), then the probability of receiving a non-death sentence is .25 (1-P). The odds ratio in this example is .75/.25 or 3 to 1. Simply put, the odds of getting the death sentence in this case is 3 to 1. The dependent variable is a natural logarithm of the odds ratio, y, of having received the death penalty. Thus, y=P / 1-P and (1) ln(y) = $\hat{a}_o$ + X$\hat{a}$ + $_i$ where $\hat{a}_o$ is an intercept, $\hat{a}_i$ are the i coefficients for the i independent variables, X is the matrix of observations on the independent variables, and $_i$ is the error term.
>
> Results for the logistics model are reported as odds ratios. Recall that when interpreting odds ratios, an odds ratio of one means that someone with that specific characteristic is just as likely to receive a capital sentence as not. Odds ratios of greater than one indicate a higher likelihood of the death penalty for those offenders who have a positive value for that particular independent variable. When the independent variable is continuous, the odds ratio indicates the increase in the odds of receiving the death penalty for each unitary increase in the predictor.

Pierce & Radelet, *supra* note 114, at 59.

138. The lack of a matching case in the SHR data set occurs because of either a failure of the police to report the homicide to the SHR reporting program or the reporting of a case missing several variables needed for matching.

number of death penalty cases in our data to 262.

Other researchers who have used this matching method have also found minor problems in matching. Samuel Gross and Robert Mauro, for example, note that, "[o]ften 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."[139]

Finally, we weighted the merged FBI/SHR offender and Death Penalty Data Set using the same methods (i.e., weights derived from vital statistics data) used in the tabular analyses. Here, however, we did not weight the 262 offenders in death penalty cases because each case represents only one offender sentenced to death after one trial, making re-weighting unnecessary. These 262 cases were therefore assigned a weight of "one."

Table 11 presents the results of the logistic regression analysis. The independent variables are all entered into the analysis as dichotomous measures. Thus, where there were no aggravating circumstances or one aggravating circumstance, such data were entered as dichotomous variables. Cases with two aggravating circumstances were left out of the equation so they could be used as the reference or comparison category. Similarly, variables measuring the race and ethnicity of victims were entered into the analysis as dichotomous variables, one for non-Hispanic African American victims, a second for Hispanic-only victims, and a third for "other race non-Hispanic victims." Non-Hispanic white victims were left as the reference or comparison category.

Variables measuring the racial/ethnic character of California counties were also entered into the analysis as dichotomous variables. These included counties with non-Hispanic white populations between 40 and 49.9%. Counties where 50% or more of the population were non-Hispanic whites were left as the reference category.

Finally, variables measuring the urban character of California counties were entered into the analysis as

139. SAMUEL R. GROSS & ROBERT MAURO, DEATH AND DISCRIMINATION: RACIAL DISPARITIES IN CAPITAL SENTENCING 38-39 (1989).

dichotomous variables. Counties with population densities of 1000 or more inhabitants per square mile were included, as were counties with 300 to 999 inhabitants per square mile. Those counties with under 300 inhabitants per square mile were set aside as the reference category.

To examine the estimated effect of a single independent variable, controlling for the effects of all other variables, we used the exponentiated value of the beta (ß) coefficient, which is the logistic regression beta coefficient, Exp(ß).[140] The Exp(ß) coefficients in Table 11 show that the odds of receiving a death sentence for killing a non-Hispanic African American victim(s) deceases by a factor of .407, controlling for the other independent variables. This is the odds ratio of an offender who killed a non-Hispanic African American victim being sentenced to death. An odds ratio of exactly 1.0 would mean that the likelihood of receiving the death sentence changed by a factor of 1, or not at all. In this case, the results indicate that the odds of receiving a death sentence for killing a non-Hispanic African American victim are, on average, 59.3% lower than those homicides with non-Hispanic white victims[141] controlling for the other variables in the analysis. Similarly, again controlling for the effects of all other variables, the odds of receiving a death sentence for killing a Hispanic victim are, on average, 67.1% lower[142] compared to homicide incidents with non-Hispanic white victims. Both of these effects are statistically significant and support the conclusion that the death penalty in California is much less likely in cases in which minorities are victimized, independent of the level of aggravation of the homicide.

140. The Exp(ß) coefficient is the ß coefficient expressed as an odds ratio.
141. 1.0 minus .407 equals .593, or 59.3% lower.
142. 1.0 minus .329 equals .671, or 67.1% lower.

Table 11

Logistic Regression Analysis of County Characteristics, Race/Ethnicity of Victim, and Aggravating Circumstances on the Imposition of a Death Sentence*

Independent Variables**	ß	Sig.	Exp(ß)
Counties 1000 and higher	-.321	.163	.725
Counties 300 to 999	-.156	.341	.856
Counties < 40% white	-.509	.005	.601
Counties 40% - 49.9% white	-.201	.213	.818
African American non-Hispanic victim(s)	-.899	.000	.407
Hispanic-only victim(s)	-1.113	.000	.329
Other non-Hispanic victim(s)	-.426	.063	.653
No aggravating circumstances	-4.202	.000	.015
One aggravating circumstance	-1.932	.000	.145
Constant	-.703	.001	.495

Number of cases = 25,648

-2 Log likelihood = 2393.20

* Death Sentence is coded: 0 = no death sentence, 1 = death sentence.

** All independent variables are coded: 0 = not present, 1 = present.

As our cross-classification in Table 6 showed, the number of aggravating circumstances associated with homicide incidents in California is a significant factor in death sentencing decisions.[143] Table 11 shows that, as expected, the effects of these aggravating factors remain even after controlling for the effects of other variables. The odds of

143. *See* discussion *supra* Part III.A.

receiving a death sentence for a homicide with no aggravating circumstances are, on average, 98.5% lower[144] than in the case of a homicide with two aggravating circumstances.[145] Likewise, the odds of receiving a death sentence for a homicide with one aggravating circumstance are 85.5% lower[146] than for a homicide with two aggravating circumstances.[147]

Our results indicate that only one of the regional variables remains a significant predictor of death sentencing, controlling for the other independent variables in the logistic regression analysis. Table 11 shows that the odds of receiving a death sentence in counties where the population is less than 40% non-Hispanic white are, on average, 39.9% lower[148] than in counties where the non-Hispanic white population is 50% or more. The whiter the county, the higher its death sentencing rate will be.

Overall, the logistic analysis shows that the level of aggravating circumstances, the race and ethnicity of victims, and selected characteristics of counties (in particular, the racial/ethnic composition of counties) remain significant predictors of the imposition of the death sentence after controlling for each of the other independent variables.

IV. SUMMARY AND CONCLUSIONS

The results of this study are limited by the quality of the data on homicides and death penalty cases that government agencies make available. Although information available from the FBI and Death Penalty Data Set enabled us to compare early and late stages of the criminal justice decision-making process, these two data sources provided limited measures of legally relevant, extra-legal, and legally inappropriate factors that might affect death penalty decisions. Measuring all of the factors that may enter into death sentencing decisions, especially in a state as large as California, would necessitate significant funds and is far beyond the scope of our research. Nevertheless, we believe that we have measured some of the most important variables.

144. 1.0 minus .015 equals .985, or 98.5%.
145. *See* discussion *supra* Part III.A.
146. 1.0 minus .145 equals .855, or 85.5%.
147. *See supra* tbl.11.
148. 1.0 minus .601 equals .399, or 39.9%.

Furthermore, our findings are remarkably consistent with the results of other studies that have found race and regional effects, even after controlling for more variables than we were able to include.[149] Thus, we believe that even if the scope of this study were greatly expanded, the regional and victim race/ethnicity effects would not disappear and may even enlarge.

Our study also highlights broader concerns about data quality and availability of the comprehensive data that would be necessary to thoroughly monitor and evaluate criminal justice decisions. Such issues raise crucial questions about the interest and, more fundamentally, the ability of the State to monitor its death sentencing process. A comprehensive and effective monitoring program needs to track all homicide cases from arrest though appeal. To accurately assess the full range of factors that may or may not affect criminal justice decisions, all links and actors in the decision-making process must be monitored. This necessitates collecting information from the very start of the process, including information on the character of police investigations and prosecutorial charging decisions. For example, if police devote more resources to the investigation of the homicides of wealthy white victims than to other cases, and/or prosecutors modify their charging decisions in such circumstances, even if all subsequent decisions are fair, then racial and class bias will still permeate the system and potentially affect the outcome. Improper decisions made early in the process later become invisible if they are not properly documented. As a result, some cases may be pursued more vigorously "based on the evidence" when, in fact, the evidentiary collection process and/or the charging process were themselves potentially biased to an unknown and undocumented degree.

Despite these limits, the above data show strong disparities in death sentencing in California for homicides committed in the 1990s. The data clearly indicate that the race and ethnicity of homicide victims is associated with the imposition of the death penalty.[150] Overall, controlling for all other predictor variables, those who kill non-Hispanic African

149. *See, e.g.*, David C. Baldus & George Woodworth, *Race Discrimination in the Administration of the Death Penalty: An Overview of the Empirical Evidence with Special Emphasis on the Post-1990 Research*, 39 CRIM. L. BULL. 194 (2003).
150. *See* discussion *supra* Part III.A.

Americans are 59.3% less likely to be sentenced to death than those who kill non-Hispanic whites.[151] This disparity increases to 67% when comparing the death sentencing rates of those who kill whites with those who kill Hispanics.[152] The differences are especially remarkable in cases where there was only one victim and where the homicide did not include additional felonies.[153] In these cases, those who kill non-Hispanic whites are 7.6 times more likely to be sentenced to death than those who kill non-Hispanic African Americans, and 11 times more likely to be sentenced to death than those who kill Hispanics.[154] Where one of the two identified aggravating circumstances above is present, those who kill non-Hispanic whites are still 2.28 times more likely to be sentenced to death than other homicide offenders.[155]

The data also show geographic variations in rates of death sentencing. Excluding counties with smaller populations, death sentencing rates vary from roughly .005% of all homicides to rates five times higher.[156] Those counties with the highest death sentencing rates also tend to have the highest proportion of non-Hispanic whites in their population and the lowest population density.[157] When the effects of all variables are considered simultaneously, death sentencing rates are lowest in counties with the highest non-white population.

Although differences in data sources and methods of measurement make precise comparisons impossible, the correlation between death sentencing and victim race/ethnicity in California is similar to patterns found in several other states where the death penalty has been studied in recent years. For example, in our study of 1696 felony-homicides accompanied by other felonies in Florida, 1976-1987, we found that those who killed whites were nearly 5 times more likely to be sentenced to death than those who killed African Americans.[158] In Illinois, an analysis of 4182

151. *See supra* note 141 and accompanying text.
152. *See supra* note 142 and accompanying text.
153. *See* discussion *supra* Part III.A.
154. *See supra* tbl.6.
155. *See* discussion *supra* Part III.A.
156. *See supra* tbl.8.
157. *See* discussion *supra* Part III.B.
158. Michael L. Radelet & Glenn L. Pierce, *Choosing Those Who Will Die: Race and the Death Penalty in Florida*, 43 FLA. L. REV. 1, 24 (1991). The

cases in which defendants were convicted of first-degree murder between 1988 and 1997 found that "3.8% of the first-degree murder cases where the victim(s) was white resulted in a death sentence, versus 1.1% of the cases where the murder victim(s) was black, and 1.5% of the cases where the victim(s) was Hispanic."[159] Thus, those who killed whites were 3.45 times more likely to be sentenced to death than those who killed African Americans.[160] A study of death sentencing in Nebraska between 1973 and 1999 found that among death-eligible cases in the major urban counties, 20% of those who killed whites were sentenced to death (17/84), compared to 11% of those who killed African Americans (3/28).[161] Similar differences have also been found by recent studies in Arizona, Maryland, North Carolina, and Philadelphia, and in studies of homicide cases under federal jurisdiction.[162]

Research on the issues addressed in this study could easily be expanded. A more comprehensive study would identify homicide cases in which a jury decided to reject a death sentence for a given defendant, thereby distinguishing prosecutorial behavior[163] from jury behavior.[164] More broadly, future researchers might identify all cases where defendants were eligible for the death penalty,[165] and distinguish them from those cases where prosecutors sought, or a jury imposed, a death sentence. Such studies could also gather more information on "special circumstances" and examine how the race/ethnicity effects are either increased or decreased when special circumstances are considered. Such data would allow

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Florida data showed that 16.2% of those who killed whites, and 3.3% of those who killed African Americans, in felony-homicides accompanied by other felonies were sentenced to death. *Id.* at 23-24.

159. Pierce & Radelet, *supra* note 114, at 62-63.

160. *See id.*

161. David C. Baldus, George Woodworth, Catherine M. Grosso & Aaron M. Christ, *Arbitrariness and Discrimination in the Administration of the Death Penalty: A Legal and Empirical Analysis of the Nebraska Experience (1973-1999)*, 81 NEB. L. REV. 486, 583 (2002).

162. For a review of these and other studies, see Baldus & Woodworth, *supra* note 149.

163. Prosecutorial behavior includes making the decision to seek the death penalty.

164. Jury behavior includes imposing death sentences.

165. Under current law, a defendant is eligible for the death penalty if he or she is convicted of first-degree murder with special circumstances. CAL. PENAL CODE § 190.2 (Deering 2005).

researchers to discover which types of cases are most strongly correlated with race and ethnic factors. The most comprehensive type of study would collect data for all discrete stages of the process, from arrest through imposition of sentence, from any potential capital case. Such a study is essential because extra-legal factors may affect decisions throughout the criminal justice legal process. For example, extra-legal factors that may affect decisions in earlier stages of the process[166] can become masked at later stages because they then appear to be legally appropriate factors.[167]

In short, the data on California homicides in the 1990s show widespread disparities in the way the death penalty is applied, and many of these inconsistencies are correlated with the homicide victim's race and ethnicity.

166. For example, a prosecutor's racially-biased decision to charge a defendant whose victim is white with an accompanying felony, but not if the victim were a non-Hispanic African American, may affect the outcome of the case.

167. Future studies should also examine the possibility of gender effects.

APPENDIX A

WEIGHTING OF FBI DATA

Table A-1 compares Vital Statistics homicide counts for 1990 through 1999 with homicide counts derived from the FBI's SHR reports. In order to align the definitions of homicide from these two data sources, justifiable homicides committed by private citizens[168] were added to FBI murder and non-negligent manslaughter data. The FBI program collected information on 734 justifiable homicides by private citizens in California over the period 1990 to 1999.[169] When added to the murder/non-negligent manslaughter counts, a total of 33,138 homicides are included in the SHR data.

168. The data about justifiable homicides committed by private citizens to which this refers are collected by the FBI Supplementary Homicide Reporting System, but not included in the official FBI homicide statistics.

169. See The National Archive of Criminal Justice Data Home Page, http://www.icpsr.umich.edu/NACJD/ (last visited Nov. 1, 2005), which provides reference materials and data for each year of the FBI Supplementary Homicide Reports used in this research.

Table A-1

Comparison of Vital Statistics to SHR Victim Data
(The Basis for Weighting SHR Data)

Race of Victim	1 Vital Statistics Victims*	2 SHR Criminal Homicide Victims**	3 Total SHR Homicide Victims***	Ratio of Column 1 to Column 3****
White non-Hispanic	8136	7208	7357	1.1059
African American Non-Hispanic	9338	8806	9101	1.0260
Hispanic	14,089	13,630	13,868	1.0159
Other Race, non-Hispanic	2037	1417	1441	1.4136
Unknown	314	1343	1371	.2290
TOTAL	33,914	32,404	33,138	1.0234

* Vital Statistics homicide data include willful and justifiable homicides, and justifiable homicides by civilians, but excludes homicides by negligence and legal homicides by police.

** This category includes criminal homicides only. It excludes homicides by negligence, homicides by police, and justifiable homicides by private citizens.

*** This category represents FBI criminal homicides, adjusted by including justifiable homicides by private citizens in order to be comparable to the Vital Statistics definition of willful homicides and for the purpose of computing a weighting factor to adjust FBI data for underreporting.

**** This column shows the weights used to adjust the FBI offender estimates, obtained by dividing Column 1 figures by Column 3 figures.

As column one of Table A-1 shows, Vital Statistics counted 33,914 homicides in California in the 1990s—776 (2.3%) more than in the FBI data. This difference is small, and not surprising, given the fact that state laws mandate the collection of Vital Statistics death certificate data and that collection procedures have been in place for decades.[170] In large part, this discrepancy is probably due to a small number

170. *See supra* note 90 and accompanying text.

of police departments that did not report some or all of their homicides to FBI data collection agencies.

Although the overall difference between the FBI and Vital Statistics homicide tallies is small, there are important variations in the counts on the basis of victim race/ethnicity. Vital Statistics counted 9338 non-Hispanic African American homicide victims, while the FBI data counted only 9101—a difference of 2.6%. Similarly, Vital Statistics counted 14,089 Hispanic homicide victims, versus 13,868 reported by the FBIs—a difference of 1.6%. In contrast, Vital Statistics reported 8136 non-Hispanic white homicide victims, versus 7,357 counted by the FBI system—a difference of 10.6%.

The somewhat greater discrepancy between Vital Statistics and FBI estimates of non-Hispanic white victim homicides undoubtedly arises because of incomplete race/ethnicity information in the FBI data. Race/ethnicity information is missing for 1,371 (4.1%) of the FBI victims in California over the 1990-1999 period. There are missing race/ethnicity data for only 314 (.9%) of the Vital Statistics victims over the same period.

Fortunately, the problem of underreporting of FBI data in California appears to be minor. To correct the small underreporting problems in these data, we used Vital Statistics data to differentially weight (by race/ethnicity of victims) the FBI data. The last column of Appendix Table 1 reports the weights that we used to adjust the FBI data. These weights are calculated for specific categories of victim race and ethnicity. They are calculated simply as the number of homicides for a specific racial/ethnic category (estimated by Vital Statistics), divided by the comparable total number estimated by the SHR program.

APPENDIX B

OFFENDER RACE AND ETHNICITY EFFECTS

The potential effects of the defendant's race and ethnicity on the probability of receiving a death sentence can be examined with FBI data since these data include information on the race, ethnicity, age, and gender of *both* the victim(s) and the offender(s).[171] This type of information also allowed us to examine any possible effects of the offender's race/ethnicity in conjunction with the race/ethnicity of the victims.

Table B-1 presents death sentence rates by the race and ethnicity of offenders using our weighted FBI homicide offender data. The results show that when there are no controls for the race and ethnicity of homicide victims, the offender's race and ethnicity are significantly related to death sentencing decisions.[172] Specifically, Table B-1 shows that white offenders are more likely to receive a death sentence than offenders from other races/ethnicities. However, because most homicide incidents are intra-racial (i.e., the offender and victim are both members of the same race/ethnic group), the potential effect of the defendant's race/ethnicity on death sentence rates needs to be examined in conjunction with the victim's race/ethnicity. Table B-2 shows the very strong relationship between the race/ethnicity of offenders and victims: 81.4% of the homicides with solely non-Hispanic white victims are committed by white offenders; 67.9% of homicides with solely non-Hispanic African American victims are committed by African American offenders; and 78.3% of homicides with solely Hispanic victims are committed by Hispanic offenders.

When death sentencing rates are examined for the race/ethnicity of offenders, controlling for the race/ethnicity of victims, the impact of offender's race/ethnicity largely disappears or is reversed. Table B-3 examines death sentencing rates by the race/ethnicity of offenders, controlling

171. *See* The National Archive of Criminal Justice Data Home Page, *supra* note 169.

172. *See infra* app. b, tbl.b-1.

for the race/ethnicity of victims. Among homicides with non-Hispanic white victims, non-Hispanic African American offenders show the highest likelihood of receiving a death sentence.[173] For homicides with non-Hispanic African American victims, Hispanic offenders are the most likely to receive a death sentence.[174] Among cases with Hispanic victims, death sentences are most likely for non-Hispanic white offenders.[175]

In contrast, comparing death sentencing rates across categories of offender race/ethnicity shows that in five of six possible comparisons, those homicides with non-Hispanic white victims show higher death sentence rates than other victim race/ethnicity groups.[176] Overall, these results indicate that the race/ethnicity of victims, but not of offenders, is consistently related to death sentencing rates.

173. *See infra* app. b, tbl.b-3.

174. *See id.*

175. *See id.*

176. *See id.* col. 3. The six comparisons are as follows: non-Hispanic white defendant and victim versus (1) non-Hispanic African American victim (1.8783 v. 0) and (2) Hispanic victim (1.8783 v. 1.8519, which is not significant); non-Hispanic African American defendant and non-Hispanic white victim versus (3) non-Hispanic African American victim (3.455 v. .672) and (4) Hispanic victim (3.455 v. .563); Hispanic defendant and non-Hispanic white victim versus (5) non-Hispanic African American victim (1.914 v. .895) and (6) Hispanic victim (1.914 v. .402).

Table B-1

Death Sentence Rates for Offenders by Offender Race/Ethnicity Based on Weighted SHR Offender Data

Race of Offender	SHR Offenders Weighted	Death Sentences	Death Sentence Rate per 100 Offenders	Ratio of White Offender Rate to Other Victim Race Rate
White non-Hispanic	5169	103	1.993	
African American non-Hispanic	7888	101	1.280	1.56
Hispanic	11,127	81	.728	2.74
Other race, non-Hispanic	1289	17	1.319	1.51
Total	25,473	302	1.186	

Chi Square = 49.431; df = 3; $p < .001$.

Table B-2

Distribution of Victim Race/Ethnicity by Offender Race/Ethnicity Based on Weighted SHR Offender Data (Multiple Race/Ethnicity Homicides Excluded; Where the Race/Ethnicity of the Offender is Unknown, the Tabulations Are Not Shown)

	Race/Ethnicity of Offender			
Race/Ethnicity of Victim	White non-Hispanic	African American non-Hispanic	Hispanic	Other non-Hispanic
White non-Hispanic	81.4	12.5	11.7	14.7
African American non-Hispanic	4.7	67.9	7.0	4.4
Hispanic	10.4	15.8	78.3	10.6
Other non-Hispanic	3.2	3.4	2.7	69.8
Unknown Race/Ethnicity	.3	.5	.2	.5
Total Cases	5169	7888	11,127	1288
Total Percent	100.0	100.0	100.0	100.0

Chi Square = 37212.601; df = 16; $p < .001$.

Table B-3

Death Sentence Rates for Offenders by Offender Race and Victim Race/Ethnicity Based on Weighted SHR Offender Data

Race of Defendant	Cases	Death Sentences	Death Sentences per 100 Suspects
Race of Victim: White non-Hispanic			
White non-Hispanic	4206	79	1.8783
African American non-Hispanic	984	34	3.455
Hispanic	1306	25	1.914
Total	6496	138	2.1244
Chi Square = 9.885; df = 3; p = .020.			
Race of Victim: African American non-Hispanic			
White non-Hispanic	244	0	.0000
African American non-Hispanic	5355	36	.672
Hispanic	782	7	.895
Total	6381	43	.6739
Chi Square = 2.228; df = 3; p = .527.			
Race of Victim: Hispanic			
White non-Hispanic	540	10	1.8519
African American non-Hispanic	1243	7	.563
Hispanic	8715	35	.402
Total	10,498	52	.4953
Chi Square = 21.830; df = 3; p < .001.			

***

EXHIBIT H

Racial Disparities in Riverside County's Death Penalty System

September 21, 2021

Nick Petersen, Ph.D.
Associate Professor of Sociology & Law
University of Miami
Coral Gables, Florida, United States
npetersen@miami.edu
(305) 284-6169

I. INTRODUCTION

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

II. ANALYSIS STRATEGY

Population Data on Death-Penalty Decision-Making

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

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

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

Death-Penalty Decisions Analyzed

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

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

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

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

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

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

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

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

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

Statistical Estimation

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

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

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

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

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

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

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

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

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

[10] *Id.*

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

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

Predicted Probabilities

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

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

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

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

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

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

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

Adjusted vs. Unadjusted Results

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

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

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

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

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

Main Race Effects vs. Victim-Defendant Racial Dyad Interactions

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

Practical vs. Statistical Significance

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

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

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

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

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

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

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

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

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

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

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

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

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

III. THE CHARGING STUDY

Data and Methodology

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

Dependent variables:

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

[27] *Id.* at 821.

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

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

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

Victim and Defendant Race:

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

Case Characteristics from Court Files:

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

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

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

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

[34] CCFAJ, *supra* note 2.

[35] Penal Code, § 190.2(a)(17).

[36] Penal Code § 190.2(a)(3).

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

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

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

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

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

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

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

DOJ Victim and Case Characteristics:

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

40 LONG AND FREESE, *supra* note 17.

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

42 CDOJ, *supra* note 30.

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

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

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

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

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

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

46 *Id.*

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

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

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

Analysis Strategy:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Results

Unadjusted Summary Statistics:

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

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

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

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

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

Figure 1. Unadjusted Defendant Racial Breakdown by Outcome

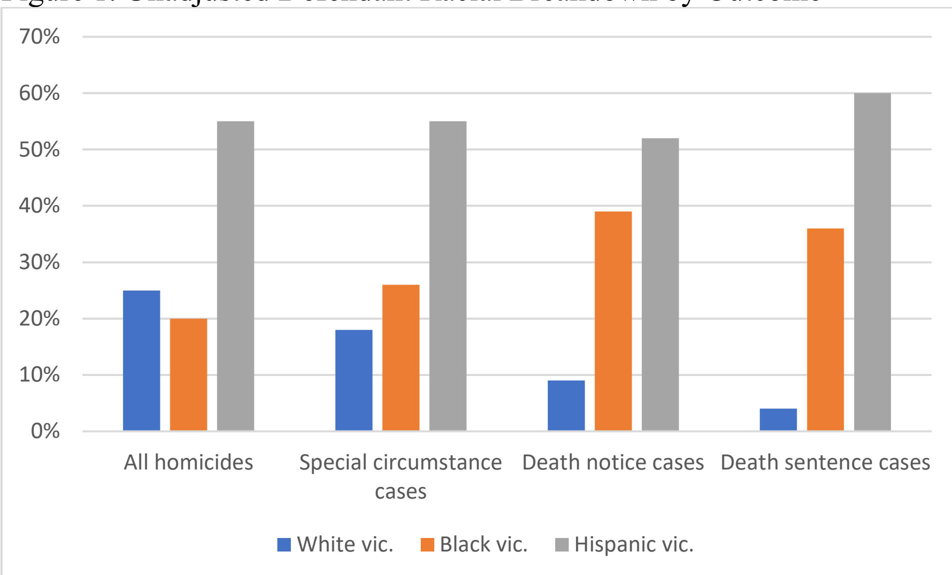
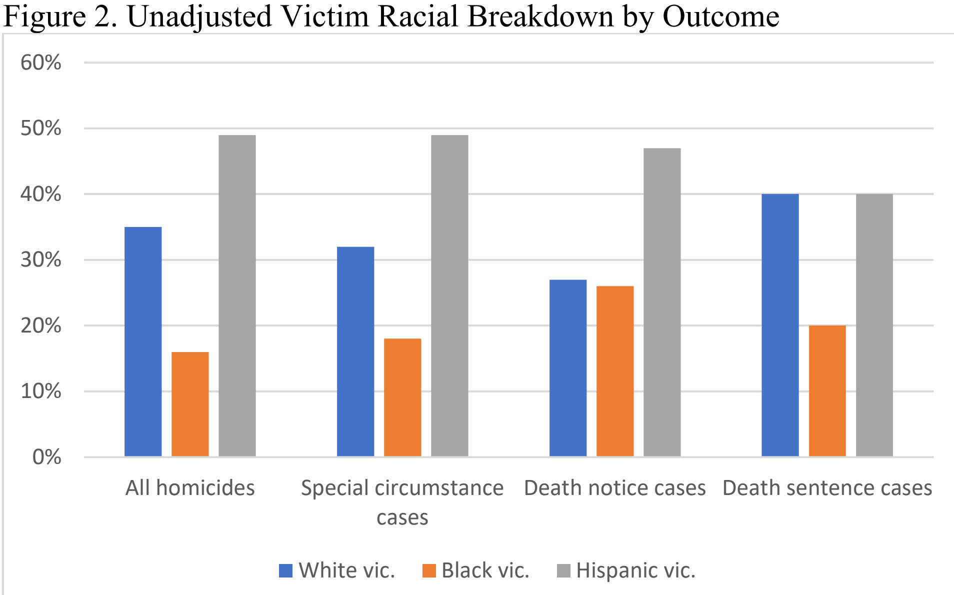


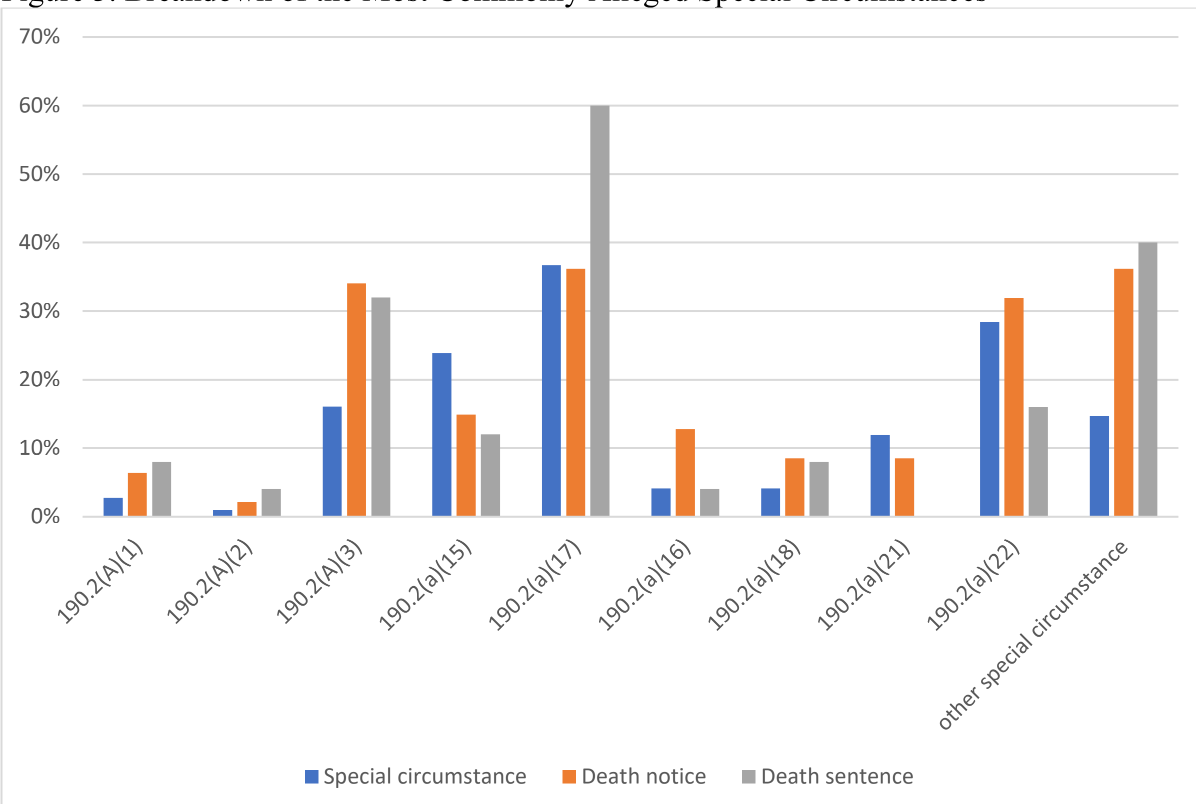
Figure 2. Unadjusted Victim Racial Breakdown by Outcome



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

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

Figure 3. Breakdown of the Most Commonly Alleged Special Circumstances



Main Effects of Victim and Defendant Race:

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

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

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

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

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

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

Exponentiated coefficients; Standard errors in parentheses

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

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

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

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

Figure 4. Predicted Probability of Special Circumstance by Defendant Race

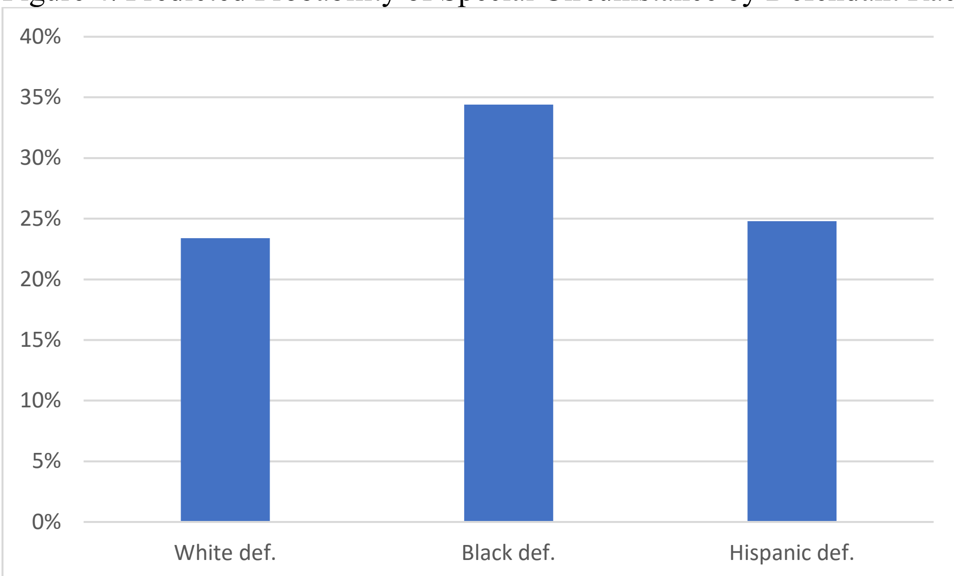
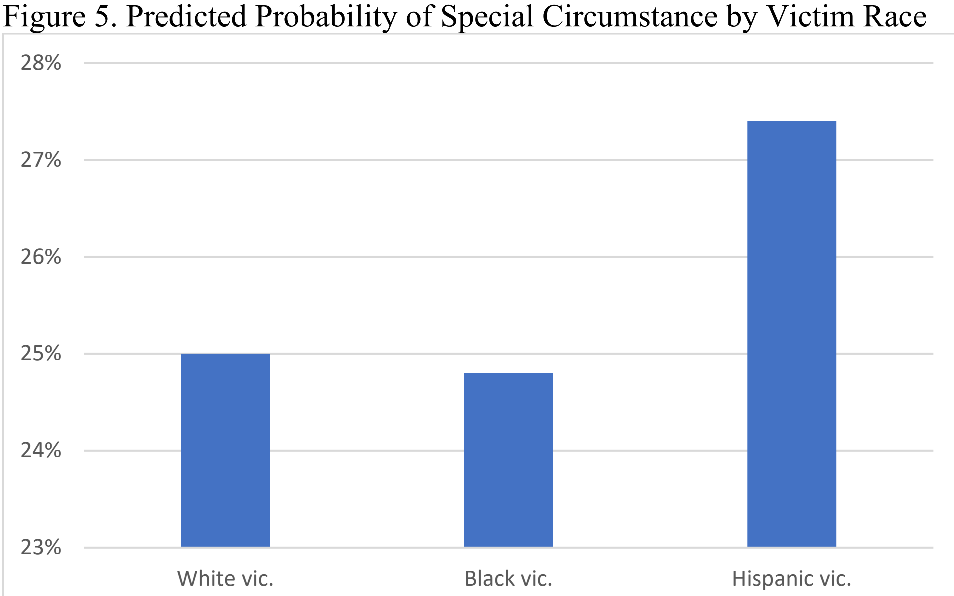


Figure 5. Predicted Probability of Special Circumstance by Victim Race



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

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

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

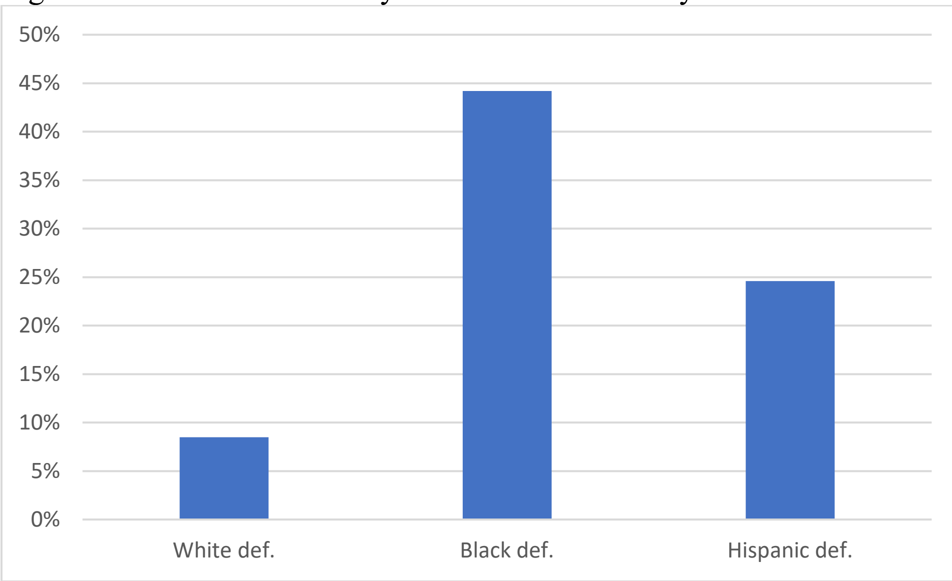
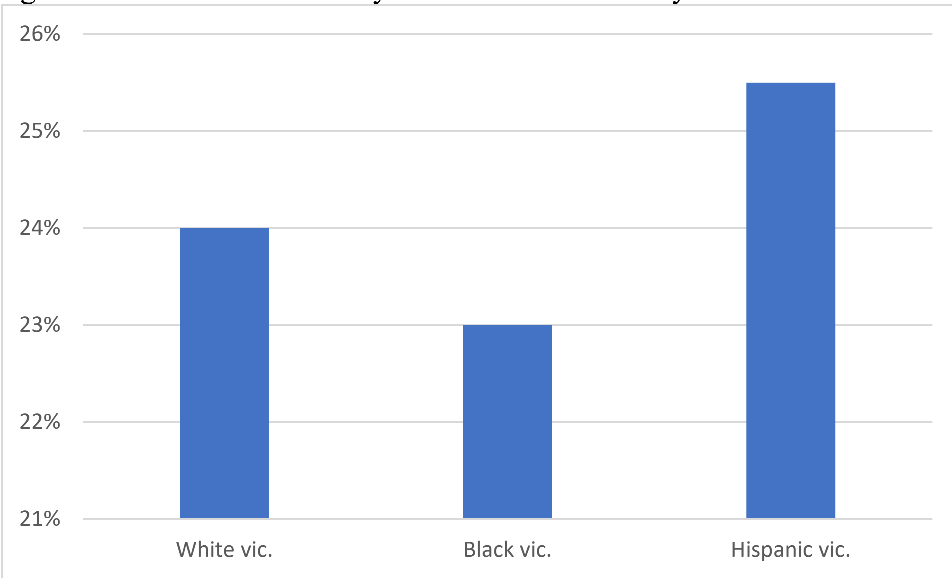


Figure 7. Predicted Probability of the Death Notice by Victim Race



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

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

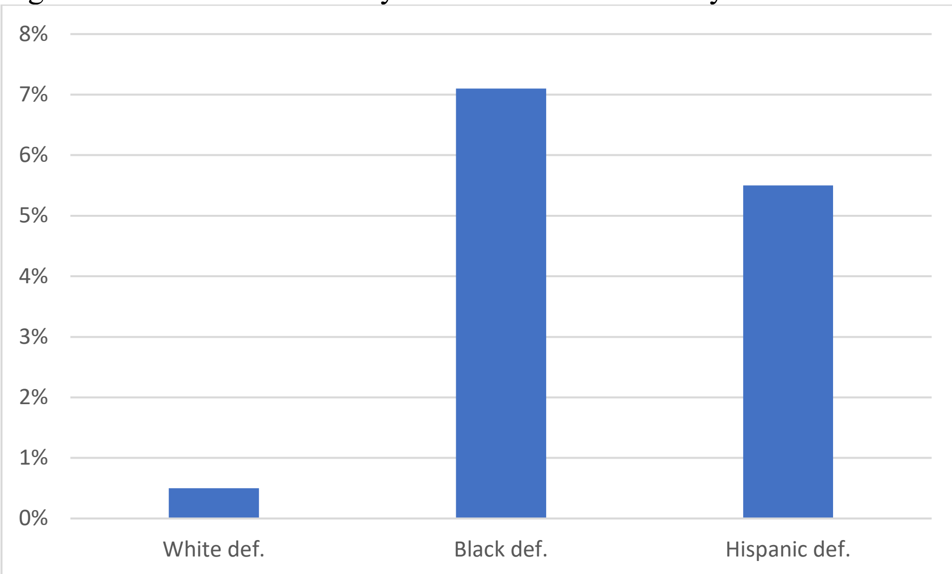
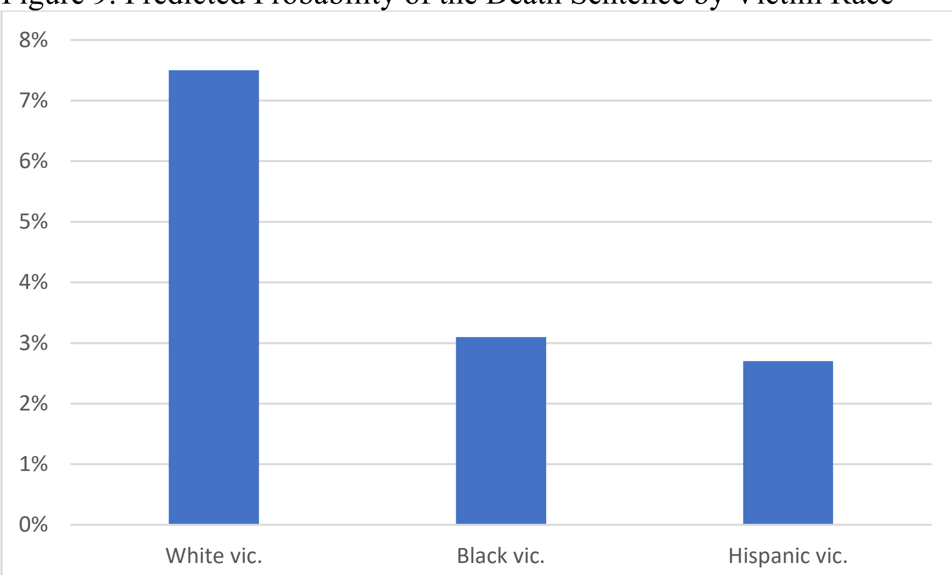


Figure 9. Predicted Probability of the Death Sentence by Victim Race

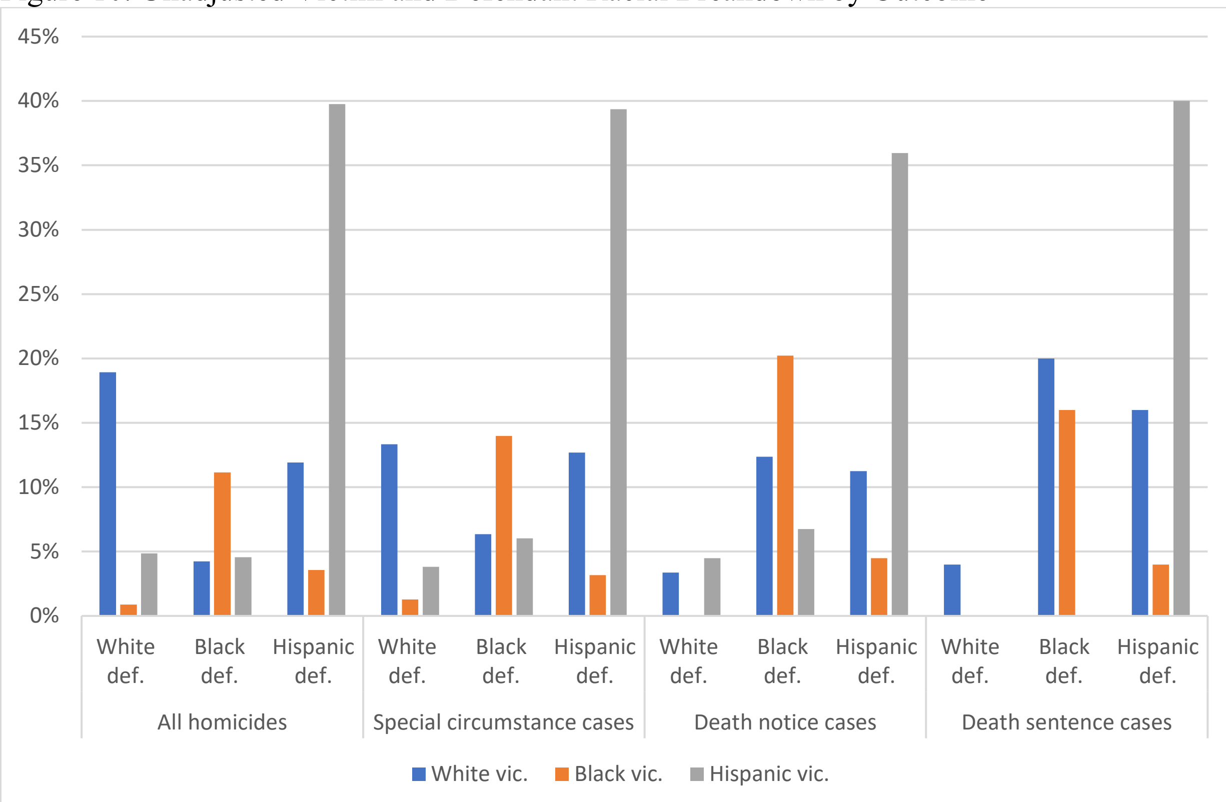


Interactional Effects of Victim and Defendant Race Dyads:

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

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

Figure 10. Unadjusted Victim and Defendant Racial Breakdown by Outcome



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

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

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

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

Exponentiated coefficients; Standard errors in parentheses

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

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

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

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

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

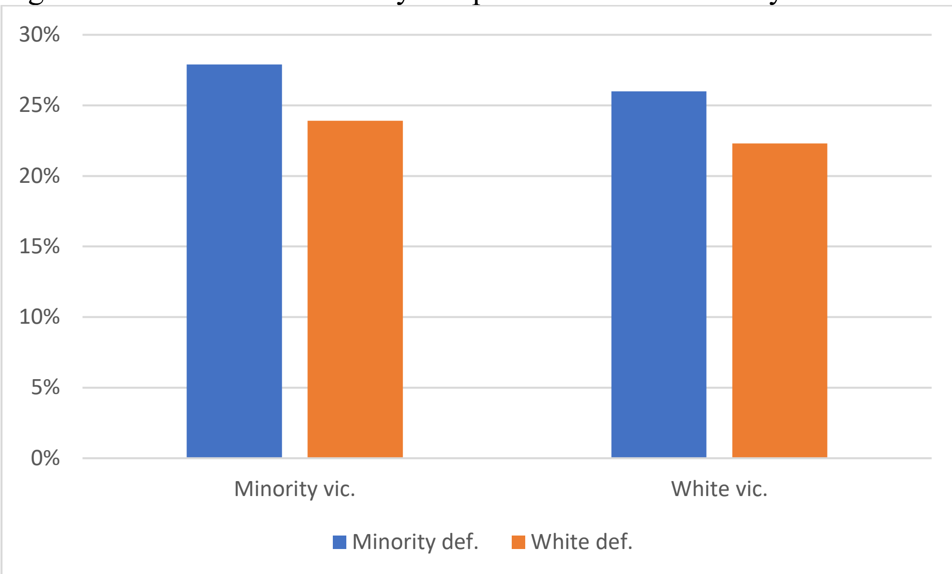


Figure 12. Predicted Probability of the Death Notice by Defendant Race & Victim Race

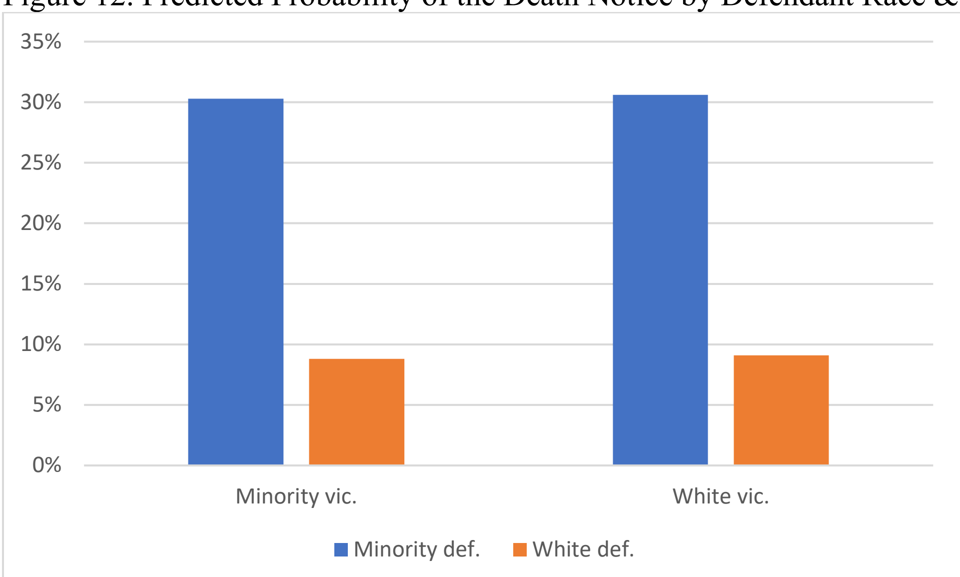
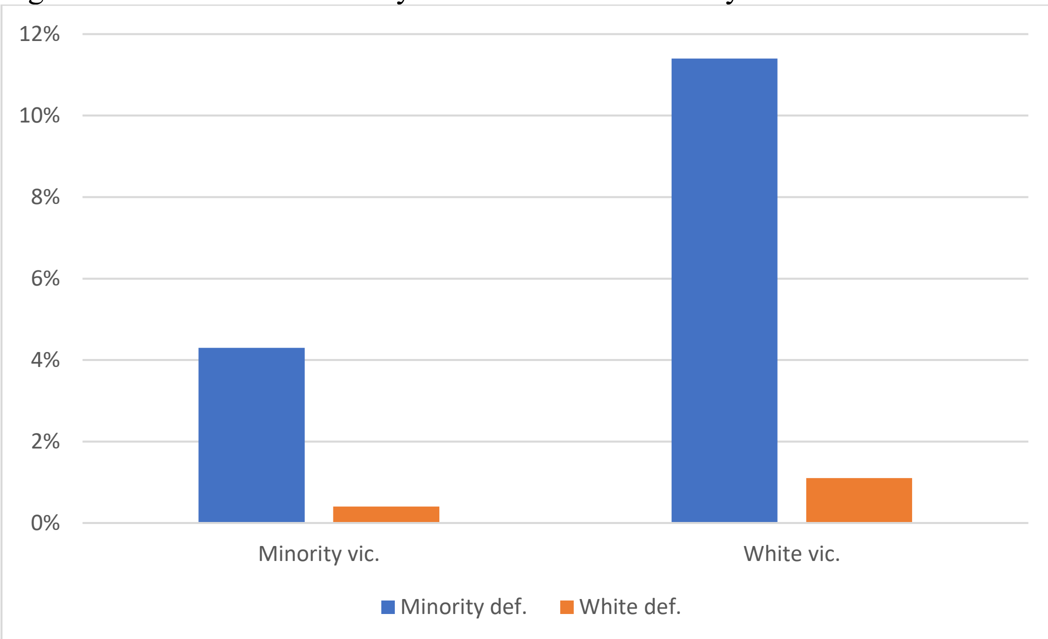


Figure 13. Predicted Probability of the Death Sentence by Defendant Race & Victim Race



Summary of Findings

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

IV. THE SHR STUDY

Data and Methodology

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

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

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

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

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

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

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

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

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

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

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

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

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

Dependent variable:

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

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

67 Penal Code 190.5 (a).

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

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

Victim and Defendant Race:

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

Case Characteristics:

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

Analysis Strategy:

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

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

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

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

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

Results

Unadjusted Summary Statistics:

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

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

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

Main Effects of Victim and Suspect Race:

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

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

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

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

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

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

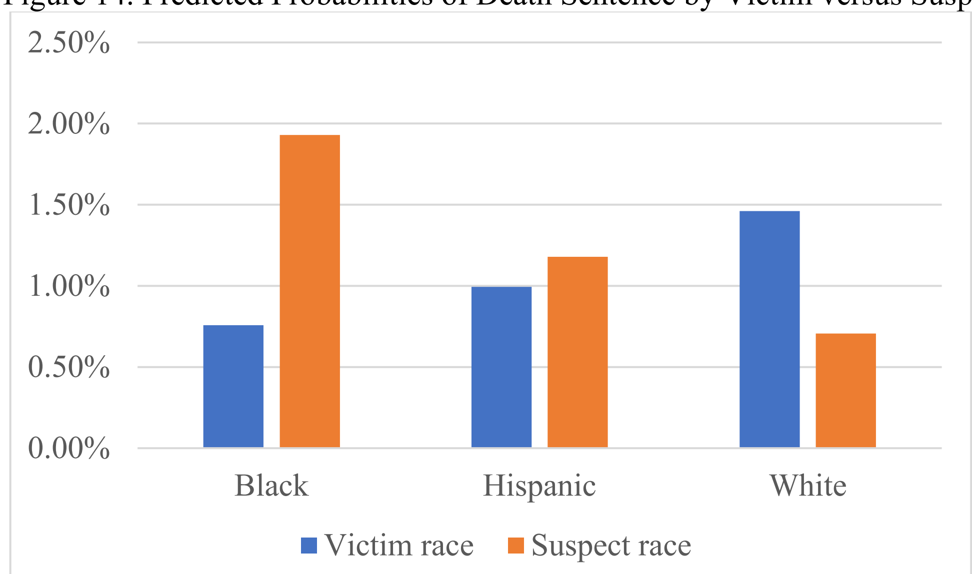
74 Pierce and Radelet, *supra* note 11.

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

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

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

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



Interactional Effects of Victim and Suspect Race Dyads:

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

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

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

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

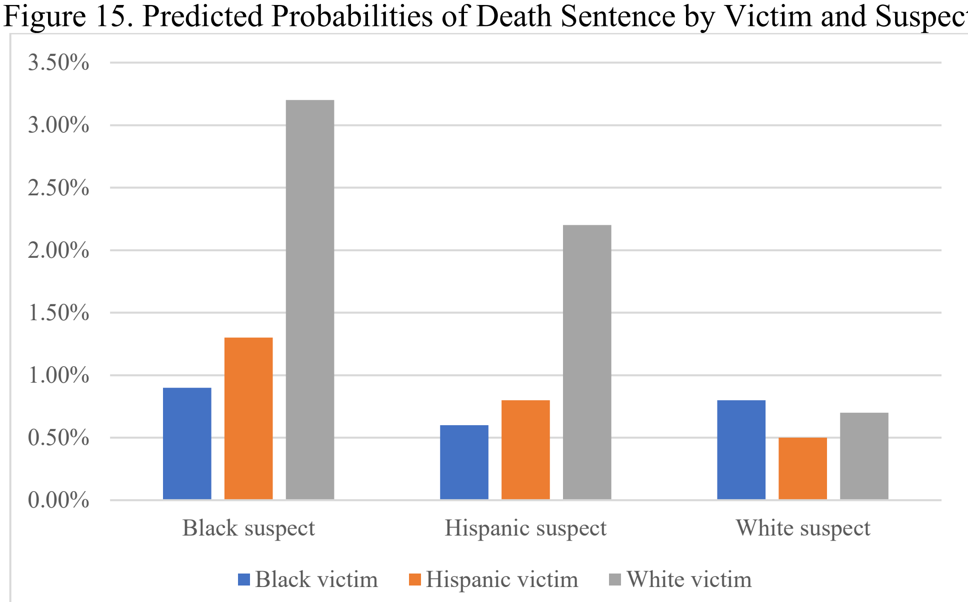
[75] Catherine M. Grosso et al., *Race Discrimination and the Death Penalty: An Empirical and Legal Overview*, *in* AMERICA'S EXPERIMENT WITH CAPITAL PUNISHMENT: REFLECTIONS ON THE PAST, PRESENT, AND FUTURE OF THE ULTIMATE PENAL SANCTION (2014); MARTIN URBINA, CAPITAL PUNISHMENT IN AMERICA: RACE AND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

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

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

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

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



Summary of Findings

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

V. CONCLUSIONS

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

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

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

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

EXHIBIT I

Racial Disparities in San Diego County's Death Penalty System

November 15, 2023

Nick Petersen, Ph.D.
Associate Professor of Sociology & Criminology
Secondary appointment in Law School
University of Miami
Coral Gables, Florida, United States
npetersen@miami.edu
(305) 284-6169

I. INTRODUCTION

1. This report presents my statistical analysis of death sentencing trends in San Diego County, California during 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 in San Diego County during this period. To estimate the likelihood of a given homicide resulting in a death sentence, I employed statistical models that allowed me to isolate the independent effect of victim/suspect race on death sentencing for homicides with similar characteristics.

2. Regression results indicate that homicides with White victims or non-White 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. Therefore, my results underscore wide-spread racial disparities in San Diego County 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

4. This study examines a *population* of 2,418 homicide incidents that occurred in San Diego County from 1979 through 2018. Homicide incident data was combined with a *population* of death verdicts in San Diego County 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 San Diego County has important methodological implications for interpretations of statistical and practical significance.

[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.

5. My analyses focus on death sentences issued by San Diego County juries from 1979 through 2018. I code death sentences using a binary variable, where the data were coded as "1" if the decision was present and "0" if otherwise.[3] Homicides in which the jury rendered a death sentence were coded as "1." Homicides in which no death sentence was rendered were coded as "0."

Statistical Estimation

6. To estimate the likelihood of a death sentence, I employed logistic regression models. I use regression models to analyze these data because they are the "most widely used vehicle for empirical analysis in economics and other social sciences," and they allow me to isolate the independent effect of victim/suspect[4] race on death sentences for similarly situated cases.[5]

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 to ensure that any observed racial disparities are not spurious.[6] 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

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

4 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.

5 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.

6 "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.*

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

9. In statistical parlance, the dependent variable refers to "the main factor that you're trying to understand or predict,"[8] whereas independent variables are "the factors you suspect have an impact on your dependent variable."[9] For 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 include victim/suspect race, as prior research has identified these are strong predictors of death penalty outcomes.[10]

10. Logistic regression is the specific type of regression used, 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

7 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.

8 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).

9 *Id.*

10 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).

reached).[11] Consistent with prior empirical research on the death penalty, I used logistic regression models to estimate the likelihood of having a death sentence by race while holding other non-racial 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.[12] The unit of analysis is the homicide incident because the SHR is an incident-based dataset.[13]

Predicted Probabilities

11. Results from logistic regression models are displayed as predicted probabilities to help visualize the relevant statistical comparisons and to improve the interpretability of my findings. Logistic regression models generate odds ratios, which can be difficult to interpret because there is no inherent scale for odds ratios as they represent nonlinear trends.[14] In contrast, predicted probabilities range from 0% to 100%, making them easier to interpret.[15] The use of predicted probabilities to display logistic regression analyses is helpful in overcoming these interpretation difficulties and is common in my own published research[16] as well as the broader

[11] BALDUS, WOODWORTH, AND PULASKI, *supra* note 8; Baldus, Woodworth, and Weiner, *supra* note 8; Baldus et al., *supra* note 8; WOOLDRIDGE, *supra* note 6.

[12] For the purposes of this document, logistic regression estimates are discussed as percentage changes in terms of odds ratios, with 1 corresponding to equal odds (i.e., "no effect"). Binary variables estimated in a logistic equation can be interpreted as a percentage change in the odds/hazard using the following formula: 1-[(β*xi*) X 100]. 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.

[13] 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.

[14] In a logistic regression model, odds (O) and probabilities (P) have the following relationship: Odds = P/1-P and Probability = O/1+O. Baldus, Woodworth, and Weiner, *supra* note 8.

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

[16] Petersen, *supra* note 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.

social scientific literature.[17] 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 0.44%, 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 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.[18] However, the American Statistical

[17] 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.

[18] 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."

Association (ASA) has sought to move away from focusing solely on statistical significance in recent years, noting that practical significance is also an essential consideration in any scientific study, particularly when researchers are analyzing a population.[19] As such, my report includes discussions of both statistical *and* practical significance.

14. Focusing on practical significance is important given that there were 34 death sentences in San Diego County during the analysis period (1979-2018). Analyses with a smaller number of cases will necessarily have greater sampling variability,[20] 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." Although some results may not be statistically significant due to the smaller number of death sentences (34) compared to the total number of homicides (2,418), any observed racial disparities are still practically significant as they speak to broader concerns surrounding fairness and equality outlined in the Racial Justice Act. Moreover, San Diego County's 34 death sentences make the county among the highest ranked in terms of the number of death sentences during this time, further highlighting the practical significance of my findings.

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 (San Diego County) and time periods of interest (1979-2018). 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." [21] In such contexts, he explains, "researchers should focus more on substantive significance and less on statistical significance." [22] Following his advice, I focus more on practical significance.

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

[20] 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).

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

[22] *Id.*

III. DATA AND METHODOLOGY

Data and Methodology

16. To examine whether racial disparities based on victim or suspect exist in San Diego County death sentencing trends in the post-*Gregg* period (1979 through 2018), I relied on a previously established methodology[23] 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 San Diego County between 1979 and 2018.[24] Next, I obtained death sentencing data from the Habeas Corpus Resource Center, a state repository statutorily tasked with collecting such data.[25] This dataset contains information on all death sentences rendered in San Diego County from 1979 through 2018.[26]

17. I conducted probabilistic matching using the "reclink2" package in Stata to link the SHR and death sentence datasets.[27] Since the SHR does not include the exact homicide date for confidentiality reasons (including the month and year instead), probability matching was required. For matching purposes, I used the following categorical variables to link the two datasets: county, date of homicide (month and year), victim race, multiple homicide victims, felony murder, number of suspects (continuously measured), as well as whether the homicidal circumstances included lewd/lascivious conduct, poison, arson, carjacking, rape, robbery, or gang activity.[28] While my

23 Gross and Mauro, *supra* note 14; Pierce and Radelet, *supra* note 11; Radelet and Pierce, *supra* note 11.

24 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/).

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

26 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.

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

28 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).

"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[29] 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 used 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 the age of eighteen (as juveniles are no longer eligible for the death penalty)[30] and eliminated from consideration any homicide lacking suspect race information (most commonly those wherein no arrest was ever made).[31] Like prior research, I also limited the SHR data to homicides involving victims and suspects who are White, Black, and Hispanic.[32]

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 resulting in a death sentence were coded as "1." Homicides that did not result in a death sentence were coded as "0."

[29] Pierce and Radelet, *supra* note 11 at 33.
[30] Penal Code 190.5 (a).
[31] Gross and Mauro, *supra* note 14; Pierce and Radelet, *supra* note 11.
[32] 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.

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,[33] as the co-occurrence of a felony and multiple murder are among the most commonly alleged special circumstances in California and other jurisdictions.[34] In addition, I control for the year in which the crime occurred and the annual homicide rate in San Diego County to adjust for any annual differences in death sentencing trends (i.e., death sentence rates might be higher/lower in specific years or periods with more/fewer homicides).

Analysis Strategy:

23. To estimate the likelihood of a homicide resulting in a death sentence, I calculated logistic regression models for all homicides occurring in San Diego County from 1979 through 2018.

33 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.

34 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).

Results

Unadjusted Summary Statistics:

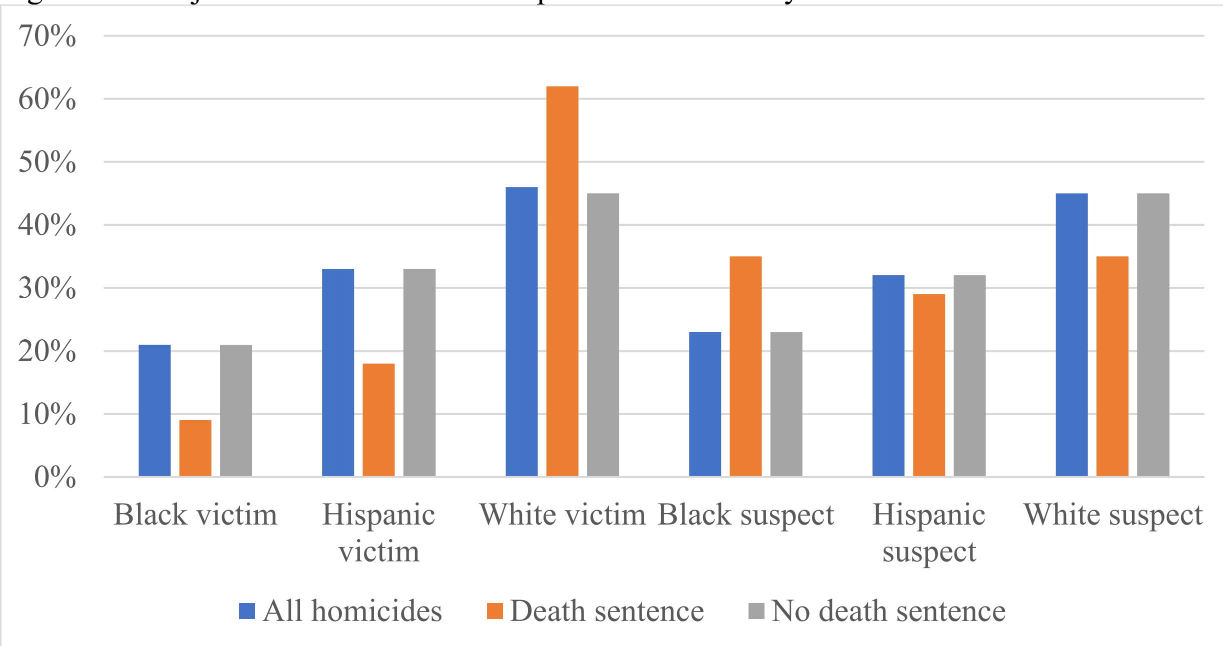
24. Table 1 shows "unadjusted" summary statistics. That is, Table 1 lists the raw statistics for various measures without controlling for any other victim, suspect, or homicide characteristics. Compared to the general population of homicides in San Diego County from 1979 to 2018, Table 1 indicates that homicides resulting in a death sentence are more likely to have a White victim and a non-White (Black/Hispanic) suspect. For example, 45% of all San Diego County homicides have a White suspect, whereas 35% of San Diego County homicides that result in a death sentence have a White suspect. In contrast, 23% of San Diego County homicides involve a Black suspect, but 35% of homicides that result in a death sentence involve a Black suspect.

Table 1. Summary Statistics for San Diego County Homicides (1979-2018)

	All homicides	Death sentence	No death sentence
	%	%	%
Victim and suspect demographics:			
Black victim	21%	9%	21%
Hispanic victim	33%	18%	33%
White victim	46%	62%	45%
Black suspect	23%	35%	23%
Hispanic suspect	32%	29%	32%
White suspect	45%	35%	45%
Case characteristics:			
Multiple murder - PC190.2(a)(3)	4%	41%	3%
Felony - murder PC190.2(a)(17)	11%	74%	10%
year	1997.13	1993.35	1997.18
Annual homicide rate	0.74	0.84	0.74
Observations	2418	34	2384

25. Figure 1 shows the unadjusted breakdowns for suspect/victim race. Importantly, we see 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



26. Table 2 displays the unadjusted breakdowns for various racial dyads by death sentencing outcome. Foremost, Table 2 reveals that most homicides in San Diego County are intra-racial. Second, Table 2 indicates that homicides involving White victims and non-White suspects are more likely to result in a death sentence. For example, homicides with a Black suspect & White victim represent only 5% of homicides, yet they represent 18% of homicides resulting in a death sentence. Likewise, homicides with a Hispanic suspect & White victim represent only 5% of homicides, yet they represent 15% of homicides resulting in a death sentence. On the other hand, 36% of homicides involve a White suspect & White victim, but only 29% of homicides resulting in a death sentence have a White suspect & White victim.

27. Table 2 also shows that some racial dyads do not result in any death sentences. Cases involving a White suspect & Black victim, a Black suspect & Hispanic victim, or a Hispanic suspect & Black victim are relatively rare among all homicides. And among homicides that result in a death sentence, none of these racial dyads are represented. Meaning that there were no death sentences involving those combinations of victim and suspect racial groups.

Table 2. Death Sentencing Outcomes in San Diego County by Suspect and Victim Racial Dyads (1979-2018).

	All homicides	Death sentence	No death sentence
	%	%	%
White suspect & White victim	36%	29%	36%
White suspect & Black victim	3%	0%	3%
White suspect & Hispanic victim	6%	3%	6%
Black suspect & White victim	5%	18%	5%
Black suspect & Black victim	15%	9%	15%
Black suspect & Hispanic victim	2%	0%	3%
Hispanic suspect & White victim	5%	15%	5%
Hispanic suspect & Black victim	2%	0%	2%
Hispanic suspect & Hispanic victim	25%	15%	25%
Observations	2418	34	2384

Adjusted Racial Disparities:

28. Next, I turn to "adjusted" regression estimates in Table 2. These are "adjusted" in the sense that the regression models control for other important legal factors, such as the presence of multiple victims or a felony. According to the logistic model, homicides involving 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.[35]

29. Even after controlling for these important legal factors, however, victim and suspect race shape death sentences. According to the logistic regression model, homicides with non-White (Black/Hispanic) victims are less likely to result in a death sentence, while those with a non-White (Black/Hispanic) suspect are more likely to result in a death sentence. Compared to homicides with a White victim, the odds of a case involving a Black victim resulting in a death sentence are 77% lower, and the odds of a case involving a Hispanic victim resulting in a death sentence are 78% lower. Compared to homicides with a White suspect, the odds that a Black suspect will result in a death sentence are 3.83 times greater, and the odds that a case involving a Hispanic suspect will result in a death sentence are 3.57 times greater. All of these effects are significant at the 0.05

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

p-value, meaning that there is less than a 5% chance of obtaining this result by random chance.[36] The effects for multiple murder and felony murder are statistically significant at the 0.001 p-value level (i.e., $p < 0.001$), meaning that there is less than a 0.1% chance of obtaining these results by random chance.[37]

Table 3. Regressions Predicting Death Sentencing Outcomes in San Diego County (1979-2018).

	OR(SE)
Victim and suspect demographics:	
Black victim	0.23* (0.17)
Hispanic victim	0.22* (0.13)
Black suspect	3.83* (2.08)
Hispanic suspect	3.57* (2.03)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	24.59*** (11.74)
Felony - murder PC190.2(a)(17)	23.26*** (10.32)
year	0.90* (0.04)
Annual homicide rate	0.13 (0.17)
Observations	2418

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

30. Next, I calculated predicted probabilities to help visualize the effects of victim and suspect race/ethnicity from the regression model in Table 2. Figure 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

36 FINLAY AND AGRESTI, *supra* note 21; BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.
37 FINLAY AND AGRESTI, *supra* note 21; BALDUS, WOODWORTH, AND PULASKI, *supra* note 8.

suspects. The inverse relationship between victim and suspect race is consistent with prior research[38] and suggests a victim-by-suspect race interaction, which I explore below.

Figure 2. Predicted Probabilities of Death Sentence by Victim Race

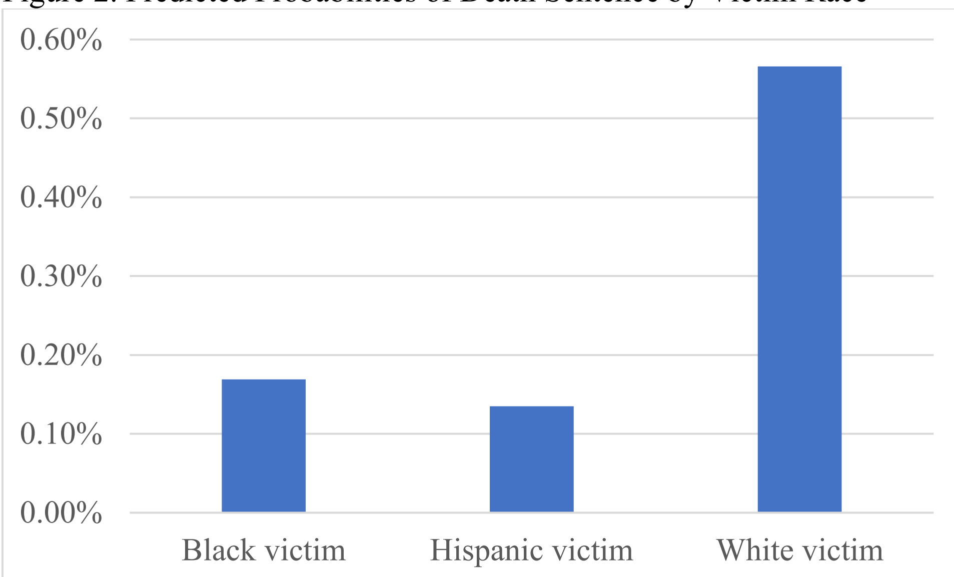
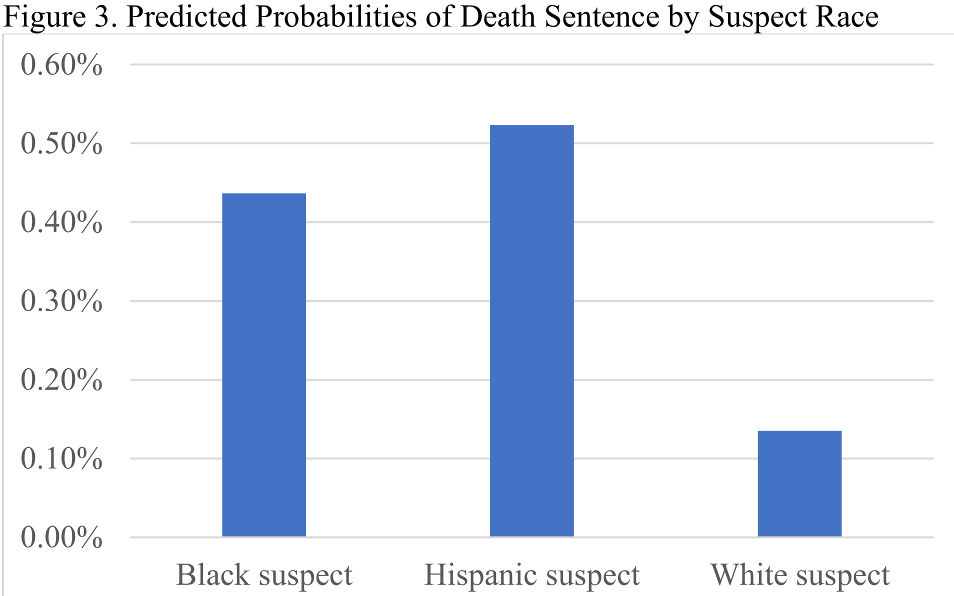


Figure 3. Predicted Probabilities of Death Sentence by Suspect Race



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

31. Since prior research on the death penalty in California[39] and elsewhere[40] 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 2.10 times more likely to result in a death sentence. Moreover, compared to homicides involving a White victim and White suspect, those with a Hispanic suspect and a White victim are 2.87 times more likely to result in a death sentence. However, these effects are not statistically significant due to the smaller sizes of these victim-by-suspect racial dyads. In other words, dividing the population based on *both* suspect and victim race means that the group sizes are necessarily smaller than those in Table 3, which impacts significance tests.[41] Nevertheless, they do show practically significant disparities in San Diego County trends by victim-by-suspect racial dyads from 1979 to 2018.

32. Several of the victim-by-suspect racial groupings could not be analyzed within a logistic regression framework due to small sample sizes and no variability on the dependent variable (i.e., no death sentences). In particular, disparities among homicides with a White suspect & Black victim, a Black suspect & Hispanic victim, or a Hispanic suspect & Black victim could not be estimated since none of these racial dyads resulted in a death sentence during the period of analysis. As a result, an "NA" note is displayed in Table 3 rather than the odds ratios for these racial dyads, signifying that the relationship could be estimated due to a lack of variability on the dependent variable.

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

40 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).

41 JEFFREY WOOLDRIDGE, INTRODUCTORY ECONOMETRICS: A MODERN APPROACH (2012); BARBARA FINLAY & A. AGRESTI, STATISTICAL METHODS FOR THE SOCIAL SCIENCES (2009).

Table 4. Regressions Predicting Death Sentencing Outcomes in San Diego County by Suspect and Victim Racial Dyads (1979-2018).

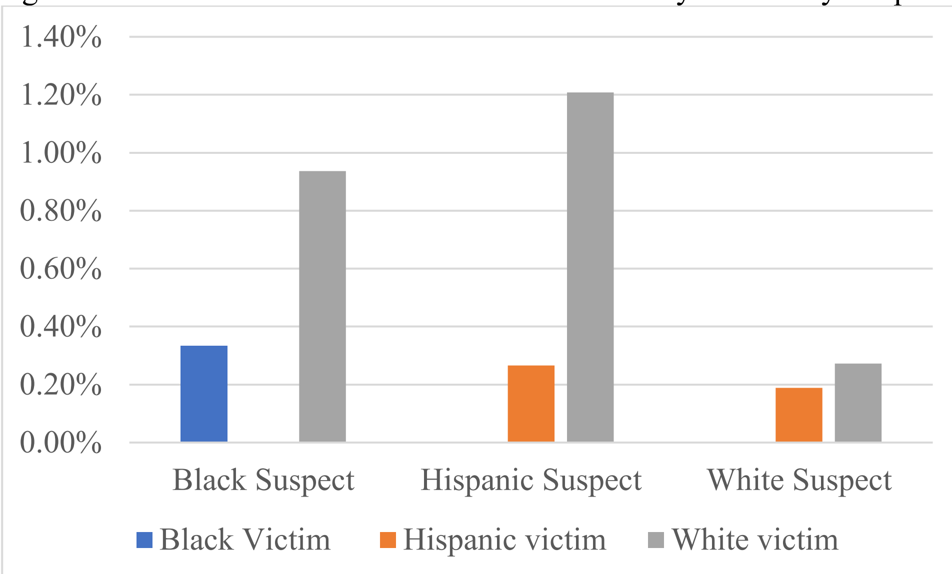
	OR(SE)
Victim and suspect demographics:	
White suspect & Black victim	NA
White suspect & Hispanic victim	0.50 (0.59)
Black suspect & White victim	2.10 (1.26)
Black suspect & Black victim	0.81 (0.58)
Black suspect & Hispanic victim	NA
Hispanic suspect & White victim	2.87 (1.75)
Hispanic suspect & Black victim	NA
Hispanic suspect & Hispanic victim	0.67 (0.41)
Case characteristics:	
Multiple murder - PC190.2(a)(3)	21.57*** (10.08)
Felony - murder PC190.2(a)(17)	25.94*** (11.39)
year	0.90* (0.04)
Annual homicide rate	0.17 (0.21)
Observations	2219

Exponentiated coefficients; Standard errors in parentheses
Notes: NA = Not applicable because the parameter could not be estimated. Listwise deleted sample. Reference groups = white victim; white suspect
* $p < .05$, ** $p < .01$, *** $p < .001$

33. To help visualize victim-by-suspect racial dyads, I calculated predicted probabilities. Figure 4, displaying victim-by-suspect racial dyads in terms of probabilities from the logistic regression in Table 3, clearly shows that homicides involving White victims and non-White suspects are more likely to result in a death sentence. In particular, Figure 4 shows that Hispanic suspects who kill White victims are the most likely to receive a death sentence, followed by Black suspects who kill White victims. These findings are consistent with prior research finding that minority suspects who kill White victims are especially disadvantaged in terms of death sentences.[42] Note that, like Table 3, no all victim-by-suspect racial dyads are displayed since some could not be estimated due to lack of variability on the dependent variable.

[42] 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).

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



IV. CONCLUSIONS

34. This study finds racial disparities in San Diego County, spanning more than four decades from 1979 through 2018. In particular, I find that homicides with Black and Hispanic suspects are more likely to result in a death sentence even when controlling for other non-racial factors when compared to homicides with White suspects. Conversely, homicides with Black or Hispanic victims are less likely to result in a death sentence than those with White victims. Moreover, results indicate that homicides involving White victims and non-White defendants are more likely to result in a death sentence.

35. These results highlight large-scale and wide-spread racial disparities in San Diego County over several decades, where Black/Hispanic victims and defendants are disadvantaged in terms of death sentences. This report offers strong empirical evidence of racial disparities within San Diego County's death penalty system from 1979 through 2018, employing state-of-the-art statistical methodologies.

EXHIBIT J

Racial and Ethnic Disparities in Santa Clara County's Death Penalty System

September 22, 2020

Nick Petersen
Assistant Professor of Sociology & Law
University of Miami
Coral Gables, Florida, United States
npetersen@miami.edu
(305) 284-6169

Abstract

This study employs multiple regression techniques to examine whether victim and suspect racial/ethnic disparities exist in Santa Clara County death sentencing trends from 1976 to 2018. Linking data on homicide incidents from the Supplemental Homicide Report (SHR) to death sentencing data from the Habeas Corpus Resource Center (HCRC), this study employs a logistic regression model to examine the death sentencing outcomes for 1,654 homicides in Santa Clara County, California from 1976 to 2018. Unadjusted summary statistics indicate that roughly 60% of victims in death sentence cases are white, while there has been no death sentence case involving a black victim during the past 42 years (1976 to 2018). Conversely, 60% of suspects in death sentence cases are non-white. A logistic regression model controlling for the presence of multiple murder victims and a concurrent felony (i.e., felony murder) indicates that homicides involving white victims are 2.07 times more likely to result in a death sentence than those with a non-white victim. In contrast, homicides involving white suspects are 14% less likely to result in a death sentence than those with non-white suspects. Therefore, results point to larger disparities based on victim race compared to suspect race. Given the aggregate nature of this analysis—focusing on general death sentencing trends rather than more detailed prosecutorial/juror decision-making—the conclusions reached here do not "prove" these racial disparities arise from racial bias or animus on the part of prosecutors or juries. Instead, these results highlight aggregate-level racial disparities that might help inform criminal justice officials and policymakers.

Study Overview

To examine whether victim and suspect[1] racial/ethnic disparities exist in Santa Clara County death sentencing trends from 1976 to 2018, I linked two data sources. First, I used the Supplemental Homicide Report (SHR) to gather data on all homicides reported to the police in Santa Clara County between 1976 and 2018.[2] Since the SHR is incident-based, it mainly includes information on victim and incident characteristics, providing less information about homicide suspect(s), and no information about criminal justice actions such as an arrest. Second, I obtained death sentencing data from the Habeas Corpus Resource Center (HCRC).[3] The HCRC contains information on all death sentences rendered in Santa Clara County, California from 1976 to 2018.[4] Several studies have linked SHR files with death sentencing data to study racial/ethnic disparities in capital punishment outcomes, and thus there is sufficient precedent to support this approach (Gross & Mauro, 1984; Pierce & Radelet, 2005; Radelet & Pierce, 2010). Given that the SHR is an incident-based dataset, the unit of analysis in this study is the homicide incident (Gross & Mauro, 1984; Pierce & Radelet, 2005; Radelet & Pierce, 2010).[5]

After cleaning the SHR and HCRC datasets, I linked them in Stata 15 using probabilistic matching. In particular, I used the "reclink2" package (Wasi & Flaaen, 2015) to link these datasets on the following categorical variables[6]: 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).[7] Since the SHR does not include the exact homicide date for confidentiality reasons (including the month and year instead), probability matching was required. Probability matching is commonly used in various social sciences when an exact match cannot be achieved, such as linking names with misspellings or variations in street address

[1] I use the term "suspect" rather than "defendant" since 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.

[2] 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/).

[3] These data were provided to me by lawyers at the California State Public Defender's Office.

[4] Where the HCRC database was missing suspect or case information, supplemental data was gathered from the CDCR's "Condemned Inmate List" (https://www.cdcr.ca.gov/capital-punishment/condemned-inmate-list-secure-request/). When the HCRC was missing victim race/ethnicity information, lawyers at the California State Public Defender's Office used death certificates or conferred with appellate attorneys familiar with the homicide to fill in this information.

[5] 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.

[6] "Categorical" variables are those with multiple categories, each representing a different characteristic or group. "Binary" or "dichotomous" variables are categorical variables with only two categories (i.e., white vs. non-white), which are coded as "0" and "1." The actual numeric values assigned to categorical variables does not influence regression results as they represent qualitative categories rather than precise numerical values (Agresti, 2010).

[7] In an "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's (2015), a visual inspection of each homicide with matched ties was conducted using Stat's clinical review package "clrevmatch."

names (for examples, see Wasi & Flaaen, 2015). Moreover, probability matching is a common method in SHR death penalty studies (Pierce & Radelet, 2005; Radelet & Pierce, 2010). In their California study, for example, Pierce & Radelet (2005, p. 33) note that "Other researchers who have used this matching method have also found minor problems in matching. Samuel Gross and Robert Mauro, for example, note that, '[often more than one SHR case would correspond to a given death row case; however, since this matching was done only for the purpose of analyzing data on variable(s) that were reported in both sources, it did not matter whether a particular death row case was identified with a unique FBI/SHR case.'" In other words, death sentencing data do not need to exactly match a specific homicide in the SHR because SHR data are only used for comparison purposes in statistical models. In contrast, data on the victim, suspect, and homicide originated from the HCRC database. In this study, I use a similar approach, only examining variables that are present in both the HCRC and SHR datasets.

I also restricted the sample in several ways. Foremost, I focus on death penalty cases that were charged and tried in Santa Clara County, excluding cases charged in Santa Clara County but tried elsewhere and vice versa.[8] Second, I limit the sample to cases with offenders 18 years of age or older since juveniles are no longer eligible for the death penalty in the U.S. (*Roper v. Simmons*). Since nearly half of the homicides reported in the SHR do not lead to an arrest, many homicides are ineligible for the death penalty simply because no arrest was ever made. By focusing on homicides with suspect race information, I am purposefully excluding homicides where an arrest did not likely occur. Since the SHR does not include information on arrests, many researchers have used suspect race or other suspect demographics as a proxy for arrest (Gross & Mauro, 1984; Pierce & Radelet, 2005). After limiting the sample in these various ways, the remaining finalized dataset includes 24 homicides that resulted in a death sentence and 1,654 homicides that did not result in a death sentence.

This study used logistic regression analysis, which looks at the likelihood of a binary event, in this case, a death sentence.[9] The use of logistic regression in analyzing death penalty outcomes is well established (Baldus et al., 2009), as it allows researchers to control for the competing influences of multiple factors on death penalty outcomes. When considering the influence of victim and suspect race/ethnicity on death penalty outcomes, it is critical to account for the influence of non-racial/ethnic variables on the outcomes. This is necessary to ensure that any observed racial differences are not, in empirical terms, "spurious."[10] To the extent that legally relevant factors (e.g., multiple victims, felony murder) vary by race/ethnicity, it is necessary to account for these factors in order to isolate the independent effect of race/ethnicity on death penalty outcomes. As such, multiple regression models "control" for – i.e., hold constant – a number of non-racial/ethnic factors that could impact death penalty outcomes. In the

[8] The following cases that were charged elsewhere but tried in Santa Clara County were excluded from the analysis: Stayner, Shermantine, Clark, Davis, Nicolaus, and Chase.

[9] Logistic regression is a specific type of multiple regression appropriate for binary dependent variables; it estimates the likelihood of "success" versus "failure" based on a series of predictors, where "success" is defined as a positive outcome (i.e., the dependent variable coded is coded as "1") (Baldus et al., 2009; Baldus & Woodworth, 2003; Grosso et al., 2014). In this case, "success" is defined as a death sentence and assigned a value of 1. In a logistic regression model, odds (O) and probabilities (P) have the following relationship: Odds = P/1-P and Probability = O/1+O (Baldus et al., 2009; Wooldridge, 2012).

[10] "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/ethnicity and death sentences would be spurious if it were explained by the presence of multiple victims, but whether the homicide included multiple victims was not included in the analysis (Baldus et al., 2009; Wooldridge, 2012).

logistic regression model, I control for important homicide characteristics (e.g., felony and multiple murder). Thus, regression results display “adjusted” racial/ethnic disparities controlling for these important homicide characteristics. I utilize multiple regression techniques to analyze these data because it is the “most widely used vehicle for empirical analysis in economics and other social sciences,” and it allows me to isolate the independent effect of the victim and suspect race/ethnicity on death penalty outcomes (Baldus et al., 2009; Wooldridge, 2012, p. 73). Specifically, the regression analyses discussed below enabled me to test whether the likelihood of a death sentence varies by victim and suspect race/ethnicity, holding constant non-racial factors that could influence death penalty decision-making, such as the presence of a contemporaneous felony or multiple victims. In doing so, regression analyses allow me to compare “similarly-situated”[11] homicides where everything in each homicide is similar except for the race/ethnicity of the victim or suspect. Logistic regressions are displayed as odds ratios where values larger than 1 indicate an increased likelihood of a homicide resulting in a death sentence, whereas odds ratios less than 1 indicate a decreased likelihood of a homicide resulting in a death sentence.[12]

Victim and suspect race/ethnicity is coded as white vs. non-white for several reasons. Foremost, there have been no death sentences involving black victims during the past 42 years (1976 to 2018), making it difficult to estimate the likelihood of death sentence for Santa Clara cases with black victims since it has never happened in recent history. Secondly, the vast majority of Santa Clara death sentences have resulted from cases involving white victims (60%), thereby making white victims a useful baseline comparison group. Given this focus on white vs. non-white victims and suspects, I follow Gross & Mauro’s (1984) coding protocol for victim/suspect race/ethnicity. In particular, I coded multiple-victim homicides with at least one white victim as “white-victim” homicides and multiple-victim homicides with at least one black or Hispanic victim as “non-white-victim” homicides.

Unadjusted Summary Statistics

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 Santa Clara County from 1976 to 2018, Table 1 indicates that homicides resulting in a death sentence are more likely to have a white victim. For example, 43% of all Santa Clara County homicides have a white victim, whereas 60% of Santa Clara County homicides that result in a death sentence have a white victim. More starkly, blacks represent 10% of victims in Santa Clara County, but there has been no death sentence case involving a black victim during the past 42 years (1976 to 2018). Table 1 indicates that death sentences are somewhat more likely to involve non-white suspects (60%) compared to white suspects (40%). While this is suggestive of a racial/ethnic disparity, I cannot say for sure since there could be other factors that might help to explain these differences. If, for example, homicides with white victims are also more likely to involve multiple murders or a felony, this may help to explain such patterns. Therefore, it is important to examine “adjusted” statistics from

[11] As used here, “similarly-situated” refers to the fact that regression models hold constant all the non-racial predictors in the model, and thus regression estimates refer to homicides that are mathematically similar in every other respect except for victim/suspect race/ethnicity.
[12] For the purposes of this document, logistic regression estimates are discussed as percentage changes in terms of odds, with 1 corresponding to equal odds (i.e., “no effect”). Binary variables estimated in a logistic and survival regression equations can be interpreted as a percentage change in the odds using the following formula: 1-[(β*xi*) X 100] (Baldus et al., 2009; Wooldridge, 2012).

regression models, which I discuss below. In terms of Table 1, it is also worth noting that while a small percentage of all homicides include multiple victims or felony murder, homicides resulting in a death sentence are much more likely to have these characteristics.

Table 1. Summary Statistics for Santa Clara County Homicides.

	All homicides	Death sentence	No death sentence
	%	%	%
Dependent variable:			
Death Sentence (yes/no)	0.02	1.00	0.00
Victim and suspect demographics:			
White victim	0.43	0.60	0.43
White suspect	0.40	0.40	0.40
Case characteristics:			
Multiple murder - PC190.2(a)(3)	0.05	0.32	0.04
Felony - murder PC190.2(a)(17)	0.16	0.60	0.15
Observations	1654	25	1629

Adjusted Regression Results

Next, I turn to "adjusted" regression estimates in Table 2. These are "adjusted" in the sense that the regression model controls for other important legal factors such as the presence of multiple victims or a felony. According to the logistic regression model, homicides involving multiple victims or a felony are more likely to result in a death sentence. These findings are consistent with California's death penalty laws, which suggest that homicides with multiple victims [PC190.2(a)(3)] or a felony [PC190.2(a)(17)] are more aggravated, and thus are eligible for the death penalty. The strong positive statistical significance of multiple murders and felony murder for death penalty outcomes in California is consistent with prior research (Petersen, 2016, 2017; Petersen & Lynch, 2013; Pierce & Radelet, 2005; Shatz, 2007).

Even after controlling for these important legal factors, however, victim and suspect race/ethnicity shape death penalty outcomes. According to the logistic regression model, homicides with white victims are 2.07 (or 207%) times more likely to result in a death sentence than homicides with a non-white victim. In contrast, homicides with a white suspect are about 0.76 (or 14%) times less likely to result in a death sentence than those with a non-white suspect.[13] As is common practice, I calculated predicted probabilities based on the logistic regression model to help visualize the effects of victim and suspect race/ethnicity (Long & Freese, 2014). Figures 1-2 show adjusted probabilities for the effects of victim and suspect race/ethnicity after controlling for other homicide characteristics like multiple murder or felony murder. Predicted probabilities were calculated by "plugging in" the mean value for non-racial control variables into the model. Thus, predicted probabilities highlight the likelihood of a death

[13] While these results are not statistically significant, I note that statistical significance is less relevant in the current context given that I am analyzing the full population of death sentences in Santa Clara County from 1976 to 2018. As Phillips (2009, p. 821) notes in his analysis of Texas death penalty cases, "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 argues "researchers should focus more on substantive significance and less on statistical significance." Given that the present dataset contains the full population of death sentences in Santa Clara county over the last 42 years, I note that non-statistically significant findings are still important because they describe patterns in this population dataset.

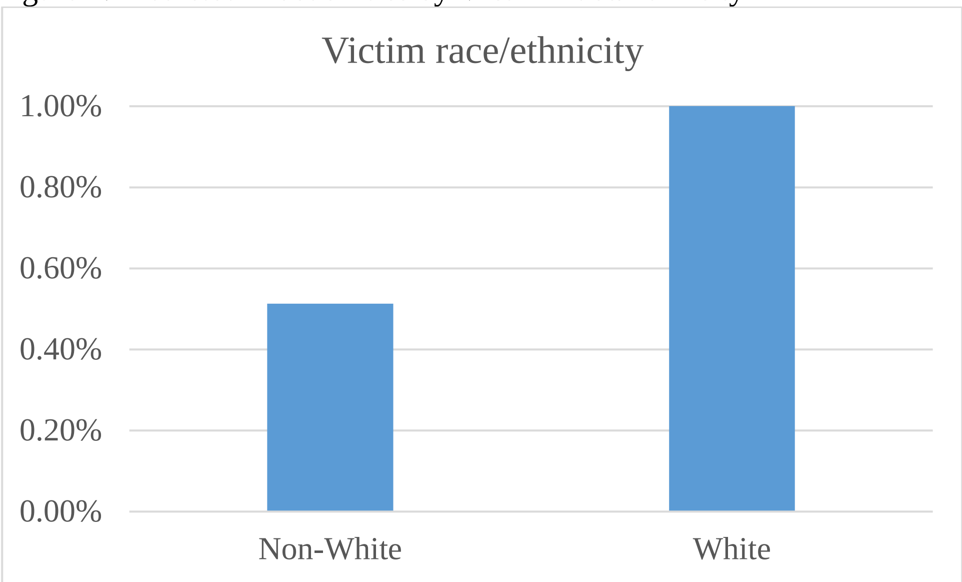
sentence among an "average" homicide that differs by victim or suspect race/ethnicity.[14] Figure 1, displaying predicted probabilities from the logistic regression model in Table 2, reveals that cases with white victims are more likely to result in a death sentence. In contrast, Figure 2 indicates that homicides with a non-white suspect are somewhat less likely to result in a death sentence.

Table 2. Logistic Regression Predicting Death Sentencing for Santa Clara County Homicides.

	Death Sentence (yes/no) OR(SE)
Victim and suspect demographics:	
White victim	2.07 (1.05)
White suspect	0.76 (0.38)
Case characteristics:	
Multiple murder – PC190.2(a)(3)	13.99*** (6.82)
Felony – murder PC190.2(a)(17)	9.12*** (4.00)
Observations	1654

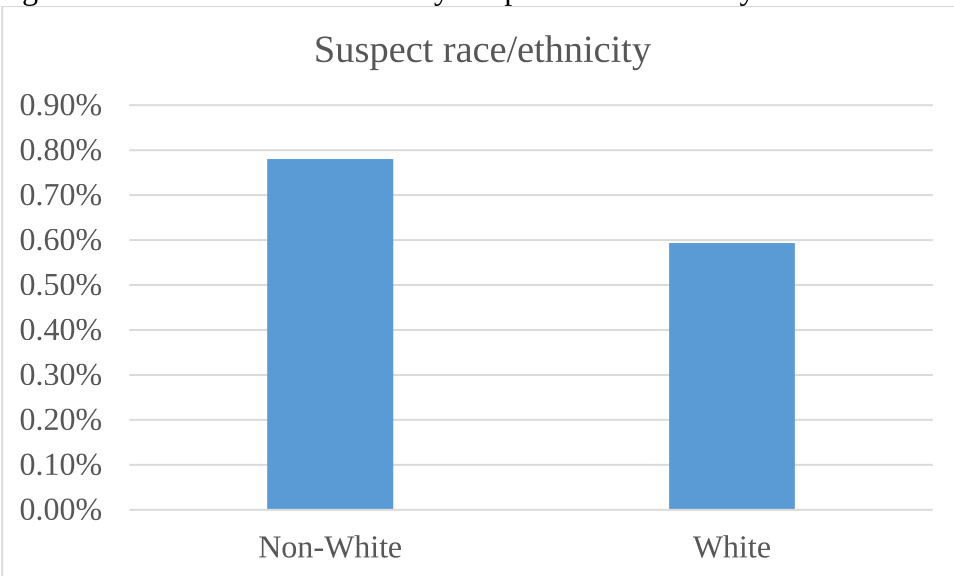
Exponentiated coefficients; Standard errors in parentheses
* p < .1, ** p < .05, *** p < .01

Figure 1. Predicted Probabilities by Victim Race/Ethnicity



[14] Adjusted probabilities using Stata's "margins" command, holding all other covariates at mean values.

Figure 2. Predicted Probabilities by Suspect Race/Ethnicity



Conclusion

These findings offer evidence of racial disparities in Santa Clara County death sentencing trends from 1976 to 2018 in the aggregate. Even after controlling for important legally relevant factors like the presence of multiple victims or a concurrent felony, aggregate-level regression results indicate that homicides with white victims are more likely to result in a death sentence. The inverse is true for suspect race/ethnicity, where homicides involving white suspects are slightly less likely to result in a death sentence than homicides with a non-white suspect. Given that this analysis looks at racial disparities in death-sentencing at the aggregate level, it cannot speak to racial bias. In other words, these results do not "prove" that aggregate racial disparities arise from racial discrimination on the part of prosecutors or juries because this aggregate-level analysis does not include data on prosecutorial/juror discretion that might help account for some of these patterns. However, these results do speak to more general patterns of aggregate racial disparities that may help inform criminal justice officials and policymakers.

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