# Why a Small Handful of Counties Generates the Bulk of US Death Sentences
# A Theory of Self-Reinforcement with Three Statistical Tests

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## Abstract

We demonstrate powerful self-referential effects in county-level data concerning use of the death penalty. Three separate statistical tests demonstrate first that death sentences across all US counties in states with a valid death penalty statute correspond to a stretched distribution, consistent with previous studies. Second, we show powerful event-dependency effects using repeated-event models. Third, we use a cross-sectional time-series approach to model the predicted number of death sentences imposed in a given county in a given year. This model shows that the cumulative number of death sentences previously imposed in the same county is a powerful predictor of the number of death sentences in a given year. Results raise troubling substantive implications: The number of death sentences in a given county in a given year is better predicted by that county's previous experience in imposing death than it is by the number of homicides in the previous year. This explains the previously observed fact that a large share of death sentences come from a small number of counties and documents the self-referential aspects of use the death penalty. A death sentencing system based on racial dynamics then amplified by self-referential dynamics is inconsistent with equal protection of the law, but describes the US system well.

Keywords: Capital punishment, lynching, geography, event-dependency, stretched distributions

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## Introduction

Imagine a death penalty that is imposed on killers in different areas of the country, or even across localities within individual states, in a manner that is substantially random but, to the extent that any systematic patterns are apparent, those are related to ugly racial dynamics, including the legacy of racial violence in decades past. Then consider the possibility that each locality settles into a pattern of use or avoidance of the death penalty based on its own accumulated history. In such a self-reinforcing system, small initial differences across counties would eventually accumulate into vast differences, with some localities virtually never using the death penalty and others using it much more frequently. Mostly, these differences would be unrelated to such factors as homicide rates, but to the extent that any statistical patterns could be discerned, two things would stand out: racial dynamics, since these were part of the dynamic that set the localities onto their different paths in history, and vast differences in use. The self-reinforcing dynamic would generate a "stretched" distribution of use with a few outlier counties using the punishment much more than others, and the vast majority not using it at all. The racial dynamics would still be apparent in the final distribution, however: The high-use counties would disproportionately come from those counties with histories of racial violence against African-Americans. Of course, counties with more people and more homicides might have more death sentences, but this linkage would be attenuated by racial and self-reinforcing dynamics.

The US Supreme Court ruled the death penalty system unconstitutional in 1972 because of concerns about patterns similar to these. According to Justice Potter Stewart, the system in place at the time was so capricious that the selection of individuals for the death penalty, among the class of offenders who were legally eligible for it, was like "being struck by lightning". In *Furman v. Georgia* (408 U.S. 238 (1972)), he wrote:

> These death sentences are cruel and unusual in the same way that being stuck by lightning is cruel and unusual. For, of all the people convicted of rapes and murders in 1967 and 1968, many just as reprehensible as these, the petitioners are among a capriciously selected random handful upon whom the sentence of death has in fact been imposed. My concurring Brothers have demonstrated that, if any basis can be discerned for the selection of these few to be sentenced to die, it is the constitutionally impermissible basis of race. But racial discrimination has not been proved, and I put it to one side. I simply conclude that the Eighth and Fourteenth Amendments cannot tolerate the infliction of a sentence of death under legal systems that permit this unique penalty to be so wantonly and so freakishly imposed" (pp. 309-310, citations omitted).

The Court, of course, was so divided in its momentous 1972 decision that each Justice finding the system unconstitutional wrote a separate opinion, and the four dissenting Justices did so as well. All five Justices finding against the penalty noted the issue of arbitrariness. As Justice Brennan noted, some argued that, if anything, racial bias was a contributing factor to any possible basis for selecting the small number of offenders sentenced to death from the vast numbers eligible for the punishment. But, as it was not definitively proven, he and other Justices "put it to one side." But the combination of capriciousness and "impermissible" racial dynamics clearly concerned the Justices. They approved a number of systems proposed by the states designed to avoid these issues in a set of decisions in 1976. These systems have failed.

In this article, we focus on the geographic distribution of use of the death penalty across all counties in states with a legally valid death penalty. This differs, of course, from the Justices' concerns in 1972. Others, however, have conducted systematic studies comparing thousands of death-eligible homicides with the smaller numbers of those selected for the death penalty (see for examples Baldus et al. 1983, 1990; Baldus and Woodworth 2003; Donohue 2014). The Court rejected the compelling evidence that racial dynamics were at play in a Georgia case where thousands of death-eligible cases were compared with the few selected for death, controlling for over 100 legally relevant variables (e.g., heinousness of the crime, number of victims) and legally irrelevant ones (e.g., race and gender of offender and victim, county of crime). Evidence presented in *McCleskey v. Kemp* (481 U.S. 279 (1987)) showed that, even controlling for legally relevant factors, legally irrelevant factors such as the race-gender characteristics of the victim and offender were powerful predictors of who did and did not get selected for death. The Court, clearly uncomfortable with the social scientific nature of the evidence presented, and perhaps concerned with the broader ramifications of a ruling that barred outcomes with demonstrable racial inequities in criminal proceedings, rejected the evidence as irrelevant. It ruled instead that appellants must prove the intent of the state to discriminate against an individual offender. That decision put an end to the legal strategy of demonstrating racial bias through statistical comparisons (see Mandery 2013 or Steiker and Steiker 2016 for reviews of Court decision-making from *Furman* through *McCleskey*). Though the national legal strategy exemplified by *McCleskey* was abandoned, it continued in various states. Such studies have provided important elements of the accumulated empirical evidence about the flaws in the system leading some states to discontinue use of their death penalty or abolish it altogether (see, e.g., Donohue 2014 for the state of Connecticut, which abolished in 2012; also Davidson et al. 2006 for Washington, which abolished in 2018).

The accumulation of dozens of Baldus-type studies has demonstrated across many time periods and legal jurisdictions that, while such legally relevant factors as the number of victims certainly matter in predicting who gets death, so do a number of legally irrelevant matters, such as the race of the victim and geography. Some counties use the death penalty much more or less than would be expected, other things equal. Crimes with white victims, particularly white female victims, are consistently more likely to lead to a death sentence, especially in those rare instances where the offender is a black male (see Baumgartner, Davidson et al. 2018, 80–85 for a review of such studies). We do not seek to replicate these individual studies, but our findings and approach are complimentary to these accumulated findings. We focus on the question of geographical concentration of the death penalty in just a handful of localities, and we seek to answer the question: Why these counties but not others? The answers reveal racial dynamics combined with caprice, exactly what the Justices were concerned about in *Furman*.

We base our analysis on every death sentence imposed in the US from 1972 through the end of 2019 and present three distinct empirical tests. These show that, if there is any statistical pattern, it is indeed the “impermissible basis of race” that Justice Stewart noted. Further, they show that the system is dominated by a self-reinforcing system that, over more than 45 years, has generated a capricious and arbitrary distribution where the number of homicides is only loosely related to the number of death sentences. The self-reinforcing or amplifying aspects of the dynamics we describe here have generated a system where the better predictor of whether a given county will sentence an individual to death in a given year is not the number of homicides in that county in the previous year, but rather the number of death sentences that county has previously imposed. A district attorney’s office may or may not accumulate the skills, knowledge, and practice needed successfully to carry out a capital trial leading to a death sentence. Whether or not previous decades of experience have led to these skills and practices, however, is unrelated to the heinousness of the next crime that may occur within any given county. Therefore, it should be unrelated to the odds of seeking or imposing a death sentence. But in fact, it is one of the most powerful and consistent predictors.

## A Puzzle: The Geographic Distribution of Death Sentences

As of 1972, 41 states, the District of Columbia, the federal government, and the military had a legal death penalty, for a total of 44 jurisdictions. Following *Furman*, which ruled all of these systems inoperable, most of these states quickly reestablished their capital punishment systems with further safeguards to ensure "proportionality" so that the "modern" death penalty would avoid the flaws, particularly capriciousness, that the Justices had noted in *Furman*. By the end of 1976, 35 states had reestablished; the number rose to 40 by 1984 and stayed roughly at that level until a series of abolitions beginning in 2007: New York, New Jersey, New Mexico, Illinois, Connecticut, Maryland, Delaware, Washington, and New Hampshire, bringing the number of retentionist jurisdictions as of 2019 to 29 (see Baumgartner, Davidson, et al. 2018, 11–12; DPIC 2019a). In the analyses below, we include only states allowing the death penalty in the year of analysis. Because we focus on the geographical variability in the use of the death penalty, we exclude the US military (which has sentenced 15 individuals to death since reestablishment in 1984, but carried out no executions) and the federal government (which has issued 79 death sentences since reinstatement in 1988, and carried out three executions).

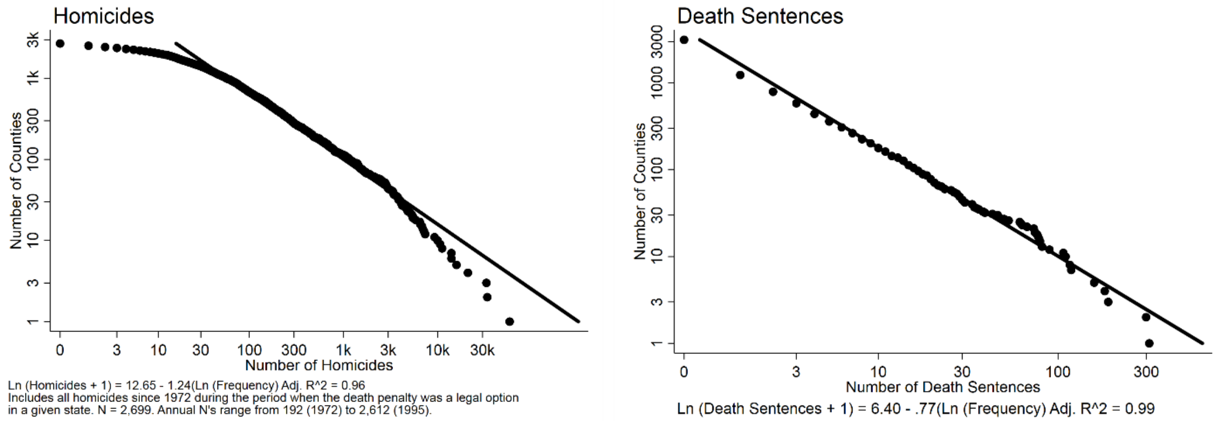
We are concerned here with the geographical concentration of the death penalty in just a few jurisdictions. This has previously been noted by many scholars and activists, so we take it as a starting point (for fuller discussions of this concentration, see Smith 2011; Dieter 2013; Kovarsky 2016). Because our focus is on counties (within states), we must first note that many counties are small with regards to population, but a few are very large. Any discussion of geographic concentration of the death penalty must start with this baseline. Obviously, there would be no surprise if Los Angeles County, California (2010 population: 9,840,024) had more homicides or death sentences than Loving County, Texas (2010 population: 85).

Counties with large populations have more homicides, logically enough, and of course the number of death sentences tends to be higher in counties with more homicides. But a map of death sentences features, in order, Los Angeles, Harris (Houston), Philadelphia, Maricopa (Phoenix), Cook (Chicago), Clark (Las Vegas), Miami-Dade, Oklahoma City, Duval

(Jacksonville FL), Riverside (CA), and Dallas. These are the only counties with 100 or more death sentences in the modern era. Homicides are not so concentrated. And the counties with the most death sentences are not always the ones with the most homicides. What causes death sentences to come from a small set of counties, though homicides are not so narrowly distributed, and stem from different locations?

Figure 1 presents a puzzle. It shows the cumulative distribution of homicides and death sentences across US counties, in states with a legal death penalty. For each variable, we present the cumulative totals for all years between 1972 and the present, for those years when the death penalty was a legally available option in that state. The two figures are presented in an identical format, with each axis presented on a logarithmic scale. Both distributions are clearly "stretched" but death sentences much more so. (Indeed, homicides are more stretched than population; see Baumgartner, Box-Steffensmeier et al. 2018). The solid line in each figure reflects the best fit linear regression of the log of the cumulative value of the variable in question regressed on the log of the cumulative number of counties having at least that number of observations. A series fitting the line would correspond to a power-law distribution. Our point here is not whether these distributions are characterized by any particular mathematical distribution, but simply to note that while both distributions are stretched, death sentences are moreso: Between homicides and death sentences, a transformation occurs. Further, as we will show, the outliers are not the same locations. Those with the most homicides do not correspond tightly to the list of the most death sentences.

Figure 1. Cumulative Distributions of Homicides and Death Sentences.




Note: Homicides data based on CDC reports through 2018; death sentencing data through 2019. In both cases, data are limited to years when the death penalty was a legally available option in that state. Missing CDC homicides data were estimated by county for missing years using trends and FBI data as predictor variables; see Appendix for details.

Table 1 shows the top 25 counties in the nation with regards to cumulative death sentences. Two counties stand out: Los Angeles CA and Harris TX, with 311 and 299 death sentences, more than the vast majority of states. Los Angeles is also the county with the highest number of homicides. Houston, however, ranks 4th in homicides, nationally. The top 25 sentencing counties include a number of counties ranked 35 or below with regards to homicides. Clark County NV (Las Vegas), Oklahoma City OK, Hamilton OH (Cincinnati), Pima AZ (Tucson), Hillsborough FL (Tampa), Pinellas FL (Clearwater-St. Petersburg) and Orange FL (Orlando) stand out particularly in having significantly higher ranks on the list of death sentencing counties than on cumulative homicides. Many high-homicides counties are absent from the list of top death sentencing counties, despite the fact that homicides are included only for those years where the death penalty was a legally available option.

Table 1. Top 25 Death Sentencing Counties, with Cumulative Homicides.

| | Homicides | | Death Sentences | |
|---|---|---|---|---|
| County | Number | Rank | Number | Rank |
| Los Angeles CA | 58,014 | 1 | 311 | 1 |
| Harris TX | 20,961 | 4 | 299 | 2 |
| Philadelphia PA | 15,882 | 5 | 187 | 3 |
| Maricopa AZ | 10,645 | 9 | 179 | 4 |
| Cook IL | 32,906 | 3 | 157 | 5 |
| Clark NV | 5,298 | 21 | 118 | 6 |
| Miami-Dade FL | 14,027 | 6 | 118 | 7 |
| Oklahoma OK | 3,425 | 38 | 116 | 8 |
| Riverside CA | 4,190 | 28 | 110 | 9 |
| Duval FL | 5,131 | 22 | 110 | 10 |
| Dallas TX | 14,005 | 7 | 107 | 11 |
| Cuyahoga OH | 6,966 | 14 | 90 | 12 |
| Orange CA | 4,210 | 27 | 82 | 13 |
| Broward FL | 4,638 | 26 | 80 | 14 |
| Hamilton OH | 2,919 | 46 | 80 | 15 |
| Jefferson AL | 5,474 | 19 | 78 | 16 |
| Bexar TX | 6,833 | 15 | 77 | 17 |
| Hillsborough FL | 3,855 | 32 | 75 | 18 |
| Tarrant TX | 5,456 | 20 | 74 | 19 |
| Shelby TN | 7,176 | 13 | 74 | 20 |
| Pima AZ | 3,067 | 43 | 68 | 21 |
| Pinellas FL | 2,182 | 60 | 64 | 22 |
| Alameda CA | 5,848 | 18 | 63 | 23 |
| San Bernardino CA | 6,471 | 17 | 62 | 24 |
| Orange FL | 2,962 | 45 | 54 | 25 |

What process would make the number of death sentences so concentrated in just a few jurisdictions? Los Angeles and Houston (Harris County) are high on both the lists of homicides and death sentences, but consider Atlanta (Fulton County), Georgia. It is high on the list of homicides, but has only a total of 16 death sentences. Phoenix (Maricopa County), Arizona, had slightly more homicides than Atlanta, but 179 death sentences. Baltimore had about the same number of homicides (roughly 10,000 over the period), but just six death sentences. There is little reason to think that homicides would be more heinous or deserving of death if they occur in one place rather than another. But when we look at different places with roughly similar numbers of homicides, and, we see widely divergent paths with regard to the use of the death penalty.[1] We turn in the next section to present our answer to this puzzle, a model of self-reinforcement. Following that, we present three distinct empirical tests.

### *Imposing a Death Sentence*

When a homicide occurs, police investigate and the district attorney brings charges. In states with a valid capital punishment statute, procedures vary but all have in common that the state must decide whether to "seek death." Typically, the state may seek death only if the crime meets certain statutory criteria (e.g., it is not a death-eligible crime as defined in the statute). But within the category of death eligible crimes, the DA has discretion to seek death or not.[2] This is the first, and generally most important, step in the process. Capital trials have two stages: guilt and punishment. The same jury sits for both, and if the defendant is found guilty of a capital crime in the first stage, then the jury sits for the "penalty phase" to consider aggravating and mitigating evidence, and pronounce a decision. In most states, the jury's decision is binding, but in some states the judge decides or may overrule the jury.

### *A Theory of Self-Reinforcement*

As some of us have previously described, the death penalty process is local and self-referential (see Baumgartner, Gram et al. 2016; Baumgartner, Box-Steffensmeier, and Campbell 2018). Legal scholar Lee Kovarsky (2016) describes it as the development of local "muscle memory": Localities either get good at the complex process of bring a capital case to its conclusion, or they do not. Some of this is based on the number of homicides, the size of the DA's office, the

[1] This pattern is the same when we look across counties within a given state, so cannot be attributed solely to differences in what crimes are death eligible, which varies across states. Many states have broad death eligibility laws, including such things as any homicide occurring during the commission of an underlying felony (such as a robbery). Others, such as New York during the time it had the death penalty, had more narrowly targeted eligibility rules. The five boroughs of New York, in fact, ranked second in homicides, but had no death sentences.
[2] North Carolina's law required DA's to seek death in all cases where the crime was capital eligible until 2001, when discretion was granted to the DA. Since 2001, every death state has DA discretion.

resources available to indigent defendants, and other predictable factors, but some is self-referential. Criminal justice is clearly a state function, so procedures differ from state to state. In those states with the death penalty, when a capital crime occurs, the District Attorney typically chooses whether or not to seek death.[3] There is, of course, no reason to expect death sentencing rates to be identical across counties. First, within the same state, some counties may randomly see slightly higher or lower numbers of capital-eligible homicides as a share of all homicides. Second, there would likely be stochastic variability in the odds that the police investigation isolates a suspect and provides enough evidence to make a case "beyond a reasonable doubt" in court. Similarly, services available to indigent defendants might differ from place to place, as would the ideology of judges, DAs, and jurors. There is no reason, therefore, to expect uniformity in death sentences as a share of all homicides. Stochastic variability would naturally generate some random differences in these rates.

Certain factors associated with capital prosecutions, on the other hand, can be self-referential, not randomly distributed. Consider the question from the perspective of the first mover, the District Attorney. Given a new capital eligible crime, should the DA's office "go for death"? One relevant concern would be fairness. Was this crime as bad or worse than any previous crime for which the same office previously sought capital punishment? If not, then the death penalty for this crime might be considered inappropriate because it is excessive compared to previous cases. If, on the other hand, the crime was worse than others where the death penalty had been sought, then a capital prosecution might seem to be required on the basis of historical consistency and fairness. Another consideration is the odds of winning: will the jury vote for death, and will the judge agree? If not, then the costs, time commitment, and effort spent seeking

[3] Many features differ by state: what crimes are capital-eligible, for example. We control for state in all models below and focus on county-level variability within state.

a death penalty might be misplaced; in most states the DA can seek a penalty of life without parole and avoid the cost and complications of a capital trial altogether.

A key element in generating a system of self-reinforcement is correlation among decision-makers. There are at least four important local actors whose actions determine whether a given homicide will lead to a death sentence: the prosecutor; the defense bar; the judge; and the jury. When such an array of actors behaves independently and their preferences are not correlated, the Central Limit Theorem shows that outcomes will be stochastic. But here the actions of one are highly dependent on the expected actions of the others. If juries will not vote for death, prosecutors will not seek it. If defense attorneys are poorly resourced and unable to stop the process, juries will be more likely to convict. If judges are enthusiastic about the death penalty, prosecutors will seek it more. In the local context, any of these factors can work in either direction: where judges raise high bars to the use of the death penalty, defense attorneys will have greater powers, juries will get more restrictive instructions, and prosecutors will know they have little chance of "getting death." Where these trends are reversed, the floodgates can open.

A second key element of our theory is that the point of reference for these local actors is their own history, not other jurisdictions in the state. In some jurisdictions, district attorneys may not have sought death in many previous cases (either because of their interpretation of whether the homicide rose to the level of the "worst of the worst" or because they did not believe they could get a local jury to vote for death, or that a judge would approve of it). Later crimes then would be subjected to a negative evaluation on the first question (is this crime worse than previous crimes where death was sought?) as well as to the second (can I succeed with the judge and jury?). In other jurisdictions, the answers to those two questions would lead to the opposite conclusion: A given crime may well be equally or more heinous than a previous one where death was sought, if death had previously been sought over 100 times (as in Los Angeles, Houston, or Dallas), and it would be clear that judges and juries do not pose an insurmountable obstacle to a death sentence.

Whereas state supreme courts and other appellate actors have a responsibility to ensure "proportionality review" (that is, ensuring that the death penalty is applied fairly across jurisdictions), scholars have pointed to this function as one that state courts have mostly failed to achieve (see Steiker and Steiker 2016). But this is a job for appellate courts, taken after a death sentence is imposed at the local level. We look here at death sentences, not post-sentencing decisions, so we can ignore these appellate actors for present purposes. Local judges, local juries, local defense attorneys, and local prosecutors look at their own histories, not those of other places.

In any case, decision-makers basing their behaviors on their expectations of the actions of others in the system, and basing these expectations on past behavior from within the system, will generate powerful self-reinforcing trends. By contrast, actors making decisions without reference to expected actions of others, and / or seeking to establish equitable outcomes across jurisdictions will tend to hew to state-wide norms with some random variation. As these processes generate opposite empirical expectations, we treat this as an empirical matter in the analysis below. A stretched distribution, with event-dependency, is evidence of self-referential decision-making; random fluctuation, with no event-dependency, would be consistent with cross-jurisdictional norms operating across the state (and, incidentally, with equal protection of the law). (For other studies of the consequences of self-reinforcing trends in other areas of human behavior, see for example Watts and Strogatz 1998; Watts 1999; Barabasi and Albert 1999; Barabasi 2005a, 2005b.)

Crucially for our analytic approach, if local variability in death sentencing were driven by such stochastic factors as the homicide clearance rate, the ability to collect convincing evidence, the nature of the crimes themselves, or comparison to other jurisdictions in the state, then the distribution of death sentences across counties in the United States would be expected to follow a random distribution (e.g., Poisson). If self-reinforcing processes are more important, then the distribution of outcomes will be stretched.

The US Supreme Court mandated extensive appellate court review of all death sentences in *Gregg v. Georgia* (1976). Death sentences are imposed by local actors, but they must be reviewed for proportionality (are they being reserved only for the most heinous criminals, state-wide?), and fairness (are all local actors following the rules of evidence and judicial fairness required state- or nation-wide?). The Court ruled that no death sentence could be carried out before review through the state's highest appeals court (typically, a state supreme court), and once those state-level reviews were complete, to the federal courts. After these "direct reviews," death row inmates also maintain other appellate rights through *habeas corpus* if they allege constitutional violations of their due process or other rights (see Baumgartner, Davidson et al. 2018 for more detail on these procedures). These are not trivial differences. Nationwide, close to 70 percent of death sentences are overturned on appeal (see Gelman et al. 2014; Liebman et al. 2000; Baumgartner, Davidson et al. 2018, chapter 7), though this number differs dramatically from state to state. Finally, executions are increasingly subjected to logistical problems and litigation relating to the method of execution: Lethal injection drugs are not available in all states, and so on. Whereas local actors determine who is sentenced to death, a range of outside actors ranging from state appellate judges to the federal courts, the Governor, and the state Department of Corrections are involved in the decision of whether or not to execute. A death sentence is a local act, but an execution requires approval from outside actors. For these reasons, and since we have looked at executions elsewhere (see Baumgartner, Box-Steffensmeier, and Campbell 2018), we focus here only on death sentences.

## Three Tests

In this section, we present three approaches. The first test is based on analyses of the cumulative distribution of death sentences, compared to homicides, across counties. Does it fit a Poisson distribution or a stretched one? Are the same counties with high homicides numbers also found with high death sentencing numbers? The second is a test for "event-dependency" in death sentencing, controlling for relevant control variables. Event-dependency models test for changes in the underlying hazard rate for the next event, controlling for risk factors related to the event as well as for the number of previous events. A common application of event-dependency models is the study of heart attacks: A patient may have a number of risk factors associated with cardio-vascular disease, but the fact that they have previously suffered one or more previous heart attacks increases the hazard (odds) of the next heart attack as well. Since these statistical models are well understood, we use them here to predict the hazard rate for the imposition of a death sentence. If the hazard rate increases with previous use, then, other things equal, the next event will come more quickly as the number of previous events moves from zero, to low numbers, to higher numbers. Finally, for our last set of empirical tests, we follow a cross-sectional time-series (CSTS) approach, estimating the number of death sentences in a given county-year, across all years from 1972 through 2019, and all US counties within death-penalty states. These tests use a Zero-Inflated Negative Binomial (ZINB) model controlling for multiple possible drivers of capital punishment and, crucially, a variable for the cumulative number of previous death sentences in that county. Like the previous estimation techniques, the idea is to see if this variable exerts an independent effect on the predicted number of death sentences in a given year, in a model also controlling for other relevant factors. In all cases, our empirical results powerfully show that history matters.

Our key hypotheses are as follows:

**H1.** The cumulative number of death sentences across US counties will be “stretched” in comparison with the distribution of homicides. Outlier cases in both distributions will not be the same.

**H2.** Controlling for relevant factors, the higher the number of previous death sentences in a county, the greater the hazard rate for the next death sentence (event-dependency).

**H3:** The cumulative number of previous death sentences imposed in a given county since 1972 will be a significant predictor of the number of death sentences in a given year, controlling for relevant factors.

### *Distributional Tests*

It appears visually from Figure 1 that homicides and death sentences are drawn from different statistical distributions, with death sentences being the more “stretched” of the two distributions. Table 2 presents bootstrapped Kolmogorov-Smirnov tests with 100,000 replications to test the correspondence of the two distributions to the Poisson, log-normal, exponential, and power-law distributions.

Table 2. Distributional fits for Homicides and Death Sentences.

| | Poisson | Log-Normal | Exponential | Power-Law |
|---|---|---|---|---|
| Homicides | .04 | .79 | .00 | .17 |
| Death Sentences | .00 | .19 | .28 | .08 |

Death sentences are certainly not fit with a Poisson distribution, which is the only one presented that is not “stretched.” Homicides most likely are not fit to that distribution, either. While the comparisons are not conclusive, the most likely distribution for death sentences is exponential and for homicides, log-normal. This, combined with the data presented in Table 1, suggests that death sentences indeed fit a different distribution than homicides, and that this distribution has more outliers. We already know from Table 1 that the outlier cases are not the same. These results provide support for H1; however, the distribution test alone does not conclusively answer our question.

### *Event-Dependency Tests*

Our next test is for event-dependency. In such a model, the odds of event *k* are conditional on various factors as well as on the number of previous events *k-n*. A common use of such models is, for example, in the analysis of heart attacks: a patient may have a number of risk-factors, but an important one is the number of previous heart attacks they have suffered. Over-and-above the other risk factors, each heart attack increases the risk of a subsequent one. Table 3 presents the relevant tests for event dependence, using the same approach as previously presented for executions in Baumgartner, Box-Steffensmeier, and Campbell (2018). We include county-level variables as follows: population size, racial threat, poverty rate, homicides, and lynchings during the period from 1883 to 1930. (Research finds a geographical connection between historical lynchings and contemporary death sentences; see Jacobs, Carmichael, and Kent 2005; Zimring 2003). We obtained lynching data for the Southern counties from Tolnay and Beck (1995) and for the remaining counties from Seguin and Rigby (2019). Racial threat is defined as $100 - |70 - \text{percentage of population white}|$; background on this variable is described in Blalock (1967) and Eitle et al. (2002).

Table 3. Conditional Frailty Models Results for Controls with Death Sentences as Outcomes.

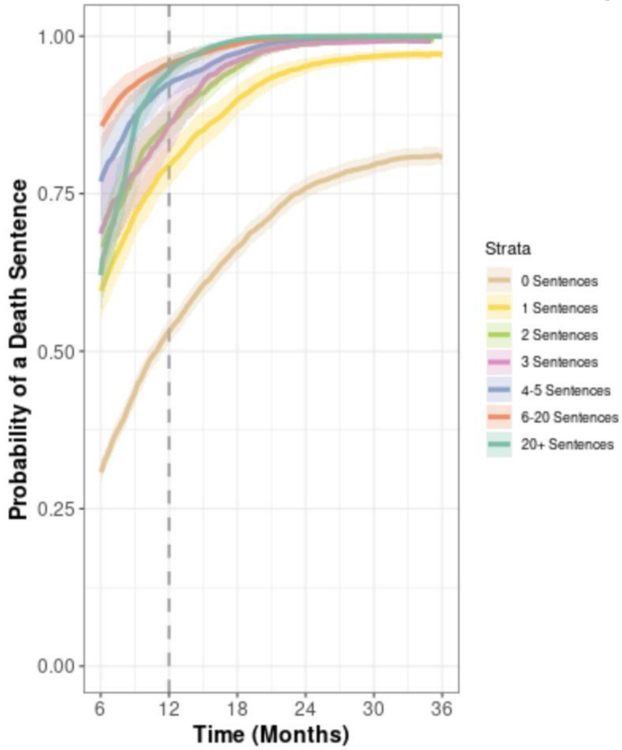
| | Coefficient | St. Error |
|---|---|---|
| Homicides | -0.00 | (0.00) |
| Percent in Poverty | 0.10*** | (0.00) |
| Racial Threat | 0.00 | (0.00) |
| Ln Population | 0.78*** | (0.02) |
| Lynchings | -0.00 | (0.00) |
| AIC | | 60105.32 |
| R2 | | 0.34 |
| Max. R2 | | 1.00 |
| Num. events | | 6491 |
| Num. obs. | | 9074 |
| Missings | | 49 |
| PH test | | 0.00 |

***p < 0.001, **p < 0.01, *p < 0.05. Note: State level frailty terms and event stratification included. Standard errors in parentheses.

The results presented in Table 3 largely match our theoretical expectations. Population size and poverty increase the probability of another death sentence within a fixed time period. This is largely similar to the findings of Baumgartner, Box-Steffensemeier, and Campbell (2018), who uncovered a similar effect for population, but a significant result for racial threat. In addition, these models appear to fit relatively well once accounting for state-level frailty, as the maximum within-sample $R^2$ is about one. In addition, the core model of interest for sentences passes the Grambsch-Therneau test. The key quantities of interest, the baseline survivor functions, remain relatively robust and approximate the results of prior versions of the model.

We are not primarily interested in the control variables presented in Table 3, but rather in the question of whether, controlling for those factors, there is evidence of event-dependency. Figure 2 shows the probability of a subsequent event, *k*, given a certain number of previous events, *k-1*, based on the results presented in Table 3 (see Box-Steffensmeier et al. 2005, 2006).

Figure 2.  Increased Hazard Rates for Death Sentences and Executions, given Previous History.




Note: 1,000 bootstrap replications were used to generate survival functions and their 95% parametric confidence intervals.

Figure 2 gives powerful evidence for event dependency. The Figure compares counties within different “strata” or groups, based on the number of previous events the county has experienced. For counties with no previous events, the bottom line shows the probability of an event over time. It increases as time goes by, of course, but the key element is that the other strata increase more quickly. If the process were not “event dependent,” then the probability of the next event would be fully explained by the underlying risk-factors, or covariates, and the strata would all have the same probabilities, equal to the lowest one.

It might appear anomalous that counties in the lowest stratum would have any probability of an event, but all counties start out in the zero stratum. Many counties, of course, never leave the zero-stratum even after 40 or more years of experience with the death penalty. The statistical estimate in the model, however, is for a synthetic “average” county, which by definition has more homicides, population, and a different racial background than many actual counties. Therefore, the lowest stratum in the model should not be taken as an estimate for the smallest US counties; over 1,000 counties have never experienced a single death sentence over 45 years of experience; this is because they have low population sizes and low numbers of homicides, compared to the "average" county simulated in the Figure. In any case, the key pattern of interest is whether the probability curves, or hazard rates, grow progressively steeper as the number of previous events increases. The Figure makes this abundantly clear: Increases are steep, indeed. We can illustrate the predictions by looking at the predicted odds of an event at 12 months from the previous death sentence, indicated in the figure with a dashed vertical line. In the simulation, the lowest stratum has a value of approximately .51 but this increases to over .75 for those with small numbers and to over .90 for those with the highest numbers of previous events. These high values correspond to the most active users of the death penalty. Note that these are predicted values from the statistical model presented, holding all other factors constant. That is, the increasing values reflect a hypothetical situation where there is no change at all in the number of death-eligible crimes in that county. The increases are associated only with the greater history of previous use. These results strongly support H2.

### *Time-Series Cross-Sectional Tests*

We conclude our analyses by applying our theory of self-reinforcement to annual county-level death sentence data. Because death sentences are rare in most counties, our dependent variable is clustered at zero. Further, this clustering is the result of two possible data-generating processes: A county would issue zero death sentences either if every capital-eligible homicide resulted in a sentence other than death or if no capital-eligible homicides occurred in the first place. Due to the nature of this variable, and following similar state-level analyses (see, e.g., Jacobs, Carmichael, and Kent 2005), we employ a zero-inflated count model, which estimates two separate equations. The first equation predicts death sentence counts exceeding zero, while the second seeks to explain the odds of no death sentences in that county. The first equation is therefore a count model and the second is a logistic regression model. After statistical tests confirmed the presence of over-dispersion in the data, we determined that ZINB regression was preferable to the Poisson equivalent. We specified the models with year fixed effects and robust standard errors clustered by county.

Our measure of event dependency in the ZINB model is the county's cumulative number of previous death sentences since 1972. For any county at time *t*, this variable represents the total number of death sentences imposed in that county from 1972 to *t-1*. If there is an effect associated with our theory of event dependency, then this variable will be positive and significant. As in the previous analysis, we include county-level variables as follows: population size, racial threat, poverty rate, homicides, and lynchings.

Given that counties are nested within states, our models also include several state-level variables. First, to account for the role of citizen ideology, we use Berry et al.'s (1998) measure of state policy mood, where higher values indicate more liberal publics. In conservative states, not only do prosecutors face greater pressure to seek death in capital-eligible cases, but legislatures have stronger incentive to devise statutes that define a broader range of crimes as death eligible. Second, we control for the presence of a Republican governor with a dummy variable. By leveraging the substantial influence of their office to espouse pro-death penalty rhetoric, Republican governors may be able to encourage prosecutors to seek death and juries to impose it. Further, prosecutors, believing that Republican governors are less likely to commute death sentences and halt executions, may feel emboldened to seek death under them. Third, we control for whether a state selects its supreme court judges via partisan election. Judicial candidates, seeking to avoid being labeled as “soft on crime” by their opponents, frequently advertise their pro-death penalty views in their campaign communications. In doing so, they may signal that they are reluctant to overturn death sentences on appeal, thereby encouraging prosecutors to seek death in capital-eligible cases. Considering that campaign expenditures are typically greater in partisan than nonpartisan supreme court elections (Bonneau 2004), partisan judicial candidates should have enhanced capacity to broadcast their support for capital punishment. Last, we denote the 11 states that constitute the South—a region that produces a disproportionate share of all death sentences (Baumgartner, Davidson et al. 2018)—with a binary indicator. Table 4 shows the results.

Table 4. Predicting Death Sentences by Year by County with Inertia and other Predictors.

| | Death Sentence Absence | One or more Death Sentences |
|---|---|---|
| *County-level Variables* | | |
| Cumulative Death Sentences$_{t-1}$/10 | 0.03*** | 1.08*** |
| | (0.02) | (0.02) |
| Homicides$_{t-1}$/100 | 1.05 | 0.99 |
| | (0.07) | (0.02) |
| Percent in Poverty/10 | 1.64** | 1.31* |
| | (0.29) | (0.17) |
| Racial Threat/100 | 0.71 | 2.75* |
| | (0.55) | (1.31) |
| Lynchings/100 | 1.38 | 7.50** |
| | (2.57) | (5.70) |
| Ln Population | 0.77*** | 1.98*** |
| | (0.06) | (0.09) |
| *State-level Variables* | | |
| Republican Governor | 0.95 | 1.01 |
| | (0.11) | (0.06) |
| Partisan Supreme Court Elections | 0.72* | 0.98 |
| | (0.10) | (0.08) |
| Citizen Ideology/100 | 4.52 | 0.34 |
| | (4.75) | (0.22) |
| South | 0.62** | 1.00 |
| | (0.11) | (0.11) |
| Constant | 4.40*** | 0.00*** |
| | (1.19) | (0.00) |
| Year FE | Yes | Yes |
| Total obs. | 102,070 | 102,070 |
| Nonzero obs. | 5,057 | 5,057 |
| Log pseudolikelihood | -17639.07 | -17639.07 |

***p < 0.001, **p < 0.01, *p < 0.05 Notes: Reported values are Incidence Rate Ratios from a Zero-Inflated Negative Binomial Regression with the county-year as the unit of analysis. Robust standard errors clustered by county are in parentheses. The first model predicts a value of zero death sentences, and the second model predicts the count of death sentences. Counties are included only in those years where the death penalty was a legally available option in that state in that year. Each variable is rescaled by the factor indicated in order to generate coefficients that can be more easily interpreted.

The results for the count portion of the model indicate that, population size, poverty, racial threat, and lynchings are all significant predictors of more death sentences. Note, however, that homicides, controlling for other factors, is not a significant predictor. The number of homicides is, however, strongly related to population size, and that variable is significant in both models. Two state-level effects are significant predictors in the model predicting no death sentences: being in the South and partisan judicial elections, both of which reduce the odds of the absence of death sentences. These controls are all important predictors in the model.

Our substantive interest is in the variable for the cumulative number of previous death sentences. The results of both parts of the model show a powerful impact. A value of 10 cumulative previous death sentences since 1972 is associated with a very large drop (97 percent) in the odds of no death sentences in a given year, and an eight percent increase in the odds of higher numbers. Because these effects continue for every year, their cumulative effects are much greater than the instantaneous effects shown in the table. We demonstrate this in Figure 3.

Figure 3 presents a simulation of the results drawn from Table 4. The top lines show the annual numbers of death sentences imposed nationally, actually observed (solid line) and predicted by the model (dashed). Clearly, the model does a good job. Note that the year-fixed effects are important controls in the model, since the numbers of death sentences imposed nationally follow powerful trends over time. These are not our concern here, but they must be modelled appropriately, which is why we have year fixed-effects in Table 4. The lower line shows simulated results for a model where we set the number of previous death sentences to zero. The difference between this lower figure and the higher dashed line is therefore the share of death sentences that can be attributed to the self-reinforcing elements of the process. This effect is much larger than the apparent eight-percent reduction in instantaneous effect in Table 4. This is the difference between an instantaneous effect and a cumulative one.

Figure 3. Observed, Predicted, and Simulated Death Sentences Annually.

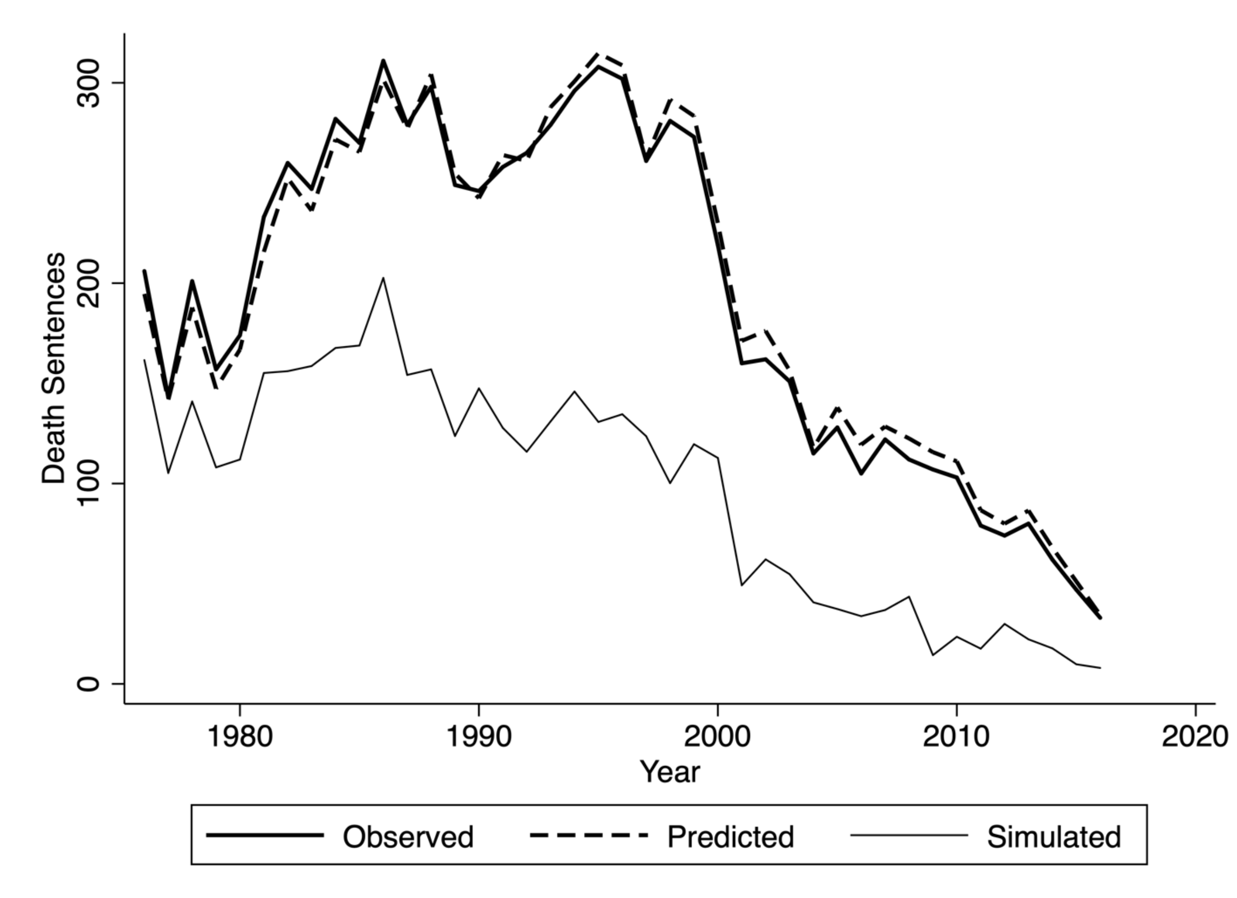


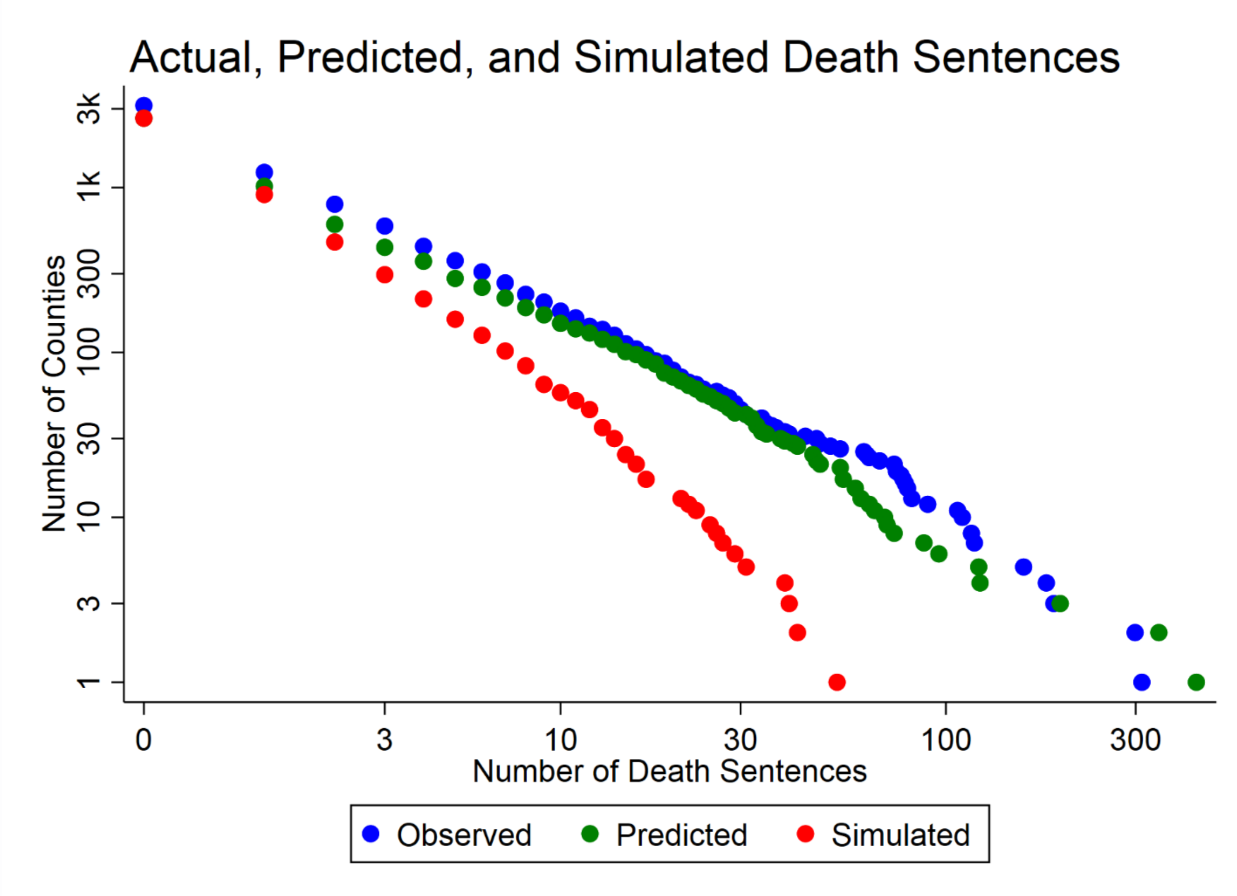

Table 5 provides further detail on this process, showing how the effect of inertia is particularly stark in those counties with the highest numbers of death sentences. The table also documents our best estimate of the cumulative share of the total number of death sentences produced nationally since 1972 that can be attributed to inertial trends. For the most frequent users of the death penalty, more than three-quarters of their death sentencing totals can be attributed to previous use. For counties with fewer death sentences, this number is lower. Overall, our analysis suggests that 51 percent of the US total in death sentences can be attributed to the impact of the cumulative number of previous death sentences in the same county.

Table 5. Observed, Predicted, and Simulated Death Sentences in top Sentencing Counties

| County | Observed | Predicted | Simulated | Percent Attributable to Previous Cases |
|---|---|---|---|---|
| Los Angeles CA | 311 | 427 | 43 | 90 |
| Harris TX | 299 | 344 | 54 | 84 |
| Philadelphia PA | 187 | 88 | 15 | 83 |
| Maricopa AZ | 179 | 122 | 27 | 79 |
| Cook IL | 157 | 194 | 40 | 79 |
| Oklahoma OK | 116 | 54 | 13 | 76 |
| Clark NV | 118 | 55 | 13 | 77 |
| Miami-Dade FL | 118 | 121 | 31 | 74 |
| Duval FL | 110 | 54 | 16 | 70 |
| Riverside CA | 110 | 46 | 13 | 72 |
| Dallas TX | 107 | 97 | 39 | 59 |
| Orange CA | 82 | 72 | 24 | 67 |
| Cuyahoga OH | 90 | 75 | 17 | 77 |
| Jefferson AL | 78 | 60 | 26 | 57 |
| Broward FL | 80 | 61 | 22 | 64 |
| Bexar TX | 77 | 71 | 30 | 58 |
| Tarrant TX | 74 | 59 | 28 | 54 |
| Shelby TN | 74 | 65 | 22 | 66 |
| Hillsborough FL | 75 | 56 | 18 | 68 |
| Hamilton OH | 80 | 48 | 11 | 77 |
| Others | 5,982 | 5,858 | 3,461 | 41 |
| Total | 8,504 | 8,027 | 3,962 | 51 |

To illustrate the cumulative impact of this process over the entire historical period, and to show how the self-reinforcement inherent in our model tested in Table 4 generates the outliers observed in Figure 1, we replicate the analysis in Figure 1 in Figure 4, also showing the simulated results for each county with previous death sentences in that county set to zero. The blue dots in Figure 4 are identical to the data from Figure 1, and the green reflect our predicted values from the model in Table 4. The red dots correspond to the simulated death sentence numbers from Table 5, where we set the value of previous death sentences to zero.

Figure 4. Distribution of Observed, Predicted, and Simulated Death Sentences by County.




Comparing the observed and predicted values show that we model that process well. Comparing the simulated with either of the other two distributions shows that the self-reinforcing element of the process generates the extreme values. Absent a system of self-reinforcement, our simulation suggest that Harris County would have 54 death sentences, not 299; Los Angeles would have 45, not 311; and no other county would have as many as 45, less than one per year in the period since 1972. In all, about half of all US death sentences may be attributed to inertia rather than other factors.

In this section we have generated a model predicting whether a given county will experience a death sentence in a given year, for all years from 1976 through 2016. Results are substantively important, in that we have shown powerful effects for population size, poverty, racial threat, and lynchings. Most importantly, we have shown the power of inertia. Results therefore clearly support H3, and reinforce the fears of Justice Brennan in his Furman decision: the death penalty, if it follows any consistent pattern, follows an impermissible one associated with race. Homicides, once other factors are included in the model, do not predict death sentences. Rather, racial dynamics, population size, poverty, and—crucially for our theory—the number of previous death sentences a county has experienced, drive the process.

## Conclusion

In 1972, US Supreme Court Justice Potter Stewart and others voting to invalidate all existing death penalty laws worried that the system was capricious and arbitrary, with those selected for the death penalty an unhappy handful randomly selected, like being struck by lightning, out of all the eligible cases. They thought that, if any discernible pattern could be ascertained, it was racial discrimination, but they lacked clear proof of that, and they “put it to one side.” Here, we have powerful evidence that explains the wanton and capricious element of the death penalty: local jurisdictions separating into two camps with the vast majority never or rarely using the punishment and a small number travelling down a slippery slope of accelerating use. We also see strong evidence in favor of the racial argument: Those counties going down the path of increasing use come disproportionately from places with histories of lynching in the Jim Crow period and with higher rates of racial competition and poverty.

Many have previously noted the extreme concentration of the death penalty in just a few jurisdictions. We have shown the mechanism by which this phenomenon has developed: Self-referential cascading. In counties that start down the path of imposing the death sentences, when the next heinous crime happens it becomes increasingly likely that the prosecutor will seek death and that a jury will impose it; this is demanded by a sense of equity compared to previous cases in the same jurisdiction. But in counties that never go down that path, or do so more slowly, that same logic more often leads to the conclusion that the next heinous crime does not rise to that level, based on previous experience in the county. Because there are no effective mechanisms to ensure that different counties evaluate according to any common standard across space, they make reference to their own histories. This self-referential process is common in other fields of human behavior, and generates extreme differences in outcomes even when initial differences across units are minor. In the particular case of capital punishment, it has troubling consequences. Those consequences were aptly noted by the Justices in 1972. The system they sanctioned since 1976, despite assurances that it would avoid these problems, has failed to do so. The death penalty remains wantonly and freakishly imposed in a largely random manner based on geography and time, with a strong dose of racial discrimination.

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