A Power-Law Analysis of the Uneven Geographic Distribution of Executions in the Post-Furman era of the Death Penalty

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Chapter 1

Introduction

In 1972 the United States Supreme Court ruled in *Furman v. Georgia* that the application of the death penalty was arbitrary and capricious, and placed a hold on executions until states could prove they had created a more consistent system for death sentencing. See *Furman v. Ga.*, 408 U.S. 238, 92 S.Ct. 2726 (1972). By 1976, 37 states had reenacted the death penalty under the claim that they had created a more consistent method. However, current statistics on the application of the death penalty in the United States show that racial and geographic inequity remains the status quo. Although a large amount of research concerning racial inequity in the imposition of capital punishment in the United States exists, statistical analysis and data on the extent of geographic inequality remains limited.

The 1972 *Furman* majority opinion explains "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." *Id.* at 310. Thus, the United States Supreme Court ruled that executions be postponed until the creation and implementation of a less arbitrary system of imposing death. Since 1976, 1,373 individuals have been executed in the United States under the promise that the post-*Furman* capital punishment system is no longer unfairly distributed.

However, an overview of literature on the death penalty trends, combined with new statistics on homicides and executions in the United States[1] supports three hypotheses contrary to

[1] This database was gathered by Dr. Frank Baumgartner at the University of North Carolina at Chapel Hill.

the concept that capital punishment is operating within an equitable system in the post-*Furman* era due to the severe unequal geographic distributions that define execution patterns since 1977.

Hypothesis #1: A large majority of executions occur in a very small number of counties and many counties have few or no executions.

Hypothesis #2: The geographic distribution of executions follows a power-law, suggesting that the outcome of capital punishment cases is heavily correlated with the location of the trial due to historical developments. This remains true even when possible lurking variables are controlled, including population and homicide numbers.

Hypothesis #3: This geographic inequality is a result of the existence of a self-perpetuating local legal culture that either promotes or prohibits executions[2].

An overview of previously published research on the distribution of executions in combination with previously unpublished statistical analysis using an original dataset will illustrate the large inequalities in the geographic distribution of executions within United States. The unequal geographic distribution of executions in America is especially striking when examined through the lens of the 8th Amendment due to its severe nature and unusual geographic pattern. The fact that the death penalty continues to persist in such an unequal manner not only violates the 14th Amendment right to "equal protection of the laws" but also violates the 1972 United States Supreme Court *Furman* ruling that the death penalty not be imposed in an unequal or biased manner.

[2] For further explanation local legal cultures see appendix section one on page 63.

Chapter 2

Literature Review

The substantial quantity of research and literature on the death penalty makes the absence of a more complete statistical overview of post-*Furman* executions surprising. However, a good base of more specific research presenting several different trends concerning the inequitable distribution of the death penalty in the post-*Furman* era does exist. In order to understand the importance of the application of a log-log test, an overview and explanation of power-law and exponential relationships will also be introduced.

<u>Literature on Racial Inequality in the Imposition of the Death Penalty</u>

The most prevalent and complete research on the unequal imposition of the death penalty concerns the inequality of racial distribution in execution rates as well as jury decisions. Amsterdam (1988) presents a clear portrait of the pervasiveness of racial prejudice concerning the application of the death penalty in Georgia. Some of Amsterdam's most notable findings include the fact that while only forty percent of post-*Furman* Georgia homicides had white victims, over eighty-seven percent of cases where the death sentence was imposed had white victims. Amsterdam presents a compelling multiple regression analysis that strongly suggests that no non-racial factors can account for this racial inequality. Amsterdam's paper provides a good example of complete statistical analysis related to the inequalities that exist in the modern era of the death penalty in America. However, Amsterdam's paper does have some limitations.

The first limitation of Amsterdam's study is the study's solitary focus on racial discrimination, which will be supplemented in this thesis by the contribution of data on all executions and homicides in the United States during the post-*Furman* era of the death penalty. Another limitation of Amsterdam's study is that the study only reports findings on the state of Georgia. The analysis presented in this thesis will hopefully alleviate this limitation through the addition of a complete geographic analysis of every execution in the United States since 1976. While Amsterdam's study is limited in some ways it provides an excellent example of a complete multiple regression analysis and presents a clear picture of racial discrimination in the death penalty throughout the post-*Furman* era.

Macher (1995) presents a history of racial prejudice in the application of the death penalty as well as an overview of some of the most important statistical studies on racial injustice concerning United States executions. This study is helpful in the discussion of *McCleskey v. Kemp*, an important 1987 United States Supreme Court case in which an African-American man was granted relief from his sentence of death on the basis of two important statistical studies that outlined the extreme racial prejudice present in the American justice system in the South. Perhaps the most important of these studies is the Baldus study (Gross, 2012), in which a sophisticated multiple regression analysis was performed to show the impact of race in the application of the death penalty. Macher's study is limited in its focus on only racial inequality. Similarly, Macher does not provide any new statistics, but rather overviews those that have already been published. Macher's overview of past statistical analyses on unequal distributions of the death penalty is a great asset in that Macher critiques certain decisions made in past studies. Macher's criticisms of past studies have been taken into account in order to improve the statistical analysis of the geographic distribution of the death penalty in this thesis. There are many more studies on the effects of racial prejudice in the current inequity of executions in America; many of which have been included in the bibliography. While these studies are beneficial in their contributions and findings, most are limited either in scope (many only study one state) or time span (some only analyze ten or fifteen year periods). Similarly, most of the studies focus only on racial inequities and largely ignore the significant role of geographic inequities. The current limitations on the study of the imposition of executions can be addressed through a more complete statistical analysis of another important inequality— the geographic distribution of all executions —in all fifty states since 1976.

Literature on the Geographic Inequality in the Imposition of the Death Penalty

The post-*Furman* capital punishment system is currently being administered in an unexpected geographic manner. Counties with higher populations generally experience a higher number of homicides, and thus if capital punishment was fairly distributed one would expect to see that large counties have both high homicide and execution numbers. However, existing literature and studies suggests that the correlation between population, homicides, and executions is not as strong as would be expected in an equitable legal system. This geographic inequality exists not only at the interstate level but also within states, suggesting the existence of cultural mechanisms that self-perpetuate a culture that either promotes or prohibits executions. Currently literature on the geographic inequality of the death penalty remains limited. However, Little (2001) provides both empirical and historical information that directly relates to geographic inequity of executions in the post-Furman era. Little discusses the availability of the death penalty to all fifty states, as the penalty is currently protected under federal law. He then illustrates the extreme geographic inequity in execution distribution through statistical analysis. One particular passage from Little's article illustrates the tendency of the South to use capital punishment in a much more frequent manner, "of the 102 defendants who had then been authorized for federal capital prosecution, half of these defendants (51 total) came from districts in the fifteen Southern or Border States which traditionally favor the death penalty. In fact, in terms of federal death penalties actually imposed fully, 80% came from these states" (Little, 2001, 9). The main limitation of Little's study is the fact that the paper's statistical analysis only examines the use of capital punishment from 1994 to 1999. However, the statistical analysis in this thesis suggests that this trend has intensified over time, with nearly forty percent of executions since 1976 being administered in Texas alone. Little also explains different reasons for this trend, which include the local nature of politics and the importance of regional cultural norms, which this thesis will discuss and expand upon as one of the potential reasons for the geographic inequality that plagues death penalty distributions in the post-*Furman* era. In our statistical overview we intend to explain the trends behind these inequities with greater detail.

Baumgartner et al. (2008) provides a detailed account of the geographic distribution and changes in public opinion towards the death penalty over time. This book provides thorough empirical analysis of capital punishment in America, including data on racial and geographic distributions of executions. In their analysis the authors show that the current distribution of death sentences and executions in the post-*Furman* era is subject to the previously mentioned geographic and racial disparities. A main component of this book is a complex multiple regression analysis. The multiple regression analysis in this book displays the tendency of a few states to execute at very high rates while most others rarely or never do so. Additionally, the authors control for many possible lurking variables, exposing the important role that race and county of conviction play in the outcome of a defendant's capital trial. While the focus of our study's statistical analysis is the use power-law tests, the analysis in this book will serve as a beneficial example of how to examine execution distributions through statistics. However, the statistics that have been gathered to date will allow a more complete and in depth picture of the unequal trends that plague execution distributions. This thesis will address some of the previously mentioned limitations through the addition of county, homicide, and population information related to the unequal nature of post-*Furman* death penalty distributions.

Introduction to Power-Laws

An understanding of the mechanism behind power-law distributions is key to understanding the importance of the results presented in later chapters, and thus an overview of the mechanisms that create networks that have power-law distributions is necessary. Barabási et al. (2002) present a compelling yet easy to understand summary of networks and the way they can lead to power-law distributions.

The authors explain that many aspects of life, from the economy to our own biological existence, are surprisingly interrelated. The connected nature of life is what creates networks, which in the context of this thesis will be represented by the local legal culture that comprises a county and the surrounding region. Although famous intellects such as Erdős and Rényi previously believed that most of these networks, even complex ones, operated in a random manner, Barabási et al. explain that nature instead prefers a slightly different approach that will be explained later in the theory section of our paper. For now, it is worth noting that a network, when values are presented as a histogram, will usually plot as a relatively even bell curve if the connections are the result of a random process. On the other hand, networks that fit power-law distributions look much different when presented as a histogram when compared to a bell curve. Power-laws, when plotted as a histogram, will have a large number of cases clustered at one end of the plot and an extreme tail that extends far from the median of the distribution.

Barabási et al. explain that several important characteristics must be considered when examining the nature of a network. The first is whether the network is the result of a random process or if the network was created and exists in a non-random manner. The next is the strength of the ties between members of the network, and whether clustering exists. As the authors explain, clustering in society is intuitive as humans have a strong tendency to enjoy the comfort of cliques. For the purpose of this thesis, clustering may occur around an execution "hub" such as Harris County in Texas. This would suggest that smaller counties surrounding Harris county, although they may experience relatively low rates of crime, execute at higher rates because the surrounding local culture promotes a culture of executing individuals[3].

Pareto's law is another way to explain the existence of power-law distributions. Pareto's law, in the most basic sense, states that eighty percent of productivity is output by only twenty percent of the network. The existence of these networks is, as Barabási et al. put it, "special", as nature generally prefers more evenly distributed connections without too many extremes on either side of the median. However, anytime that Pareto's law applies it can be assumed with a high degree of certainty that the network follows a power-law (also called Pareto) distribution. Histograms depicting power-law distributions are illustrated as a continuously decreasing line in a log-log scale. This means that many small events coexist with a few very large events. A helpful analogy that Barabási et al. provide is to imagine the existence of a power-law in terms of human height. If human height followed a power-law, it would not be uncommon for a large

[3] Refer to section one of the appendix for a more detailed explanation of the concept of local legal cultures and the potential for these cultures to spread to surrounding areas.

majority people to be less than six feet tall, but it would also not be unusual to see a person who was more than five hundred feet tall. However, as previously mentioned, these power-laws rarely exist in basic nature distributions, as nature tends to favor a more equal and less extreme distribution, but the more complex the system the more likely a power-law is to emerge. Complexity is especially important in the context of this study, as the historical development of local cultural and legal norms is an extremely complex process.

Examining the distribution of executions in the post-*Furman* era of capital punishment using power-law analysis will help to determine whether executions occur in an equally distributed manner or are driven by previous cultural, legal, and other biases. County homicide numbers and population sizes are distributed as a power-law, meaning that there are a few very highly populated and violent counties that coexist with many small and non-violent counties. Thus, if capital punishment were administered on a non-biased, case-by-case manner it would be logical to assume that highly populated and violent counties experience the highest number of executions. If the results of the statistical analysis performed in this thesis show that there are a large number of counties with high population and homicide numbers yet low execution numbers, or vice-versa, it can be assumed that there are other non-random processes at work. Some of these processes include the historical development of local legal and ideological mechanisms that self-perpetuate either high or low rates of executions.

A potential mechanism behind the existence of power-law degree distributions in complex networks is that although individual choices are highly unpredictable, as a group humans follow much more predictable patterns. This point will be key in examining later findings related to execution distributions and will be expanded upon in the theory section. The existence of a power-law suggests the presence of non-random processes are driving these extreme distributions. One of the most likely culprits for the existence of power-law or exponential distributions in execution data is the concept of self-perpetuation created through the historical development and prolonged existence of a local legal culture that either promotes or prohibits the use of capital punishment. One way to imagine self-perpetuation is in terms of the "rich-get-richer" phenomenon. This phenomenon states that if one imagines every dollar in the world, it is more likely that these dollars will connect to someone who already has a large number of dollars over someone who has very few dollars. In the context of this study, a the "rich-get-richer" phenomenon would occur if counties with high numbers of executions continue to execute at high rates, while counties with very few or no executions continue to rarely or never administer capital punishment.

Today it is known that while real complex networks are not completely random, as once proposed by Erdős and Rényi, randomness and chance still play an important role in the makeup and characteristics of networks. This overview of the nature of networks and power-laws from Barabási et al. will provide an important framework for the rest of this paper and will become instrumental in suggesting potential societal mechanisms, such as self-perpetuation and the development of a local legal culture, have led to the results shown.

Chapter 3

Theory

We are interested in determining whether the network of executions in the United States during the post-*Furman* era is distributed randomly or whether there is a self-perpetuating system that is currently dictating which individuals are executed and which individuals are not. In other words, are these cases independent judicial events, each being judged on the merits of the facts at hand, or are they mutually dependent? Once a United States county executes one individual, does that county become more comfortable with the concept of execution? Does this comfort lead to more executions at higher rates as time progresses? We hypothesize that it does through the development of a local legal culture, which is explained in greater depth in the appendix. These are the questions that must be answered in order to determine whether the current United States' system of imposing executions is adhering both to the constitution and to the *Furman* ruling. It will be essential to control for the most likely potential lurking variables in order to fully and correctly answer these questions.

If our results concerning the characteristics of the network of executions throughout the United States at the county level are relatively close to adhering to a normal distribution, or if they are strongly correlated to homicide and population numbers, it will be clear that most cases are being judged on their merits and each execution is an independent event. However, if the results are more closely related to Pareto's law, or a power-law distribution, this result will suggest that there is something else occurring, at its most basic level some type of self-perpetuating legal process that encourages executions in some counties and discourages executions in other counties. If the results are closer to Pareto's law, this will mean that the network of United States executions resembles a power-law distribution. This recalls the analogy from Barabási et al. of the man who was several hundreds of feet tall, but instead this would be depicted as a majority of counties with very few executions and very few counties with a comparably large number of executions.

Lurking variables must be controlled for in order to know whether the geographic distribution of executions is logically rooted in demographic characteristics or whether there is a less logical historical, legal, and cultural process at work. The variables that we have addressed in attempts to gain a more complete knowledge of execution trends are county population and number of murders, as well as the rates we can derive from these variables: homicide per capita, execution per homicide, and execution per capita rates.

In order to obtain the results necessary to properly examine execution distribution trends each previously discussed variable and rate will be examined through a similar process. Generating a frequency distribution of the variable using statistical software and the data we have collected is the first step in our statistical analysis. These frequency distributions will be analyzed at the United States county level for all variables. If the frequency distribution has almost all counties clustered near zero executions (or rates), and a long tail that reaches to a much larger number, it is possible that this relationship might fit the power-law distribution. The fatter the tail, the more extreme a distribution is. Even if the relationship does not perfectly fit a power-law distribution, it is possible that an exponential distribution may exist, which means that while the relationship may not be as extreme as a power-law, it is still far from normal. In terms of our results, the existence of both power-law and exponential relationships would indicate that non-random factors are driving these geographic distributions. However, in order to correctly determine whether a relationship fits the characteristics of a power-law or exponential distribution, more steps will be necessary.

After the frequency distribution has been generated and analyzed the next step will be to show the cumulative distributions of the variable. In other words, we will generate another distribution that will show the number of counties that fit into each value of the variable of interest. This will allow us to better examine the nature of the relationship between the variables and whether or not the trend of interest is the result of unbiased independent judicial processes or the result of a self-perpetuating and ever-growing local county-level or regional-level trend. In order to determine whether the relationship truly fits the distribution of a power-law one final test will be required. The cumulative frequencies must be placed on a log-log plot in order to determine whether the relationship is a true power-law or simply a skewed normal distribution. These log-log plots will have a best-fit power-law equation for the variable of interest, and if a log-log plot using the data falls along or very close to this line, it is likely that the relationship is a true power law, meaning non-random processes, such as the development of a local legal culture and self-perpetuation, are a driving factor behind the distributions of executions.

If the relationship does not appear to be either a power-law or normal distribution, a final test will be employed, displaying the data on a semi-log plot. If the results of a semi-log plot are close to a straight horizontal line, this would indicate the existence of an exponential relationship or possibly even a more extreme extended exponential relationship. In other words, it is likely that there is a degree of self-perpetuation occurring in terms of the imposition of executions, possibly as a result of varying local legal cultures.

Barabási et al. explains that the most basic equation for testing whether a dataset falls into a power-law distribution is: $f(k) = ak^{-c}$. The next step is to take the logarithms of both sides, changing the equation to read: $\log f(k) = \log a - c \log k$. In this equation we are plotting $\log f(k)$ as a function of $\log k$. The (-c) exponent in this equation is the slope of the results, and 'a' is the y-intercept. Thus, the higher the exponent (-c) in a power-law equation, the higher the severity of the network's power-law features will be, as the log of the cumulative frequency is related to the cumulative severity of the event. This means that a higher exponent indicates the degree exponent. If the relationship exhibits characteristics of a power-law distribution, the resulting plot from this equation should be a relatively straight downward sloping diagonal line when plotted on a log-log scale. If the line does not conform to the line of best fit for a power-law very well, it is likely that the relationship is not exhibiting characteristics of a power-law distribution but rather an exponential one.

If the relationship does not appear to adhere to a normal distribution and is instead a power-law or exponential distribution, there will be several important factors to consider when examining the results. The first is that this indicates a large disparity between very few counties and all others in terms of the variable of interest (such as homicides, executions, or a rate). The counties that are extreme outliers then could be considered execution heavy, having many more executions occur there than at all others. These counties would then dominate the network of executions in the United States to a degree that self-perpetuation born from a local legal culture and historical developments would be a potential driving factor. In other words, it could be possible that these counties have grown accustomed to executions and thus execute far more frequently than all other counties in the United States. This would suggest the existence of the "rich-get-richer" phenomena, only instead of money that is coming into already huge pockets we are seeing executed individuals joining the ranks of already large numbers of executed individuals within that county.

If power-law distributions do define the geographic distribution of executions, it must be considered that the construction of the United States execution network is not a totally random process. Thus, it is likely that some U.S citizens are being prosecuted and in some occasions executed in a different manner than other U.S citizens because of some historical event or decision which occurred in a county or a region many years ago. Mechanisms that may drive this culture include religion, political ideology, the existence of a prior crime that was so heinous as to incite the death penalty, and racial prejudice. These mechanisms have the potential to shape the modern local legal culture of a county, even if the development of this culture occurred decades earlier. If each capital case is being judged on historical trends and not independently on the facts presented, this could potentially constitute a violation of the Fourteenth Amendment of the United States Constitution. It may be possible that some citizens are not able to receive equal protection of the laws due to something as trivial as the county they were tried in and its corresponding legal culture born from historical developments that are unrelated to the particular case in question in terms of capital punishment trials and results.

Before analyzing the results it is important to note that as of 2015 eighteen states have elected to abolish capital punishment. Of these eighteen states, none lie below Maryland and most are in the northeastern United States. It is likely that the geographic inequalities are the result of historical developments of legal mechanisms and a state or counties past use of executions. The general trend present in a state’s use of the death penalty is that high execution states continue to execute frequently, while those that have not employed the death penalty frequently will rarely or never do so. In fact, since the 1972-1976 injunction of executions—which some death-penalty abolitionist states took as a reason to abolish the death penalty entirely—our statistics demonstrate that the inequality of geographical distribution has only increased. Of the 1,373 executions imposed between 1972-2014, more than sixty-five percent, or 906, have occurred in five Southern states alone[iv].

One proposed mechanism behind this geographic inequality is that some states simply have larger populations and higher crime rates, and thus, execute on a more frequent basis. However, by controlling for population size and homicide rate, it will become clear that this geographic inequality between states is not a result of either of these proposed mechanisms. By illustrating that geographic differences are not solely a result of population size or homicide rate, it will become clear that more complicated and arbitrary mechanisms—regional historical use, prejudice, and developments of the death penalty and its corresponding legal culture in individual communities—are more likely the true culprits for the current unequal geographic distribution of the United States execution system.

[iv] Texas has by far the most executions during this period at 518, followed by Virginia and Oklahoma tied at 110. Florida is fourth at 89, and Missouri is fifth with 79.

Chapter 4

Data Collection Procedures

The first step in collecting this data was to obtain the annual county level homicide data from the Bureau of Justice Statistics (BJS) website[v]. The data from this website covers annual homicide rates in each United States county from 1984 to 2012. Depending on the year of the data presented, the data may either be in Stata .dta or ASCII format. The data for years 2003 to 2008 was in ACSII format, while all other years were in Stata .dta format. For the data that was in ASCII format it was necessary to convert this data to .txt format and then to convert the .txt file to a .dta file. The do-file used to complete this format conversion can be found in the appendix[1]. The data for the years 1995 and 1997 was combined into one dataset on the BJS website, so these years were separated into individual years using a do-file that can be found in the appendix[2].

Once all the reported homicide data was in .dta format for all years from 1984 to 2012 the next step was to combine all of the years into one large dataset using a join-by command[3]. After the datasets were combined it became evident that many different counties were missing homicide data for certain years. To ameliorate this the average for the most recent five years in that county were used as a substitute for this missing data using a Stata do-file[4]. Six Arkansas counties were missing all homicide data and thus were excluded from the dataset. There were also several counties that were changed FIPS codes and thus the reported homicide data for these counties was converted to the most recent FIPS code for that county and the old FIPS codes were

[v] http://www.icpsr.umich.edu/icpsrweb/NACJD/series/57/studies?archive=NACJD&q=county-level

removed from the dataset[5]. After completing these steps there was now a complete dataset for reported homicide statistics for 3137 United States counties from 1984 to 2012. The next step was to add execution data to this dataset.

The execution database is one that was created by the UNC-Chapel Hill Political Science department's Dr. Frank Baumgartner and contains data on every execution in the United States since the death penalty was first revived in 1977. This dataset was originally in Microsoft Excel format (.xls) and was converted to .dta format using a Stata do-file[6]. This data was then added to the homicide dataset using a join-by command[7]. The executions were then collapsed by FIPS, meaning that for every county with an execution there would be a count of the number of executions in that county. For counties with no execution, this variable was missing. These missing numbers were then recoded to zero, meaning that counties with no executions would have a value of zero in this column. Once this was completed the homicide data was summed by county so that a new variable, called "allhom" indicates the total number of homicides in each county from 1984 to 2012. After this new summed variable was created the annual homicide data was removed from the dataset.

Next, data was obtained from the census database. In order to properly examine trends in homicides and executions data was obtained at the county level for population[vi], percent white population[vii], and poverty percentage[viii]. All of these datasets are publicly available on the census website in .txt format. In order to convert these files to the full dataset it was necessary to use an in-file command in Stata[8]. After this census data was added the homicide and execution rates were calculated. Dividing the reported county homicide number by county population and multiplying the result by one thousand calculated the homicides per capita rate. Dividing the

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[vi] http://www.census.gov/population/www/cen2000/briefs/phc-t4/index.html
[vii] https://www.census.gov/population/www/cen2000/briefs/phc-t14/index.html
[viii] https://www.census.gov/did/www/saipe/data/statecounty/data/2010.html

number of executions by homicide number multiplied by one thousand calculated the execution per homicide rate. Dividing the number of executions by the population multiplied by one million calculated the execution per capita rates. A final variable, titled "deathstate" was calculated in which a dummy variable was created, where "0" indicates that the particular state abolished capital punishment prior to 1977, while "1" indicates that the state had not abolished capital punishment before executions were re-implemented in 1977. The finalized version of this dataset can be found online, and a codebook of the data can be found in the appendix.

Chapter 5

Homicides

The first step in our analysis of this new dataset was to determine what homicide data would look like when examined at the county level. This was a unique opportunity for us, as we have not yet seen a dataset concerning longitudinal homicide data for so many counties over such an extended period of time as the one examined in this study. The first tests that were run were simple frequency distributions, the first plot, which can be found in figure 5.1.a, contains all 3,137 counties in the dataset. The y-axis contains the number of counties for each x-axis value, or number of homicides. The results were interesting to say the least, and seemed to immediately have some properties of power-law distributions, including a large number of counties with very small values that coexist with a very small number of counties with extremely high homicide values indicated by the extremely long tail. The second frequency distribution, which can be found in table 5.1.b, is the same concept in terms of data, the only difference being that a threshold of 100 homicides is employed as the minimum. These tables and an explanation of the results they show are on the next page.

Figure 5.1. Homicides by county from 1984 to 2012.

a. All Counties

b. Excluding Counties with less than 100 homicides

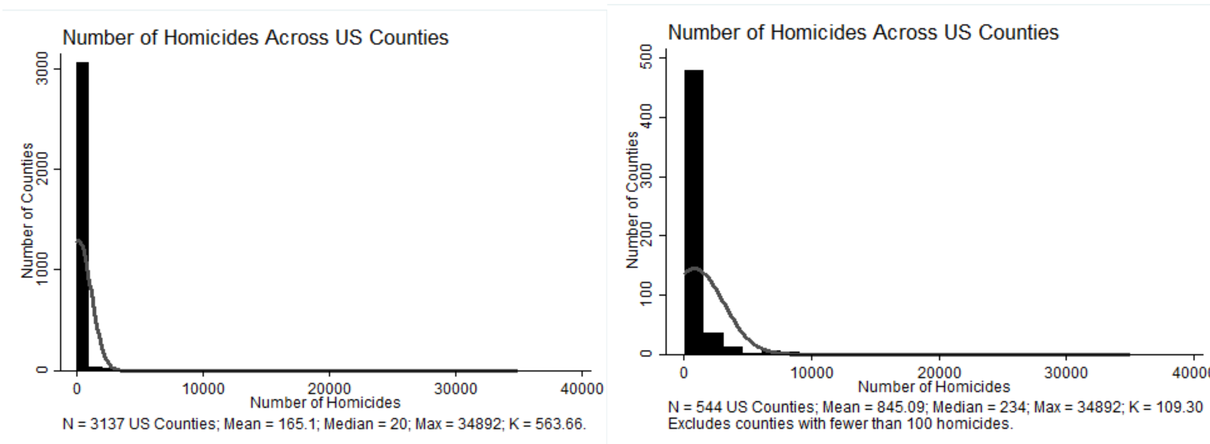


Figure 5.1.a contains a simple frequency distribution plot of the sum of homicides from 1984 to 2012 in all 3,137 counties in our database. The distribution shows the characteristics of a power-law distribution, including a large number of counties with fewer than 100 homicides and a few extremely large cases. The maximum number of homicides during this period among all U.S counties is 34,892; which occurred in Los Angeles, California. The average number of homicides per county across all U.S counties during this time is 165, although this number is skewed by the outlying counties that have more than a few thousand homicides. The median number of homicides for all counties during this period is 20, which shows the extent to which this average is skewed. While the data is almost complete, it is important to remember that some counties were missing homicide data for several years, and thus the average of the closest five years was used as a substitute for these years. Thus, while this data is representative of homicide rates as a whole, there may be small errors in the exact numbers recorded when compared to actual homicide rates. However, this data does show homicide trends and provides a good overall picture of what the distribution of homicides among United States counties between

1984-2012 truly is. In order to get a better idea of the distribution of homicides among larger or more violent counties, a second plot was necessary.

Figure 5.1.b shows another simple frequency distribution plot of the sum of homicides among United States counties and also employs a threshold. This threshold excludes all counties with less than 100 counties. Placing this threshold reduced the sample size from 3,137 counties to 544. This means that 2,593 counties, or roughly 82 percent, experienced less than 100 homicides over a twenty-eight-year timespan. Thus, a large percentage of counties experience very little homicides, and less than 18 percent experience more than an average of 4 homicides annually. What is revealing, however, is that the basic frequency distribution with the threshold in place is similar in nature to the distribution containing no threshold. However, the average homicide for this data is clearly much larger at 845, and the median is also substantially larger at 234 homicides per county. This distribution still contains some major outliers, the majority of which can be found on the following table 5.1.

Table 5.1. U.S Counties with the highest number of homicides from 1984 to 2012.

Rank	County, State	Percent White	Percent in Poverty	Population	Executions	Homicides
1	Los Angeles, CA	52.8	17.9	9,818,605	2	34,892
2	Cook, IL	58.2	13.5	5,194,675	5	19,474
3	Wayne, MI	53.7	16.4	1,820,584	0	15,111
4	Harris, TX	61.2	15	4,092,459	123	12,359
5	Kings, NY	43.7	25.1	2,504,700	0	10,572
6	Philadelphia, PA	46.4	22.9	1,526,006	1	10,561
7	Queens, NY	47.4	14.6	2,230,722	0	9,139
8	Dallas, TX	60.6	13.4	2,368,139	53	8,568
9	District of Columbia, DC	32.2	20.2	601,723	0	7,685
10	Baltimore, MD	32.6	22.9	620,961	0	7,341
11	Orleans, LA	28.9	27.9	343,829	4	7,040
12	Maricopa, AZ	79.8	11.7	3,817,117	11	6,829
13	New York, NY	57.1	20	1,585,873	0	6,780
14	Miami-Dade, FL	72.3	18	2,496,435	12	6,494
15	Bronx, NY	33.1	30.7	1,385,108	0	5,595

16	Fulton, GA	49.1	15.7	920,581	4	4,892
17	St. Louis City, MO	45.2	24.6	319,294	8	4,462
18	San Bernardino, CA	63.1	15.8	2,035,210	1	4,462
19	Shelby TN	48.1	16	927,644	3	4,350
20	San Diego, CA	70.3	12.4	3,095,313	1	4,270
21	Bexar, TX	72	15.9	1,714,773	38	4,232
22	Alameda, CA	53.1	11	1,510,271	1	4,179

Table 5.1 is a good indicator of the scale of these outliers compared when compared to the average number of homicides between all counties, which was 165 homicides per county. Similarly, there are yet more counties (87 to be exact) with over 1,000 homicides during the period between 1984 and 2012. Los Angeles has the highest homicide number by far, with nearly 35,000. However, as the table shows, Los Angeles is also an extremely large county in terms of population. In chapter 6 we examine homicide per capita rates, which is helpful in understanding which counties are actually the most violent per capita. Cook County, home of a large portion of Chicago, is a distant second with nearly 20,000 homicides. However, Cook County is also significantly smaller in terms of population size. Another interesting case in table 5.1 is Harris, Texas. Harris is home to the city of Houston, and holds the record for hosting the highest number of executions by a very large margin. However, Harris is even smaller than Cook County, yet Cook County has only 4 percent of the executions that Harris does. Execution trends and data will be examined further in later chapters. The following figure shows similar data, displaying the counties with the highest number of homicides in a bar chart format.

Figure 5.2. Counties with the Highest Number of Homicides from 1984 to 2012.

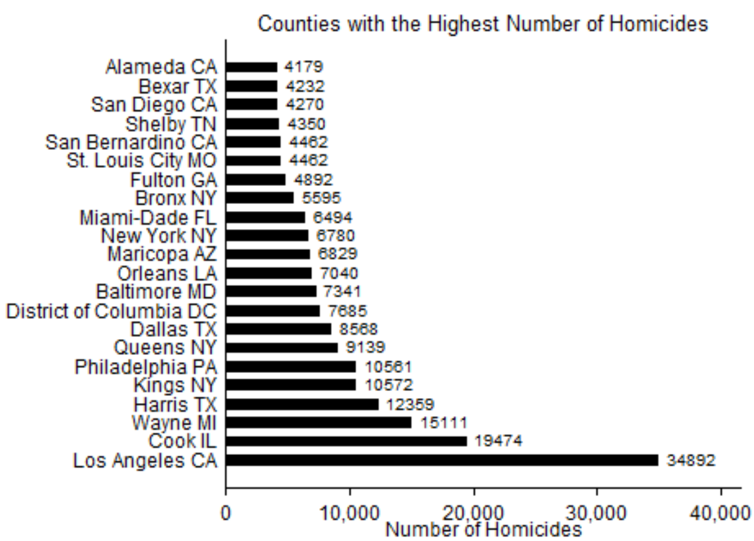
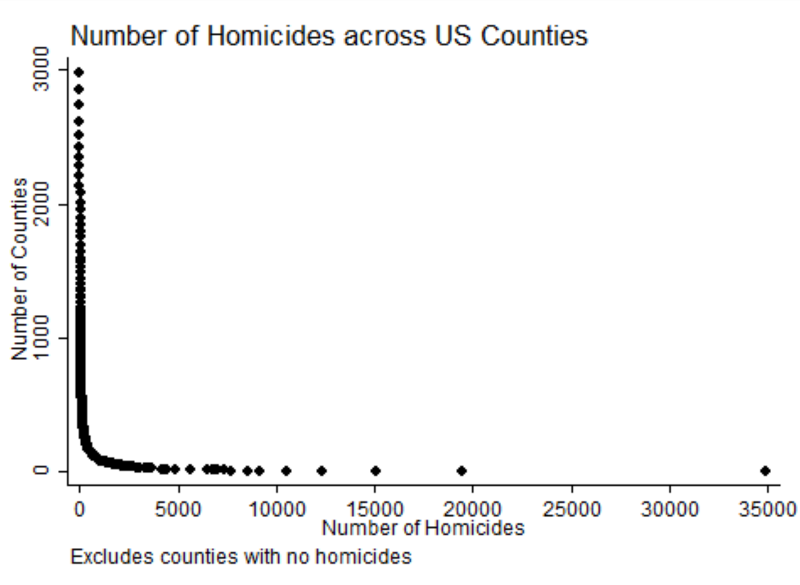


Figure 5.2 shows the scope to which Los Angeles is an outlier compared to all other United States counties and provides another way to examine homicide trends in the United States from 1984 to 2012. Interestingly, while a huge majority of executions occur in the South or Midwest, nearly half of these counties lie above or far west of the Mason-Dixon line. After examining the normal frequency distribution plots, the next step was to analyze this homicide data as a cumulative frequency distribution. Cumulative frequency distributions allow us to better examine the nature of distributions and to better identify whether the data is distributed with the characteristics of a power-law. There is a do-file in the appendix that shows the process of converting normal frequencies into cumulative frequencies in Stata. Figure 5.3 shows a cumulative distribution of all 3,137 counties, excluding the 157 counties with no reported homicides during this period.

Figure 5.3. Cumulative frequency distribution of homicides across U.S. counties, 1984 to 2012.



For the purposes of our analyses the cumulative distribution shown in figure 5.3 displays the number of counties that fall into every count of homicides, starting with all counties included in the sample and decreasing for each homicide count. For example, while the cumulative frequency of all counties with at least one homicide from 1984 to 2012 is 2,980 counties, the cumulative frequency of counties with at least two homicides would be 2,855, as 125 counties have exactly 1 homicide and thus are excluded from this cumulative number. The shape of this distribution, which some say resembles a hockey stick, suggests that homicides across US counties are distributed with power-law characteristics. To be sure that homicides are distributed amongst US counties as a power-law one final analysis was required, which can be found directly below in figure 5.4.

Figure 5.4. A log-log plot of the distribution of homicides across U.S counties.

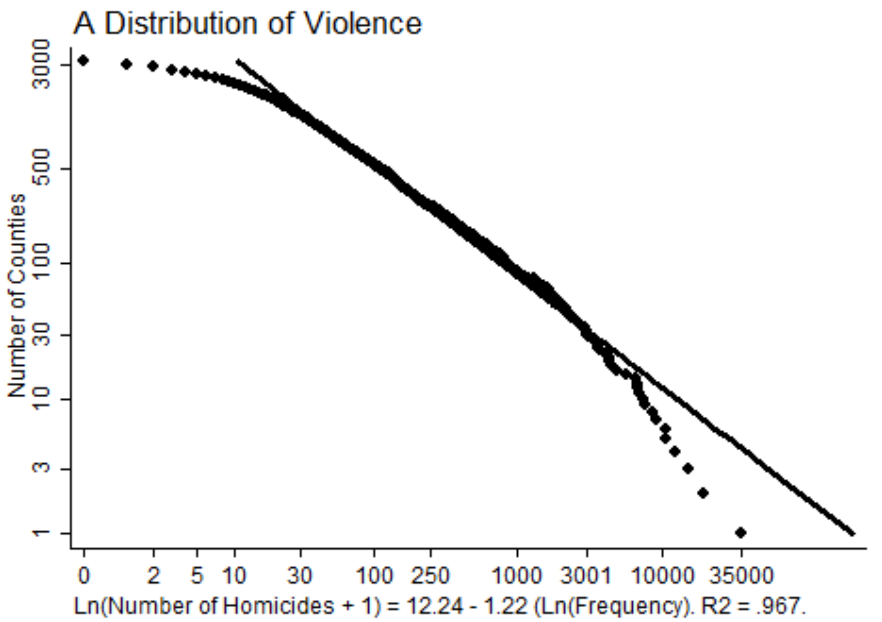


Figure 5.4 displays a log-log plot of the cumulative frequency distribution of homicides across all US counties from 1984 to 2012. While a perfect power law would fall directly along the solid line (as the solid line shows the best fit power-law equation: Ln (Homicides + 1) = 12.24 – 1.22 * Ln(Frequency), this equation appears to fit the data between 30 and 3000, or for two orders of magnitude. The r-squared of 0.967 suggests that much of the data is relatively close to the line of best fit (or predicted value of this data) if the entirety of this data was truly distributed as a power-law.

This data provides strong evidence that for a large majority of counties homicides follow a power-law distribution. However, it is also useful to know whether this applies when the distribution of homicide per capita rates are analyzed, which has been done in the following chapter.

Chapter 6

Homicides per Capita

Every results chapter in our study follows a similar format, which will become clear while reading. However, while the format may appear similar in terms of the types of graphs and results that are presented, the data they display often tells a very different story, which this chapter will reveal in comparison to the chapter on homicides alone. This chapter examines homicide per capita rates from 1984 to 2012 across all 3,137 counties in our sample. Because this number would be extremely small, the ratio was multiplied by 1,000. This means the results will read as homicide per 1,000 population across US counties.

Figure 6.1. Homicides per capita rates by county from 1984 to 2012.

a. All counties b. Counties with more than 10,000 population

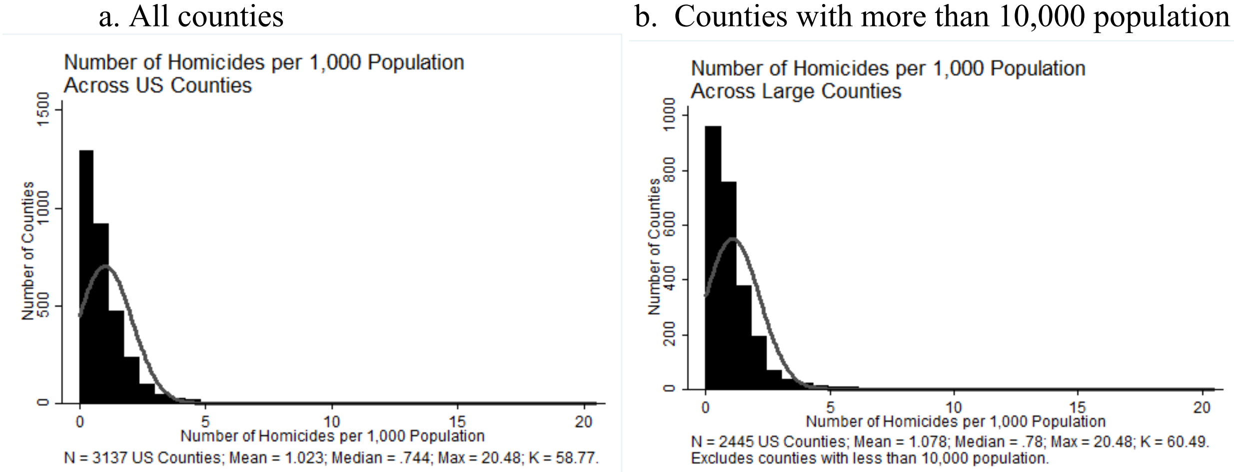


Figure 6.1.a displays a normal frequency distribution of homicide per 1,000 population rates across all 3,137 US counties included in our dataset. The data is striking, and will become even more so when compared to tables that will be presented later in this chapter. However,

similarly to figure 5.1.a, figure 6.1.a appears to have the basic characteristics of a power-law, or at the very least does not appear to be evenly distributed in a standard normal distribution. The fact that this distribution resembles a power-law makes sense considering the fact that both county homicide and population numbers are distributed as power laws. However, while this is the case the tail is certainly less extreme in homicide per capita rate distributions when compared to homicide rates alone, which may suggest the distribution is not truly a power-law but rather an exponential one. Additionally, the data in figure 6.1.a is more widely distributed, with a large majority of the results falling between 0 and 5 homicides per 1,000 capita over this period of time. The max of 20 homicides per 1,000 population is a clear outlier; especially considering the mean of these results was only 1 homicide per 1,000 population.

It should be noted that we still see a large number of counties with few homicides per capita coexisting with a small number of counties with a high number of homicides per capita. Figure 6.1.b shows the same type of frequency distribution; the only difference is that a threshold of at least 10,000 population has been employed. While homicide per capita rates do not seem to have the same severity of power-law characteristics as homicide numbers alone, it is still beneficial to run further tests to look for other information, such as the existence of an exponential distribution. The following table displays the counties with the highest homicide per capita rates in the United States.

Table 6.1. Counties with the Highest Homicide Per Capita Rates from 1984 to 2012

Rank	County, State	Percent White	Percent in Poverty	Population	Executions	Homicides	Homicides per Population
1	Orleans LA	28.9	27.9	343,829	4	7,040	20.48
2	St. Louis City MO	45.2	24.6	319,294	8	4,462	13.97
3	District of Columbia DC	32.2	20.2	601,723	0	7,685	12.77
4	Richmond VA	39.2	21.4	204,214	2	2,513	12.31
5	Baltimore MD	32.6	22.9	620,961	0	7,341	11.82
6	Wayne MI	53.7	16.4	1,820,584	0	15,111	8.30
7	Washington MS	34.3	29.2	51,137	0	364	7.12
8	Hinsdale CO	97.8	7.2	843	0	6	7.12
9	Philadelphia PA	46.4	22.9	1,526,006	1	10,561	6.92
10	Hinds MS	37.7	19.9	245,285	2	1,625	6.62
11	Taliaferro GA	38.7	23.4	1,717	1	11	6.41
12	Chicot AR	43.8	28.6	11,800	0	73	6.19
13	Glascock GA	90.8	17.2	3,082	0	19	6.16
14	Petersburg VA	19.1	19.6	32,420	2	197	6.08
15	Portsmouth VA	47	16.2	95,535	5	573	6.00
16	Martinsville VA	56	19.2	13,821	0	81	5.86
17	Phillips AR	39.7	32.7	21,757	0	126	5.79
18	Norfolk VA	50.1	19.4	242,803	1	1,387	5.71
19	Macon AL	14.3	32.8	21,452	1	121	5.64
20	Leflore MS	30.2	34.8	32,317	0	180	5.57
21	Edwards TX	85	31.6	2,002	0	11	5.49

Table 6.1 shows several interesting trends. The first is that Orleans County in Louisiana has by far the highest homicide per capita rate in the county, with over 20 homicides per 1,000 capita between 1984 and 2012. St. Louis in Missouri is a close second with nearly 14. However, quickly after this the homicide per capita rate begins to steeply decline, suggesting that violence throughout the country is not as pervasive as some may believe. Another trend of interest is the relatively low number of executions in all of these counties. While these counties are the most violent per capita in the United States, none have executed more than 8 individuals over 28 years. This suggests that murder rates may not be the primary driving factor in terms of the unequal distribution of executions in the U.S. Figure 6.2 below shows the counties with the highest homicide per capita rates if the population is over 1.5 million, which may be helpful as a more visual way of examining this trend and in illustrating the effect of population size on homicide per capita rates.

Figure 6.2. Large counties with the highest homicide per capita rates from 1984 to 2012.

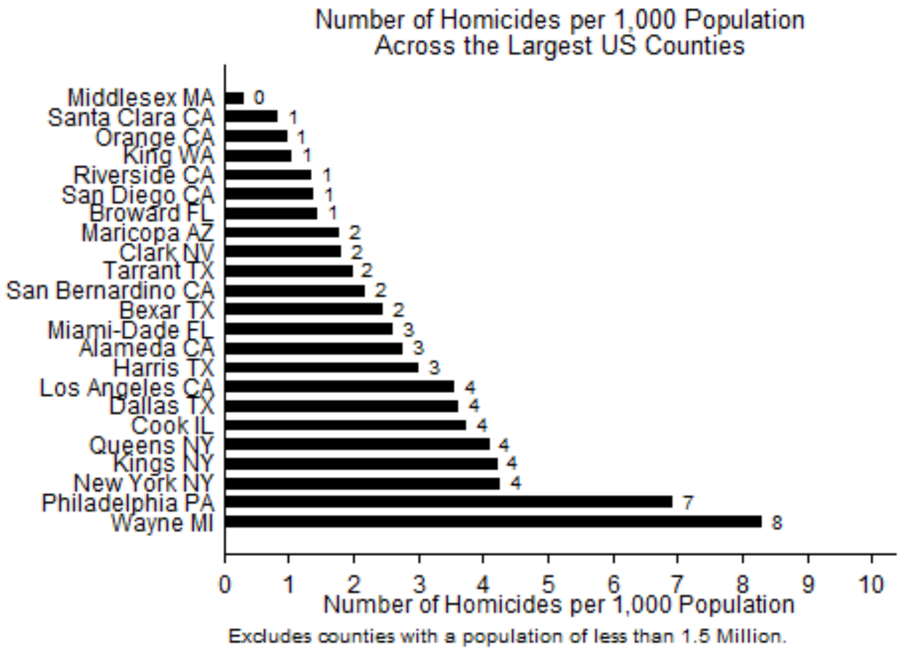
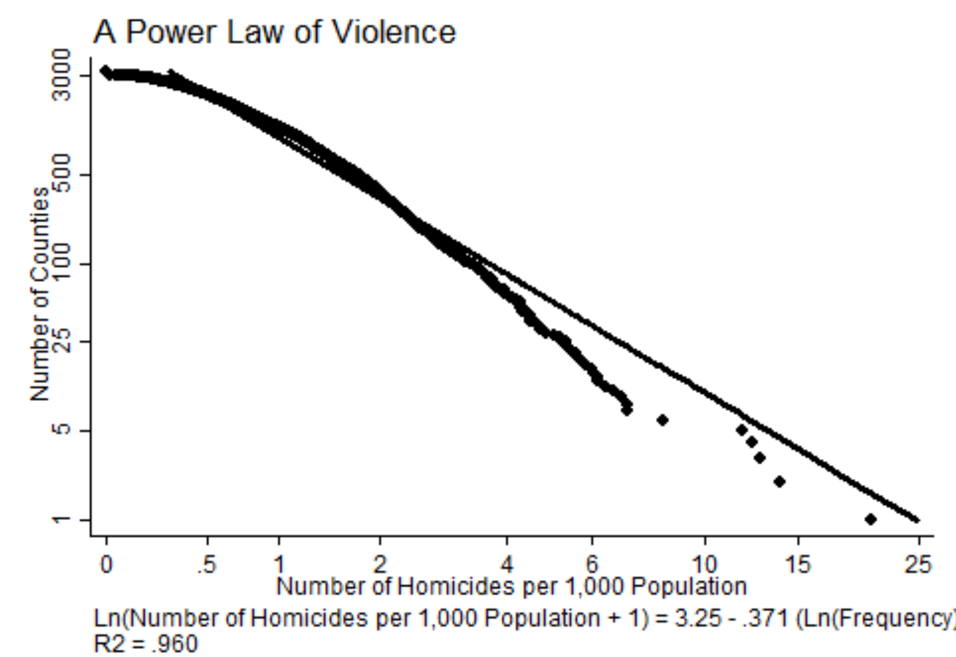


Figure 6.2 is interesting when compared to table 6.1 for several reasons. The first is that only two of the counties in table 6.1 have a population of 1.5 million or more, which may suggest that larger cities have a better hold on homicide rates. Because this data is in rate form, there are different values sorted for each integer. In other words, although Harris and Queens both appear to have a homicide per 1,000 capita rate of 4, in reality Queens County has a higher homicide per capita rate by some degree. Thus Dallas County, which places second among execution numbers in the United States, is not even in the top five most violent counties in the United States. This data, as previously mentioned, did not appear to have as strong of a power-law distribution as number of homicides. However, it is still important to test the cumulative frequency distribution of homicide per capita rates on a log-log plot to determine if this data is distributed as a power-law or exponential relationship. Figure 6.3 shows the results of this test.

Figure 6.3. A log-log plot of homicide per capita rates across US counties.



As in the previous chapter, this distribution is actually very close to being a complete power-law, and certainly is one from around 0.5 to 6 homicides per 1,000 population. The straight line again illustrates the line of best fit for a power-law distribution of this data, and the formula for this line can be found directly beneath the figure. The results of this log-log plot are interesting because of the fact that very few of the counties with the highest homicide per capita rates have executed anyone, and of the top 21 counties in terms of executions per capita, only one (St. Louis) falls within the top counties in terms of number of executions. This means that most of the outliers, or values that fall relatively far outside of the line of best fit, are not even among the top executing countries. Even in large counties with high homicide rates a large portion have not executed very many individuals. In the next chapter we will introduce the execution data that has been composed and organized over the past several years by Dr. Frank Baumgartner and the UNC Political Science Department. This data will reveal that while homicides and executions numbers are correlated, they are not the primary mechanism behind the geographic inequality that defines the post-*Furman* era of capital punishment.

Chapter 7

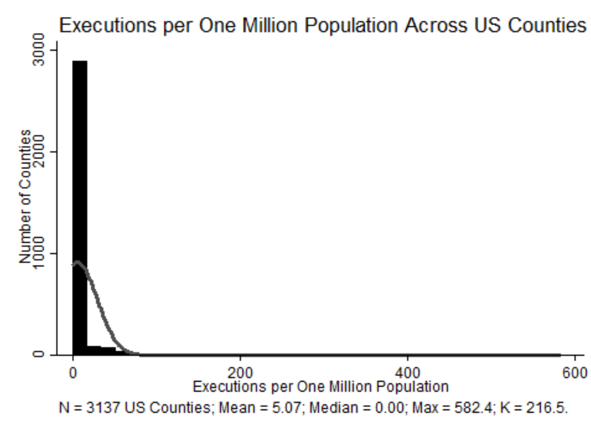
Execution per Capita Rates

A potential factor in the unequal geographic distribution of executions in the United States is population, so in order to test the effect of county population on execution distribution, a rate of execution per one million capita was calculated. We know that the distribution of population across US counties is not random and follows a power-law distribution, and thus, if executions, which also follow a power-law, are a result of differences in population we would expect for counties with a high population to have high execution rates. The distributions and results are interesting and provide insight into the extent of the effect of population on execution counts.

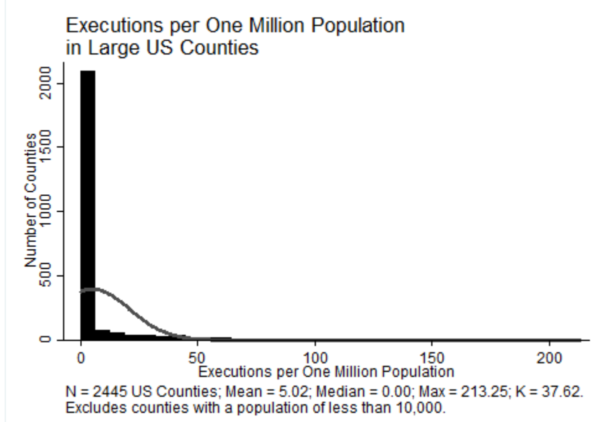
Figure 7.1 contains two plots. Figure 7.1.a displays a frequency distribution of execution per capita rates across all U.S counties, while figure 7.1.b displays a frequency distribution of the same rate with a threshold of 10,000 population. The purpose of this threshold is to eliminate outliers in the case of certain counties that are very small but have executed one person. The results of both tests are interesting.

Figure 7.1. Execution per Population Rates Across United States Counties

a. All Counties



b. Only counties with at least 10,000 people



As can be seen above, the differences between these distributions is not very substantial. Figure 7.1.a has a mean of 5.07, a median of 0, and a max of 582.4. The Kurtosis of this distribution is 216, suggesting the existence of extreme outliers, as indicated by the long tails. The elimination of small cases that may be outliers did not have much of an effect on the overall distribution of the statistics, although there are several important changes to note. Figure 7.1.b shows the frequency distribution of all counties with at least 10,000 people. As can be seen, the sample size of this distribution was 2445, meaning that 692 counties in our sample have less than 10,000 people. However, the closeness of the means between these distributions is interesting. The distribution of all counties had a mean of 5.07, while the distribution of larger counties had a mean of 5.02. This is a very small difference, especially considering the large number of small counties that were removed from the sample shown in figure 7.1.b. Similarly, the median for both plots is 0, meaning that even without small county's, 0 still remains the most common number of executions across all counties. The addition of the threshold did however remove an outlier in terms of the maximum execution per capita rate, decreasing the max from 582 to 213. Similarly, the Kurtosis was reduced from 216 to more than 37. While this is a substantial decrease, a kurtosis score of 37 still indicates a large amount of nonrandom mechanisms are propelling the unequal distribution in executions. At first glance, these results seem to suggest that while population does play a role in execution distributions, there are still other mechanisms such as the local legal culture and the self-perpetuation it creates that propel the unequal geographic distributions. In order to examine the distribution of these executions, table 7.1 has been displayed below. This table shows the counties with the highest execution per capita rates of all 3,137 counties included in our sample. Table 7.1 is displayed on the following page, preceding a discussion of the results.

Table 7.1. Counties with the highest number of executions per population from 1977 to 2014.

Rank	County, State	Percent White	Percent in Poverty	Population	Homicides	Executions	Homicide per Population*	Executions per Homicides#	Executions per Population◆
1	Taliaferro, GA	38.7	23.4	1,717	11	1	6.4	90	582.4
2	Schuyler, MO	99.3	17	4,431	4	2	0.9	500	451.4
3	Richmond, VA	65.4	15.4	9,254	13	4	1.4	307	432.2
4	Roger Mills, OK	93.4	16.3	3,647	3	1	0.8	333	274.2
5	Refugio, TX	81.7	17.8	7,383	5	2	0.7	400	270.9
6	Crockett, TX	78.5	19.4	3,719	7	1	1.9	142	268.9
7	Williamsburg, VA	80.8	18.3	14,068	16	3	1.2	187	213.2
8	Noble, OK	89.7	12.8	11,561	12	2	1.0	166	173
9	Coal, OK	81	23.1	5,925	8	1	1.4	125	168.8
10	Pondera, MT	85.1	18.8	6,153	4	1	0.7	250	162.5
11	Greer, OK	84	19.6	6,239	17	1	2.7	59	160.3
12	Bleckley, GA	73.8	15.9	13,063	14	2	1.1	143	153.1
13	Wilbarger, TX	79.9	13.1	13,535	24	2	1.8	83	147.8
14	Powell, MT	94.7	12.6	7,027	1	1	0.1	1,000	142.3
15	Bailey, TX	69.1	16.7	7,165	15	1	2.1	67	139.6
16	Pecos, TX	78.3	20.4	15,507	32	2	2.1	63	129
17	Navarro, TX	72.2	18.2	47,735	85	6	1.8	71	125.7
18	Tillman, OK	76.9	21.9	7,992	19	1	2.4	53	125.1
19	Leon, TX	84.5	15.6	16,801	21	2	1.2	96	119
20	Hamilton, TX	94.8	14.2	8,517	13	1	1.5	77	117.4

Note: A discussion of this table continues on the next page. *= Per 1,000 population. #= per 1,000 homicides. ◆= Per 1 million population.

Table 7.1 shows the 20 counties with the highest execution per population rates of all US counties. As can be seen there are a large number of counties in this sample that have very high execution per population rates and have a very small population. This is to be expected, as small counties are not immune to the self-perpetuation of legal culture. This is especially true when considering that many of these counties are geographically near larger counties where execution numbers are very high. For example, many of these counties are in Texas, a state that has more than 500 executions.

Another interesting trend evident in this table is that almost all of these counties are south of the Mason-Dixon line. One of the reasons that this is strange is that if executions were truly a result of a practical process where each case was judged on its own merits and not on some arbitrary historical development, we would likely see a few more small northern or western counties with high execution rates on this list. If these data were a result of population distributions we would expect this list to be filled with many large counties that have many executions as a result of high crime rates, however, all of the counties on this list are small and have not experienced very high numbers of murders. While there are some counties on this list that are indeed violent for their size, the execution rates are extremely high when compared with the national average of 5. A few last interesting trends to note on this table is that all of these counties have a relatively high poverty rate, with none falling below 12 percent and some reaching above 23 percent. Finally, every county on this list is majority white with the exception of only Taliaferro, GA. To examine what the execution rates of large counties a second table, table 7.2, is displayed below. This table shows counties with more than 10,000 people in death penalty states with the highest execution per population rates. If geographic execution inequality is due to population we can assume that most of these counties will be fairly large, especially considering that large counties in non-death penalty states have been removed.

Table 7.2. Large counties with the highest execution per population rates across all US counties

Rank	County, State	Percent in Poverty	Population	Homicides	Executions	Execution per Homicide#	Homicide per Population◆	Executions per Population*
1	Williamsburg VA	18.3	14,068	16	3	187.5	1.1	213.2
2	Noble OK	12.8	11,561	12	2	166.7	1.0	173.0
3	Bleckley GA	15.9	13,063	14	2	142.9	1.1	153.1
4	Wilbarger TX	13.1	13,535	24	2	83.3	1.8	147.8
5	Pecos TX	20.4	15,507	32	2	62.5	2.1	129.0
6	Navarro TX	18.2	47,735	85	6	70.6	1.8	125.7
7	Leon TX	15.6	16,801	21	2	95.2	1.3	119.0
8	Brunswick VA	16.5	17,434	42	2	47.6	2.4	114.7
9	Callaway MO	8.5	44,332	22	5	227.3	0.5	112.8
10	Morgan GA	10.9	17,868	8	2	250.0	0.5	111.9
11	McIntosh OK	18.2	20,252	42	2	47.6	2.1	98.8
12	Clay TX	10.3	10,752	15	1	66.7	1.4	93.0
13	Sabine TX	15.9	10,834	15	1	66.7	1.4	92.3
14	Middlesex VA	13.0	10,959	13	1	76.9	1.2	91.2
15	Potter TX	19.2	121,073	274	11	40.1	2.3	90.9
1	Logan AR	15.4	22,353	16	2	125.0	0.7	89.5
17	Fairfax VA	5.7	22,565	8	2	250.0	0.4	88.6
18	Monroe AL	21.3	23,068	63	2	31.7	2.7	86.7
19	Jackson TN	18.1	11,638	5	1	200.0	0.4	85.9
20	Perry MS	22.0	12,250	3	1	333.3	0.2	81.6

Note: A discussion of this table continues on the next page. *= Per 1 million population. #= per 1,000 homicides. ◆= Per 1,000 population.

The results displayed in table 7.2 are shocking. The threshold set at 10,000 population was meant to eliminate the possibility of very small counties that have executed only a few people and thus have an extraordinarily high execution rate. When the same test was run on all very large counties in America (cities with over 1.5 million people), the only state included was Texas. As can be seen again, almost all of these counties are below the Mason-Dixon line and most reside in extremely high execution states.

While this may seem counterintuitive when considering the development of the local legal culture, it is likely that prosecutors in smaller counties know that because the surrounding culture perpetuates executions they are more likely to achieve a death penalty sentence when prosecuting. If execution distributions were based on population we would expect to see high population counties on this list, yet we do not. This is troubling as it suggests that the influence of a local legal culture may not only exist in large cities but may seep into the surrounding areas as well. This would mean that even very small counties around an "execution hub" (counties such as Harris or Oklahoma) may be influenced by the legal system present in the larger cities or may have been influenced by the same historical creation of a local legal culture, which has since been self-perpetuated to create the odd distribution that defines the distribution of executions in the post-*Furman* era. Figure 7.2, below, displays the cumulative frequency distribution of execution per population rates across all US counties that have experienced at least one homicide from 1984 to 2012.

Figure 7.2. A cumulative frequency distribution of execution per one million population rates across all US counties.

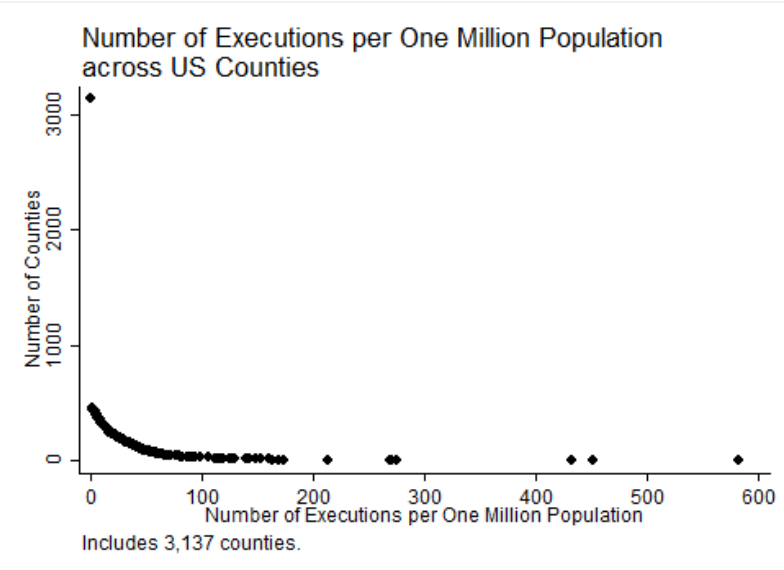
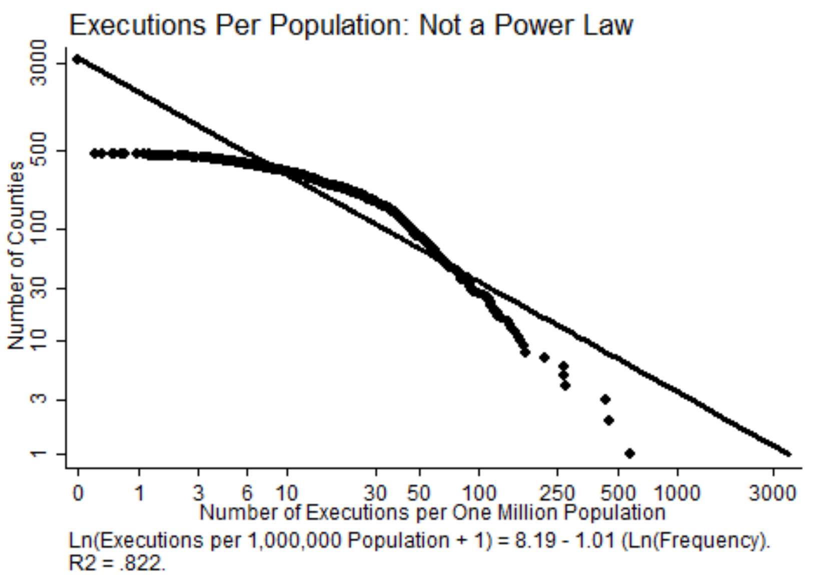


Figure 7.2 suggests that while the distribution of executions per population may not be a power-law, the relationship is clearly not normal and instead suggests the existence of an exponential distribution, as indicated by the long tail that indicates the existence of counties with extremely high execution per population rates. The large number of counties with no executions, as only 465 have any executions at all, clearly contributes to the severity of this relationship. The following figure shows the log-log plot of execution per capita rates when compared to the predicted log-log plot if the relationship between population and executions was a power-law.

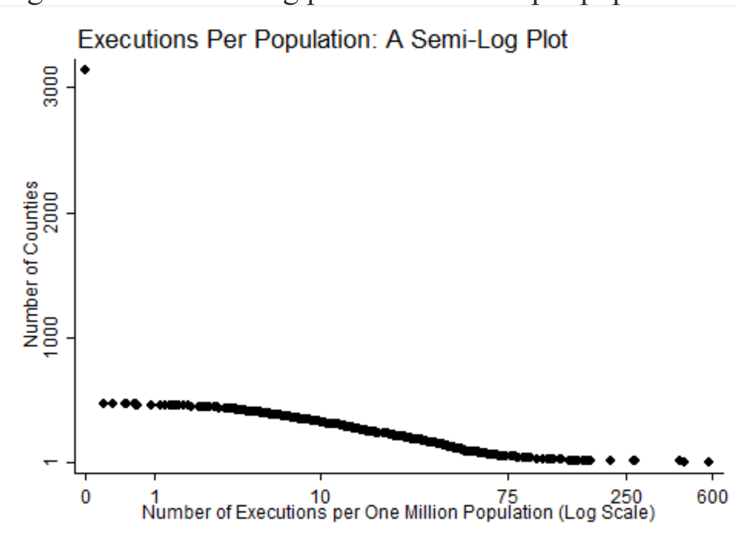
Figure 7.3. Log-log plot of executions per population rates.



While the relationship displayed above is clearly not a complete power-law distribution, this relationship also does not resemble a normal distribution. As can be seen above in figure 7.3, the r-squared of the distribution when compared to the best fit line of a power-law is .822, suggesting that a large amount of the non-randomness of execution distributions (due to the development of local legal culture and perhaps other non-random factors) persists to a high degree even when population is accounted for. While this discovery is probably not surprising considering the significant evidence of the unequal geographic distribution of executions that has been presented to this point, it is still interesting as the effect of population is commonly offered as the driving factor behind the geographic execution inequality that defines the United States capital punishment system.

While the distribution in figure 7.3 is not a true power-law, it is very clear that the relationship does not resemble a normal distribution. Thus, for this section we have employed an additional test, a semi-log plot of the data. As mentioned in the theory section, on a semi-log plot a power-law would contain a slight downward slope that then turns outwards and produces a straight long tail. A normal distribution would be representened by a line that slopes directly down to the x-axis and does not have a tail, while an exponential distribution would have a significantly longer tail. The more severe the tail, the more severe the expoential relationship (and subsequent non-randomness of execution per population rates) is. Figure 7.4 displays this semi-log relationship.

Figure 7.4. A semi-log plot of execution per population rates across US counties



The results displayed in figure 8.4 suggest the existence of a strong exponential relationship due to the long nature of the tail as well as the straight nature of the tail. The existence of an exponential distribution of homicide per population rates across all United States counties is perhaps not surprising but is still concerning considering the fact that all United States citizens are protected by the constitution against unequal or uneven protection of the laws, and these results suggest that this is not currently the case in terms of the geographic distribution of executions. This relationship also suggests that while population does have a correlation to execution rates, population size is not the primary mechanism in determining execution rates, as the presense and number of extreme outliers show. This fact that many of these outliers occur in small counties, and that many counties with very small numbers of executions are very large, indicates that there are other processes creating this exponential relationship, likely historical developments, prejudice, or the local legal culture that allows for the self-perpetuation of executions even in small counties. However, It is possible that homicide rates, which can be considered the prevalence of violence, are the driving factor behind the extremely unequal geographic distributions in the United States. In the next chapter we examine execution per homicide rates in a similar fashion in an attempt to discover what effect the level of violence a county experiences has on the county's liklihood of executing individuals.

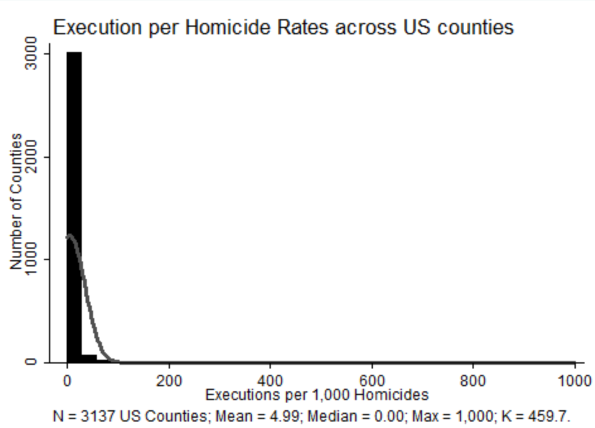
Chapter 8

Execution per Homicide Rates

Another possible factor for the uneven geographic spread of executions in the post-*Furman* era is that it is possible the high execution counties are executing more individuals as a result of extremely high murder rates and a desire to curb these high homicide numbers. The execution per homicide rate analyzed throughout this chapter is per 1,000 homicides in order to make the plots and charts more comprehendible. As shown in chapter 5, homicides are also a power-law, as some counties such as Baltimore and Los Angeles have over 20,000 homicides from 1984-2012 while the majority of counties have numbers far below 100. Executions are also distributed as a power-law, so if high homicide rates are the reason for the uneven geographic distribution of executions we should expect to see that these rates will show that a high homicide number leads to a high execution number. Figure 8.1 displays two frequency distributions, one with and one without a homicide threshold.

Figure 8.1. Execution per homicide rate across US counties

a. All counties.



B. Counties with more than 100 homicides.

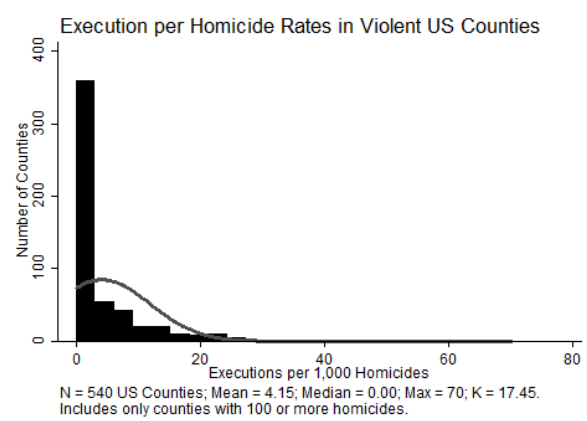


Figure 8.1.a presents a simple frequency distribution of the execution per 1,000-homicides rate from 1984-2012 across all 3137 US counties included in our sample. The mean of this distribution is 5, while the median is 0. This suggests that outliers are significantly skewing these results, as is obviously seen when viewing the very long tail that reaches all the way to 1000. In other words, at least one county has executed one individual for one homicide. The Kurtosis of this distribution is nearly 460, indicating the presence of an extremely sharp peak and that a large degree of non-random factors are responsible for this result other than homicide rate alone. In order to minimize the number of outliers created by rare cases such as the 1 execution per 1 homicide we see in figure 8.1.a, it was necessary to complete another frequency distribution excluding all counties with less than 100 homicides from 1984-2012, as displayed in figure 8.1.b.

Figure 8.1.b shows several interesting changes from figure 8.1.a. When compared, figure 8.1.b has a mean of 4.15 when compared to the 5 we saw when all counties were included. However, the sample size for the distribution seen in figure 8.1.b is 540 counties, and even though this includes all counties with more than 100 homicides, the median is still zero, suggesting that a large number of these violent counties have not executed anyone. This is especially surprising when considering that only 18 states have abolished the death penalty. These results suggest that in many counties, even those where the death penalty not abolished, individuals prosecuting either do not desire to or do not believe they will be successful in attempting to secure the death penalty for the defendant. It should be noted that while the kurtosis is 17, suggesting that there are a large number of other factors contributing to this trend, this number is much smaller than the 460 seen in figure 8.1.a when all counties were included. To examine the distribution of execution per homicide rates, table 8.1 was produced, which

displays the 20 counties with the highest homicide per 1,000 capita rates. This table is on the following page.

Table 8.1. Counties with the highest execution per homicide rates.

Rank	County, State	Percent White	Percent in Poverty	Population	Executions	Homicides	Executions per Population*	Homicides per Population#	Executions per Homicides◆
1	Powell MT	94.7	12.6	7,027	1	1	142.3	0.1	1,000
2	Schuyler MO	99.3	17	4,431	2	4	451.4	0.9	500
3	Refugio TX	81.7	17.8	7,383	2	5	270.9	0.7	400
4	Perry MS	76.6	22	12,250	1	3	81.6	0.3	333
5	Moniteau MO	93.8	9.9	15,607	1	3	64.1	0.2	333
6	Roger Mills OK	93.4	16.3	3,647	1	3	274.2	0.8	333
7	Leake MS	56.5	23.3	23,805	1	3	42	0.1	333
8	Richmond VA	65.4	15.4	9,254	4	13	432.2	1.4	308
9	Pondera MT	85.1	18.8	6,153	1	4	162.5	0.7	250
10	Morgan GA	70.3	10.9	17,868	2	8	111.9	0.5	250
11	Fairfax VA	75.6	5.7	22,565	2	8	88.6	0.4	250
12	Callaway MO	92.9	8.5	44,332	5	22	112.8	0.5	227
13	Boone IN	98.5	5.2	56,640	2	10	35.3	0.2	200
14	Jackson TN	99.3	18.1	11,638	1	5	85.9	0.4	200
15	Williamsburg VA	80.8	18.3	14,068	3	16	213.2	1.1	188
16	Noble OK	89.7	12.8	11,561	2	12	173	1.0	167
17	Meade SD	95	9.4	25,434	1	6	39.3	0.2	167
18	Gillespie TX	93.9	10.2	24,837	2	12	80.5	0.5	167
19	Crockett TX	78.5	19.4	3,719	1	7	268.9	1.9	143
20	Bleckley GA	73.8	15.9	13,063	2	14	153.1	1.1	143

Note: A discussion of the contents of this table can be found on page 58. *= Per 1 million population. #= Per 1,000 population.
◆= Per 1,000 homicides.

Table 8.2. The highest execution per homicide rate counties in counties with more than 100 homicides

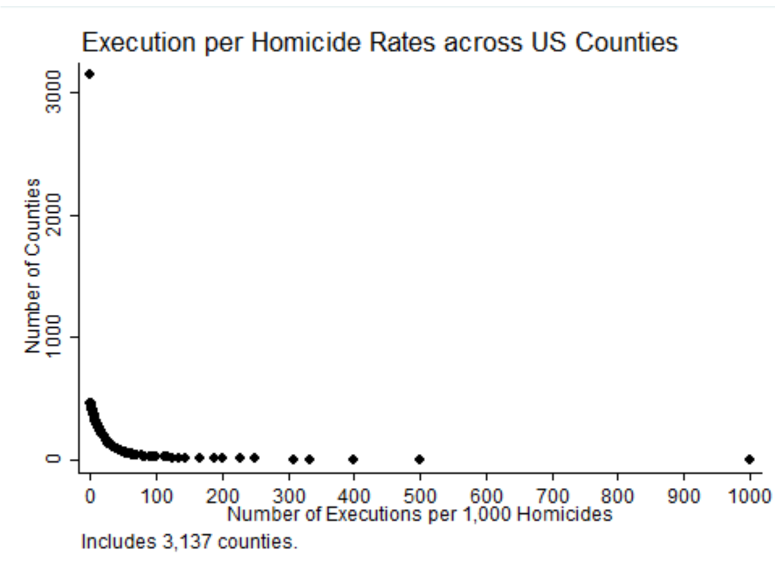
Rank	County, State	Percent in Poverty	Population	Homicides	Executions	Executions per Population*	Homicides per Population#	Executions per Homicide◆
1	Brazos TX	26.9	194,851	171	12	61.6	0.9	70.2
2	Pittsylvania VA	11.8	63,506	100	5	78.7	1.6	50.0
3	Kent DE	10.7	162,310	132	6	37.0	0.8	45.5
4	Prince William VA	4.4	402,002	224	9	22.4	0.6	40.2
5	Potter TX	19.2	121,073	274	11	90.9	2.3	40.1
6	Jefferson MO	6.8	218,733	105	4	18.3	0.5	38.1
7	Anderson TX	16.5	58,458	109	4	68.4	1.9	36.7
8	Chesterfield VA	4.5	316,236	220	8	25.3	0.7	36.4
9	Montgomery TX	9.4	455,746	367	13	28.5	0.8	35.4
10	Bowie TX	17.7	92,565	206	6	64.8	2.2	29.1
11	Comanche OK	15.6	124,098	218	6	48.3	1.8	27.5
12	Smith TX	13.8	209,714	369	10	47.7	1.8	27.1
13	Taylor TX	14.5	131,506	189	5	38.0	1.4	26.5
14	Coconino AZ	18.2	134,421	114	3	22.3	0.8	26.3
15	St. Charles MO	4.0	360,485	117	3	8.3	0.3	25.6
16	Sebastian AR	13.6	125,744	158	4	31.8	1.3	25.3
17	Lubbock TX	17.8	278,831	497	12	43.0	1.8	24.1
18	Liberty TX	14.3	75,643	126	3	39.7	1.7	23.8
19	Williamson TX	4.8	422,679	126	3	7.1	0.3	23.8
20	St. Louis County MO	6.9	998,954	1008	23	23.0	1.0	22.8

Note: A discussion of the results of this table can be found on the following page. *= Per 1 million population. #= Per 1,000 population. ◆= Per 1,000 homicides

Table 8.1 displays the 20 counties that have the highest execution per homicide rates in the United States. Similarly to table 7.1, almost all of these counties are extremely small. This is to be expected however, considering that it is likely a few counties will execute at a high rate if they have done so in the pass. What is surprising, however, is that once again many of these counties lie below the Mason-Dixon line and only a few have very high homicide rates. Once again, as with executions per population, it is very possible that many of these states, due to their proximity to death penalty "hubs", are comfortable seeking the death penalty as a result of the pervasive pro-execution legal culture leaking into the surrounding communities. It should be noted that most of these counties have very few executions, and none have more than five. Similarly, none of these counties have experienced more than 22 homicides from 1984 to 2012, a very small number compared to the national mean of 165. However, while these homicide and execution numbers are small, the rates at which individuals are executed in these counties are astonishing when considering that the national average is 5 per 1,000 homicides for all counties and around 33 for the 465 counties with any executions. In order to examine whether violence does play a major role in execution rates, it was essential to examine the highest execution per homicide rate counties in counties within death states that have more than 100 homicides from 1984-2012, as displayed in table 8.2.

The results in table 8.2 show that even when very small counties have been removed (it would be very unlikely to see a very small county with more than 100 homicides), Texas and a few other southern states still dominate the list of counties with the highest execution per homicide rates. If this was a random process we would expect to see many different states represented on this list, as there are 540 counties throughout the country that have more than 100 homicides. This table reveals the power of self-perpetuation and the effect that a local legal culture can have not only on counties with huge numbers of executions but also on the regions that surround them. Not only do these processes seem to display the characteristics of a self-perpetuating legal process, but they also indicate that one a local culture begins to execute, this tendency to execute gains inertia. In other words, it is very difficult for a local capital punishment culture to change once a path has been set, even in the face of changing political or legal environments. To examine the nature of this distribution, a cumulative frequency distribution of execution per homicide rates is displayed below in figure 8.2.

Figure 8.2. A cumulative frequency distribution of execution per homicide rates across US counties



As figure 8.2 shows, the distribution of execution per homicide rates across United States counties is far from normal, and the length of the tail suggests that there a number of counties with extremely high rates. The high execution per homicide rate counties' coexistence with the high number of counties with very small rates similarly suggests that homicide distributions alone do not explain the uneven geographic distributions of executions. This relationship resembles an exponential distribution. Figure 8.3 shows a log-log plot of execution per homicide rates, and the results are similar to those seen when execution per population rate was examined in the previous chapter in figure 7.3.

Figure 8.3. A log-log plot of executions per homicide rates across all US counties.

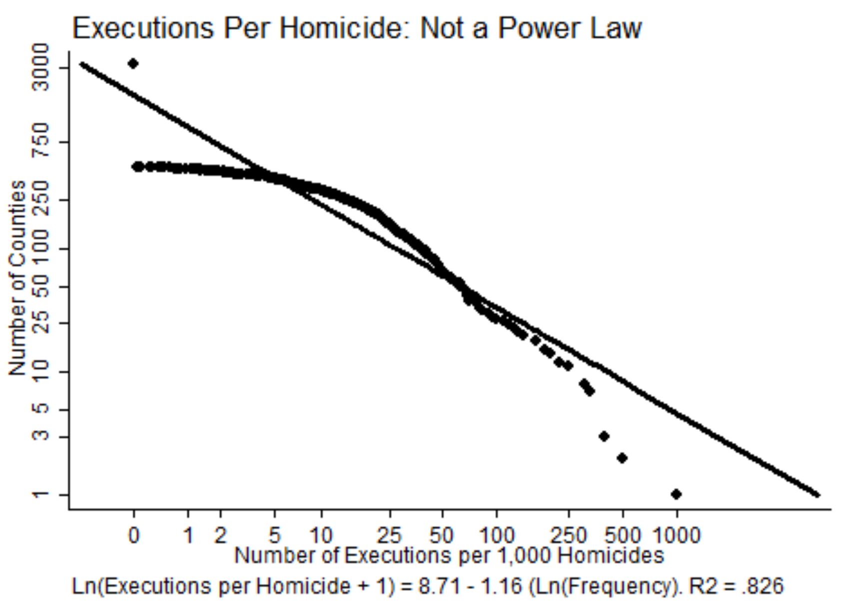
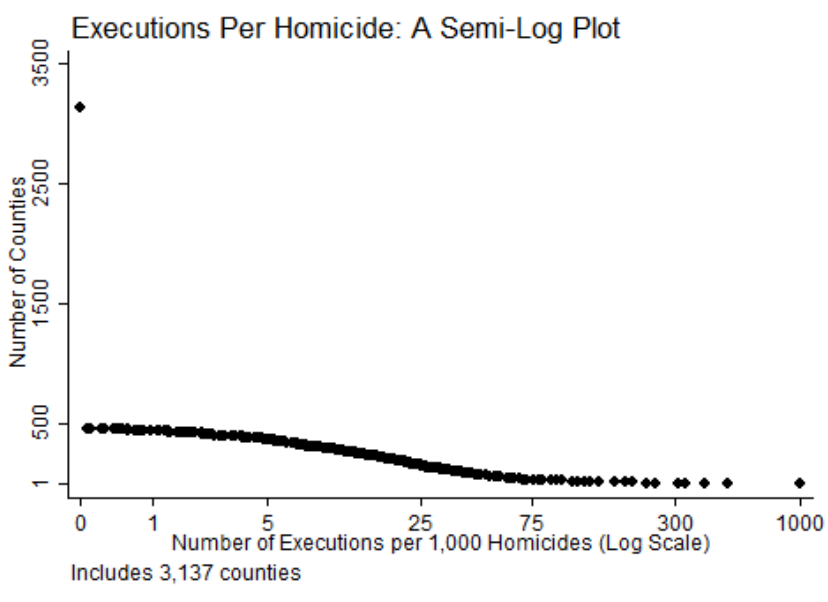


Figure 8.3 shows results similar to those seen in figure 7.3, yet even less pronounced in some ways. In fact, this distribution still seems to be very close to a power law from around 1 to 250 executions per 1,000 homicides. If violence rates were the reason for the uneven geographic inequality of executions we would likely see a much more random distribution, and the r-squared of .822 to the line of best fit for a power law distribution suggests that the local legal culture, as well as other arbitrary regional historical developments, are responsible for a significant portion of the uneven distribution of executions that define the United States capital punishment system. So while homicide numbers do play a role in execution distributions, it is clear that if capital punishment was delivered on an individual, case by case basis without a prior local-level bias for or against executing individuals this distribution would be more normal. As mentioned, the distribution of executions per homicide is clearly not a true power-law distribution, as figure 8.3 shows, but also does not have the characteristics of a normal distribution. Thus, a semi-log

analysis is required to display and determine the nature of the geographic nature of execution per homicide distributions, as presented in figure 8.4.

Figure 8.4. A semi-log presentation of execution per homicide rates across US counties.



This distribution is very similar to the exponential one seen in figure 7.4, again suggesting that homicides are not the primary factor for the uneven distribution of executions in the post-Furman system of capital punishment. As can be seen in figure 8.4, the relatively straight slightly downward sloping long tail of this semi-log plot shows that executions per homicide are distributed in an exponential manner, in other words, that cases are not being tried on an individual basis regardless of the violence of a county. The next chapter, which focuses solely on the distribution of executions since 1977, will highlight the extent of the uneven geographic distribution of executions during the post-*Furman* period.

Chapter 9

Executions

As mentioned previously, our database has information on every execution in the United States since the death penalty was reinstated in 1977. This means that we have as accurate of a picture of the distribution of all 1,373 executions that have occurred since 1977 as possible in terms of location to the county level. As previously, this chapter will follow a very similar format, first introducing regular frequency distributions of execution numbers, then tables and figures of the top counties, and finally a cumulative frequency analysis and power-law test. The results are very interesting, and although published previously by Dr. Frank Baumgartner, this data contains two additional years of execution statistics. Figure 9.1 shows two different frequency distributions of executions across US counties.

Figure 9.1. Number of Executions across US Counties
a. All counties b. Excludes counties with no executions

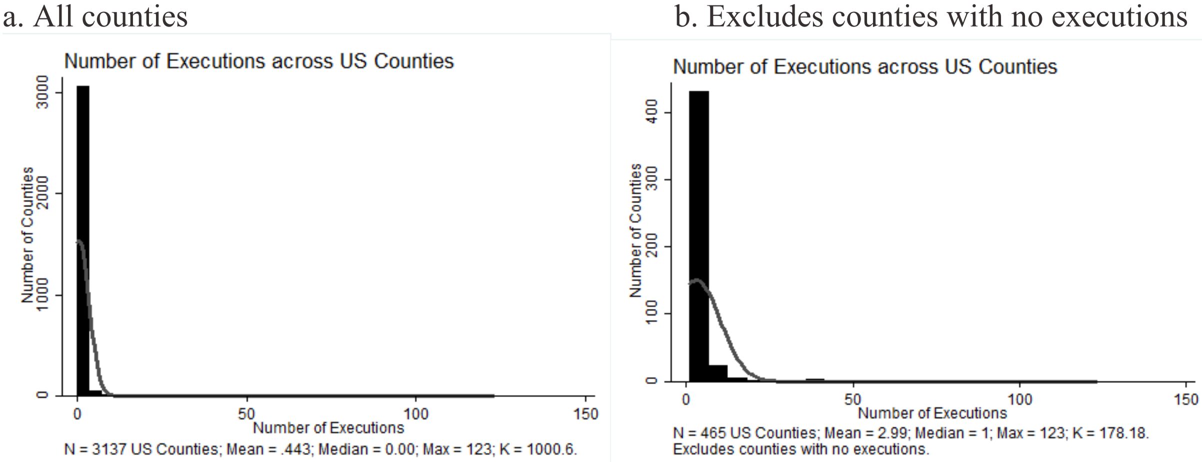


Figure 9.1.a displays all 3,137 counties and a frequency distribution of how many individuals have been executed across the US counties. Clearly the data is heavily skewed by a

few outliers, the most noticeable of which is Harris County in Texas at 123 executions, the maximum number of executions of any county in the United States since 1977. Another noticeable feature of this distribution is the massive number of counties with 0 executions. In fact, only 465 counties have executed even one person as of 2014 (all of these counties have been included in our dataset). This means that out of the total 3,145 counties in the United States, 2,680 have not executed a single person. This is especially interesting considering the fact that 2,980 counties have experienced at least one homicide since 1984, and 540 counties have experienced over 100 homicides during that period. The average number of executions between all US counties from 1977 to 2014 is 0.44, and the median is 0. The extremely long tail of this distribution certainly seems to suggest the existence of a power-law distribution, but more tests are required before we can correctly make that assumption.

Figure 9.1.b shows another frequency distribution, however, this figure only shows the distribution of execution numbers across counties that have executed at least one person. Interestingly, even when eliminating the large number of execution-free counties, this distribution essentially mimics the distribution found in figure 9.1.a and maintains an extremely long tail with many counties lying between 1 and 4 executions. This shows us that even among the 465 counties that have executed anyone (these are considered outliers in the overall sample of 3,173 counties), some counties are still executing at a huge degree above the average. In fact, even in this distribution with the execution threshold the average is only 3 executions between all 465 counties, and the median is only 1 execution. Another way to consider the extremity of the inequality of this distribution is the fact that of the 465 executing counties, only 57 have executed more than four people. Again, this suggests that the maximum executions in Harris County—and several other outliers—are skewing the average of executions per county to be

much larger than it would be if counties distributed executions in a more evenly dispersed way. Table 9.1 shows the counties with the highest number of executions and exposes some very interesting trends as well.

Table 9.1. Counties with the highest number of executions from 1977 to 2014.

Rank	County, State	Percent White	Percent in Poverty	Population	Homicides	Executions
1	Harris, TX	61.2	15	4,092,459	12,359	123
2	Dallas, TX	60.6	13.4	2,368,139	8,568	53
3	Oklahoma, OK	73.7	15.3	718,633	1,880	39
4	Bexar, TX	72	15.9	1,714,773	4,232	38
5	Tarrant, TX	73.4	10.6	1,809,034	3,590	37
6	St. Louis County, MO	77.8	6.9	998,954	1,008	23
7	Tulsa, OK	78.9	11.6	603,403	1,400	18
8	Jefferson, TX	58.4	17.4	252,273	699	15
9	Nueces, TX	74.8	18.2	340,223	661	14
10	Montgomery, TX	89.9	9.4	455,746	367	13
11	Pima, AZ	77.8	14.7	980,263	1,933	13
12	Brazos, TX	76.2	26.9	194,851	171	12
13	Lubbock, TX	76	17.8	278,831	497	12
14	Miami-Dade, FL	72.3	18	2,496,435	6,494	12
15	Maricopa, AZ	79.8	11.7	3,817,117	6,829	11
16	Orange, FL	70.9	12.1	1,145,956	1,784	11
17	Potter, TX	70.8	19.2	121,073	274	11
18	Smith, TX	73.9	13.8	209,714	369	10
19	Mobile, AL	63.9	18.5	412,992	1,512	10
20	Hamilton, OH	74	11.8	802,374	1,676	10

Table 9.1, above, shows the top 20 counties with the highest number of executions between 1977 and 2014. Texas has a strong presence among this list, in fact accounting for more than 338 executions in the top 20 execution counties alone. This is a staggering figure; especially considering the fact that very few of these counties fall anywhere near the top of the homicide rate lists. Another interesting trend present in this table is that even some extremely small counties, such as Potter County in Texas, have executed a very large number of people

compared to the size of the population. Another interesting figure present in this table is that almost all of the counties are around 60 to 80 percent white, and none have a minority white percentage. This may lend some credibility to the concept that the post-*Furman* capital punishment is still subject to deep-rooted racial prejudice and factors that follow, including a skewed local legal culture developed over decades.   On the other hand it is clear that a large number of these counties have a poverty rate that is around or above the national average of 14.5 percent (per 2013). These statistics are all of interest and illustrate of the distribution of executions in the post-*Furman* era. The following figure shows the top execution counties in a bar chart format.

Figure 9.2. United States counties with the highest number of executions.

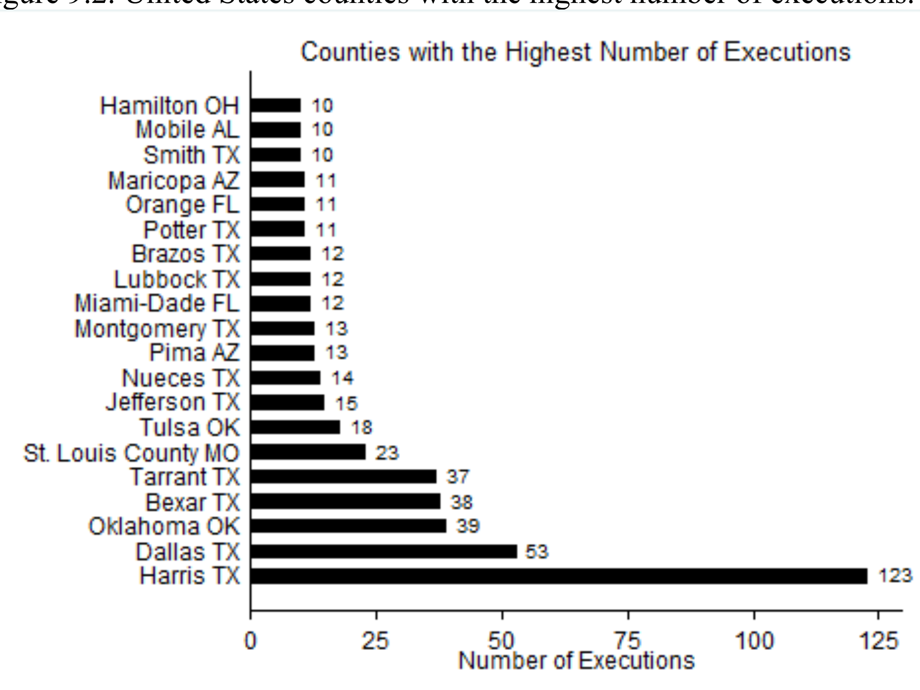


Figure 9.2 may be helpful as the figure is simple to read and exposes the extent of how much of an outlier counties such as Harris, Dallas, and Oklahoma are in terms of executions—even when compared to the other top 20 execution counties.   Figure 9.3, below, shows the

cumulative frequency distribution for the 465 counties with at least 1 execution.

Figure 9.3. Cumulative frequency distribution of executions across executing US counties

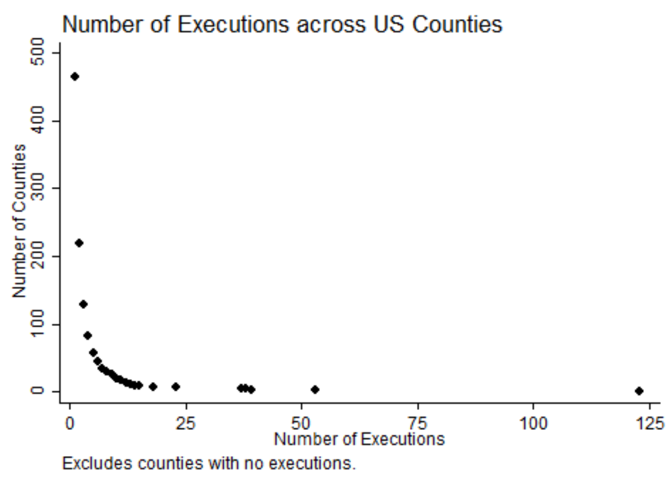
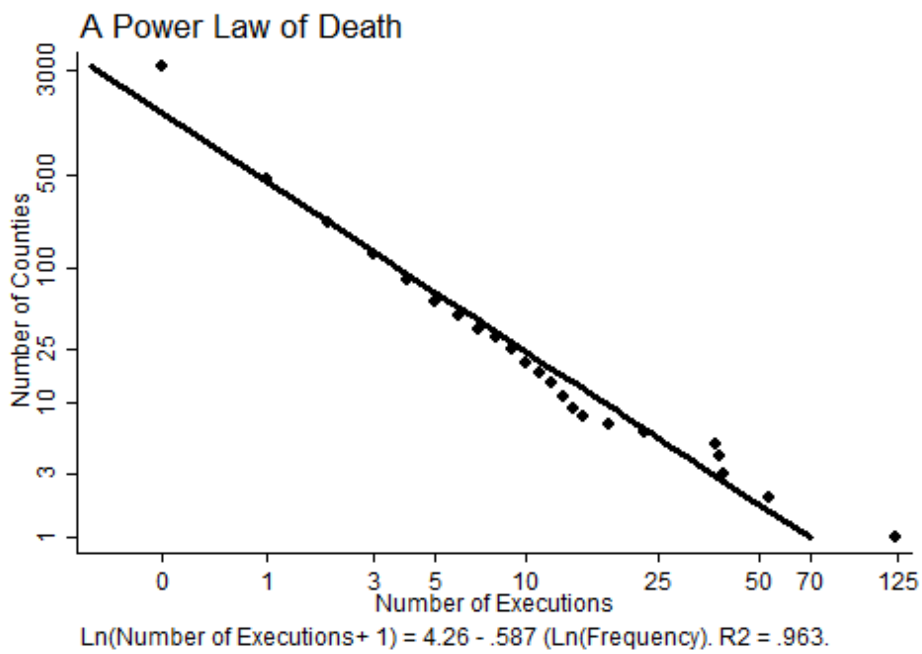


Figure 9.3 again has the basic shape of a power-law distribution, the previously mentioned hockey stick indicated by a very large tail, and also shows that even among executing counties 1 execution is still by far the most common number of executions across all 465 of these counties. In fact, only 218 counties of these 465 have two or more executions, and only 128 counties have more than 3 or more executions across this entire 37-year period. This data suggests the presence of inertia, meaning that most counties only execute one or two individuals and then cease to do so in the future. However, some counties continue to execute beyond these small execution figures, eventually reaching extremely high numbers that are present in figure 9.3. On figure 9.3 one can clearly spot Harris County at 123 and Dallas County at 53 executions, respectively. This figure and the distribution it represents beg the question: what is so different in these countries that they have executed so many more people than the rest of the country? Similarly, it is interesting to think about what is going on in the top five executing states –Texas, Virginia, Oklahoma, Florida, and Missouri. It is clear that some method of self-perpetuation is attributing to the growth of these execution "hubs", as they are still growing even as of 2014.

However, to ensure that this distribution follows a power-law relationship, it is essential to perform the log-log test, as done below in figure 9.4.

Figure 9.4. A log-log plot of the cumulative frequency of executions across all US counties



This line fits the predicted line of best fit for a power law of executions. Especially between 1 and 70 executions, the proximity to the line of best fit is nearly perfect. Even outside of that range, the proximity to the line of best fit for a power-law is extremely strong. With an R-squared score of .963, it is clear that this power-law prediction closely matches the reality and exposes the inequality of the geographic distribution of executions in the post-*Furman* era. This execution data can safely be considered as being distributed as a power-law and points to the existence of local legal cultures formed over decades that have self-perpetuated to the point of no longer resembling a fair and equal capital punishment system in the slightest.

Chapter 10

Conclusion

As has been shown throughout this study, executions are unevenly geographically distributed, either resembling power-law or exponential relationships. We have also examined these distributions in an attempt to discover whether these uneven distributions are the result of possible lurking variables such as population and high rates of violence, yet the results did not suggest that population size nor rates of violence are the primary motivating factors for the existence of these exponential and power-law distributions. Because population, executions, and homicide numbers are distributed as power-laws, if these executions were the result of random factors we would expect the rates of these statistics to also be distributed along a power law. The rate of homicide per capita was very closely distributed as a power-law, which is to be expected considering the fact that larger counties will generally have higher homicide rates than smaller ones. By this logic, it should also be assumed that in a fairly operated capital punishment system high homicide rates would be strongly correlated to high execution rates. However, when the rates are calculated the r-squared value of both execution per capita and execution per homicide decreases significantly from the value of 0.96, suggesting that something is interfering with these trends.

As mentioned throughout our study, we hypothesize that the primary driving factor behind these distributions is not population size nor homicide rates but rather the existence of a local legal culture that has developed and adapted differently in different regions as a result of historical cultural, religious, and legal developments. A more in-depth explanation of the hypothesized components that lead to the development of these local legal cultures, which can increase, minimize, or eliminate the use and frequency of executions, can be found in the appendix.

As the 14th Amendment of the United States Constitution explicitly states, all United States citizens are guaranteed equal protection of the law. However, the results of this study suggest that this is not currently the case, as evidenced by examples such as when counties like Los Angeles and Cook—both in non-abolition states and with more than a combined 40,000 homicides—have less than 10 combined executions while counties like Harris and Oklahoma have only 15,000 combined homicides yet more than 160 executions. Distributions and ratios such as these point to something much different than a simple "more homicides and higher population leads to more executions" answer and expose a system that continues to operate in a unfairly distributed manner created by decades of local historical, legal, racial, and religious cultural developments that in no way guarantee every United States citizen equal protection of, or perhaps more concerning, from the law.

Appendix

Appendix Section 1. Additional Information on the Development of Local Legal Culture

Baumgartner et al. first hypothesized the concept of the impact of local legal culture on capital punishment in 2008. This concept provides a potential explanation for the extreme geographic skews we have seen dominate execution distributions in the post-*Furman* era of the death penalty. As shown throughout this study, most states execute very few individuals, and even in states with counties that execute high numbers of people there are a large number of counties with none or very few executions. While population size and homicide numbers do play a role in these uneven distributions, they do not appear to be the primary driving factor for the power-law and exponential distributions we have seen throughout an examination of our results.

Therefore, the historical development of a local legal culture is a viable reason for the existence of the self-perpetuation, or the "rich-get-richer" phenomenon, which dominates the network of executions during the post-*Furman* era. One way to explain this hypothesis is through an example of a county that has not yet experienced an execution or has not executed an individual since 1977. Even though a very large number of counties experience high numbers of homicides—some of which are probably heinous—many prosecutors did not seek the death penalty, at least for the first several murders that occurred in that county. Therefore, when another heinous murder was committed, it is very likely that a murder of such a heinous or possibly even more heinous nature had been committed previously. During the prosecution of this heinous murder, it may be difficult for the prosecutor to argue that the defendant in this case should be executed while similar homicides in the past may have been equally or perhaps even more heinous, yet the defendant was not executed. Thus, suggesting capital punishment for this defendant would probably not coincide with the tenants of an equitably functioning legal system and as such the prosecutor will likely not seek the death penalty in this case.

These early decisions, which were likely based on a number of relatively arbitrary decisions and developments, is a self-perpetuating system, the few counties that have performed executions from an early period are likely to continue to grow more comfortable doing so in the future. This ability to successfully seek the death penalty and carry out executions becomes greater as the number of executions in a legal district increase. As the number of executions in a county become more common, the prosecutor in that district likely have more confidence that his staff has the experience to successfully achieve a sentence of death for the defendant, that the juries will be more likely to come to an agreement on a death sentence, and that the judges in the district—as well as the appellate courts in the region—will sanction the sentence.

The results of this self-perpetuation work both ways, as can be illustrated using a hypothetical county in which no execution has yet occurred. In these counties, the prosecutor is more likely to believe that he does not have the staff experience to successfully secure a death sentence, that the defense attorney's will be incapable of properly representing the defendant (a requirement for capital cases), that the jury would be willing to suggest a death sentence, nor that the appellate courts in the region would agree with the sentence of death should it occur and reach the appellate state of deliberation. Because of these factors, it is very unlikely— except perhaps in especially heinous crimes— that the prosecutor will attempt to charge the defendant with capital charges.

The final aspect of this "local legal culture" hypothesis considers the historical components that create the local norms which are likely to have contributed to the power-law and exponential distributions of executions we have examined throughout this study. Because local norms develop independently, and in different ways, the extremely unequal geographic distribution of executions is perhaps not as surprising as it is indicative of an arbitrarily based system of capital punishment. While these local legal cultures seem to be correlated to the existence of former slave states and those with high minority populations as well as other factors, not all former slave counties or high minority population counties have high numbers of executions. This is likely due to a random and/or arbitrary beginning of the use of capital punishment that could have occurred over decades or even a longer period of time. After a course of executions is originally set (whether for or against the use of executions), self-perpetuation of this trend is likely to continue and increase in the way that is reminiscent of the "rich get richer" phenomenon introduced in the theory section of this study, which eventually leads to the power-laws that we have presented throughout our results. These geographic distributions should not be predictable based on geography alone if capital punishment operates as an equitable system; however, the results of our study suggest that there is a strong non-random component at work, which we hypothesize is the historical and arbitrary local legal developments that have just been discussed.

Appendix Section 2: Do-files for Dataset Creation

These do files are available upon request from Professor Frank Baumgartner or student Wallace Gram at the University of North Carolina at Chapel Hill Political Science Department.

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[1] Do-file for converting text files to dta files
[2] Do-file for separating the combined years
[3] Do-file for join-by command
[4] Do-file for missing homicide data.
[5] Do-file for combining datasets that had changed fips codes
[6] Do-file for converting execution database to stata format
[7] Do-file for adding execution data to homicide database
[8] Do-file for in-filing census data to full dataset.

Appendix Section 3: Summary Statistics of Variables in Dataset

Sample Size: 3,137 counties.

Name of Variable	**Name in Dataset**	**Sample Size**	**Mean**	**Median**	**Minimum**	**Maximum**	**Kurtosis**
Percentage White by County	white00	3,137 counties	85.7	92.5	5.2	99.9	5.84
Percentage in Poverty by County	pov00	3,137 counties	14.2	13	0	56.9	5.9
Population by County	pop10	3,137 counties	98,403	25,893	82	9,818,605	347.3
Homicides by County, 84-12	allhom	3,137 counties	165.1	20	0	34,892	563.7
Executions by County, 77-14	execcount	3,137 counties	0.444	0	0	123	1000
Executions per 1,000 Homicides by County	execsper1khom	3,137 counties	4.99	0	0	1,000	459.7
Executions per 1 Million Population by County	execsper1mcap	3,137 counties	5.07	0	0	582.4	216.5
Homicides per 1,000 Population by County	homper1kcap	3,137 counties	1.02	0.74	0	20.47	58.8

Bibliography

Amsterdam, Anthony G. 1988. "Commentary: Race and the Death Penalty." *Criminal Justice and Ethics* 7 (2).

Atwell, Mary. 2007. *Wretched Sisters: Examining Crime and Capital Punishment*. Peter Lang International Academic Publishers.

Banner, Stuart. 2003. *The Death Penalty: An American History*. Cambridge, MA: Harvard University Press.

Barabasi, A. (2002). Linked: The New Science of Networks. New York: Penguin Group.

Barkow, Rachel E. 2009. "The Court of Life and Death: The Two Tracks of Constitutional Sentencing Law and the Case for Uniformity." *Michigan Law Review* 107 (7) (January 4).

Baumer, Eric P, Steven F Messner, and Richard Rosenfeld. 2003. "Explaining Spatial Variation in Support for Capital Punishment: A Multilevel Analysis." *American Journal of Sociology* 108 (4) (January 1).

Baumgartner, Frank R, Suzanna L De Boef, and Amber E Boydstun. 2008. *The Decline of the Death Penalty and the Discovery of Innocence*. Cambridge University Press.

Bienen, Leigh B. 1996. "The Proportionality Review of Capital Cases by State High Courts After 'Gregg': Only 'The Appearance of Justice'?" *The Journal of Criminal Law and Criminology* 87 (1) (August 1).

Brace, Paul, and Brent D Boyea. 2008. "State Public Opinion, the Death Penalty, and the Practice of Electing Judges." *American Journal of Political Science* 52 (2) (April 1).

Cottrel, Robert J. 2004. "Finality with Ambivalence: The American Death Penalty's Uneasy History." *Stanford Law Review* 56 (6) (January 4).

George, Diana, and Diane Shoos. 2005. "Deflecting the Political in the Visual Images of Execution and the Death Penalty Debate." *National Council of Teachers of English* 67 (6) (January 7).

Goldberg, Arthur J, and Alan M Dershowitz. 1970. "Declaring the Death Penalty Unconstitutional." *Harvard Law Review* 83 (8) (January 6).

Gross, S. R. (2012). David Baldus and the Legacy of McCleskey v. Kemp. Iowa Law Review, 97.

Harries , Keith. 1992. "Gender, Execution, and Geography in the United States." *Swedish Society for Anthropology and Geography* 74 (1)

Heise , Michael. 2003. "Mercy by the Numbers: An Empirical Analysis of Clemency and Its Structure." *Virginia Law Review* 89 (2) (January 4).

Jacobs, David, and Jason T Carmichael. 2002. "The Political Sociology of the Death

Penalty: A Pooled Time-Series Analysis." *American Sociological Review* 67 (1) (February 1).

Lain, Corinna B. 2007. "Deciding Death." *Duke Law Journal* 57 (1) (January 8).

Lev, Ori. 1994. "Personal Morality and Judicial Decision-Making in the Death Penalty Context." *Journal of Law and Religion* 11 (2).

Little , Rory K. 2001. "Good Enough for Government Work? The Tension Between Uniformity and Differing Regional Values in Administering the Federal Death Penalty." *Federal Sentencing Reporter* 14 (1) (August 1).

Macher, David. 1995. "Race and the Death Penalty: McCleskey V. Kemp." *Wesleyan Law Review* 80 (95).

Mullin, Courtney. 1980. "The Jury System in Death Penalty Cases: A Symbolic Gesture ." *Law and Contemporary Problems* 43 (4).

Nice, David C. 1992. "The States and the Death Penalty." *The Western Political Quarterly* 45 (4) (December).

Patterson, Krista L. 2006. "Acculturation and the Development of Death Penalty Doctrine in the United States." *Duke Law Journal* 55 (6) (April).

Peffley, Mark, and Jon Hurwitz. 2007. "Persuasion and Resistance: Race and the Death Penalty in America." *American Journal of Political Science* 51 (4) (October).

Phillips, Scott, Laura Haas, and James Coverdill. 2012. "Disentangling Victim Gender and Capital Punishment: The Role of Media." *Feminist Criminology* 7 (2).

Young, Robert L. 1991. "Race, Conceptions of Crime and Justice, and Support for the Death Penalty." *Social Psychology Quarterly* 54 (1) (March).