Does Capital Punishment Save Lives?

An Examination of the Deterrent Effect of Capital Punishment

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Abstract

This paper employs fixed and random effects regressions to analyze panel data from the 50 states and Washington, D.C., between the years of 1980 and 2005, to estimate the relationship between the death penalty and homicide rate, and the degree to which this relationship affects crime outcomes. Controlling for a number of economic and demographic characteristics, the results of the fixed and random effects models suggest that there exists a negative, statistically significant relationship between the dependent variable, homicides/100,000 in the population, and the independent variable of interest, the number of executions. The results from an alternative specification, where the independent variable of interest is an execution dummy variable, suggest that it is not the presence of executions that deters homicides, but the actual executions that has a depressing effecting on homicide rate. A final model estimates the relationship between law enforcement officer murders and the number of executions in a given state, in a given year. This model yields shows no statistically significant relationship between the number of executions and the number of law enforcement officer deaths.
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Introduction

The taking of human life is unambiguously an irreversible process – on this much those who fall on opposing sides of the polemical death penalty debate can agree. But this is where the common ground ends for most. People take issue with every other facet of the death penalty, from the morality of the practice, to its ranking as the harshest form of punishment; from the process by which it is implemented, to the people to whom the punishment is meted out. The morality of the capital punishment and the issues surrounding its continued use as an instrument of the justice system are divisive, and are sometimes split along party lines. Still, that the issue sparks such impassioned debate is in of itself promising, as it speaks to a recognition of the urgency of the situation; whether we are going to take life as punishment, or if we are going to choose an alternative route, we must ensure that we have examined exhaustively every necessary moral, theoretical, and practical consideration. This paper seeks to address one aspect of the death penalty debate in particular – that of its potential deterrent effect on crime. Though it is only one of many possible avenues by which to explore the issue of capital punishment, the question of deterrence proves to be one of considerable and central importance.

As important as deterrence is to some, there are others who believe it to be a moot point: strong opponents to capital punishment find no argument compelling enough to justify the taking of a life, while staunch defenders of the practice are proponents of an argument for proportionality of crime to punishment that sounds unabashedly like “an eye for an eye.” Nonetheless, there are some for whom a hypothetical deterrent effect or lack thereof would be the deciding factor: a deterrent effect on homicide would be justification for the continued use of execution as means of punishment, while absent a deterrent effect, executions would be
considered excessively cruel and the practice should be discontinued. In light of this, detecting a possible deterrent effect and the magnitude of this effect is an interesting and valuable exercise.

Beyond the scope of this paper are other important issues relevant to the debate, such as the morality of capital punishment, the proportionality of crime to punishment, or the (unfair and potentially racially biased) process by which the death penalty is implemented. Here, I aim only to discern a relationship between homicides and execution. If there does in fact exist a causal relationship between the two variables, I intend to examine the degree to which this relationship influences crime outcomes. If no such relationship exists, I believe that this is a finding in of itself. Ultimately, whichever side of the debate my results happen to be consistent with will have perhaps additional evidence with which to support their claims.

**Capital Punishment and Deterrence**

During the late eighteenth century, a group of thinkers (who would later be referred to as Classical Criminologists) developed an idea that would revolutionize Western penal systems. Rather than serving a retributive end, they reasoned, punishment could feasibly benefit society by dissuading would-be criminals from committing crimes. Within this model, people are presumed – correctly or incorrectly – to perform a cost-benefit analysis before engaging in an action wherein the perceived cost of the action is weighed against its perceived benefit. This model of human action, which assumes rationality, when extended to crime, tends to produce very reductionistic views of criminal behavior. Nonetheless, it was around these principles of classical criminology that many penal systems were reformed.
Isaac Ehrlich, a Yale law professor who authored the seminal econometric study on deterrent effects of executions, reasoned that willing commutation of death sentences to life imprisonment sentences confirms an intuitive ranking of death sentences as the harshest form of punishment (Ehrlich 1973). The deterrence theory of punishment can reasonably be extended to capital punishment because, if other forms of crime could be deterred by tougher punishments (e.g. extended prison sentence), it should follow that the most severe instrument of the system should have at least comparable, if not magnified, effect. When applied to the death penalty, this deterrent theory of punishment suggests that would-be murderers, before committing a crime, consider the possibility (and possibly also the probability) of execution as a cost to murder. If the would-be murderer deems that paying for their crime with their lives is too high a price and chooses an alternative course of action, the risk of execution will have deterred a would-be murderer and served to prevent crime. Because a possible deterrent effect is a critical element in the death penalty debate, it is a valuable exercise to try and determine whether this effect does indeed exist, and, if it does, the extent to which it affects crime outcomes. The answer to these questions could help to inform the ways in which we evaluate the use of execution as means of punishment.

**Brief History of Capital Punishment in the United States**

Capital punishment has been used as an instrument of the penal system in the United States since the 1600s, when the practice was imported to the colonies by British settlers. However, during the 1960s, the constitutionality of the death penalty was called into question by a series of cases passed before the Supreme Court. These cases addressed various issues raised
by the continued use of capital punishment by most states, from the incongruity of capital punishment with an “evolving standard of decency that mark[s] the progress of a maturing society,” to the unfair nature of its implementation.

Finally, in a 1972 decision (Furman v. Georgia), the Supreme Court struck down all state death penalty laws, declaring their application “arbitrary” and “capricious”. This, the Court said, made executions unconstitutional under the 14th and 8th Amendments. These amendments prohibit the government from depriving its citizens of life, liberty, or property without the “due process of law”, and from using cruel and unusual punishment, respectively. This ruling suspended 40 death penalty statutes, thus commuting the sentences of 629 inmates nationwide, and effectively suspending the death penalty indefinitely.

Though the Court suspended the death penalty by virtue of its voiding of state capital punishment laws, this hiatus would only be temporary, as the ruling only addressed the constitutionality of the death penalty statutes, rather than of the death penalty itself. Thus, shortly after the Furman v. Georgia decision, several states began to develop laws that were at least on their surface less arbitrary. These new statutes directly addressed the Court’s issue with the previous laws, and consequently, in 1976, the Court upheld Georgia’s new death penalty procedures. (deathpenaltyinfo.org)

Data from the Bureau of Justice dates only as far as 1930. Nonetheless, we can see that the trend is declining usage of executions, presumably, more life imprisonment. There were, for instance, 155 executions in 1930, compared with just 42 in 2007. Currently, thirty six states have death penalty laws; of these thirty six, two have not had any executions since 1976. Texas leads the nation in executions, having executed 405 prisoners since 1976. It has sentenced to
death over four times as many prisoners as the state with the second most executions, Virginia (85) since the end of the moratorium in 1976.

Possible methods by which the death penalty may be implemented are: lethal injection; electrocution; gas chamber; hanging; and firing squad. Of these methods, lethal injection is by far the most commonly used. There is variation across states regarding the crimes for which one can be sentenced to death. Aggravated homicide, however, is consistently punishable by death across all states, with the aggravating conditions varying from state to state.

Men are disproportionately represented on death row: at the end of 2006, only 1.7% of inmates on death row were female while the remaining 98.3% were male, even though males accounted for 49.3% of the total national population in 2006. Blacks are also disproportionately represented on death row: at the end of 2006, 41.9% of death row inmates were black, while blacks constituted only 12.8% of the total national population in 2006. 11.6% of the inmates on death row in 2006 were Hispanic, compared to 14.8% in the national population in the same year. (http://quickfacts.census.gov/qfd/states/00000.html)

**Related Literature**

There has been extensive inquiry into the question of deterrence by scholars of a variety of disciplines. Criminologists, sociologists, and economists have all authored many significant works regarding punishment and the issue of deterrence. In this section detailing works related to this paper, I will examine those papers employing econometric techniques to discern a relationship between crime and capital punishment. Several of these have found that capital
punishment has a deterrent effect. There does, however, exist a vast body of literature on the topic which finds itself in direct conflict with this conclusion.

The criminology and sociology literature in general seem to converge on the conclusion that capital punishment has little to no deterrent effect on homicide. One 1996 study, by Radelet and Akers, surveys leading criminologists on their view of the issue of deterrence, in an attempt to gauge the opinions of the experts on crime. Their working definition of “expert” was “one who had been recognized by peers by being elected to the highest office in scholarly organizations” (Radelet 1996). Surveying the presidents and former presidents of these leading criminology societies, the researchers found that, overwhelmingly, these experts did not believe that capital punishment deters crime. However, despite this seemingly unequivocal evidence attesting to the absence of a deterrent effect, we must bear in mind the breadth and diversity of literature (and opinion) on the topic and remember that there is still no consensus on the subject.

Isaac Ehrlich, a Yale law professor, authored the seminal econometric study on deterrence in 1975. In a controversial paper, he collects national, state-level data from 1933 to 1969 and uses regression analysis to detect a relationship between homicide rate and capital punishment. He then argues that the results of his regression analysis show that each execution deterred up to eight would-be murderers from committing crimes. Both the paper and its findings have undergone much scrutiny, especially as other economists and social scientists failed in their efforts to replicate his results. Their critiques range in focus from the functional form Ehrlich employs, the potential problems posed by aggregation of data to the national level, to the possibility that his results are specific only to his sample time period. Since that piece, however, there have been many econometric studies on deterrence that attempt to avoid the pitfalls of Ehrlich’s study.
Some social scientists have approached the deterrence issue by way of smaller-scale time series analysis. By limiting their research to one geographic area and over a shorter sample period, authors have been able to overcome the problems associated with aggregated data, and are able to obtain statistics on a finer scale than those studies whose scope is wider. Philips (1980) authors a paper on the effect of capital punishment on homicide rates in London, from 1858 to 1921. Because of his limited geographical area, Philips is able to obtain and use weekly homicide data. He finds that there is a short-term deterrent effect of publicized executions: homicides decrease on average 35.7% immediately following a publicized execution. Conversely, Bailey (1983) uses monthly data for Chicago, Illinois for 1915-1921, and performs a time-series analysis. He examines the effect of executions on first-degree murders using regression analysis, and finds that there exists a positive, statistically significant relationship between homicides and execution. This suggests that, not only does there not exist a deterrent effect of capital punishment on murder, but that, following what is referred to as the “brutalization hypothesis”, executions tend to encourage rather than discourage murder. (Bailey 1983)

Perhaps by virtue of their small scope, these studies, and others like them, typically yield compelling results in support of one side of the argument or the other. The trouble with studying deterrence on a small scale, however, is that despite their ability to overcome the problems plaguing studies that need to use aggregated data, the findings of these very place-and-time-specific studies cannot be considered widely applicable. Thus, in order to obtain results that can be generalized and applied to the question of a deterrent effect of capital punishment, one must broaden the scope of the study, bearing in mind, that the choice to do so also comes with its own set of limitations.
Returning to the panel data method that Ehrlich employs, we find that many econometric studies use variations on the same set of independent and dependent variables. If one is interested in studying a hypothetical deterrent effect on crime of the death penalty, the dependent variable will be some measure of homicide rate, as murder is virtually the only crime for which one can be executed in most states. (In most states, only first-degree murderers are eligible for the death penalty, with the aggravating factors differing across states. Treason is also punishable by death in some states.) Zimmerman (2004) uses state-level homicide data from 1977 and 1999, measuring homicides in a state, in a given year, per 100,000 residents of the state. In her study, Shepherd (2004) collects monthly state murder data between 1977 and 1999, measuring homicides per 100,000 in the state population; she argues that the use of monthly data helps her to overcome the aggregation problems associated with annual data.

Because I was not able to obtain monthly data as Shepherd was, the data I employ in this paper is most similar to that of Zimmerman: state-level homicide data from 1980 to 2005, for my dependent variable. Following Zimmerman and Shepherd, I also transform this variable, as it is not normally distributed. The variation on this measure that I include is homicide rate per 100,000 in the population (Zimmerman 2004, Shepherd 2003).

Most of the studies reviewed considered variations on the same demographic and economic factors to have an impact on the homicide rate, and these were included as independent variables in the regressions. Among the recurring demographic variables were: age distribution within a population, the proportion of males in the state population, and a measure of racial diversity. The intuition behind the selection of these particular variables can be found in the Bureau of Justice’s statistical analyses of crime, which breaks down crimes by the age, gender, and race of the offender (and victims).
With regards to age, these data show that young adults aged 18-24 have had historically the highest homicide offending rates, nearly doubling their rate of offense between 1985 and 1993. The average age of offenders fell from 30.3 years in 1976 to 26.4 years in 1994.

With regard to gender: In 2005, males were ten times more likely to commit homicide than were females. Between 1976 and 2005, 88.8% of offenders were males.

With regard to race: In 2005, offending rates for blacks were seven times that of whites. Additionally, the data show that murders are, more often than not, intraracial: 86% of white victims were killed by whites, while 94% of black victims were killed by blacks. (All Bureau of Justice stats: http://www.ojp.usdoj.gov/bjs/homicide/homtrnd.htm)

This suggests that there are age, gender, and race components to homicide, and that the distribution of each demographic within a population could have an effect on crime outcomes. Omitting one or more of these variables might lead to biased coefficients on the remaining independent variables, causing us to over estimate the impact of those included variables. For this reason, many of the papers reviewed included some measure of each of these demographic as a proportion of the overall population in a given state, in a given year.

Economic characteristics of states are also always included as independent variables, as there is, intuitively and empirically, a relationship between crime and certain economic variables. (Hseih 1993). Recurring variables in this category typically measure economic conditions within the state in that year. Among these variables are: poverty; unemployment rate; and income per capita. The expected direction of the relationship depends entirely on the mechanism by which the economic measures are affecting crime.

On one hand, there could exist a positive relationship between the murder rate and the poverty and unemployment rates. Raphael (2001) finds that there is a consistent positive
relationship between unemployment rate and general crime outcomes, though that of violent crime and unemployment is somewhat weaker. In this instance, a possible mechanism underlying this relationship could result from poor economic conditions (reflected in a high poverty rate, high unemployment rate, or low income per capita) causing a reduction in the number of legal alternatives to crime. If this were the way in which economic variables acted on crime rates, inclusion of demographic variables in this case measures the job prospects of potential murderers as well as potentially capturing the need to perform illicit activities in order to sustain oneself. (Shepherd 2004).

Alternatively, a negative relationship could exist between an economic measure that might otherwise indicate that the economy is in good condition. Among these measures is income per capita. While this reflects an increase in general welfare, it could also indicate that there is additional wealth to steal, as well as a potential increase in disparity among different socioeconomic groups within the population. Some authors thus use measures of disparity in their analyses, reasoning that it is not the overall state of the economy, but the differences between the rich and the poor that motivate criminal activity (Balkwell 1990).

In either case, omitting these variables would cause us to inaccurately estimate the effect of executions on homicides. Thus, following the deterrence literature reviewed, I also include a number of economic variables, hoping to capture both the potential interactions with crime. These are: yearly unemployment rate, yearly income per capita, and the percentage of the population living below the poverty line.

The independent variable of interest in these econometric studies is a measure of capital punishment and the degree to which it is carried out. Authors of previous studies have used a variety of different ways to measure this effect. Shepherd (2004) in her study, for instance,
measures the number of executions using a 12-month moving average of executions by state. The reasoning behind this methodology is that the executions that occurred most recently should carry more weight than those that took place some time in the distant past. Other papers use a vector of deterrence variables, measuring the probability of arrest, probably of conviction, given arrest, and then the probability of execution, given conviction. (Zimmerman 2004, Mocan and Gittings 2003) The reasoning behind the vector of variables is because of a possibility of endogeneity in the number of executions and crime data. Bailey (1983) employs the actual number of monthly executions, as well as a dummy execution variable, where execution months equaled one and non-execution months equaled zero.

**Data Description**

The data compiled and used in this analysis are collected from the 50 states and Washington D.C., from 1980 through 2005. All variables are measured on by state, on a yearly basis. The demographic data were obtained primarily through the Census Bureau Statistical Abstracts, while the economic data were obtained through the Bureau of Labor. Execution data were obtained through a State University of New York at Albany website, which cites the Department of Justice Bureau of Statistics. Homicide data were also obtained through a third party site that cites the Department of Justice as its source, while data for police expenditure data were obtained directly from the Department of Justice.

Consistent with other econometric studies of deterrence, I use homicides as my dependent variable. Initially, I tested two variations of this variable: number of homicides in a given state, in a given year; and homicide rate per hundred thousand of the state’s population in a
given year. However, because the raw homicide data was not normally distributed when plotted on a histogram, the latter was ultimately used in the regressions whose results are presented in this paper.

The independent variables measuring age structure within a population are: %18-24, %25-44, %45-64, and %65+, within a given state, in a given year. These ranges differ from those used in the FBI crime statistics, which are %18-24, %25-34, %35-49, %50+, because the data readily available from the Census Bureau had set these intervals. I do not believe that conflating the middle two age groups, as the Census Bureau data does, will affect the outcome significantly. The ranges differed from paper to paper of the studies reviewed, but the age structure that I employ is similar to that of Zimmerman (2004). To obtain these percentages, I divided the number of people in each age range by the total population for each state for each year between 1980 and 2005.

Independent economic variables are: percentage of the population below poverty line in a given state, in a given year; income per capita in a given state, in a given year; and the average yearly unemployment rate in a given state, in a given year. These variables were consistent with the vector of economic variables employed by the authors of the papers reviewed, and were imported directly from their sources, without any additional manipulations.

Another independent variable whose effect on homicide rate I examined was that of state police expenditure, as a proxy for the presence of law enforcement on the streets. While there exists a relationship between the presence of law enforcement and crime rate, the direction and strength of this relationship has at times been called into question (Siegel 2006). Nonetheless, other authors have included this measure because of its possible deterrent effect on crime. This variable was not normally distributed, so the natural log transformation was used in its place.
My independent variables of interest are different measures of the presence of capital punishment within a given state, in a given year. These are: a death penalty dummy variable, which equals one if the state had death penalty laws on the books in that year, and equals zero if it had no such laws; the number of executions in a given state, in a given year.

Additionally, I measure the effect of capital punishment on the killing of law enforcement officers, a specific type of homicide. The interaction between capital punishment and this particular type of murder has remained relatively unexamined compared to that of other types of homicides. Belying this research is the idea that the killing of law enforcement officers is commonly perceived as a particularly heinous type of crime, since these men and women were putting their lives at risk in order to protect others. In this light, criminals who have committed this specific kind of murder might expect to be treated more severely than those who have committed other types of murders. The ranking of this type of homicide as being in some way “worse” than others is reflected, for example, in the 2005 New York state proposed legislation to reinstate the death penalty for police-killers, even though the state had deemed capital punishment unconstitutional in 2004. Furthermore, there is anecdotal evidence of prosecutors pushing for the death penalty when criminals are convicted of killing police officers.

The effect of this view of law enforcement officer homicides could conceivably raise the perceived cost of killing a police officer, since the likelihood of being sentenced to death is thus increased. Should a deterrent effect of capital punishment exist for homicides in general, we might expect this effect to be more pronounced in a model whose dependent variable is a measure of this particular kind of homicide.

In this specification, the number of law enforcement officers feloniously murdered in a given state, in a given year is the primary dependent variable of interest. This variable, however,
is not normally distributed, and thus, an alternative specification included the natural log of the number of law enforcement officers feloniously killed in a given state, in a given year. The natural log of the original variable yields a distribution that appears closer to a normal distribution than just the raw measure of the number of deaths. As the officer death data was only readily available starting 1996, the sample period I used was 1996 through 2005, for the fifty states and Washington, D.C.

**Methodology**

In analyzing my panel data, I regress the homicide rate on a number of independent variables, including my independent variable of interest: the number of executions in a given state, in a given year. The relationships were estimated by the following equation:

1) \( \frac{\text{Homicides}}{100,000} \)\(_{i,t} = \beta_0 + \beta_1 \text{executions}_{(t-1)} + \beta_2 \text{Unemployment} + \beta_3 \text{Poverty} + \beta_4 \text{Income} + \beta_5 \text{Pop18-24} + \beta_6 \text{Pop25-44} + \beta_7 \text{Pop45-64} + \beta_8 \text{Pop65} + \beta_9 \text{Black} + \beta_{10} \ln \text{Police} \)

The economic variables measured for a given state, in a given year, as previously mentioned were: income per capita, unemployment rate, and the percent of the population living below the poverty line. The demographic variables included were: the age distribution within the population as previously described, and the black population as percentage of the total population. An additional independent variable was the natural log of the amount of police expenditure. The results from this regression can be found in Table 1.

One pitfall of deterrence research is the potential endogeneity between the dependent variable (i.e. some measure of homicide rate) and the independent variable of interest (i.e. some
measure of execution). That is to say that, although we are looking to measure a potential causal relationship between homicide and execution such that executions are influencing the number of homicides, there could conceivably be interaction between the two variables in the reverse direction; the rate of homicide in a given state, in a given year could well be affecting the number of executions in that year. To overcome this potential problem, I chose to lag the execution variable by one year, because homicides taking place in a given year could not be influencing executions taking place in the previous year in the aforementioned way. Thus, lagged a lagged independent variable will help eliminate the problem of endogeneity.

I use a fixed effects regression to control for unobservable factors affecting homicide rate existing within specific states throughout the sample period. By this method, dummy variables were created for each state, which equal one when it was the state in question, and zero for all other states. The rationale belying this analysis is that there are potentially unobservable factors that influence the homicide rate in specific states over the entire sample time period which could not be accounted for by any of my independent variables. Generating dummy variables for each state using the fixed effect regressions controlling for state accounts for those unobservable differences between state that are consistent across time.

Next, I use the random effects model to allow for the possibility that some omitted variables might vary by state but remain constant over time, while others might vary over time but be fixed between states. The results generated from this specification in both of these models can be found in Table 1 in the results section.

Following this initial analysis of the effect of the independent variables on the number of executions, I test the possibility that the very existence of death penalty laws, and not necessarily executions themselves, have the ability to deter people from committing murders. In doing so, I
substitute a death penalty dummy variable into specification 1, and run the fixed and random effects models to estimate the relationships between the independent variables and this measure of the presence of the death penalty.

2) Homicide rate/100,000,000,000,000 = \beta_0 + \beta_1DPdum + \beta_2Unemployment + \beta_3Poverty + \beta_4Income + \\
\beta_5Pop18-24 + \beta_6Pop25-44 + \beta_7Pop45-64 + \beta_8Pop65 + \beta_9Black + \beta_{10}lnPolice

The results of this specification using both models can be found in Table 2.

In addition to the question of deterrence on homicides in general, as previously discussed, I also examine the effect of capital punishment on the murders of law-enforcement officers. The specification I use here is identical to that which I use earlier to estimate general homicides, except that the number of officer deaths is substituted for homicide rate as the dependent variable. Again, I use fixed and random effects models to estimate the relationships between the independent variables and this particular type of homicide.

3) Number officer deaths,000,000,000,000,000 = \beta_0 + \beta_1DPdum_{(t-1)} + \beta_2Unemployment + \beta_3Poverty + \beta_4Income + \\
\beta_5Pop18-24 + \beta_6Pop25-44 + \beta_7Pop45-64 + \beta_8Pop65 + \beta_9Black + \beta_{10}lnPolice

The results of this analysis can be found in Table 3.
Results

Table 1

<table>
<thead>
<tr>
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<th>F.E.: Homicides/100,000</th>
<th>R.E.: Homicides/100,000</th>
</tr>
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<tbody>
<tr>
<td>Executions</td>
<td>-.1673 *** (.05745)</td>
<td>-.1726*** (.05810)</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>-.1294 (.09888)</td>
<td>-.08936 (.09958)</td>
</tr>
<tr>
<td>Income Per Capita</td>
<td>-.0000499 (.0000429)</td>
<td>.0000168 (.0000423)</td>
</tr>
<tr>
<td>% Living in Poverty</td>
<td>.2400*** (.06211)</td>
<td>.2642*** (.06074)</td>
</tr>
<tr>
<td>% Pop. 18-24</td>
<td>-.1077 (.06519)</td>
<td>-.07717 (.06638)</td>
</tr>
<tr>
<td>% Pop. 25-44</td>
<td>.01192 (.01998)</td>
<td>.01367 (.02059)</td>
</tr>
<tr>
<td>% Pop. 45-64</td>
<td>-.2595*** (.09171)</td>
<td>-.3907*** (.09151)</td>
</tr>
<tr>
<td>% Pop. 65+</td>
<td>.6489** (.2116)</td>
<td>.2981 (.1685)</td>
</tr>
<tr>
<td>% Black</td>
<td>-.1161 (.09296)</td>
<td>.3771*** (.03987)</td>
</tr>
<tr>
<td>Ln(Police spending)</td>
<td>.04621 (.07593)</td>
<td>.05319 (.07734)</td>
</tr>
</tbody>
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Specification 1:

In the fixed effects model, the relationship between executions and the homicide rate is negative and statistically significant at the 99% level such that, on average, one additional execution reduces the number of homicides by .1673, per 100,000 in the population of a given state. Using the random effects model, the relationship is negative and statistically significant such that, on average, one additional execution reduces the number of homicides by .1726, per 100,000 in the population of a given state. If we take, for instance, Alabama, in 1980, with a total
population of 3,894,000, both the fixed effects and random effects model estimate that one execution would have resulted in a decrease of approximately seven murders.¹

The relationship between the unemployment rate and the homicide rate across the fixed and random effects model are both negative, though neither is statistically significant at the 95% confidence level. Since we might predict a positive relationship between unemployment rate (a measure of economic conditions and overall welfare) and homicide, this finding is somewhat counterintuitive.

The relationship between the percent of the population living under the poverty line (another measure of the state of the economy and overall welfare) and the homicide rate is positive and statistically significant at the 99% confidence level in both of the models. The fixed and random effects models estimate that a 1% increase in the percent of the population living under the poverty line causes an increase of .2400 and .2642 homicides per 100,000 in a state’s total population in a given year, respectively. In order to understand these coefficients in more meaningful terms, it is helpful to translate them into the number of murders in a given state, in a given year. Thus, taking, for example, Alabama, in 1980, where the total population was 3,894,000, the fixed model predicts that a one percent increase in the percent of the population living under the poverty line would have caused an increase of nine murders; the random effects model predicts that the same increase in results in an increase of approximately ten murders.

The sign of the coefficient on the income per capita variable differs between the fixed effects model and the random effects model, but neither of these coefficients is statistically significant.

Of the age distribution variables, only the variable measuring the percent of the population between the ages of 45 and 64 is statistically significant across the fixed and random

¹ Sample calculation: Arkansas, 1980: (.1570 homicides/100,000 in population) X 3,894,000 in population = 6.114
effects models. In these models, the relationship between the percent of the population between the ages of 45 and 64 is negative and statistically significant, such that if the population between 45 and 64 increases by one percent, there is a decrease in the homicide rate of .2595 and .3907, per 100,000 in the population, for the fixed and random models, respectively. Again, taking Alabama in 1980 as an example in order to gauge what these coefficients might mean in real-world terms: the fixed effect model predicts that a one percent increase in the percent of the population between the ages of 45 and 64 would result in a decrease of approximately ten homicides, while the random effects model predicts that the same increase would result in a decrease of fifteen homicides.

It is somewhat surprising to find that the relationship between the percentage of the population between the ages of 18 and 24 and the murder rate is negative, as the crime trend statistics from the Bureau of Justice indicated that this was the highest-offending demographic. Additionally, the coefficient on the percentage of the population above 65 years old is positive (and statistically significant in the fixed effects model), and this is also unexpected since we would not intuitively associate the elderly with crime. However, one possible explanation for the positive relationship could be that the elderly are more vulnerable to attacks (e.g. robberies that escalate to murder), and thus, as the population ages, the crime rate goes up.

The coefficient on the variable measuring the number of blacks as a percentage of the total population changes direction between the fixed and random models, though the coefficient from the fixed effects model is not statistically significant. The relationship between the percentage of blacks within the total population, as predicted by the random effects model, is positive and statistically significant such that when the percentage of blacks increases by 1%, homicides increase by .3771 per 100,000 in the population. Considering again Alabama in 1980,
we see that the random effects model estimates that a 1% increase in the black population would have increased the number of homicides that year by fifteen.

The final variable in this specification is the natural log of a measure of police spending. The relationship between police spending and homicide rate positive, which runs contrary to conventional wisdom, but neither of the coefficients is statistically significant.

Table 2:

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<th></th>
<th>F.E.: Homicides/100,000</th>
<th>R.E.: Homicides/100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Death Penalty Dummy</td>
<td>-.1680 (.1058)</td>
<td>-1.021 (.8007)</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>-.1228 (.09966)</td>
<td>-.08929 (.1004)</td>
</tr>
<tr>
<td>Income Per Capita</td>
<td>-.0000612 (.000043)</td>
<td>5.09e-06 (.0000424)</td>
</tr>
<tr>
<td>% Living in Poverty</td>
<td>.2440*** (.06240)</td>
<td>.2675*** (.06099)</td>
</tr>
<tr>
<td>% Pop. 18-24</td>
<td>-.09698 (.06552)</td>
<td>-.06387 (.06660)</td>
</tr>
<tr>
<td>% Pop. 25-44</td>
<td>.01254 (.02007)</td>
<td>.01396 (.02069)</td>
</tr>
<tr>
<td>% Pop. 45-64</td>
<td>-.2550*** (.09220)</td>
<td>-.3905*** (.09190)</td>
</tr>
<tr>
<td>% Pop. 65+</td>
<td>.6682 (.2126)</td>
<td>.3004 (.1686)</td>
</tr>
<tr>
<td>%Black</td>
<td>-.1216 (.09349)</td>
<td>.3789*** (.03968)</td>
</tr>
<tr>
<td>Ln(Police spending)</td>
<td>.04267 (.07630)</td>
<td>.04749 (.07768)</td>
</tr>
</tbody>
</table>

Specification 2:

I estimate the relationship between the homicide rate and a series of independent variables, where the independent variable of interest is a death penalty dummy variable, where
the variable takes a value of one when the death penalty is legal in a given state, in a given year; and equals zero when the death penalty is not legal.

In this specification, only the coefficients on the poverty and percent of the population between the ages of 45 and 64 variables retain statistical significance in both the fixed and random effects models, while the percent black variable is only statistically significant using the random effects model.

The coefficient on the independent variable of interest, the death penalty dummy, is negative, but not statistically significant. This result, along with the results of the Specification 1, wherein the independent variable of interest is the number of executions (i.e. negative and statistically significant relationship), suggests that it is not the presence of the death penalty which deters murder, but the implementation thereof which serves to reduce the homicide rate.

Table 3:

<table>
<thead>
<tr>
<th></th>
<th>F.E.</th>
<th>R.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Homicides/100,000</td>
<td>Homicides/100,000</td>
</tr>
<tr>
<td>Officer Deaths</td>
<td>-.03819 (.04042)</td>
<td>.05843 (.2548)</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>.1282 (.1134)</td>
<td>.08935 (.08348)</td>
</tr>
<tr>
<td>Income Per Capita</td>
<td>.0000628 (.0000734)</td>
<td>-8.99e-06 (.0000287)</td>
</tr>
<tr>
<td>% Living in Poverty</td>
<td>-.01579 (.05755)</td>
<td>.03890 (.03366)</td>
</tr>
<tr>
<td>% Pop. 18-24</td>
<td>-.1082 (.1653)</td>
<td>-.1531 (.09934)</td>
</tr>
<tr>
<td>% Pop. 25-44</td>
<td>-.1517 (.1209)</td>
<td>-.1276 (.06988)</td>
</tr>
<tr>
<td>% Pop. 45-64</td>
<td>-.1383 (.1651)</td>
<td>-.1007 (.06663)</td>
</tr>
<tr>
<td>% Pop. 65+</td>
<td>.3572021 (.3461)</td>
<td>-.1422 (.07002)</td>
</tr>
<tr>
<td>%Black</td>
<td>.2330 (.2103)</td>
<td>.01789 (.01151)</td>
</tr>
<tr>
<td>Ln(Police spending)</td>
<td>-.5363 (1.193)</td>
<td>.5018*** (.09983)</td>
</tr>
</tbody>
</table>
Specification 3:

None of the coefficients in this model were statistically significant, with the exception of the police spending coefficient in the random effects model. This relationship is positive and suggests that when police spending increases, it causes an increase in the number of police deaths. Though statistically significant, the magnitude of this effect is extremely small.

Discussion

After controlling for a number of demographic and economic variables as well as unobservable factors (via the fixed and random effect models), the relationship between homicides and the number of executions is positive and statistically significant. This result is similar to the negative coefficients obtained by Mocan and Gittings (2003), Zimmerman (2004), and Shepherd (2004), and points to a possible deterrent effect of capital punishment on crime. However, that the relationship between the homicide rate and the capital punishment dummy variable is not statistically significant suggests that, though there may exist a deterrent effect, it only works if executions actually take place; the presence of death penalty laws is not enough to deter would-be murderers from committing crimes.

The most consistent variable in the sign and magnitude of the coefficient estimating its relationship to homicide rate was the poverty measure. Throughout the regressions shown here (with the exception of the officer death specification) as well as alternative specifications not included in the paper, the coefficient on the percent of the population living in poverty was consistently positive and statistically significant. This suggests that there is likely a strong positive relationship between poverty and homicide rate.
The remaining variables were, for the most part, not statistically significant, and at times were inconsistent in their sign and magnitude across specifications. Fortunately, this was not unlike the results of obtained by other authors reviewed. Additionally, the direction of the coefficients on their variables was often the opposite of what would have been predicted from the crime trends statistics, and this direction was subject to change across regressions. Although the behavior of the coefficients on the independent control variables was not ideal, it was not unlike that which can be observed in the results obtained by other authors.

Examination of the relationship between officer deaths and capital punishment proved to be less fruitful than initially hoped, as all but one of the coefficients on the independent variables were not statistically significant. One possible source of error in this analysis is the assumption that the feloniously deaths of police officers can be predicted by the same equation specified for general homicides. Because of the paucity of literature on the subject as well as constraints on time, I was not able to discern a specification that would have perhaps had more explanatory value. It would be valuable for future researchers, should they decide to explore this topic, to focus on finding a specification that is tailored expressly toward explaining police officer deaths, not just homicides in general.

A second potential source of error is in the officer death data itself. Because there are so few officer deaths to begin with, and that there is minimal variation in the dependent variable between observations, the officer deaths were difficult to predict. These problems might prohibit the effective use of regression analysis to estimate a relationship between officer deaths and various independent variables, thus it is possible that other social science tools – statistical or otherwise – are better suited for exploring the question of deterrence of capital punishment on this particular type of homicide.
Conclusion

The relationship between the homicide rate and the number of executions in a given state, in a given year, as estimated by the regressions in this paper, is negative and statistically significant. This is to say that, on average, executions tend to cause homicide rate to fall. These findings suggest that there is, in fact, a deterrent effect of capital punishment on murder. However, we must bear in mind that the results of our analyses are very much influenced by the assumptions that dictate the specifications of our model.

Although the results of several regressions of this paper support the existence of the deterrent effect, it appears that the sign and magnitude of such an effect is sensitive to certain changes in functional form and specification. The susceptibility of the coefficient on executions to such changes helps to explain why so many econometric studies on deterrence have found divergent results. Moreover, it also helps to explain why these types of studies are met with such skepticism and criticism, despite seemingly conclusive results in one direction or the other.

Although these are powerful and valuable tools to have at our disposal, we must remember that the results we obtain from statistical analyses are only as unbiased as the author of the study, and as accurate as the assumptions he or she makes in creating their specifications. Conclusions are bound to differ between authors, who accept different premises, and begin their inquiry with different goals in mind. Consequently, we cannot hope to unambiguously declare the presence or absence of a deterrent effect from the results of just one econometric study. Each study can only seek to contribute to a vast body of literature from which concerned citizens can draw information to better inform their opinions.
Ultimately, deterrence is only one relevant issue of many to consider when evaluating the legitimacy of the death penalty as means of punishment in our modern society. No matter how close we come to an answer to the question of whether or not the death penalty deters would-be murderers, we have to return eventually to other concerns – for instance, the morality of the practice, or the racial biases that seem to plague the judicial process by which the punishment is meted out – and we will have to wrestle with these issues ourselves, as we cannot as easily turn to statistical analyses for answers. But because the issue of deterrence can be so integral to the debate surrounding capital punishment, it is important that we continue to explore the possibility of a deterrent effect through econometric analysis and other statistical tools – bearing in mind that each study can only contribute to a piece to puzzle of deterrence that may never be completed.
Works Cited


Balkwell, James W. “Ethnic Inequality and the Rate of Homicide” Social Forces. 69, 1 (1990) 53-70. JSTOR.


<www.census.gov>.


Appendix 1:

Summary Statistics:

Sum general homicide data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>1326</td>
<td>1992.432</td>
<td>7.946585</td>
<td>1897</td>
<td>2005</td>
</tr>
<tr>
<td>homiciderate</td>
<td>1326</td>
<td>7.092383</td>
<td>7.436345</td>
<td>.2</td>
<td>80.6</td>
</tr>
<tr>
<td>executions</td>
<td>1326</td>
<td>.7520362</td>
<td>2.882702</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>unemployment</td>
<td>1326</td>
<td>5.919457</td>
<td>2.04288</td>
<td>2.3</td>
<td>17.4</td>
</tr>
<tr>
<td>poverty</td>
<td>1022</td>
<td>13.1911</td>
<td>3.998017</td>
<td>2.9</td>
<td>27.2</td>
</tr>
<tr>
<td>incomepercap</td>
<td>1326</td>
<td>18430.26</td>
<td>6782.108</td>
<td>6305</td>
<td>47070</td>
</tr>
<tr>
<td>pop1824</td>
<td>1326</td>
<td>10.81761</td>
<td>2.358171</td>
<td>.0109884</td>
<td>29.64666</td>
</tr>
<tr>
<td>pop2544</td>
<td>1326</td>
<td>30.30873</td>
<td>4.86007</td>
<td>24.45731</td>
<td>183.9944</td>
</tr>
<tr>
<td>pop4564</td>
<td>1326</td>
<td>20.19088</td>
<td>2.588742</td>
<td>9.61263</td>
<td>28.69838</td>
</tr>
<tr>
<td>pop65</td>
<td>1326</td>
<td>12.24675</td>
<td>2.09237</td>
<td>2.868852</td>
<td>18.6</td>
</tr>
<tr>
<td>policeexpe=s</td>
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<td>6.09e+08</td>
<td>8.67e+08</td>
<td>1.97e+07</td>
<td>7.37e+09</td>
</tr>
<tr>
<td>homicides</td>
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<td>388.4487</td>
<td>553.649</td>
<td>1</td>
<td>4096</td>
</tr>
<tr>
<td>totalpopul-n</td>
<td>1326</td>
<td>5090395</td>
<td>5618388</td>
<td>402000</td>
<td>3.62e+07</td>
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<tr>
<td>dpdum</td>
<td>1326</td>
<td>.73454</td>
<td>.4417445</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>black</td>
<td>1326</td>
<td>10.82495</td>
<td>11.89947</td>
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<td>71.91011</td>
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<tr>
<td>lnhomicides</td>
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<td>5.115531</td>
<td>1.437228</td>
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<td>8.317766</td>
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<tr>
<td>lnpolice</td>
<td>1148</td>
<td>19.32269</td>
<td>2.010636</td>
<td>3.881366</td>
<td>22.72107</td>
</tr>
<tr>
<td>lnexecutions</td>
<td>308</td>
<td>.5565239</td>
<td>1.035281</td>
<td>-1.609438</td>
<td>3.688879</td>
</tr>
</tbody>
</table>

Sum officer death data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>officerdea-s</td>
<td>509</td>
<td>1.053045</td>
<td>1.540508</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>executions</td>
<td>510</td>
<td>1.34902</td>
<td>4.218463</td>
<td>0</td>
<td>40</td>
</tr>
</tbody>
</table>
Appendix 2: Output for regressions

xtreg homiciderate L.executions unemployment poverty incomepercap pop1824 pop2544 pop4564 pop65 black lnpolice, fe

Fixed-effects (within) regression
Number of obs = 934
Group variable: statecode
Number of groups = 51
R-sq: within = 0.1141
between = 0.2486
overall = 0.1190
F(10,873) = 11.24
corr(u_i, Xb) = -0.5802
Prob > F = 0.0000

homiciderate | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-------------|----------------------------------
executions | L1. | -.1673258 .0574532 -2.91 0.004 -.2800883 -.0545633
unemployment | | -.1293746 .0988786 -1.31 0.191 -.3234421 .0646929
poverty | | .2400015 .0621125 3.86 0.000 .1180942 .3619088
incomepercap | | -.0000499 .0000429 -1.16 0.245 -.0001341 .0000343
pop1824 | | -.1077255 .0651919 -1.65 0.099 -.2356766 .0202257
pop2544 | | .0119163 .0199798 0.60 0.551 -.0272978 .0511303
pop4564 | | -.2594855 .0917146 -2.83 0.005 -.4394925 -.0794786
pop65 | | .648862 .2116212 3.07 0.002 .2335162 1.064208
black | | -.1161051 .0929617 -1.25 0.212 -.2985582 .066348
lnpolice | | .0462136 .0759273 0.61 0.543 -.1028078 .1952351
_cons | | 4.129086 3.658355 1.13 0.259 -.0515112 11.30928

xtreg homiciderate L.executions unemployment poverty incomepercap pop1824 pop2544 pop4564 pop65 black lnpolice, re

Random-effects GLS regression
Number of obs = 934
Group variable: statecode
Number of groups = 51
R-sq: within = 0.0848
between = 0.6551
overall = 0.5704
Wald chi2(10) = 206.08
corr(u_i, X) = 0 (assumed)                Prob > chi2 = 0.0000

|                | Coef. | Std. Err. | z     | P>|z|  | [95% Conf. Interval] |
|----------------|-------|-----------|-------|------|----------------------|
| executions     |       |           |       |      |                      |
| L1.            | -0.1725735 | 0.0581027 | -2.97 | 0.003 | -0.2864527, -0.0586944 |
| unemployment   | -0.0893648 | 0.0995818 | -0.90 | 0.370 | -0.2845415, 0.105812  |
| poverty        | 0.2641678  | 0.0607352 | 4.35  | 0.000 | 0.145129, 0.3832066  |
| incomepercap   | 0.0000168  | 0.0000423 | 0.40  | 0.691 | -0.0000661, 0.0000998 |
| pop1824        | -0.077169  | 0.0663773 | -1.16 | 0.245 | -0.2072661, 0.0529281 |
| pop2544        | 0.0136747  | 0.0205882 | 0.66  | 0.507 | -0.0266774, 0.0540267 |
| pop4564        | -0.3907375 | 0.0915078 | -4.27 | 0.000 | -0.5700895, -0.2113856|
| pop65          | 0.2980553  | 0.1685083 | 1.77  | 0.077 | -0.0322149, 0.6283255 |
| black          | 0.3770667  | 0.0398716 | 9.46  | 0.000 | 0.2989198, 0.4552137  |
| lnpolice       | 0.0531929  | 0.0733885 | 0.66  | 0.507 | -0.0266774, 0.0540267 |
| _cons          | 3.341991   | 3.170615  | 1.05  | 0.292 | -2.8723, 9.556282    |

xtreg homiciderate dpdum unemployment poverty incomepercap pop1824 pop2544 pop4564 pop65 black lnpolice, re

Random-effects GLS regression
Group variable: statecode
Number of obs = 934
Number of groups = 51

R-sq: within = 0.0749
between = 0.6694
overall = 0.5812

Wald chi2(10) = 200.69

sigma_u | 8.547663
sigma_e | 3.0019948

xtreg homiciderate dpdum unemployment poverty incomepercap pop1824 pop2544 pop4564 pop65 black lnpolice, fe

Fixed-effects (within) regression
Number of obs = 934

R-sq: within = 0.1055
between = 0.2489
overall = 0.1267

F(10,873) = 10.30
Prob > F = 0.0000

sigma_u | 8.547663
sigma_e | 3.0019948
homiciderate | Coef.  Std. Err.  z  P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dpdum |  -1.021434   .8007111    -1.28   0.202    -2.590799    .5479307
unemployment |  -.0892878   .1003593    -0.89   0.374    -.2859883    .1074128
poverty |   .2674971   .0609921     4.39   0.000     .1479548    .3870394
incomepercap |  5.09e-06   .0000424     0.12   0.904    -.0000781    .0000882
pop1824 |  -.0638662    .066604    -0.96   0.338    -.2044077    .0766753
pop2544 |   .0139622   .0206945     0.67   0.500    -.0265983    .0545226
pop4564 |  -.3904888   .0918956    -4.25   0.000    -.5706008   -.2103768
pop65 |   .3004163   .1685783     1.78   0.075    -.0299911    .6308238
black |    .378921   .0396806     9.55   0.000     .3011484    .4566935
lnpolice |   .0474889    .077675     0.61   0.541    -.1047514    .1997291
_cons |   4.057822   3.263718     1.24   0.214    -2.338947    10.45459
-------------+----------------------------------------------------------------
sigma_u |  3.4082862
sigma_e |  3.0019948
rho |   .5631276   (fraction of variance due to u_i)

xtreg officerdeaths L.executions unemployment poverty incomepercap pop1824 pop2544 pop4564 pop65 black lnpolice, re
Random-effects GLS regression  Number of obs      =       265
Group variable: statecode                       Number of groups   =        51
R-sq:  within  = 0.0057                         Obs per group: min =         4
        between = 0.5432  avg =       5.2
        overall = 0.2997  max =         9
Random effects u_i ~ Gaussian                 Wald chi2(10)      =     55.33
       corr(u_i, X)       = 0 (assumed)    Prob > chi2        =    0.0000

officerdeaths | Coef.  Std. Err.  z  P>|z|     [95% Conf. Interval]
----------------+--------------------------------------------------
executions      |     L1. |  .0275905   .025399   1.09   0.277    -.0221907    .0773717
unemployment    |  1012579 |   .922369   1.10   0.272    -.0795232    .282039
poverty         |   .0480298 |   .0378584   1.27   0.205    -.0261712    .1222309
incomepercap-a  | -.6.46e-06 |   .0000291  -0.22   0.824    -.0000635    .0000506
pop1824         | -.1553741 |   .1030139  -1.51   0.131    -.3572775    .0465293
pop2544         | -.1256167 |   .0772802  -1.63   0.104    -.277083    -.0258496
pop4564         | -.0938533 |   .0676169  -1.39   0.165    -.226383    .0386734
pop65           |  -.1642343 |   .0720165  -2.28   0.023    -.305384    -.0230846
blackinpop-n    |   .0190453 |   .011552  1.65   0.099    -.0035962    .0416868
lnpolice        |   .422272 |   .1006089   4.20   0.000    .2250822    .6194618
_cons            |   .736583 |   4.373252  16.27   0.000    10.38169    9.307999
----------------+--------------------------------------------------
sigma_u |  .58991439
sigma_e |  1.1031785
rho |   .24657554   (fraction of variance due to u_i)