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An Econometric Analysis of the Death Penalty and Other Measures of Punishment

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AN ECONOMETRIC ANALYSIS OF THE DEATH PENALTY AND OTHER MEASURES OF PUNISHMENT: DO THESE PUNITIVE MEASURES REDUCE THE RATE OF MURDER?

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Southern states carry out more than 80 percent of the executions but have a higher murder rate than any other region. Texas has by far the most executions, but its homicide rate is twice that of Wisconsin, the first state to abolish the death penalty. Look at similar adjacent states: There are more capital crimes in South Dakota, Connecticut and Virginia (with death sentences) than neighboring North Dakota, Massachusetts and West Virginia (without death penalties). Furthermore, there has never been any evidence that the death penalty reduces capital crimes or that crimes increased when executions stopped. Tragic mistakes are prevalent.

–Jimmy Carter, 39th President of the United States

It's cheaper to lock up inmates for life than to put them on the Death Row carousel of legal appeals. The annual difference in cost is about $51 million, according to a 10-year-old Palm Beach Post study. Another study by The Miami Herald estimated that it costs about $3.2 million to execute a prisoner as compared with $750,000 to lock that prisoner up for life.

–Frank Cerabino, Staff Writer with the Palm Beach Post

I. INTRODUCTION

Kirchgässner (2011) criticized an article written in the Wall Street Journal written by Adler and Summers purporting to found statistical evidence of a deterrence effect of the number of executions per year on the rate of murders committed per year. Summers and Adler (2007), studied a 26-year period from 1979 to 2004, compiled a chart showing the number of executions per year, and the number of murders per year, and concluded there “seems to be an obvious negative correlation in that when executions increase, murders decrease, and when executions decrease, murders increase.” Summers and Adler find that each execution is negatively correlated with the number of murders, and that each execution results in 74 less murders in the

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following year, and that the association was significant at the .00003 level of statistical significance.

The article has been criticized by more people than just Kirchgässner; Stubbs & Allen (2007), pointed out that “[o]ne does not have to be a statistician to know the inherent danger of mistaking correlation for causation.” Another commentator has likewise criticized the results, finding shocking that Adler and Summers admitted that other variables might well be at play, but that until those variables can be identified, by Occam’s Razor that the simplest solution is most likely the best solution. Another commentator has suggested that quite simply there is not enough quality research in this area to properly determine what effect if any, the rate of executions is having on the rate of murders as a whole, particularly considering that not all those convicted of homicide receive the death penalty.

The National Academies reviewing the report of the National Research Council has observed:

The lack of evidence about the deterrent effect of capital punishment -- whether it is positive, negative, or zero -- should not be construed as favoring one argument over another, the report stresses. ‘Fundamental flaws in the research we reviewed make it of no use in answering the question of whether the death penalty affects homicide rates,’ said Daniel S. Nagin, Teresa and H. John Heinz III University Professor of Public Policy and Statistics at Carnegie Mellon University Pittsburgh, and chair of the committee that wrote the report. ‘We recognize that this conclusion may be controversial to some, but no one is well-served by unsupportable claims about the effect of the death penalty, regardless of whether the claim is that the death penalty deters homicides, has no effect on homicide rates or actually increases homicides.’

Therefore in order to move towards research that is more credible, it is necessary to try to collect data that considers both capital and noncapital punishments for homicide, and conduct a principled study on how potential future killers might perceive a range of punishments in homicide cases. Using statistical and econometric methods based on more credible and realistic assumptions about the effect of capital punishment, incarceration, and other factors on the number of homicides might portray a more accurate picture of what is really going on.

II. A Brief Survey of the Literature

“For decades, murder has been more common in states with capital punishment than in those where it is not used.”\(^9\) These findings would seem to defy the conventional notion that regions with the most executions should result in a lower rate of murders, than those states without it.\(^10\) Some of the studies that set out to examine these theories proceeded in the following fashion:

In order to answer the question of whether or not the death penalty deters crime, two hypotheses were developed. These were: 1) States with a death penalty statute will have lower rates of crimes punishable by death than states without death penalty statutes, and 2) States that have the most executions will have fewer crimes punishable by death than states that do not use their death penalty and those without a statute. For each of these hypotheses, two case studies were performed. For example, to test the first hypothesis, the crime rates of Texas, which executes convicts more than any other state, were compared with Michigan’s, which has no death penalty statute. According to the first hypothesis, Texas should have a lower crime rate as a result of the deterrence of usage of the death penalty. Findings in this study, as well as the other three studies, however, refute this assertion, rejecting the null hypotheses.\(^11\)

The first of the studies were done by Thorsten Sellin, of the University of Pennsylvania who in the 1920s and 1930s pioneered many efforts to use criminal statistics at the state and federal level.

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\(^{10}\) *Id.*
level, and did straightforward simple studies on the deterrence effect of executions in 1957 and 1967.\textsuperscript{12} Sellin’s findings essentially found no correlation between executions and the number of murders.

The next major work was that of Ehrlich (1975), whose premise was that most murders are not the product of strangers, and are more the work of distant acquaintances, coworkers, friends, family and close loved ones, who engage in malevolent exchanges.\textsuperscript{13} As a result, he viewed the choice of murder as related to utility and consumption, although he recognized the irrationality of a murder choice would probably violate Pareto optimal conditions.\textsuperscript{14} In this sense, his model depends on conditions and probabilities, primarily the chance of detection, conviction, and execution versus escape from detection and punishment.\textsuperscript{15} Another possibility would be a lesser punishment, particularly stemming from conviction of a lesser offense.

He also analyzes factors such as income and employment and weighs them against the duties of law enforcement in trying to minimize the per capita social cost of homicide.\textsuperscript{16} He looked at the natural logarithms of variables of the crime rate, probability of arrest, conditional probability of conviction, conditional probability of execution, labor force participation, unemployment rate, Friedman's estimate of real permanent income per capita, per capital real expenditures, and per capita real expenditures of police in dollars lagged one year.\textsuperscript{17} He found that in the face of strict successful law enforcement there was a negative relationship between

\begin{itemize}
  \item \textit{Id.} at 399.
  \item \textit{Id.} at 400.
  \item \textit{Id.} at 403.
  \item \textit{Id.} at 409.
\end{itemize}
crime rates and punishment, as well as execution, refuting the findings of Sellin and others, and finding Sellin’s analysis too simplistic.\textsuperscript{18} Although the strength of the relationship was not strong, as long as some refrain from murder due to disincentives, there is some connection; he views the partial aspect as being offset by some unexplored possibility, like greater chances for escape when the murderer eliminates witnesses.\textsuperscript{19}

Ehrlich’s effort was considered a major advancement, and it led others to conduct more sophisticated studies.\textsuperscript{20} Yunker (1982) studied socioeconomic trends, social shocks after the Kennedy assassination, capital punishment and homicide rates, and included as variables the per capital Gross National Product, the Nonwhite ratio (total white population / total population), the youth ratio (population aged 15-24 / total population), urban ratio (population in cities over 250,000 / total population), and a dummy variable that accounts for demographic and psychological wartime conditions.\textsuperscript{21} Yunker found that the socioeconomic variables failed to properly explain an increase in crimes, particularly violent crime and homicides, but that the phasing out of capital punishment seemed to be a plausible explanation: where criminals are less deterred homicides increase, and the police focus their resources more on homicides to the neglect of other nonlethal crimes.\textsuperscript{22}

In the modern era, Dezhbakhsh, Rubin and Shepherd (2003)\textsuperscript{23} along with Mocan and Gittings (2003),\textsuperscript{24} have produced findings that defend the capital punishment as deterrence

\textsuperscript{18} Id. at 415.
\textsuperscript{19} Id. at 416.
\textsuperscript{20} Yunker, supra note 12, at 631.
\textsuperscript{21} Yunker, supra note 12, at 630-632.
\textsuperscript{22} Id. at 645-646.
hypothesis. The studies of Katz, Levitt and Shustorovich (2003), Fagan (2005), and Fagan, Zimring and Geller (2006) call the deterrence effect of capital punishment into serious question. Then there is the option of prison, which is typically not deemed to be a deterrent, but more a function of incapacitation: taking people off the streets, reduces the amount of criminals available to commit crimes. Kirchgässner (2011) finds that for economists, all measures of punishment must serve as some form of deterrent, but the question often becomes whether the marginal effects of the measure is enough of a deterrent. Petersilia & Deschenes (1994) have found that probation is another punishment factor that should be considered among the factors, not as a direct punishment of murder, but as an punishment for lesser crimes which can ultimately impact the overall crime rate. To this effect, we will study capital punishment versus imprisonment, as well as probation, since the latter (if properly used and enforced) could have an indirect effect on the frequency of murders.


The HOPE program, if widely adopted as a model for probation and parole reform, could make a surprisingly large contribution to reducing the prison population. In many states, the majority of prison admissions come not from arrests for new crimes, as you might think, but from probation and parole violations. Nationwide, roughly two-thirds of parolees fail to complete parole successfully. Todd Clear, a professor at John Jay College of Criminal Justice in New York, estimates that by eliminating imprisonment across the nation for technical parole violations, reducing the length of parole supervision and ratcheting back prison sentences to their 1988 levels, the United States could reduce its prison population by 50 percent.

Some in government are beginning to take notice. In November, invoking the HOPE program as a model, the Democratic congressman Adam Schiff of California and his Republican colleague Ted Poe of Texas introduced legislation in the House that would
To properly create a regression model, we should correctly specify dependent and independent variables, but we also should not omit relevant variables, and we should not include irrelevant variables. Additionally we should correctly specify the functional form: whether the relationship under study is actually linear or nonlinear.

Per the Bureau of Justice Statistics, 16.30% of all homicides in the U.S. between 1980-2008, were based on an intimate relationship, and 83.70% were based on a non-intimate relationship. Only 63.1% of homicides have a determination of whether a relationship existed between victim and aggressor: 21.9% of homicides were committed by strangers, 10% were committed by spouses, 6.3% by boyfriend/girlfriend, 12.4% by other family, and 49.4% by friends and acquaintances. Nonetheless, this also meant that relationships were not unknown in 36.9% of the cases. Regardless of circumstance or relationship, the weapon of choice was the gun more often than not. The largest majority are committed by an aggressor who is male, in the 18-24 age group. If the homicide involved an intimate relationship, the victim was

create federal grants for states to experiment with courts that deliver swift, predictable and moderate punishment for those who violate probation.

There also appears to be a national audience for a broader conversation about new ways to shrink the prison population. Last year, a three-judge panel in California ordered the overcrowded state prison system — the largest in the country, with more than 170,000 prisoners at its peak — to reduce the inmate population by tens of thousands of prisoners within two years in order to comply with constitutional standards for medical and mental health care. Facing a tightening budget crisis in September, California legislators added to the pressure by demanding a reduction in the prison budget of $1.2 billion. In the U.S. Senate, Jim Webb of Virginia is leading a crusade for prison reform, insisting that fewer jail terms for nonviolent offenders can make America safer and more humane, while also saving money. And in the Obama administration, Attorney General Eric Holder is questioning the value of relentlessly expanding prisons. In July, he declared that “high rates of incarceration have tremendous social costs” and “diminishing marginal returns.”

32 Id.
33 Id.
overwhelmingly female on average, and the majority were wives.\textsuperscript{34} With male victims, the aggressors tended to be acquaintances and friends. On average, victims tended to be in their 30’s, and aggressors in their 20’s.\textsuperscript{35} Blacks have a higher homicide offending rate than whites.\textsuperscript{36} Most homicides tend to be the product of arguments, but also a significant number from felonies, and also significant numbers from the categories of “Other” and “Unknown.”\textsuperscript{37}

For starters, we must think about when the death penalty is used: for example, in the State of Florida, we have four kinds of homicide categories: third-degree murder, second-degree murder, first-degree murder, and manslaughter. Of the four, only first-degree murder is capital murder and merits the death penalty. The two ways to commit first-degree murder are by premeditation (perpetrated from a premeditated design to effect the death of the person killed or any human being),\textsuperscript{38} and by felony murder (an unlawful killing that occurs when a person is engaged in the commission, or attempted commission, of the specified statutorily enumerated felonies, regardless of whether they intended to kill anyone).\textsuperscript{39}

Therefore, some researchers might fail to consider: (1) that one could set out not to murder others, but necessarily a murder may result during the commission of certain felonies,\textsuperscript{40} and now the felon may be put to death; and (2) that deaths being counted in the murder rate can

\textsuperscript{34} Id.
\textsuperscript{35} Id.
\textsuperscript{36} Id.
\textsuperscript{37} Id.
\textsuperscript{38} § 782.04(1)(a)1, Fla. Stat. (2011).
\textsuperscript{39} Id. at § 782.04(1)(a)2.
\textsuperscript{40} Those felonies are: trafficking offense prohibited by s. 893.135(1), arson, sexual battery, robbery, burglary, kidnapping, escape, aggravated child abuse, aggravated abuse of an elderly person or disabled adult, aircraft piracy, unlawful throwing, placing, or discharging of a destructive device or bomb, carjacking, home-invasion robbery, aggravated stalking, murder of another human being, resisting an officer with violence to his or her person, a felony that is an act of terrorism or is in furtherance of an act of terrorism; or unlawful distribution of any substance controlled under s. 893.03(1), cocaine as described in s. 893.03(2)(a)4, opium or any synthetic or natural salt, compound, derivative, or preparation of opium, or methadone by a person 18 years of age or older, when such drug is resulted in, and is proven to be the proximate cause of the death of the user. § 782.04(1)(a)2-3, Fla. Stat. (2011). The last felony on the list is perhaps the most interesting because if it can be proven that a minor died from a drug
stem from crimes of which the criminal cannot be put to death. Consider Texas law, which has a similar but different scheme of division of murders: there is murder, capital murder, manslaughter, and criminally negligent homicide.\textsuperscript{41} Murder can occur when one intends to kill another, when one intends to cause serious bodily harm but death results, and when one is committing certain enumerated felonies and takes an act dangerous to human life that causes death to another (felony murder).\textsuperscript{42} Capital murder occurs when the individual commits the crime of murder, and there is the existence of an additional factor.\textsuperscript{43}

That additional factor can range from a great number of things, one of which may the status of the offender, another of which may be the status of the victim. However, like Florida, it is only the person who commits capital murder who is at risk of being executed. Additionally, there are federal death penalty crimes as well,\textsuperscript{44} which are above and beyond the state level crimes. There is a third distinction, which is well documented: that not everyone who commits capital murder is put to death, and thus some receive life without the possibility of parole sentences. Therefore, \textit{ceteris paribus} in trying to build a more accurate model, one would need to take this assumption into account as well, that a rational actor who is attempting to weigh the costs of taking an action, would necessarily also have to weigh the possibility of death against the possibility of life without parole in prison.

\textsuperscript{41} \textit{Tex. Penal Code Ann.} §§ 19.01-19.05 (2011).
\textsuperscript{42} \textit{Id.} at § 19.02(b)1-3.
\textsuperscript{43} \textit{Id.} at § 19.03(a)1-8. Factors include killing a police officer or firefighter, escaping from prison, committing certain enumerated felonies, killing another while in prison serving a life sentence for another homicide, killing a prison employee while intending to be part of a combination, killing a child under 10 years of age, murdering more than one person during the same incident or pursuant to a scheme or course of conduct, and killing a judge.
IV. **EMPirical Analysis**

Running a linear time-series analysis from 1977 to 2010, and simply regressing the number of murders committed yearly against the number of executions, yields the following:

\[ \text{MURDER}_t = \text{the number of murders reported nationwide in one year} \]

\[ \text{EXEC}_t = \text{the number of executions that were carried out nationwide} \]

We write our proposed regression equation as follows:

\[ MURDER_t = \alpha + \beta_1 \text{EXEC}_t + u_t \quad (1)(a) \]

Rewriting the equation with the numbers generated being substituted for the coefficients and the intercept in our regression, it becomes:

\[ MURDER_t = 21839.22 + (-70.07658) \text{EXEC}_t + u_t \quad (1)(b) \]

\[ (F = 23.34) \quad (t = -4.83, \text{ S.E.} = 14.50671) \]

\[ R^2 = 0.4217 \quad \text{Adj.} \, R^2 = 0.4036 \quad \text{Root MSE} = 2293 \]

Our result from this extremely simplistic linear regression is very similar to results from Adler and Summers: for every execution that occurs, 70.07658 less murders occur in a given year. If we lag the number of executions by one year, then the results are even more dramatic:

\[ MURDER_t = 22032.1 + (-75.85885) \text{EXEC}_{t-1} + u_t \quad (2) \]

\[ (F = 30.06) \quad (t = -5.48, \text{ S.E.} = 13.83605) \]

\[ R^2 = 0.4923 \quad \text{Adj.} \, R^2 = 0.4759 \quad \text{Root MSE} = 2182.8 \]

Thus for every execution that occurs in a previous year, 75.85885 lives are saved in the following year. Adler and Summers obtained the result of 74 lives.

The F statistics of both equations (1) and (2) assist us to determine whether the regression equation as a whole is significant. In other words, we look to measure the loss of fit that results when we impose the restriction that the slopes of all the coefficients (except the constant term) are zero. These results are larger than the 95 percent critical value, meaning that the data is

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inconsistent with the null hypothesis (H\(_0\)) that the slopes are zero. By contrast, the t test can be used to test any single linear constraint.\(^47\) We form this statistic by taking an estimated coefficient and subtracting the true population parameter from it, and dividing that by the square root of the variance of the estimated coefficient. Our null hypothesis assumes that the true population parameter is 0, and if the statistic is greater than the critical t value at the level of significance we rely on (in this instance 0.05 or 5 percent), then we can reject the null hypothesis (H\(_0\)) that the true population parameter is 0.\(^48\) The t statistics for the coefficients of \(EXEC_t\) and \(EXEC_{t-1}\), exceed their critical t values, and therefore both coefficients are statistically significant at the 5 percent significance level.

In modeling the mean squared error typically makes up the difference between the actual observations in the sample, and the model’s predicted responses, and thus may be used to gauge whether the model does fits the data correctly, or whether the model can be made simpler by removing terms.\(^49\) The root mean square error (RMSE) is the square root of the average of the squared values of the forecast errors.\(^50\) The RSME is appropriate for situations where the cost of the error increases as the square of that error, and is a “quadratic loss function” which is popularly used. In this instance, we can see that equation (2) has a lower RSME than equation (1).

The coefficient of determination measures how well the regression line fits the data, and thus ranging from 0 to 1, helps us to determine the goodness of fit, R\(^2\).\(^51\) Subsequently the

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\(^{48}\) Greene, *supra* note 46, at p. 265.


\(^{50}\) Kennedy, *supra* note 47, at p. 334.

\(^{51}\) Greene, *supra* note 46, at p. 250-255.
RSME decreases, as the $R^2$ increases towards the limit of 1. Yet $R^2$ never decreases as other variables are added to the regression equation; for this reason, an adjusted $R^2$ is used for reporting, because it’s value factors the number of explanatory variables, and it determines “whether the contribution of the new variable to the fit of the regression more than offsets the correction for the loss of an additional degree of freedom.” Yet in this instance, we have not increased the number of variables, we have only swapped $EXEC_{t-1}$ for $EXEC_t$. Let us run the regression again, but include both variables to observe the difference.

$$MURDER_t = \alpha + \beta_1 EXEC_t + \beta_2 EXEC_{t-1} + u_t$$

(3)(a)

So we are regressing the murder rate against the current year, and the previous year. We rewrite the equation, with the numbers generated being substituted for the coefficients and the intercept in our regression:

$$MURDER_t = 22148.32 + (-20.89839)EXEC_t + (-57.39726) EXEC_{t-1} + u_t$$

(3)(b)

(\text{F} = 14.92) \hspace{1cm} (t = -0.62, \text{ S.E.} = 33.70373) \hspace{1cm} (t = -1.75, \text{ S.E.} = 32.89063)

$R^2 = 0.4987$ \hspace{0.5cm} $Adj. R^2 = 0.4653$ \hspace{0.5cm} $Root MSE = 2204.8$

Our $R^2$ has not changed, but our adjusted $R^2$ decreased from 0.4759 in equation (2), to 0.4653 in equation (3), which shows some loss due to the addition of $EXEC_t$ (our RSME is slightly higher as well correspondingly). Our F statistic is still high enough that the regression is statistically significant as a whole, but the t statistics of the coefficients have declined to the point, whether neither of them are statistically significant at the 5 percent level any more.

Looking at equation (2), it might seem like the best model we have developed of the three, however, its $R^2$ still explains slightly less than half of the movements in the dependent variable. Of numerous errors that can be made in the specification of the estimated equation, the

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52 Agresti & Finlay, supra note 49, at p. 637.
53 Greene, supra note 46, at p. 255.
most common are the omission of relevant variables and the inclusion of superfluous variables.\textsuperscript{54} Stepwise regression allows us to add or delete variables sequentially, but only after evaluating each variable in turn on the basis of significance level.\textsuperscript{55} We previously noted that murders can occur in the course of other felonies, therefore we will consider several other crimes,\textsuperscript{56} adding them to the regression model to see what impact they have on the number of murders.\textsuperscript{57}

\[ BURGLARY_t = \text{the number of burglaries reported nationwide for the year} \]

\[ ROBBERY_t = \text{the number of robberies reported nationwide for the year} \]

\[ LARCENY_t = \text{the number of nonviolent thefts reported nationwide for the year} \]

\[ CARTHEFT_t = \text{the number of vehicle thefts reported nationwide for the year} \]

\[ PRISON_{t-1} = \text{the number of people serving time in prison in the previous year, for a sentence a year or longer} \]

So we write our new proposed regression equation:

\[ MURDER_t = \alpha + \beta_1 EXEC_{t-1} + \beta_2 BURGLARY_t + \beta_3 ROBBERY_t + \beta_4 PRISON_{t-1} + \beta_5 LARCENY_t + \beta_6 CARTHEFT_t + u_t \] (4)(a)

From the regression, we rewrite the equation, with the numbers generated being substituted for the coefficients and the intercept:

\[ MURDER_t = 8126.311 + (1.197868)EXEC_{t-1} + (.0017077)BURGLARY_t + (.0260241)ROBBERY_t + (-.0000848)PRISON_{t-1} + (.0016197)LARCENY_t + (.0040718)CARTHEFT_t + u_t \] (4)(b)

\[ (t = 1.11, \text{S.E.} = 10.45436) (t = 2.00, \text{S.E.} = .0008526) \]

\[ (t = 7.06, \text{S.E.} = .0036847) \quad (t = -0.10, \text{S.E.} = .0008179) \]

\[ (t = -3.10, \text{S.E.} = .0005229) \quad (t = 3.41, \text{S.E.} = .0011945) \]

\[ R^2 = 0.9704 \quad \text{Adj. } R^2 = 0.9635 \quad \text{Root MSE} = 575.8 \]

\textsuperscript{54} Id. at p. 399.
\textsuperscript{55} Id. at p. 401.
The addition of these five variables tell an interesting and different story. Equation (4) now has an $R^2$ of 0.9704, meaning that our goodness of fit is very close to 1, and it explains 97.04% of the movement in the dependent variable. Our improvement in our Adjusted $R^2$, from 0.4759 in equation (2), to 0.9635, means we are not suffering any significant loss, and have gained from the addition of these explanatory variables (our RSME has dropped significantly as well).

Our F statistic indicates that our regression remains statistically significant, as do all of the t tests on the coefficients except $BURGLARY_t$, $PRISON_{t-1}$ and $EXEC_{t-1}$, all of which are statistically insignificant at the 5 percent level. There could be some reasoning to this: robbery is a particularly violent crime, during which death may occur, whereas burglaries (its t statistic fell a hair short of the critical value) and car thefts may also involve differing degrees of violence. Larceny is the least violent of these crimes, and by definition cannot involve any degree of physical confrontation, which is perhaps why unlike all other coefficients, is having a negative rather than positive effect. Yet it is highly strange why prison would not serve as a significant deterrent, and it bears need for further investigation.

Nonetheless we drop the insignificant variables $PRISON_{t-1}$ and $EXEC_{t-1}$ to arrive at the following result from equation (4) to come to the following results:

$$MURDER_t = 8126.311 + (.001807)BURGLARY_t + (.0254862)ROBBERY_t$$

(F = 229.56) (t = 6.02) (t = 8.97)

$$+ (.0017703)LARCENY_t + (.0044765)CARTHEFT_t + u_t$$

(t = -4.33) (t = 4.45)

$$R^2 = 0.9694 \hspace{1em} Adj. R^2 = 0.9652 \hspace{1em} Root MSE = 554.21$$

Our F statistic has increased, and our regression remains statistically significant. All of our t statistics are greater than their critical values, at even the 1 percent level of significance now. We suffered a slight loss in our $R^2$, but an actual gain in our adjusted $R^2$. Rethinking our strategy, we could consider additionally, that our model may need to be nonlinear.
Turning to a double-log model, we could remove certain variables, add other variables, and express our model as follows:

\[ \text{DIFFCRIM}_t = \text{VIOLCRIM}_t - \text{VIOLCRIM}_{t-1} = \text{the difference in the amount of violent crimes committed from one year and the previous year.} \]

\[ \text{PROBATION}_{t-1} = \text{the number of people under probation supervision in the previous year.} \]

\[ \text{DIFFPRSN}_t = \text{PRISON}_t - \text{PRISON}_{t-1} = \text{the difference in people incarcerated in prison from one year and the previous year.} \]

\[ \text{AGGASSAULT}_{t-1} = \text{the number of serious assaults committed in the prior year (excludes simple assaults)} \]

We rewrite the equation, with the numbers generated being substituted for the coefficients and the intercept in our regression:

\[ \ln MURDER_t = \alpha + \beta_1 \ln ROBBERY_t + \beta_2 \ln PROBATION_{t-1} + \beta_3 \ln DIFFPRSN_t + \beta_4 \ln DIFFCRIM_t + \beta_5 \ln AGGASSAULT_{t-1} + u_t \]  

\begin{align*}
(6) \text{(a)} & \\
\text{(F = 216.44)} & (t = 10.01) & (t = -4.42) \\
\text{\quad + (t = -1.83)} & (t = 1.98) \\
\text{\quad + (t = 1.377641)} & (t = 1.91) \\
\text{\quad + (t = .9757) \quad Adj R^2 = .9712 \quad Root MSE = .02648} \\
\end{align*}

Although technically, the coefficients for DIFFPRSN, DIFFCRIM and AGGASSAULT are not significant at the 5 percent level of significance, they are significant at the 10 percent level of significance. The coefficients for all other variables are significant at the 1 percent level of significance. This makes equation (6) of considerable use to us: both its \( R^2 \) and adjusted \( R^2 \) are higher than any previous model we have experimented with. Its RSME is extremely low.
(0.02648), the next closest being 554.21 for equation (5), which is a tremendous difference. Of course in all fairness, none of the previous models were included taking the log of the left hand side (LHS) or right hand side (RHS). To be fair, we tried a few other equations, with variations to see what the results would be on the coefficients, and on the regression as a whole. The results are displayed in Table 1.

The problem is of course, that our errors or disturbances should $u_i$, should have the same variance across all observation points, i.e. homoscedasticity. Additionally they should not be autocorrelated either. To start being more rigorous with our regression models, we try to overcome autocorrelation, or correlation, and heteroscedasticity in the error terms in the models by using Newey-West estimators. Newey and West (1987), developed this procedure of improving the ordinary least squares (OLS) regression when the variables have heteroscedasticity or autocorrelation. In OLS the assumption is that the residuals are uncorrelated, whereas with autocorrelation, the residuals are in fact correlated. This is often used to correct the effects of correlation in the error terms in regressions applied to time series data. “The standard error estimated by the Newey-West will be an increasing function of the lag length in this simulation. When the lag length is set to zero, the estimated standard error is numerically identical to the White standard error which is only robust to heteroscedasticity.”

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58 Greene, supra note 46, at p. 232.
59 Id.
61 Id.
Thus we try to achieve more robust standard error determinations by using these heteroscedasticity and autocorrelation consistent (HAC) variances (and standard errors).\(^{63}\)

If true disturbances are autocorrelated, this will be revealed through autocorrelations of the least squares residuals; the Durbin-Watson test is a widely used test to detect this.\(^{64}\) With the Cochrane-Orcutt transformation, we assume that the errors in the residual are autoregressive of order one, i.e. AR(1) noise, with a serial autocorrelation of \(\rho\). Once we know what the \(\rho\) is, we can then transform the equation to eliminate the autocorrelation of the residuals.\(^{65}\) Prais and Winsten (1954) provided an alternative the transformation,\(^{66}\) the difference being that Cochrane-Orcutt excludes the first observation, whereas Prais-Winsten does not, and evidence suggests that retention of the first observation is preferable.\(^{67}\)

**Equation (7):**

\[
MURDER_t = \alpha + \beta_1 EXEC_{t-1} + \beta_2 BURGLARY_t + \beta_3 ROBBERY_t + \beta_4 LARCENY_t \\
+ \beta_5 CARTHEFT_t + \beta_6 PRISON_{t-1} + \beta_7 PROBATION_{t-1} + \beta_8 DIFFCRIM_t + u_t
\]

For this equation, we ran a regression with Newey-West standard errors. For equation (7) we used a lag length of 4.

**Equation (8):**

\[
\ln MURDER_t = \alpha + \beta_1 \ln EXEC_{t-1} + \beta_2 \ln BURGLARY_t + \beta_3 \ln ROBBERY_t \\
+ \beta_4 \ln LARCENY_t + \beta_5 \ln CARTHEFT_t + \beta_6 \ln PRISON_{t-1} \\
+ \beta_7 \ln PROBATION_{t-1} + \beta_8 \ln DIFFCRIM_t + u_t
\]

For this equation, we ran a regression with Newey-West standard errors.

**Equation (9):**


\[^{64}\] Greene, *supra* note 46, at p. 591.

\[^{65}\] Id. at p. 601.


\[^{67}\] Greene, *supra* note 46, at p. 601, 603.
\begin{align*}
\ln MURDER_t &= \alpha + \beta_1 \ln EXEC_{t-1} + \beta_2 \ln BURGLARY_t + \beta_3 \ln ROBBERY_t \\
&+ \beta_4 \ln LARCENY_t + \beta_5 \ln CARTHEFT_t + \beta_6 \ln PRISON_{t-1} \\
&+ \beta_7 \ln PROBATION_{t-1} + \beta_8 \ln DIFFCRIM_t + u_t
\end{align*}

For this equation, we ran a Cochrane-Orcutt AR(1) regression with iterated estimates.

**Equation (10):**
\begin{align*}
\ln MURDER_t &= \alpha + \beta_1 \ln EXEC_{t-1} + \beta_2 \ln BURGLARY_t + \beta_3 \ln ROBBERY_t \\
&+ \beta_4 \ln LARCENY_t + \beta_5 \ln CARTHEFT_t + \beta_6 \ln PRISON_{t-1} \\
&+ \beta_7 \ln PROBATION_{t-1} + \beta_8 \ln DIFFCRIM_t + \beta_9 \text{DIFFPRSN}_t \\
&+ \beta_{10} \text{AGGASSAULT}_{t-1} + u_t
\end{align*}

For this equation, we ran a Prais-Winsten AR(1) regression with iterated estimates.

The left hand column of *Table 1* indicates RHS coefficients, and then other figures concerning the regression.

<table>
<thead>
<tr>
<th></th>
<th>Equation (7)</th>
<th>Equation (8)</th>
<th>Equation (9)</th>
<th>Equation (10)</th>
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<tr>
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<tr>
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<td>(t = -2.19, S.E. = .2400242)</td>
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<tr>
<td>$\beta_5$</td>
<td>$\ln CARTHEFT_t$</td>
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<td>(t = 3.10, N.W.S.E. = .0018331)</td>
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<tr>
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<tr>
<td>$\beta_7$</td>
<td>$\ln PROBATION_{t-1}$</td>
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<td>.0364993</td>
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<td>(t = 0.66, S.E. = .1950517)</td>
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<td>$\beta_9$</td>
<td>$DIFFPRSN_t$</td>
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<tr>
<td>$\beta_{10}$</td>
<td>$AGGASSAULT_{t-1}$</td>
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</table>
Table 1.
Estimation of Impact of Various Parameters on the Number of Homicides Occurring Yearly

To begin to factor in socioeconomic conditions, we remove some variables and add other variables to our model.\(^6\) We look at government spending as a fraction of the Gross Domestic Product, we look at the annual unemployment rate, we consider the number of jobs created annually by the private sector, and the rate of students who do not complete and drop out of high school each year.

\[ GOVGDP_{t-1} = \text{the amount of government spending as a fraction of GDP in the prior year} \]

\[ UNEMP_{t-1} = \text{the unemployment rate for the previous year} \]

\( \text{PRIVJOBS}_{t-1} \) = the amount of jobs in the private sector (non-agriculture) in the
previous year, in thousands of jobs

\( \text{HSDROP}_{t-1} \) = percentage of students who did not complete and dropped out of high
school in the previous year

**Equation (11):**

\[
\ln MURDER_t = \alpha + \beta_1 \ln EXEC_{t-1} + \beta_2 \ln GOVGD_{t-1} + \beta_3 \ln ROBBERY_t \\
+ \beta_4 \ln UNEMP_{t-1} + \beta_5 \ln PRIVJOBS_{t-1} + \beta_6 \ln PRISON_{t-1} \\
+ \beta_7 \ln PROBATION_{t-1} + \beta_8 \ln DIFFCRIM_t + \beta_9 \ln HSDROP_t + u_t
\]

For this equation, we ran a simple linear regression.

**Equation (12):**

\[
\ln MURDER_t = \alpha + \beta_1 \ln EXEC_{t-1} + \beta_3 \ln ROBBERY_t + \beta_5 \ln PRIVJOBS_{t-1} \\
+ \beta_6 \ln PRISON_{t-1} + \beta_7 \ln PROBATION_{t-1} + \beta_8 \ln DIFFCRIM_t + u_t
\]

For this equation, we ran another simple linear regression. We dropped statistically insignificant
variables from equation (11), and thus wanted to ensure that only relevant variables were
included. Once we realized the numbers from equation (12) were promising, we then re-ran the
equation a second time, but using a Prais-Winsten AR(1) regression with iterated estimates, to
find striking differences once we corrected for heteroskedasticity and autocorrelation.

The left hand column of *Table 2* indicates RHS coefficients, and then other figures concerning
the regression.

<table>
<thead>
<tr>
<th></th>
<th>Equation (11)</th>
<th>Equation (12)</th>
<th>Equation (12)</th>
</tr>
</thead>
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<td>-0.0042632 (t = -0.27, S.E. = 0.015734)</td>
<td>-0.0007183 (t = -0.07, S.E. = 0.0102822)</td>
<td>0.0114034 (t = 1.22, S.E. = 0.0093713)</td>
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<tr>
<td>( \beta_2 \ln GOVGD_{t-1} )</td>
<td>-0.2793579 (t = -0.97, S.E. = 0.286954)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>( \beta_3 \ln ROBBERY_t )</td>
<td>0.7922654 (t = 14.48, S.E. = 0.0547303)</td>
<td>0.7795419 (t = 21.22, S.E. = 0.0367331)</td>
<td>0.7709316 (t = 13.56, S.E. = 0.0568492)</td>
</tr>
</tbody>
</table>
\[ \beta_4 \ln UNEMP_{t-1} = 0.0101483 \quad (t = 0.13, \text{ S.E.} = 0.0809305) \]
\[ \beta_5 \ln PRIVJOBS_{t-1} = -0.7771031, -0.4951453, -0.3805053 \quad (t = -1.44, -2.29, -1.93, \text{ S.E.} = 0.5412479, 0.2164238, 0.1975716) \]
\[ \beta_6 \ln PRISON_{t-1} = 0.2468667, 0.2454446, 0.1124013 \quad (t = 2.92, 3.37, 1.20, \text{ S.E.} = 0.0845011, 0.0729328, 0.0933203) \]
\[ \beta_7 \ln PROBATION_{t-1} = -0.0925697, -0.1592443, -0.1173419 \quad (t = -0.67, -2.23, -1.28, \text{ S.E.} = 0.139157, 0.0712941, 0.0917557) \]
\[ \beta_8 \ln DIFFCRIM_t = 0.4280327, 0.4442217, 0.0980457 \quad (t = 2.98, 3.41, 0.95, \text{ S.E.} = 0.1434151, 0.1304054, 0.1027366) \]
\[ \beta_9 \ln HSDROP_t = -0.1324587 \quad (t = -1.13, \text{ S.E.} = 0.1169391) \]

<p>| | | | |</p>
<table>
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<tr>
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<td>(\beta_4) \ln UNEMP_{t-1}</td>
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<td>(t = 0.13,</td>
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<td>S.E. = 0.0809305)</td>
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<tr>
<td>(\beta_5) \ln PRIVJOBS_{t-1}</td>
<td>-0.7771031</td>
<td>-0.4951453</td>
<td>-0.3805053</td>
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<td>(t = -1.93,</td>
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<td>S.E. = 0.5412479)</td>
<td>S.E. = 0.2164238)</td>
<td>S.E. = 0.1975716)</td>
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<td>(\beta_6) \ln PRISON_{t-1}</td>
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<td>S.E. = 0.0845011)</td>
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<td>S.E. = 0.1304054)</td>
<td>S.E. = 0.1027366)</td>
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<tr>
<td>S.E. = 0.1169391)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(R^2\) | 0.9821 | 0.9808 | 0.9998 |

\(\text{Adj. }R^2\) | 0.9744 | 0.9760 | 0.9998 |

\(\text{Root MSE}\) | 0.02502 | 0.02422 | 0.01913 |

\(F\) statistic | 127.85 | 204.43 | 20469.88 |

\(\alpha\) (constant) | 6.354787 | 4.30662 | 4.270717 |

\(\rho\) (rho) | --- | --- | 0.7839423 |

\(D-W\) statistic (original) | --- | --- | 1.174894 |

\(D-W\) statistic (transfrmd) | --- | --- | 1.445570 |

**Table 2.**

**Estimation of Impact of Additional Parameters on the Number of Homicides Occurring Yearly**

So our socioeconomic variables also proved to be statistically insignificant. This only leaves us with crime trends and measures of punishment. Nonetheless, every time we tried to include the rate of executions, it proved to be statistically insignificant, so we drop this from our model. The
crime trend of robbery has remained consistently significant through most of our models. Running several variations, we also find that the crime trend of aggravated assault, bears some relationship to the number of murders. Lastly, the punishment measure of probation has proven to be significant in some of the models. Using only these three explanatory variables, we used a Prais-Winsten estimation with iteration, and for standard errors, specified the robust option which uses a Huber-White sandwich estimator.\(^6^9\) The reported standard errors are labeled “semi-robust”.\(^7^0\)

Equation (13):

\[
\ln MURDER_t = \beta_1 \ln ROBBERY_t + \beta_2 \ln AGGASSAULT_t + \beta_3 \ln PROBATION_{t-1}
\]

For this equation, we ran a Prais-Winsten AR(1) regression with iterated estimates. The left hand column of Table 3 indicates RHS coefficients, and then other figures concerning the regression.

<table>
<thead>
<tr>
<th>Equation (13)</th>
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<tbody>
<tr>
<td>(\beta_1 \ln ROBBERY_t)</td>
<td>(.5749626)</td>
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<tr>
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<td>((t = 6.91,) (S.R.S.E. = .0831926))</td>
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<tr>
<td>(\beta_2 \ln AGGASSAULT_t)</td>
<td>(.2804675)</td>
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<tr>
<td></td>
<td>((t = 2.07,) (S.R.S.E. = .13539))</td>
</tr>
<tr>
<td>(\beta_3 \ln PROBATION_{t-1})</td>
<td>(-.1758044)</td>
</tr>
<tr>
<td></td>
<td>((t = -4.38,) (S.R.S.E. = .0400993))</td>
</tr>
<tr>
<td>(R^2)</td>
<td>(.9992)</td>
</tr>
</tbody>
</table>


\(^7^0\) “Semi-robust standard errors are closely related to robust standard errors and can be interpreted as representing the sample-to-sample variability of the parameter estimates, even when the model is misspecified, as long as the mean structure of the model is specified correctly.” Glossary. (n.d.). Stata. Retrieved from http://www.stata.com/bookstore/stata12/pdf/xt_glossary.pdf.
Table 3.

Estimation of impact of robberies, aggravated assaults, and probation on the number of homicides.

Thus with this nonlinear model, the t statistics of the coefficients are all above the critical values, making the three variables statistically significant at the 5 percent level. The regression is statistically significant as a whole.

An increase in the number of robberies and aggravated assaults, resulted in an increase in the number of murders. The following graph, demonstrates the close connection between robberies and homicides (National Research Council, 2008, p. 15, fig. 2-1):
Using a similar approach to create a suitable graphical display to descriptively describe what is going on between all of the dependent and independent variables in our model, we create a time-series graph, which shows the behavior of the data, by using different frequencies. We plot the number of murders divided by 4,000 persons, against the number of robberies per 100,000 persons, against the number of aggravated assaults per 200,000 persons, against the number of people placed on probation per 400,000 persons.

Figure 1. Trends in murder and robbery.\textsuperscript{71}

**Figure 2.** Trends in murder, robbery, aggravated assault, and probation.

An increase in the number of persons placed on probation resulted in a decrease in the number of murders. Compared to the findings of Summers and Adler, the high $R^2$ (provides an explanation for 99.92% of the movement in the dependent variable), low RSME, and low standard errors associated with the estimates, after correcting for autocorrelation and heteroscedasticity, allows our model to provide very informative and reliable results.

V. CONCLUSION

Our findings imply that where there is a rise in the violent felonies of robbery,\textsuperscript{72} and aggravated assault,\textsuperscript{73} there is a corresponding increase in the number of murders.\textsuperscript{74} While some

Robberies are committed by strangers, robberies by acquaintances do occur, e.g., inside jobs and robberies where one of the participants or conspirators is familiar with the victim’s security measures, daily routine and when and where they would be likely to possess significant amounts of money and valuable goods. Many aggravated assaults are typically the results of arguments, where tempers flare, and usually occur between people known to one another, rather than total strangers. “Females victims are more likely to be murdered by a current or former intimate partner, while males are more likely to be murdered by an acquaintance or friend (BJS 2006). A similar pattern holds true for assault: acquaintances or relatives (60%) versus strangers (40%).”

Additionally where there is an increase in the number of people placed on probation, there is a corresponding decrease in the number of murders. This is logical because people placed on probation have a greater risk of being detected and caught for their crimes. Probationers typically surrender partial constitutional rights when they are placed on supervision, particularly Fourth Amendment and Fifth Amendment rights which facilitate the ability of probation enforcement to collect evidence against them. Additionally, there is no right to a speedy trial, no right to a trial by jury, and many other due process constitutional safeguards are lost in a violation of probation hearing, which make violation of a probationer easier, and thus

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punishment is more certain and swift.\textsuperscript{80} The loss of partial privacy and partial due process rights make this form of punishment highly effective as a deterrent.\textsuperscript{81} Still though, many experts remain unconvinced of what causes a decrease in crime as a whole,\textsuperscript{82} nonetheless these promising results help to at least confirm some of our traditional common sense ideas about violent crime at least.


\textsuperscript{81} Petersilia, J. (1990). When Probation Becomes More Dreaded than Prison. \textit{Federal Probation}. 54(1), 23-27. It was this author’s personal experience as a criminal prosecutor, that most criminal hardened offenders would rather negotiate for a longer prison sentence, and to accept a split sentence which involved incarceration followed by probation supervision. Additionally, even where an offender with some experience in the criminal justice system had a minor record, and was offered straight probation, they would attempt to negotiate for a straight jail sentence without probation.