Juvenile Crime and Punishment:
Assessing the Relationship between Violent Crime Rates and Punishment, 1982-1992

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Abstract:
Over the past twenty years juvenile violent crime rates have increased tremendously. In light of this disturbing trend, this paper examines whether variation in punishment levels has any impact on juvenile violent crime. To examine this relationship I first establish a behavioral model of juvenile crime, from which point I introduce an empirical model and use available data to estimate this model. Ultimately, my analysis reveals that juvenile violent crime rates are negatively affected by increases in juvenile punishment. Additionally, I also show that the relative punitiveness of the adult and juvenile justice systems negatively affects changes in violent crime rates between juveniles immediately before and after they enter the adult justice system.

Acknowledgements:
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Key Words:
Juvenile Violent Crime, Economics of Crime, Relative Punitiveness, Deterrence
Chapter I. Introduction

This thesis examines the relationship between punishment and violent crime rates for juveniles. Additionally, it looks at the impact of the relative punitiveness of adult versus juvenile justice systems on changes in violent crime rates as juveniles enter the adult system.

Assessing these relationships becomes especially relevant in light of recent trends in juvenile crime and the resultant policy. During the 1980s there was an alarming trend in juvenile arrests; between 1982 and 1991 juvenile arrests for violent crime rose by 41 percent, reaching an all-time high in 1991 (Wilson and Howell 1993). Partially contributing to this rise was the increase in juvenile arrests for murder and aggravated assault, which increased by 93 and 72 percent, respectively. This upward trend continued into the mid-nineties, and despite a recent relative decline in juvenile violent crime back to mid-eighties levels, juvenile crime is still an important agenda that is continually being addressed with new policy.

Historically, the focus of juvenile justice policy has vacillated between punitive responses to juvenile crime and more rehabilitative efforts (Jenson and Howard 1998). In response to the sharp increase in juvenile violent crime in the 1980s legislation was enacted to increase the punitiveness of the justice system (Jenson and Howard 1998). One such bill lowered the age at which juvenile offenders could be tried in an adult court. Other changes to the juvenile justice system include “increased waivers of juvenile cases to be heard in adult courts, increased penalties for juvenile crime, and greater reliance on detention and incarceration” (Schneider 1990, p.1).

Increases in juvenile law enforcement have led to overcrowding in many juvenile detention facilities. In 1990 admissions to detention facilities reached an all-time high, resulting in 47 percent of juveniles being detained in overcrowded facilities (Wilson and Howell 1993).
Additionally, recent reports have cast serious doubt on the suitability of detention facilities for today’s youth. A recent study put out by the California Youth Authority revealed rampant violence in youth detention facilities and also commented that the facilities provided insufficient living conditions and were not well equipped to deal with issues such as “mental health, substance abuse, gang violence and education” (San Jose Mercury News 2004, p.1A). It becomes clear that if we are to correctly evaluate policy we need to determine whether these punishment-based policies will actually help lower juvenile violent crime. Thus, it is imperative that we formulate some understanding of how effective punishment is at deterring future juvenile crime.

The rest of this thesis is divided into six sections. First, I conduct a literature review documenting relevant papers in the field of the economics of crime. Second, I develop a behavioral model that reflects the juvenile decision to commit violent crime. Third, I describe the available data and detail the construction of relevant variables. Fourth, I create an empirical framework with which to test the hypothesis that punishment does in fact negatively affect juvenile violent crime. Fifth, I estimate the empirical models and offer a discussion of results. Finally, I conclude with a summary of my findings as well as a few other closing remarks.
Chapter II. Literature Review

This thesis applies an extension of the economic model of crime developed by Becker (1968). The economic model of crime rests on the assumption that expected utility theory can be applied to criminal behavior. Individuals are assumed to have expected utility functions associated with committing a crime that depend on the various costs and benefits attached to a crime. When deciding whether to commit a crime the would-be criminal is expected to conduct a personal cost-benefit analysis that informs his or her final decision. Given this framework, economics tries to determine what specific factors influence the costs and benefits underlying individuals’ expected utility functions. For example, a large volume of economics research examines how changes in the severity of punishment or the probability of capture affect the expected costs of committing a crime. The results of these analyses can be extremely useful from a social perspective because when specific costs that reduce crime are identified, these costs can be upwardly augmented through actual policy.

Literature on the Economics of Adult Crime:

Numerous economic studies have tested the economic model of crime on the adult criminal system. In 1968, Becker produced a seminal paper on this topic. Becker’s analysis was groundbreaking because it was one of the first papers to apply expected utility theory to the criminal system. In *Crime and Punishment: An Economic Approach*, Becker develops a formal economic model designed to reveal the socially optimal amount of enforcement. By incorporating costs of enforcement, costs and benefits of committing a crime for both the criminal and society, and costs of punishment into his model, Becker derives optimality conditions for all these factors. Essential to Becker’s model of criminal behavior is that
increases in punishment will reduce the value of committing a crime for potential offenders (1968).

Shortly following Becker’s theoretical exploration of the economic model of crime, Ehrlich conducted an empirical analysis of this model. In his 1973 paper titled, *Participation in Illegitimate Activities: A Theoretical and Empirical Investigation*, Ehrlich looked at index crime rates at the state-level and examined their relationship with enforcement-related expenditures. Ehrlich concludes that increased expenditures reduced criminal behavior, and furthermore this result could not solely be attributed to incapacitation, but that deterrence was also contributory.

Many researchers have further examined the economic model of crime since Becker’s seminal work (Brown and McDougal 1978; Cohen and Cooke 1980; Currie 1985; Ehrlich 1975; Grogger 1991; Hoenak and Weiler 1980; Mathur 1978). The majority of this research has strengthened the case for an economic model of crime. For example, in 1978 Mathur used city-level data to specifically examine the relationship between crime and punishment in the urban context. His study confirmed that both increases in certainty and severity of punishment reduced the likelihood of crime; although Mathur’s study casts doubt on the practice of using police expenditures as a measure of punishment (1978). In *Noncompliance with the law: A Utility Analysis of City Crime Rates*, Brown and McDougal expanded the list of factors contributing to the utility function of a criminal, including more benefits compared to prior research (1978). In general, research has aimed to refine and expand the application of the economic model of crime.

**Literature on the Economics of Juvenile Crime:**

One blaring deficiency in current research is that most studies only examine the adult criminal system. In fact, very little research has concentrated on juveniles and their criminal
behavior. Steven Levitt’s paper on juvenile crime and punishment is one of the primary sources of research in this area (1998). Levitt’s paper highlights the problem of distinguishing deterrent effects from incapacitation effects when studying the economic model of crime. The thought here is that when you simply regress crime on some variables representing levels of punishment, an observed relationship does not ensure deterrence is functional. If crime declines with increased punishment, this might be a result of more criminals being locked up as opposed to actual reductions in criminal behavior. Levitt addresses this problem by devising a model that examines changes in crime rates as juveniles reach the age of majority. Specifically, Levitt observes the effect the punitiveness of the adult justice system relative to the juvenile justice system has on crime rates for juveniles who become legal adults and enter the adult system. Levitt asserts that changes in crime rate during this transition from juvenile to adult justice system are immediate and thus reflect deterrence as opposed to incapacitation (1998). Thus, when Levitt observes that higher relative punitiveness of the adult justice system reduces crime rates, he concludes punishment has a deterrent effect.

Affirming Levitt’s results, Mocan and Rees published a paper titled, Economic Conditions: Deterrence and Juvenile Crime, which was the first to use micro-level data to test the economic model of crime for juveniles (1999). By having data at the individual level, this eliminated the problem of distinguishing deterrence from incapacitation because the analysis took into account the exact situation of each individual. In line with the Levitt study, this paper also found a negative relationship between punishment and juvenile criminal activity. Specifically, higher violent crime arrest rates reduced the probability of selling drugs and assaulting someone for males, and reduced the probability of selling drugs and stealing for females (Mocan and Rees 1999).
However, while these two papers support the application of the economic model of crime to juveniles, there exists research suggesting its inappropriateness. Jenson and Howard published a study in 1998 that examined the relationship between fluctuations in juvenile justice policy and violent youth crime. After constructing a measure that varied depending on whether justice policy was more punitive or more rehabilitative-focused, Jenson and Howard found that violent youth crime did not vary significantly with juvenile justice policy (1998).

Additionally, research has been conducted that challenged the economic model of crime introduced by Becker. In 1990, Schneider published a study titled, *Deterrence and Juvenile Crime*. Schneider questions the economic model of crime by introducing competing theories such as decision “heuristic theory” and “labeling theory”. In her study, Schneider questions whether the decision to commit a crime is influenced by self-perceptions (specifically, Schneider assesses if a person sees themselves as a law abiding citizen) as opposed to precise cost-benefit calculations. Data for Schneider’s study consisted of interviews with adjudicated delinquents at the time of release from their respective detention facilities and follow up interviews that were conducted in the following years. Six separate juvenile facilities were included in the study. Schneider’s study reveals that expected punishment did not impact actual behavior. While the more chronic offenders did say they would be less likely to commit future crimes if expected punishment increased, these individuals actually committed more crimes despite increased expected punishment (Schneider 1990). This result thus goes directly against the findings from the Levitt (1998) and Mocan and Rees (1999) papers. More damning though, Schneider also found that serving time in a juvenile detention facility caused less-severe offenders to view themselves as criminals and this self-perception increased the likelihood of their committing future criminal acts (Schneider 1990). While the Schneider paper promotes the need for
alternative examinations of juvenile crime beyond the economic model, this specific issue will not be addressed within my thesis. Rather, I will focus on refining our understanding of the implications of applying the economic model on about juvenile violent crime. Nevertheless, future research should certainly make a point to compare various perspectives on crime, be it economical, sociological, or psychological against each other.
Chapter III. Behavioral Framework

Economic Model:

To estimate the effects of punishment on juvenile violent crime I first develop a behavioral model that captures the decision to commit a crime. This decision depends on a person’s expected utility from criminal behavior versus the utility from legitimate work. I represent these two utility functions as follows:

\[
\begin{align*}
(1) \quad EU(\text{Violent Crime}) &= p \cdot U(Y - f) + (1-p) \cdot U(Y) \\
(2) \quad U(\text{Legitimate Work}) &= U(I)
\end{align*}
\]

Equation (1) states that the expected utility of crime equals the probability of capture, \( p \), multiplied by the utility of the benefits from committing the crime, \( Y \), minus the costs associated with capture, \( f \), plus the probability the criminal is not captured, \( 1-p \), multiplied by the utility of the benefits from committing the crime.

Equation (2) takes a much simpler form than equation (1) because there is no risk associated with legitimate work. If a person chooses legitimate work they are guaranteed an income, \( I \), and thus total utility equals the utility of this income, \( I \). More complex models could be used to account for variability in the income variable, however, I primarily focus on equation (1) in my analysis and thus using a more complex form of equation (2) would not be instructive.

In the context of these equations, the decision to commit a violent crime depends on whether the expected utility of committing a violent crime exceeds the utility of legitimate work (this assumes legitimate and illegitimate activities are mutually exclusive). Thus, increases in the expected utility of violent crime should induce increases in crime rates and vice versa. These comparative statics in equation (1) drive the majority of my analysis.
Relationships Among Variables:

Given equation (1), the next task is to determine how variation in the probability of capture, \( p \), the severity of punishment, \( f \), and the gains from violent crime, \( Y \), affect the expected utility of violent crime. These relationships become evident when I look at the partial derivatives of expected utility with respect to \( p \), \( f \), and \( Y \):

\[
\frac{dEU}{dp} = U(Y-f) - U(Y)
\]

\[
\frac{dEU}{df} = -p \cdot U'(Y-f)
\]

\[
\frac{dEU}{dY} = p \cdot (U'(Y-f) - U'(Y)) + U'(Y)
\]

First let us examine equations (3) and (4). Assuming \( U \) is an increasing function, the partial derivatives of expected utility with respect to \( p \) and \( f \) are both less than zero; increases in either the probability of capture or the severity of punishment should reduce crime rates. The logic behind this result is as follows: if the probability of capture increases, this raises the likelihood of the person facing the cost, \( f \), associated with punishment. This lowers the expected utility associated with the crime and thus decreases a person’s incentive to commit the crime. Likewise, increases in \( f \), the severity of punishment, decrease the expected utility attached to a crime because the individual will face higher costs if caught. So a higher value of \( f \) also lowers the incentive to commit a crime. Additionally, I should note that equal changes in the probability of capture and the severity of offense will not necessarily have the same impact on expected utility. This depends upon whether or not a person is risk neutral, risk preferential, or risk averse. This question becomes particularly relevant when one tries to set policy. Unfortunately,
in this paper I do not develop empirical measures that get at the differences between changes in probability of capture versus changes in severity of punishment, and thus I will not discuss what notion of risk best describes the target population. Nevertheless, for future research it is important to keep this characteristic in mind.

Equation (5), for an increasing $U$, is always greater than zero, thus implying that the violent crime rate increases as $Y$ gets larger. When analyzing the affect of changes in the value of crime, $Y$, on crime rates it is instructive to invoke a more thorough analysis compared to the prior examination of variations in the probability of capture and the severity of punishment. Conceptually, the value of crime is less self-explanatory compared to both $p$ and $f$, and so in constructing a function for the crime rate it helps to reveal factors determining $Y$. The value of crime can be expected to vary largely with personal preferences, however, I introduce a few measured variables to describe variation in the value of crime. Specifically I look at age, residence, time, and other demographic variables such as crowdedness of a region and race. The value of crime can be expected to vary with these variables for a number of reasons. Here, I offer a few plausible explanations: first, accessibility to crime might impact the value of crime: easier access to crime entails less expense of effort in committing a criminal act which in turn raises the value of that criminal act. Accessibility of crime is likely related to crowdedness of a region, as higher population density implies a larger source of potential victims. Additionally, the value of crime might vary with social perceptions of crime. If a criminal lives in a society that values moral behavior, there might exist a cost of acting immorally. This cost would decrease the value of crime. Societal valuations of moral behavior could be expected to vary over time, residence, and perhaps even age.
Finally, I will address the utility associated with legitimate work (equation (2)). This equation has a simple interpretation: assuming an increasing utility function, the utility of legitimate work increases as income from legitimate work increases. In terms of the impact on the violent crime rate, as income increases this will cause a lower violent crime rate because for some individuals the expected utility of violent crime will no longer exceed the utility of legitimate work. Income from legitimate work likely varies over time, residence, and age. Also, general economic conditions might be expected to impact income levels.

The Crime Rate Function:

Having created a behavioral framework that details the factors affecting the violent crime rate, the next step is to construct a function representing this rate:

(6) \[ \text{Violent Crime Rate} = C(\text{punishment, age, residence, time, other}) \]

In equation (6), punishment consists of both the probability of capture and the severity of punishment. Instead of including variables for the value of crime and income from legitimate work, I include age, residence, time, and a variety of other variables that impact these values. Specifically, the variable \textit{other} consists of any economic or demographic variables such as crowdedness of a region and racial make-up that impact the violent crime rate. Following from the previous analysis of equations (3) and (4), the violent crime rate is expected to be a declining function of punishment:

(7) \[ \frac{dC}{dpunishment} < 0 \]
The empirical model, to be described later, will look to test the hypothesis that increases in punishment reduce the violent crime rate.

Additionally, I should note here that my empirical analysis will specifically focus on the violent crime rate for a distinct portion of the population. First, I examine the relationship between juvenile violent crime and juvenile punishment. Second, I conduct a relative analysis that looks at differences in violent crime rates for juveniles just prior to and immediately after entering the adult justice system. This analysis thus takes into account differences in punitiveness between the juvenile and adult justice systems. To conduct both of these empirical analyses, I require age-specific crime rate measures as well as punishment measures for both the adult and juvenile justice systems. The following chapter details the construction of these measures.
Chapter IV.  Construction of the Violent Crime Rate and Punishment Variables

This chapter is divided into two sections. First, I introduce the available data and second, I describe the construction of all relevant variables.

Description of Data:

Detention Data:

To construct some measure of punishment I require data identifying both juvenile and adult detained populations. Juvenile detention data are collected by the Office of Juvenile Justice and Delinquency Prevention and included in the Children in Custody Census (CIC). Data collection for the CIC began in 1971, and has continued roughly every two years since then. The official title of the data set is the Juvenile Detention and Correctional Facility Census up through 1985, at which point it is renamed the Census of Public and Private Juvenile Detention, Correctional, and Shelter Facilities through 1995. These data are publicly available through the Inter-University Consortium for Political and Social Research (ICPSR). The data set contains information on state-level population characteristics of both public and private juvenile facilities throughout the United States. I specifically look at populations of committed and detained delinquents in juvenile detention facilities over the years 1982 through 1993.

Additionally, I should note a deficiency in these data sets. Until 1997, the CIC identified the state in which a facility sits as opposed to the state in which the detained juvenile committed a crime. This is problematic because when trying to associate arrest and crime data with detention data, the data will not match up perfectly. Fortunately, this problem is not too widespread, as no more than 2% of the juvenile population is placed in out-of-state facilities (Sickmund and Snyder 1999). Additionally, detained juveniles are less likely to be placed out-
of-state compared to other juveniles covered in the CIC (Sickmund and Snyder 1999). Nevertheless, this problem should be acknowledged as a potential source of deficiency in the analysis.

As far as adult detention statistics, I utilize end-of-year prison levels provided by the Bureau of Justice Statistics (Hill and Harrison 2000). These data are collected on an annual basis and are specified by state. Annual state-level data on jail populations (specifically for non-adjudicated adults or adults with sentences of less than one year) are not available, and thus I omit this portion of the detained population from my analysis. However, this population does not significantly vary over time and in prior research on the economics of adult crime it has been common to exclude this group (Levitt 1998).

*Arrest and Crime Data:*

Arrest and crime data are necessary to construct a measure of violent crime rates. The primary source for arrest data is the FBI Uniform Crime Reports. These data reflect monthly arrest reports submitted by police agencies across the nation. These data are made readily available for analysis by the National Consortium on Violence Research (NCOVR), located at Carnegie Mellon University. NCOVR reproduces annual counts of arrest data by state, age, and type of offense from the FBI Uniform Crime Reports starting in 1980. However, as with the juvenile detention data, there are unavoidable deficiencies in the arrest data. It is common practice for police precincts to fail to report their arrest data on-time and, in some cases, at all to the FBI. Additionally, precincts might have gaps in months in which they do report (Maltz 1999). The problem thus arises that in using raw data directly from the FBI Uniform Crime reports, one understates actual arrests. The Bureau of Justice Statistics (BJS) addresses this problem by taking note of reporting populations and weighing the recorded arrest data.
appropriately so to produce estimates of total arrests. Unfortunately, the BJS only performs this weighting scheme at the national level, and it would be extremely difficult, if not impossible, to implement a weighting scheme that produces accurate estimates of total state arrests. I address the problem of missing arrest data by relying on arrest ratios which are supposedly less problematic (Levitt 1998). A more thorough discussion of why use of ratios diminishes the problem of missing arrest data is included in the construction of variables section.

In addition to the arrest data, the FBI Uniform Crime Reports also contains crime data. Crime levels listed by state, year, and offense type are readily available through the Bureau of Justice Statistics.

*Demographic and Economic Data:*

Finally, in addition to detention, arrest, and crime data, population data are required to normalize arrest and crime data across states. Data describing economic and other demographic conditions are also needed for use as control variables in the empirical analysis. Population measures are collected by the Current Population Survey (CPS). The CPS is a monthly survey conducted by the census bureau. The raw CPS data can be manipulated to get annual population counts by state and by age. Other state-level demographic and economic variables, such as percent of population that is black and percent of population living in metropolitan areas are provided by the decennial census. Annual estimates for these variables can be constructed by linearly interpolating the data. Finally, unemployment rates data by state and year are also available through the Current Population Survey.
**Construction of Variables:**

To empirically test the relationship between punishment and the juvenile violent crime rate I require variables that measure these two values as well as variables that account for age, time, residence, and the other factors affecting the juvenile violent crime rate.

**Violent Crime Rate:**

First, in constructing the juvenile violent crime rate I am limited by the lack of age-specific crime data. These data are not available because age values are only attached to a crime once the crime is cleared by an arrest. Thus, it becomes necessary to construct a variable that estimates age-specific violent crime levels, which in turn can be used to derive age-specific violent crime rates. I rely on the crime measure developed in Levitt’s 1998 paper titled, *Juvenile Crime and Punishment:*

\[
\text{Violent Crime}_{ast} = \frac{\text{Violent Arrests}_{ast}}{\text{Total Violent Arrests}_{st}} \times \text{Total Violent Crime}_{st}
\]

Where \(a\) represents the age group, \(s\) represents the state and \(t\) represents the year. This estimation assumes that the ratio of arrests for a specific age group versus total arrests reflects the ratio of crimes for that same age group compared to total crime. Additionally, using ratios of arrests as opposed to levels allows me to circumvent the notorious problem of underreporting in raw arrest data. A large portion of arrest data understates actual arrest counts, thus resulting in significant fluctuation of arrest levels by age and by state over time. Fortunately, ratios of arrests tend to be much more stable over time, and thus it would appear that using these ratios is less problematic for analysis compared to the inaccurate arrest level data (Levitt 1998). Also, as indicated in equation (6), this paper will empirically test the relationship between the juvenile
violent crime rate and punishment. The violent crime rate can easily be computed once determining the level of violent crime in the following manner:

\[
\text{Violent Crime Rate}_{ast} = \frac{\text{Violent Crime}_{ast} \times 1000}{\text{Population}_{ast}}
\]

As specified above, \(a\) represents the age group, \(s\) represents the state and \(t\) represents the year. Dividing the relevant population by one thousand gives us violent crime rate per thousand individuals.

*The Punishment Variable:*

Next, in order to precisely test the economic model depicted earlier I require measures of the probability of capture and the severity of punishment. Unfortunately, data specifically describing severity of punishment and probability of capture are not available for this analysis. Instead I rely on two custody variables: one reflecting the juvenile population and one reflecting the adult population (this custody specification is introduced in Levitt 1998):

\[
\text{JuvenileCustody}_{st} = \frac{\text{Committed and Detained Juvenile Delinquents}_{st}}{\text{Juvenile Violent Crime}_{st}}
\]

\[
\text{AdultCustody}_{st} = \frac{\text{Adult Prison Population}_{st}}{\text{Adult Violent Crime}_{st}}
\]

Where \(s\) represents the state and \(t\) represents the year. It is necessary to include both an adult and juvenile custody measure because a portion of the empirical analysis examines changes in crime rates for juveniles as they enter the adult justice system, and so it is necessary to have measures of the punitiveness of both systems. The custody variables can be interpreted as general punishment variables. These custody variables should increase with increases in both the probability of capture and the severity of punishment. This follows because higher probability of
capture implies a larger fraction of criminals being captured and entering the detained population. Additionally, an increase in severity of punishment implies that fewer detainees will exit the detained population as compared to the situation where there was a lighter severity of punishment, and thus this will result in a larger detained population. Increases in the detained population resulting from increases in probability and severity of punishment will thus provoke a rise in the custody measure. For juveniles, the detained population consists of committed and detained juvenile delinquents. For adults, I use end-of-year prison totals. Both these measures represent stocks as opposed to flows. This is necessary because information on flows for detained and committed juveniles is not available, and to keep consistent I must use adult stock levels as well. The crime value for the custody measure is derived using equation (8).

Economic and Demographic Variables:

Aside from deriving variables to represent crime and punishment, I also need variables that control for the other factors affecting the decision whether or not to commit a violent crime. To control for variation in the access to criminal opportunities, I include a metropolitan variable that indicates the percentage of a population living in metropolitan areas by state and year. The thought here is that people living in metropolitan areas have easier access to criminal opportunities due to larger populations and more commercial settings, and thus this reduces search costs associated with carrying out a criminal act. Ideally, I would include data on racial composition, however, I only have data on the percentage of state population that is black. I include this variable thus controlling for variations in violent crime rates with this specific racial group. Finally, I include the variable unemployment to capture certain economic variations that might affect violent crime rates. The unemployment variable lists annual state unemployment rates.
Beyond these control variables, because all the variables used in this analysis vary by state and time, I can introduce state and year dummy variables or use certain empirical techniques to control for factors that might impact crime rates and that might be correlated with the punishment variable. This will help avoid a biased estimate of the relationship between punishment and juvenile violent crime rates.

**Descriptive Statistics:**

Descriptive statistics for the variables used in my analysis are provided in Table 1:

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Summary Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Mean</td>
</tr>
<tr>
<td>Juvenile Crime Rate (per 1,000 population)</td>
<td>3.15</td>
</tr>
<tr>
<td>Juvenile Custody Rate (per juvenile violent crime)</td>
<td>0.49</td>
</tr>
<tr>
<td>Adult Custody Rate (per adult violent crime)</td>
<td>0.59</td>
</tr>
<tr>
<td>State Unemployment Rate</td>
<td>6.87</td>
</tr>
<tr>
<td>% Metropolitan</td>
<td>64.26</td>
</tr>
<tr>
<td>% Black</td>
<td>10.55</td>
</tr>
<tr>
<td>Juvenile Population (*1000)</td>
<td>1251.41</td>
</tr>
</tbody>
</table>

These statistics cover alternating years for the period 1982 – 1992. The number of observations is 305.
Chapter V. Empirical Framework

In this section I develop three empirical models that portray the relationship between juvenile violent crime rates and juvenile punishment levels as well as the relationship between differences in violent crime rates for juveniles and adults and relative punishment levels between juvenile and adult justice systems.

Empirical Model 1:

The first empirical model examines the relationship between juvenile violent crime and juvenile punishment. In creating this model I must assume a functional form for the violent crime rate function (equation (6)). I assume a log relationship between crime rate and the custody variable, giving:

\[
(12) \ln(JuvViolCriRate_{st}) = \psi_s + \gamma_t + \beta_1 \ln(JuvCustody_{st}) + \beta_2 \cdot \text{Unemployment}_{st} + \beta_3 \cdot \text{Metropolitan}_{st} + \beta_4 \cdot \text{Black}_{st} + \varepsilon_{st}
\]

where \( s \) references state and \( t \) references year. The dependent variable is the natural log of the juvenile violent crime rate. This variable is constructed using equation (9), where the age group is defined as all persons less than eighteen years of age. The primary independent variable is the custody measure, which estimates punishment. Because this analysis is limited to the juvenile population I use the juvenile custody measure given by equation (10). In addition to the custody measure, I also include a variety of control variables so to control for other factors that influence juvenile violent crime rates. The terms \( \psi \) and \( \gamma \) are indicator variables controlling for state and year fixed effects, respectively. The variables metropolitan, black, and unemployment are also included as control variables.
I should note here that one limitation of the first empirical model, as represented by equation (12), is that it fails to control for state-specific time effects. It seems reasonable that different states might have violent crime rates that have unique time trends, and so it is important to construct an additional empirical model that controls for state-specific time effects.

**Empirical Model 2:**

The second empirical model controls for state-specific time effects by focusing on a relative analysis of changes in crime rates, which allows for the differencing out of any state-specific time effects. To do this I specify two new equations that look at crime rates for juveniles immediately before they enter the adult justice system and immediately after they enter the adult justice system:

\[
(13) \ln(\text{ViolCriRate}_{15-16_{st}}) = \psi_s + \gamma_t + \beta_1 \ln(\text{JuvCustody}_{st}) + \rho_1 \times \text{Unemployment}_{st} + \rho_2 \times \text{Metropolitan}_{st} + \rho_3 \times \text{Black}_{st} + \epsilon_{st}
\]

\[
(14) \ln(\text{ViolCriRate}_{19-21_{st}}) = \psi_s + \gamma_t + \beta_1 \ln(\text{AdultCustody}_{st}) + \theta_1 \times \text{Unemployment}_{st} + \theta_2 \times \text{Metropolitan}_{st} + \theta_3 \times \text{Black}_{st} + \mu_{st}
\]

Here $s$ references state and $t$ references year. In equations (13) and (14) the dependent variable is the natural log of the average violent crime rate for 15 to 16 and 19 to 21 year-olds, respectively (Note: I omit seventeen year-olds from equation (13) because in some states a juvenile legally becomes an adult at seventeen as opposed to the more common eighteen. Likewise, eighteen year-olds are omitted from equation (14) because in some states a juvenile legally becomes an adult at nineteen. Thus, by omitting these two populations I ensure that both equations only include individuals who are under the jurisdiction of the same justice system. Additionally, a few states define legal adults as people sixteen years of age and older. I do not limit equation (13) to individuals less than sixteen because there are only a few states with this lower age of
majority. Furthermore, dropping these observations does not materially affect the results). The
dependent variable is determined by using equation (9) to determine violent crime rates for
individual age groups. Violent crime rates for the relevant age groups are then averaged
together. The independent variables in equations (13) and (14) are almost identical to those in
equation (12). The only difference being that equation (14) uses the adult custody as opposed to
juvenile custody measure because its dependent variable consists of crime rates for a portion of
the adult population.

In order to difference out state-specific time effects I take the difference of equations (14)
and (13), giving:

\[
(15) \ln(VCR19-21) - \ln(VCR15-16) = \beta_1 [ \ln(\text{AdultCustody}_{st}) - \ln(\text{JuvenileCustody}_{st}) ] \\
+ \alpha_1 * \text{Unemployment}_{st} + \alpha_2 * \text{Metropolitan}_{st} \\
+ \alpha_3 * \text{Black}_{st} + \nu_{st}
\]

where \(s\) references state and \(t\) references year. The dependent variable is the difference in the
natural log of the average violent crime rate for 19-21 year-olds and the natural log of the
average violent crime rate for 15-16 year-olds (I abbreviate violent crime rate with the term VCR
in equation (15)). The primary independent variable is equal to the difference between the
natural log of the two custody measures. This can be rewritten as the natural log of the term,
Adult Custody divided by Juvenile Custody. Intuitively, this quotient can be thought of as
representing the relative punitiveness of the adult justice system compared to the juvenile justice
system (Levitt 1998). Differentiating equations (14) and (13) causes the terms \(\psi\) and \(\gamma\) to drop out
of the equation. The differencing should in theory also eliminate any variables that are constant
over the two age groups (this includes state-specific time effects). The only situation in which
differencing would fail to eliminate a variable that is constant over the two age groups is when
the two age groups respond differently to that variable. This is why unemployment, metropolitan, and black are included in equation (15). The testable assumption here is that the coefficients $\rho_{1,3}$ and $\theta_{1,3}$ are different and thus equation (15) has new coefficients, $\alpha_{1,3}$, for unemployment, metropolitan, and black.

**Empirical Model 3:**

The final empirical model I introduce is a variation on the second model and provides a different way in which to observe the effect of relative punitiveness on changes in violent crime rates. Rather than include the contemporaneous independent variable, natural log of relative punitiveness (defined as adult custody divided by juvenile custody), I replace this with two indicator variables labeled Least Relative Punitiveness (LRP) and Most Relative Punitiveness (MRP). LRP takes on a value of 1 when relative punitiveness is less than 1 and MRP takes on a value of 1 when relative punitiveness is greater than 2. This gives us the following equation:

$$(16) \ln(VCR19-21) - \ln(VCR15-16) = \beta_1 * MRP_{st} + \beta_2 * LRP_{st} + \alpha_1 * Unemployment_{st}$$

$$+ \alpha_2 * Metropolitan_{st} + \alpha_3 * Black_{st} + \nu_{st}$$

where $s$ and $t$ represent state and year, respectively. This equation is almost identical to equation (15), the only difference being the use of the indicator variables MRP and LRP in place of the contemporaneous relative punitiveness variable. Equation (16) should in theory have differenced out any state-specific time effects as well as general state and time-fixed effects.
Chapter VI. Empirical Implementation

This section includes results and analysis for the estimations of the three empirical models introduced in the prior chapter. For each model I detail the estimation procedures, list the results, and offer analysis. Finally, I conclude this section by assessing my results in the context of previous research on juvenile crime.

Empirical Model 1:

Estimation:

To estimate the first empirical model, represented by equation (12), I use state-level data for the period 1982 – 1992. I first perform this analysis using an ordinary least squares estimation. The results from this regression are listed in table 2. However, using ordinary least squares estimation is problematic because of potential measurement error in the violent crime level component of the independent variable, juvenile custody. First, because the numerator of the dependent variable and the denominator of the custody variable both equal violent crime for juveniles (this term is described by equation (8)) the presence of measurement error might cause division bias. This occurs because high measurement error will drive down the value of the custody variable and drive up the value of the dependent variable, thus producing a negative bias. Second, measurement error in the juvenile custody variable will in general cause it to be correlated with the error term, ε. Thus, using OLS estimation might lead to an inconsistent estimate of the coefficient, β₁.

I address the measurement error problem in the independent variable by using a two-stage least squares estimation procedure that introduces an instrumental variable. Specifically, I use a lagged version of the juvenile custody variable as an instrumental variable (Note: this instrument is lagged by two years because data on detention populations are only available every
other year. Additionally, using the lagged custody variable as an instrument requires dropping one year’s worth of observations.). In using the lagged custody variable as an instrument, I assume the lagged custody variable is not correlated with the error term, $\varepsilon$. Also, the lagged custody variable is considered a strong instrument because, as confirmed by regression analysis, it is highly correlated with the non-lagged custody variable. This instrumental variable technique should hopefully eliminate the measurement error problem. The results for this regression are also included in table 2.

Results:

| Table 2 |
|------------------|------------------|
| Estimation of Equation (12) | |
| Dependent Variable: ln(Juvenile Violent Crime Rate) | OLS | 2SLS |
| Estimation Type: | |
| Variable: | |
| ln(Juvenile Custody) | -0.519 | -0.586 |
| | (15.05)** | (5.97)** |
| Unemployment Rate | 0.312 | -0.668 |
| | (.39) | (.75) |
| % Metropolitan | 0.014 | 0.004 |
| | (1.71) | (.35) |
| % Black | -0.007 | -0.016 |
| | (.25) | (.46) |
| Observations | 305 | 253 |
| R-squared | .996 | .997 |
| Includes State and Year fixed effects? | Yes | Yes |
| Absolute value of t-statistics in parentheses | |
| * significant at 5% level; ** significant at 1% level | |

Analysis:

Both the least squares and two-stage least squares estimations produce similar results with the exception of the coefficient on the unemployment variable. Most importantly, both
estimation techniques indicate a significant negative relationship between juvenile violent crime rates and juvenile punishment. Specifically, the least squares estimation indicates that the juvenile violent crime rate approximately decreases by .52 percent for every 1 percent increase in punishment as measured by the custody variable. This result is significant at the 1 percent level. The two-stage least squares estimation produces a slightly more negative coefficient, however, the result is more or less the same. Thus, it appears that punishment is negatively related to juvenile violent crime rates as predicted by the economic model introduced earlier in this paper. Using either estimation procedure the coefficients on percent black and percent metropolitan are both statistically as well as economically insignificant. Finally, the least squares estimation procedure produces a positive coefficient of .31 on the unemployment rate variable, whereas the two-stage least squares produces a negative coefficient of -.67 for the unemployment rate variable. The negative coefficient seems counter-intuitive, as one would expect higher unemployment rates to increase violent crime. However, the results from both estimation procedures are statistically insignificant, and so I need not give too much attention to these contrary and in one-case counter-intuitive results.

Additionally, it is important to add a caveat to these results. Ideally, I could interpret the negative coefficient on the custody variable as proof that higher punishment levels reduce juvenile violent crime rates due to a deterrent effect. However, it is also possible that the observed negative relationship between punishment and juvenile violent crime rates results from an incapacitation effect. This line of argument suggests that harsher punishments don’t succeed in deterring criminal behavior, but rather the observed declines in violent crime rates result from a larger portion of criminals being detained. Thus, the drop in crime rates might not result from fewer people wanting to commit crimes, but rather from fewer people being able to commit
crimes. Unfortunately, the analysis in this paper does not distinguish between the deterrent and incapacitation effect. And so, while I can conclude that harsher punishments do reduce juvenile violent crime rates, I cannot with certainty credit this reduction to deterrence.

**Empirical Model 2:**

*Estimation:*

I estimate the second empirical model, equation (15), using state-level data for the period 1982 – 1992. I first perform this analysis using an ordinary least squares estimation. The results from this regression are listed in table 3. However, as with the first empirical model, this model is also problematic because of potential measurement error in the independent variable, relative punitiveness. Because the dependent variable and the relative punitiveness variable include crime levels for juveniles and adults the presence of measurement error might lead to division bias. Also, measurement error in the relative punitiveness variable will in general cause this independent variable to be correlated with the error term, \( \nu \). Thus, using OLS estimation might lead to an inconsistent estimate of the coefficient, \( \beta_1 \).

I address this problem of measurement error in the independent variable by using a two-stage least squares estimation procedure that introduces an instrumental variable. Specifically, I use a lagged version of the relative punitiveness variable as an instrumental variable. As in the first model, the instrument is a two-year lagged relative punitiveness measure, and because relative punitiveness data exist for every other year I must drop a year’s worth of observations when conducting the two-stage least squares estimation. The lagged relative punitiveness variable is a strong instrument because, as confirmed by regression analysis, it is highly correlated with the non-lagged relative punitiveness variable. Also, I assume that lagged relative
punitiveness is not correlated with the general error term, $\nu$. I present the results for the least squares and two-stage least squares regressions in table 3.

Results:

<table>
<thead>
<tr>
<th>Table 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation of Equation (15)</td>
</tr>
<tr>
<td>Dependent Variable: $\ln(\text{ViolCriRate}<em>{19-21}) - \ln(\text{ViolCriRate}</em>{15-16})$</td>
</tr>
<tr>
<td>Estimation Type:</td>
</tr>
<tr>
<td>Variable:</td>
</tr>
<tr>
<td>$\ln(\text{Adult Custody}) - \ln(\text{Juvenile Custody})$ (or $\ln(\text{Relative Punitiveness})$)</td>
</tr>
<tr>
<td>(10.61)**</td>
</tr>
<tr>
<td>Unemployment Rate</td>
</tr>
<tr>
<td>(.67)</td>
</tr>
<tr>
<td>% Metropolitan</td>
</tr>
<tr>
<td>(9.10)**</td>
</tr>
<tr>
<td>% Black</td>
</tr>
<tr>
<td>(6.67)**</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
</tbody>
</table>

Absolute value of t-statistics in parentheses
* significant at 5% level; ** significant at 1% level

Analysis:

Both the least squares and two-stage least squares estimation techniques produce similar results when regressing equation (15). The most important result is the negative coefficient on the relative punitiveness variable. The least squares estimation indicates that the change in violent crime rates declines by approximately .34 percent for every 1 percent increase in relative punitiveness. This result is significant at the 1 percent level. This implies that when a juvenile enters an adult system that is relatively more punitive compared to the system they are currently in, this has a negative effect on any change in their crime rate. The two-stage least squares
produces a slightly less negative coefficient, however it is also significant and the general interpretation is the same. Additionally, both estimation techniques yield significant coefficients for both the percent black and percent metropolitan variables, however, these coefficients are extremely small and economically speaking rather insignificant. This does not mean that these two variables don’t affect juvenile violent crime rates, but perhaps my initial assumption that facilitated including these control variables despite having differenced out effects consistent across the two respective age groups was incorrect. Finally, both estimation techniques produce a positive coefficient on the unemployment variable. This seems correct, as one would expect higher unemployment to increase the attractiveness of criminal behavior, and thus this should cause changes in crime rates as juveniles transition to the adult justice system to be higher. However, this result is not statistically significant, and so I cannot draw any conclusions from the positive coefficient.

Additionally, the problem of distinguishing incapacitation from deterrence still exists for this model. Thus, while I can conclude that higher relative punitiveness does lower changes in crime rates, I cannot with certainty attribute this effect to deterrence.

**Empirical Model 3:**

*Estimation:*

The third empirical model, represented by equation (16), is estimated using state-level data spanning the period 1982-1992. Unlike the prior two models, I do not introduce a two-stage least squares estimation, but rather I only estimate this model with ordinary least squares estimation (I assume, a priori, that any measurement error in the relative punitiveness variable is not large enough to affect the corresponding value for the Most Relative Punitiveness and Least Relative Punitiveness indicator variables). Results from this estimation are listed in table 4.
Results:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Absolute value of t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Relative Punitiveness</td>
<td>0.233</td>
<td>(4.60)**</td>
</tr>
<tr>
<td>Most Relative Punitiveness</td>
<td>-0.281</td>
<td>(5.81)**</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>0.873</td>
<td>(.99)</td>
</tr>
<tr>
<td>% Metropolitan</td>
<td>-0.009</td>
<td>(9.29)**</td>
</tr>
<tr>
<td>% Black</td>
<td>0.012</td>
<td>(6.38)**</td>
</tr>
</tbody>
</table>

Observations: 305

R-squared: 0.47

Absolute value of t-statistics in parentheses

* significant at 5% level; ** significant at 1% level

Analysis:

As should be expected, the results of regressing model 3 are similar to the results from regressing model 2. The coefficient on the Most Relative Punitiveness variable is both negative and significant at the 1 percent level. This result indicates that in states where the adult justice system is relatively more punitive than the juvenile justice system this has a negative effect on changes in crime rates as juveniles enter the adult justice system. Additionally, table 4 produces a positive coefficient on the Least Relative Punitiveness variable that is also significant at the 1 percent level. This indicates that in states where the adult justice system is not relatively harsh
compared to the juvenile justice system I observe larger increases in violent crime rates for juveniles who enter the adult justice system. Thus, it appears that the lack of harsh punishment causes larger increases in violent crime rates. With respect to the demographic and economic variables, the coefficients on percent metropolitan and percent black are both economically insignificant. The unemployment rate coefficient is positive, as expected, however it is statistically insignificant and thus I cannot draw any conclusions.

**Comparison of Results with Previous Research:**

Comparing my research to prior studies, my results seem to affirm the general conclusions made by both Levitt (1998) and Mocan and Rees (1999). Like my paper, both these studies found a negative relationship between juvenile punishment and juvenile crime. Thus, in a field that has observed limited research with mixed results, my paper provides further support for examining juvenile crime in the context of the economic model of crime.

However, aside from these general comparisons, I am also able to offer a more detailed comparison between my study and the Levitt study because I utilize almost identical data sets, the only difference being I lack arrest data for 1978 and 1979. Firstly, the empirical framework I use is not identical to that used in the Levitt paper. However, when I run Levitt’s empirical specifications I am not able to replicate his results. Specifically, when I compare juvenile violent crime rates and juvenile punishment using Levitt’s specifications I do produce significant results in the expected direction, however, my coefficients are much smaller in magnitude compared to his. (Tables comparing my results with Levitt’s are located in Appendix 1.)

Additionally, the Levitt paper tries to devise a model that distinguishes deterrence from incapacitation. Levitt’s general argument is that by showing how increases in relative punitiveness negatively affect changes in violent crime rates for a cohort immediately before and
immediately after entering the adult justice system that this reveals deterrence as opposed to incapacitation (Levitt 1998).  Levitt backs this conclusion by asserting that immediate changes in crime rates when a juvenile becomes an adult reflect deterrence as opposed to punitiveness (1998).  This assertion is highly questionable, but a more concrete critique of Levitt’s argument is that his conclusion requires that decreases in the adult crime rate variable drive the negative relationship between changes in crime rates and relative punitiveness.  However, because Levitt’s analysis only looks at changes in crime rates, he cannot with certainty attribute the negative relationship between relative punitiveness and changes in crime rates to declines in the adult crime rate.  Thus, it is not clear that harsher adult justice systems deter criminal behavior in youths who have recently become adults.  The bottom line here is that while Levitt claims he proves punishment deters juvenile crime, there is reason to be skeptical about this result.  I contend that given the data utilized in my thesis as well as the Levitt paper, one cannot distinguish the incapacitation and deterrent effects.
VII. Conclusions

At the onset of this paper, I introduced the reader to the economic model of crime and conducted an analysis of the expected utility associated with criminal behavior versus the utility of legitimate work. This analysis produced a general function for violent crime rates which depicted violent crime rates as a function of punishment, age, residence, time, and other economic and demographic factors. Specifically, this function predicted that violent crime rates would decline with increases in punishment.

Given this basic prediction, I then created a set of variables and an empirical framework that allowed me to examine this relationship between violent crime rates and punishment. Ultimately, I produced three empirical models; one that looked at juvenile violent crime rates and juvenile punishment, and two that examined differences in violent crime rates for juveniles and young adults and how relative differences in the punitiveness of the adult and juvenile justice systems affected changes in these crime rates. After estimating these empirical models using both least squares and two-stage least squares estimation procedures, results for the regressions confirmed that juvenile violent crime rates respond negatively to increases in punishment and that differences in punitiveness of juvenile and adult justice systems translate into differences in crime rates for these respective groups.

Having confirmed this expectation, it is crucial to assess what this implies for future research and if there are any policy implications. First, this paper suggests that criminal behavior can be predicted and modeled through the application of expected utility theory to crime. However, much more research needs to be conducted on this front. As discussed earlier, one problem with this analysis is that it does not distinguish deterrence from incapacitation. The problem of separating incapacitation effects from deterrent effects is significantly challenging
when trying to conduct age-specific analysis of crime at the state level. Limited data, particularly with respect to juvenile recidivism, is a key factor impeding the construction and testing of more detailed economic models that better predict criminal behavior. However, this paper does suggest that the economic model of crime has the ability to produce valuable insights about criminal behavior, and thus in so much as this knowledge would aide policy design, it seems imperative that we set out to develop more detailed data sets that enable future analysis.

On the policy front, this paper offers evidence that would-be criminals do respond to incentives, and thus from a policy perspective, justice policy should be seen as a potential means of combating crime. Every year billions of dollars are spent at both the state and federal level in response to juvenile justice issues, with a portion of these funds directed towards detained juvenile delinquents (National Association of State Budget Officers (NASBO) 2004). Additionally, a large portion of the funds directed towards combating more serious juvenile crimes (including violent crimes) currently go towards preventive measures (NASBO 2004). While I do not question the legitimacy of this approach, my results suggest that policymakers might be able to broaden the scope of tools they use to combat serious juvenile crime. Thus, in addition to preventive measures policymakers should also consider alternative changes to punishment levels. By expanding policy options this would hopefully allow for more efficient ways of minimizing juvenile violent crime.
Appendix 1:

In the Levitt paper, Levitt looks at the relationship between juvenile violent crime rates and juvenile punishment by estimating the following equation:

\[
\ln(\text{JuvViolCriRate}_{st}) = \beta_1 \times (\text{JuvCustody}_{st-1}) + \beta_1 \times X'_{st} \Gamma + \lambda_t + \theta_s + \varepsilon_{st}
\]

where \(s\) and \(t\) reference state (1998). Levitt defines juvenile violent crime rate as crime rate for 15 to 17 year olds and this value is derived using equation (9). The custody variable is slightly different than that defined by equation (10); instead of dividing the delinquent detained population by juvenile violent crime, Levitt uses juvenile violent crime for 15 to 17 year olds. \(X\) is a vector of control variables including “the percentage black, the percentage residing in metropolitan areas, the state unemployment rate, the legal drinking age, and the fraction of the state population in the following age groups: under 15, 15-17, 18-24, 25-44, 45-64, 65 and over” (Levitt 1998, p.1162). The \(\lambda\) and \(\theta\) variables indicate year and state dummies, respectively. This equation is similar to equation (12) from my paper. The key differences are that Levitt lags the custody variable and does not take the natural log of this custody variable. Additionally, Levitt defines juveniles slightly differently and he introduces a few additional control variables including dummy variables for the legal drinking age in each state. Also, Levitt runs an additional regression where he includes the natural log of adult violent crime rates and the adult custody measure as independent variables. I present a comparison of my results with Levitt’s results from estimating this equation using ordinary least squares in table 5. Both my estimation and Levitt’s estimation utilize state level-data. The only difference between Levitt’s and my estimation is that my data set lacks arrest data for the years 1979 and 1980, so my estimation has fewer observations.
<table>
<thead>
<tr>
<th>Variable</th>
<th>My Results</th>
<th>Levitt's Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>OLS</td>
</tr>
<tr>
<td>Estimation Type:</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>Juvenile Custody</td>
<td>-0.199</td>
<td>-0.574</td>
</tr>
<tr>
<td></td>
<td>(4.39)**</td>
<td>(5.22)**</td>
</tr>
<tr>
<td>ln(AdultViolCriRate)</td>
<td>0.495</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>(3.28)**</td>
<td>(2.5)*</td>
</tr>
<tr>
<td>Adult Custody</td>
<td>-0.258</td>
<td>-0.135</td>
</tr>
<tr>
<td></td>
<td>(2.34)*</td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>-2.596</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(1.95)</td>
<td>(9)</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(8)</td>
</tr>
<tr>
<td></td>
<td>(1.561)</td>
<td>(6.9)</td>
</tr>
<tr>
<td>% Metropolitan</td>
<td>0.038</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(2.88)**</td>
<td>(2.31)*</td>
</tr>
<tr>
<td></td>
<td>(2.53)*</td>
<td>(2.25)*</td>
</tr>
<tr>
<td>% Black</td>
<td>-0.018</td>
<td>-0.118</td>
</tr>
<tr>
<td></td>
<td>(0.41)</td>
<td>(3.11)**</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(2.94)**</td>
</tr>
<tr>
<td>Drink 18</td>
<td>-0.016</td>
<td>-0.132</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(2.64)*</td>
</tr>
<tr>
<td></td>
<td>(0.51)</td>
<td>(3.24)**</td>
</tr>
<tr>
<td>Drink 19</td>
<td>-0.024</td>
<td>-0.179</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(3.81)**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(3.63)**</td>
</tr>
<tr>
<td>Drink20</td>
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<td>0.005</td>
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<td></td>
<td>(0.65)</td>
<td>(0.069)</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.136)</td>
</tr>
<tr>
<td>Observations</td>
<td>302</td>
<td>395</td>
</tr>
<tr>
<td></td>
<td>302</td>
<td>395</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.94</td>
<td>0.939</td>
</tr>
<tr>
<td></td>
<td>0.95</td>
<td>0.941</td>
</tr>
<tr>
<td>Includes age, year, and state fixed-effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Absolute value of t-statistics in parentheses

* significant at 5% level; ** significant at 1% level

I am not going to offer a detailed analysis of the results, but rather I want to draw attention to the disparity in the juvenile custody coefficients for my regressions versus Levitt’s regressions. This tends to undermine the magnitude of the relationship between juvenile violent crime rates and juvenile punishment as indicated in the Levitt paper.
References


