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POLICE, PROSECUTORS, CRIMINALS, AND DETERMINATE SENTENCING: THE TRUTH ABOUT TRUTH-IN-SENTENCING LAWS*

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ABSTRACT

This study explores the impact of truth-in-sentencing (TIS) legislation on police, prosecutors, and criminals. Truth-in-sentencing laws are determinate-sentencing laws that require violent offenders to serve at least 85 percent of their prison sentences. The standard economic model of crime suggests that TIS laws will deter violent offenders but also reduce probabilities of arrest and conviction. However, I explain that if states share the goals of TIS legislation, police and prosecutors may increase these probabilities. My theoretical model also predicts that the legislation will cause more trials and impose higher maximum prison sentences. Using a county-level data set, empirical results confirm that TIS laws deter violent offenders, increase the probability of arrest, and increase maximum imposed prison sentences. Truth-in-sentencing laws decrease murders by 16 percent, aggravated assaults by 12 percent, robberies by 24 percent, rapes by 12 percent, and larcenies by 3 percent. However, offenders substitute into property crimes: burglaries increase by 20 percent and auto thefts by 15 percent.

I. INTRODUCTION

BEFORE the 1970s, criminal punishment was based on a system of indeterminate sentencing. This system allowed much discretion: judges had almost complete discretion over court-imposed prison sentences, and state parole boards controlled the actual length of time that offenders served.[1] To reduce this discretion, which critics argued promoted unfair disparity, structured or determinate-sentencing reforms arose in the 1970s. They included sentencing guidelines, mandatory minimums, parole board abolition, habitual-offender laws, and truth-in-sentencing legislation.

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[1] Brian J. Ostrom *et al*., Sentencing Digest: Examining Current Sentencing Issues and Policies 8 (1998).

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Studies have found that determinate policies indeed reduce sentencing disparity.[2] However, they create two potential costs. First, they prevent judges and officials from adjusting penalties to assure proportionality between crime and punishment.[3] Second, they cause longer prison sentences and prison stays,[4] which increases incarceration costs.

Supporters respond that determinate sentencing's costs are offset by its crime-reducing benefits through rehabilitation, incapacitation, and deterrence. However, longer determinate sentences may produce few benefits through rehabilitation and incapacitation. Some contend that laws that warehouse offenders for long periods reflect the criminal justice system's conclusion that rehabilitation is impossible.[5]

Likewise, additional incapacitation from mandatory penalties, while expensive, may have few benefits. The commission of serious crimes is age specific. Almost all violent crimes are committed by offenders in their late teens and early twenties, and most property crimes are committed by offenders in their late teens.[6] Long sentences have little incapacitation effect on crime reduction because prisoners remain in jail at ages when they would have stopped offending.[7]

Even if determinate sentencing produces few benefits through incapacitation and rehabilitation, it could still provide large benefits by deterring potential offenders. Determining the size of this deterrent effect is one of this paper's objectives. In addition, I examine the general effects of determinate-sentencing policies on criminals and the criminal justice system.

I first discuss and develop theoretical models of the behavior of police, prosecutors, and criminals and their expected response to the longer threatened incarceration periods of determinate sentencing. Then, in my empirical examination, I focus on truth-in-sentencing (TIS) legislation, by far the most

[2] James M. Anderson, Jeffrey R. Kling, & Kate Stith, Measuring Interjudge Sentencing Disparity: Before and after the Federal Sentencing Guidelines, 42 J. Law & Econ. 271, 298 (1999); Joel Waldfogel, Does Inter-judge Disparity Justify Empirically Based Sentencing Guidelines? 18 Int'l Rev. L. & Econ. 293, 303 (1998).

[3] Waldfogel, *supra* note 2, at 304.

[4] U.S. Sentencing Commission, The Federal Sentencing Guidelines: A Report on the Operation of the Guidelines System and Short-Term Impacts on Disparity in Sentencing, Use of Incarceration, and Prosecutorial Discretion and Plea Bargaining, Executive Summary (1991); Chantale LaCasse & A. Abigail Payne, Federal Sentencing Guidelines and Mandatory Minimum Sentences: Do Defendants Bargain in the Shadow of the Judge? 42 J. Law & Econ. 245, 252 (1999); Jose Meade & Joel Waldfogel, Do Sentencing Guidelines Raise the Cost of Punishment? 16 (Working Paper No. 6361, Nat'l Bur. Econ. Res. 1998).

[5] Frank E. Zimring & Gordon Hawkins, Incapacitation 22–25 (1995).

[6] Alfred Blumstein, Prisons, in Crime 387, 392 (James Q. Wilson & Joan Petersilia eds. 1995); Michael Tonry, Sentencing Matters 139 (1996).

[7] Carl Schmertmann, Adansi Amankwaa, & Robert Long, Three Strikes and You're Out: Demographic Analysis of Mandatory Prison Sentencing, 35 Demography 445, 459 (1998); Ryan S. King & Marc Mauer, Aging behind Bars: "Three Strikes" Seven Years Later 4, 6 (report, The Sentencing Project, August 2001).

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common determinate-sentencing reform in the 1990s at both the federal and state levels.[8]

This paper is the first study to use regression analysis to explore the impact of TIS laws on criminals and state criminal justice systems.[9] The results show that TIS laws deter offenders from committing violent crimes but that these offenders substitute into property crimes instead. Truth-in-sentencing laws also cause the probability of arrest to increase for crimes covered by the laws, which suggests that police and prosecutors do not counteract the intentions of the TIS legislation. Likewise, my results suggest that TIS laws cause maximum prison sentences to increase as more offenders choose trials instead of plea bargains to avoid longer prison stays. Although my empirical estimation focuses on TIS laws, the theory and implications apply to other determinate-sentencing policies as well.[10]

The paper is organized as follows. Section II presents the background of TIS laws, and Section III discusses the theoretically predicted effects of TIS laws on the probabilities of apprehension, prison sentences, and crime. Section IV presents the econometric model and the data that are used in this analysis. Section V gives the results of the estimation, and Section VI concludes.

II. Truth-in-Sentencing Legislation

In 1994, the U.S. Congress authorized incentive grants to build or expand correctional facilities through the Violent Offender Incarceration and Truth-in-Sentencing Incentive Grants Program in the 1994 Crime Act.[11] The federal TIS grants, which are administered by the Department of Justice's Corrections Program Office, are awarded to states that can prove that offenders convicted of a part 1 violent crime[12] serve at least 85 percent of their sentences. In Table 1, we see that five states had adopted TIS laws before the passage of

[8] Ostrom *et al*., *supra* note 1, at 14.

[9] The only other empirical study compares the raw data on crime rates and prison admissions for TIS and non-TIS states. Turner *et al*., Symposium: The Impact of Truth-in-Sentencing and Three Strikes Legislation: Prison Populations, State Budgets, and Crime Rates, 11 Stan. L. & Pol'y Rev. 75 (1999). The authors conclude that because TIS and non-TIS states have similar violent crime rates before and after the legislation, there is no deterrent effect. They also conclude that because the percent of prison admissions for violent crimes is similar for TIS and non-TIS states, these laws have no effect on arrest rates. The authors concede that "more sophisticated analytic techniques no doubt can be used to tease out" the effects of TIS laws. See *id*. at 79.

[10] For example, the increased penalty resulting from two- and three-strikes legislation deters crime. Joanna M. Shepherd, Fear of the First Strike: The Full Deterrent Effect of California's Two- and Three-Strikes Legislation, 31 J. Legal Stud. 159 (2002).

[11] Pub. L. No. 103-322, 108 Stat. 1796 (1994).

[12] Part 1 violent crimes include murder and nonnegligent manslaugter, forcible rape, robbery, and aggravated assault as reported to the Federal Bureau of Investigation (FBI) for purposes of the Uniform Crime Reports. U.S. General Accounting Office, Truth in Sentencing: Availability of Federal Grants Influenced Laws in Some States 2 (1998).

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TABLE 1

ENACTMENT OF STATE TRUTH-IN-SENTENCING LAWS BEFORE 1997

State	Year Enacted	State	Year Enacted
Arizona	1994	Missouri	1994
Connecticut	1996	New York	1995
California	1994	North Carolina	1994
Delaware	1990	North Dakota	1995
Florida	1995	Ohio	1996
Georgia	1995	Oregon	1995
Illinois	1996	Pennsylvania	1911
Iowa	1996	South Dakota	1996
Kansas	1995	Tennessee	1995
Maine	1995	Utah	1985
Michigan	1994	Virginia	1995
Minnesota	1993	Washington	1990
Mississippi	1995		

SOURCE.—U.S. General Accounting Office, Truth in Sentencing: Availability of Federal Grants Influenced Laws in Some States (1998).

the 1994 Crime Act.[13] Twenty states qualified between 1994 and 1996, and since 1996, the 25 remaining states, the District of Columbia, and the U.S. territories have enacted such laws. In 1996, the Department of Justice awarded a total of $195.8 million in TIS grants.[14]

III. THEORETICALLY PREDICTED EFFECTS OF DETERMINATE SENTENCING

I now discuss the theoretical predictions for TIS laws that increase the penalty for violent offenders. The implications would be similar for other determinate policies that increase the penalties for some crimes more than others.

[13] There were slight differences between the earlier laws and the eligibility requirements of the federal TIS program. For example, in Delaware, individuals convicted of any crime, property or violent, were required to serve at least 75 percent of their maximum sentence. The early law in Washington State mandated that individuals convicted of a serious violent felony serve 85 percent of their maximum sentence, but the law was later broadened to include all violent felons as required by the federal TIS program. The early Pennsylvania law required that the minimum sentence of all offenders be not more than half of the maximum sentence; prisoners served an average of 124 percent of the minimum sentence. Bureau of Justice Statistics (BJS) data indicate that Minnesota is one of the top states in time-served calculations; the TIS law in this state requires all felons to serve 100 percent of their maximum prison sentence. Many of the earlier laws were adjusted to meet the eligibility requirements of the 1994 Crime Act. National Institute of Corrections, State Legislative Actions on Truth in Sentencing 6-28 (1995).

[14] U.S. General Accounting Office, *supra* note 12.

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A. Crime Levels

The standard economic model of crime predicts that the enactment of TIS laws will deter the crimes covered by the laws.[15] The legislation's increased penalties for violent crimes will lower the expected utility from violent offending and deter some offenders from committing violent crimes.

The economic model of crime also predicts that a TIS law that increases the penalty for violent crimes may cause some offenders to substitute out of violent crimes and into property crimes.[16] Other studies have found that laws that increase the costs for certain crimes will cause substitution into other crimes.[17]

In addition, there may be a trade-off between marginal deterrence and total deterrence. A stronger penalty for robbery may deter some robberies, but it may result in more murders as some robbers choose to kill the victims to eliminate witnesses.[18] Other studies have found that longer prison sentences result in an increase in murder.[19]

We are at a fortunate point to study the impact of TIS legislation; examining crime levels in the years immediately following a law change allows for the separation of the legislation's deterrent effect from its incapacitation effect.[20] The data analyzed in this paper end in 1996, so there are 3 years of post–1994 Crime Act data. The lowest mean minimum sentence for a violent crime in 1990 is over 4 years.[21] Therefore, any additional incapacitative effect on

[15] Gary S. Becker, Crime and Punishment: An Economic Approach, 76 J. Pol. Econ. 169, 177 (1968).

[16] If both a violent crime and a property crime have positive expected net benefits before the passage of the TIS law, the rational criminal should commit both crimes. However, because time is scarce, at least some offenders will have time to commit only one of the crimes. For those who have initially chosen the violent crime, a TIS law that increases the costs of violent crimes may make the property crime more attractive in comparison. Moreover, many violent crimes, such as assault and murder, are initially motivated by monetary concerns. For example, a pocket picking or burglary may become a murder or aggravated assault if the criminal is caught in the act. However, when multiple offenses occur at one time, police classify the crime by the most serious offense. For example, when police find a murder victim in their own house or with their wallet missing, they classify the crime as a murder, not a burglary and murder or pocket picking and murder. A law that deters murders would result in these crimes being classified as property crimes instead.

[17] John DiNardo & Thomas Lemieux, Alcohol, Marijuana, and American Youth: The Unintended Effects of Government Regulation (Working Paper No. 4212, Nat'l Bur. Econ. Res. 1992); John R. Lott, Jr., & David B. Mustard, Crime, Deterrence and Right-to-Carry Concealed Handguns, 26 J. Legal Stud. 1 (1997); Shepherd, *supra* note 10.

[18] Richard A. Posner, An Economic Theory of the Criminal Law, 85 Colum. L. Rev. 1193, 1207 (1985).

[19] Thomas B. Marvell & Carlisle E. Moody, The Lethal Effects of Three-Strikes Laws, 30 J. Legal Stud. 89, 96 (2001).

[20] Daniel Kessler & Steven D. Levitt, Using Sentence Enhancements to Distinguish between Deterrence and Incapacitation, 42 J. Law & Econ. 343, 345 (1999).

[21] Paula M. Ditton & Doris Wilson, Truth in Sentencing in State Prisons 7 (1999).

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crime rates resulting from TIS laws cannot yet be seen in these data, so most of the variation in crime can be attributed to deterrence.

In addition, we can gain insight into the relative importance of deterrence and incapacitation by examining the response of property crimes to changes in the penalties for violent crimes. If the deterrent effect predominates, we would expect an increase in the expected penalty for one crime to cause substitution into other crimes.[22] The incapacitation effect, on the other hand, predicts that the increased penalty for one crime would reduce the number of both crimes as offenders who commit either type of crime remain incarcerated.

B. Probability of Arrest

The economic model of crime and punishment also offers two conflicting testable hypotheses about the attitudes of states and counties toward the TIS laws. The traditional economic model indicates the relationship between the optimal magnitude of the penalty and the optimal probability of receiving a penalty: the larger the penalty, the lower the optimal probability of detection.[23] Applying the model, if social welfare is initially maximized, an increase in penalties from TIS laws should be accompanied by a decrease in the probability of apprehension. Because increasing the penalty increases the costs of enforcement (larger prison populations, greater prosecution and court expenditures for more trials, and so on), the probabilities must decrease to bring the marginal cost of enforcement back into balance with the marginal benefits. Intuitively, a state or county that is initially content with the deterrence from its law enforcement may accept the federal TIS money but then attempt to counteract the longer sentence's additional unwanted deterrence by reducing the probability of arrest. This counteraction effect has been found empirically in analyses of the impact of mandatory minimum laws, which effectively increase the penalty for certain offenses. Such laws cause declining rates of arrests, indictments, and convictions.[24]

However, with one different assumption, theory predicts that TIS laws could cause higher arrest rates. A new "tough on crime" sentencing law may signal that the marginal costs and benefits of law enforcement are no longer in equilibrium and social welfare is not maximized. The TIS laws, instead of being imposed by the federal government on reluctant states and counties, may instead reflect and inspire new vigor in the states for combating crime. Responding to the public's new demand for tougher crime-fighting policies, police and prosecutors, emboldened and encouraged by the TIS laws, may increase the probabilities of arrest and conviction. Empirical estimation will

[22] Steven D. Levitt, Why Do Increased Arrest Rates Appear to Reduce Crime: Deterrence, Incapacitation, or Measurement Error? 36 Econ. Inquiry 353, 354 (1998).

[23] Becker, *supra* note 15, at 183.

[24] Michael Tonry, Sentencing Reform Impacts (1987).

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reveal which assumption is true: whether police and prosecutors seek to counteract TIS goals by decreasing the probability of detection or whether they share and promote them by increasing the probability.

C. Prison Sentences

Truth-in-sentencing laws should have an impact on both the fraction of a prison sentence actually served and the maximum imposed sentence. A convicted criminal receives a maximum sentence, but the time actually served in prison may be substantially less than the maximum sentence. Before TIS laws, prison parole boards often released prisoners early. Because TIS laws restrict early-release programs, the prison term should increase, at least in terms of the percentage of the prisoner's maximum sentence.

In addition, TIS legislation should increase the median and average maximum imposed court sentence, as the following theoretical model suggests. A defendant can choose either to accept a plea bargain or to try the case.[25] The expected losses from a plea bargain and demanding a trial are, respectively,

$$L_b = sF_b \tag{1}$$

and

$$L_t = psF_t + C_t, \tag{2}$$

where F_b is the prison sentence agreed upon in the plea bargain, F_t is the sentence the prosecutor demands if the case is tried, s is the percentage of the prison sentence the individual expects to serve ($0 \leq s \leq 100$), p is the defendant's expected probability of losing in a trial ($0 \leq p \leq 100$), and C is the defendant's costs from trial.

Assuming risk neutrality, a defender will be indifferent between accepting a plea and going to trial when the expected losses are equal:

$$sF_b = psF_t + C_t. \tag{3}$$

Suppose a TIS law changes the prison time served by proportion x. The new indifference condition is

$$xsF_b = pxsF_t + C_t, \tag{4}$$

or, rearranging,

$$x = C_t/(sF_b - psF_t). \tag{5}$$

[25] For simplicity, I am assuming that the prosecutor and the justice system have already optimally chosen the penalties for a plea bargain and a trial. The penalties will reflect the benefits to the prosecutor of getting a conviction and the costs of going to trial. In my model, these penalties have already been set; the alleged criminal must now choose between plea bargaining and trial.

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When x exceeds this value, the defendant chooses trial, and when x is less than this value, he or she pleads. The defendant who before the law was just indifferent between accepting a plea and going to trial (equation (3)), will remain indifferent if equation (5) holds.[26] However, if equation (3) holds, then equation (5) holds only if $x = 1$. For any $x > 1$, the formerly indifferent defendant will now choose trial. That is, a TIS law should cause some additional defendants to demand trials and thereby reduce the proportion of guilty pleas.[27]

The reduction in pleas should cause average and median maximum sentences, as recorded in the data, to increase. Defendants who plead tend to receive shorter sentences than those who are convicted at trial; prosecutors offer "plea discounts" to avoid trial costs.[28] In addition, some defendants who were induced to change from accepting a plea to going to trial will be acquitted and receive no prison sentence and thus disappear from my sample. Had they accepted a plea, as they would have prior to the TIS law, their plea-discounted sentence would have lowered the average and median maximum imposed sentence.

IV. Econometric Model and Data

To test the implications suggested by the theory in Section III, I must specify an estimable model. A system of equations representing the response of criminals and the criminal justice system will characterize the behavior that results from the passage of TIS laws. I will use the economic model of crime to identify the equations and then estimate them in a simultaneous-equation model.

A. Supply of Offenses

The "market model" of crime is based on the interaction between offenders and law enforcers.[29] The behavior of offenders is represented by a supply-of-offenses equation in which a person's decision to engage in criminal activity is motivated by the expected costs and gains from offenses. Expected costs include the direct costs incurred by acquiring loot, prospective penalties that are discounted by the probability of apprehension and conviction, and the forgone wages from legitimate activity. The expected illegitimate payoff

[26] This assumes that the change in x does not alter the other variables in the model.

[27] Anecdotal evidence confirms this. See Steven Wisotsky, Exposing the War on Cocaine: The Futility and Destructiveness of Prohibition, 1983 Wis. L. Rev. 1305, 1389; David Schultz, No Joy in Mudville Tonight: The Impact of "Three Strike" Laws on State and Federal Corrections Policy, Resources, and Crime Control, 9 Cornell J. L. & Pub. Pol'y 557, 575 (2000).

[28] U.S. General Accounting Office, Report to Congressional Committees: Sentencing Guidelines: Central Questions Remain Unanswered (1992).

[29] Isaac Ehrlich, Crime, Punishment, and the Market for Offenses, 10 J. Econ. Persp. 43 (1996).

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(monetary and/or psychic) is the gain from criminal activity. The supply of offenses can therefore be represented by

$$C = C(Pa,\ Pc|a,\ \text{TIS},\ Z,\ \text{TD},\ u), \tag{6}$$

where C is the crime rate. The probability of arrest, Pa, the probability of conviction given arrest, $Pc|a$, and the TIS dummy variable, which indicates when a state passes a TIS law, represent the expected costs of engaging in criminal activity. An increase in these variables is an increase in the expected costs of crime, and, therefore, we would expect the crime rate to decrease.

The variable Z contains a series of demographic and economic variables that proxy for legitimate and illegitimate earning opportunities. An increase in legitimate earning opportunities increases the opportunity cost of committing crime and should result in a decrease in the crime rate. An increase in illegitimate earning opportunities increases the expected benefits of committing crime and should result in an increase in the crime rate.

The economic variables in Z are real per capita personal income, real per capita unemployment insurance payments, and real per capita income maintenance payments. The income variable measures both the labor market prospects of potential criminals and the amount of wealth available to steal. The unemployment payments variable is a proxy for overall labor market conditions and the availability of legitimate jobs for potential criminals. The transfer payments variable represents other nonmarket income earned by poor or unemployed people. Other studies have found that crime responds to measures of both income and unemployment but that the effect of income on crime is stronger.[30]

The demographic variables included in Z are population density, the percentage of the county population that is between 10 and 19 years of age, the percentage of the county population that is between 20 and 29 years of age, the percentage of the county population that is male, the percentage of the county population that is African-American, the percentage of the county population that is a member of some minority group other than African-American, the National Rifle Association (NRA) membership rate, and the crime rate of other-category crimes. Population density is included to capture any relationship between drug activities in inner cities and crime rates. The age, gender, and race variables represent the possible differential treatment of certain segments of the population by the justice system, changes in the opportunity cost of time through the life cycle, and gender- or race-based differences in earning opportunities. The NRA membership rate in the state is included to capture the effect of state gun ownership on crime rates. The other-category crime rate is the crime rate of property crimes when a violent crime is estimated and the crime rate of violent crimes when a property crime

[30] Eric D. Gould, David B. Mustard, & Bruce A. Weinberg, Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997, 84 Rev. Econ. & Stat. 45 (2002).

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is estimated. This variable is included to capture overall trends in crime and the possible substitution between property and violent crimes. These county-level economic and demographic variables are included following other studies based on the economic model of crime.[31]

The time dummies in equation (6), TD, capture trends in crime that do not vary across counties but change over time. In addition, county dummies are included to control for unobservable variables that differ among counties, such as differences in crime, attitudes toward crime, or differences in the justice system. The variable u represents other unobservable variables that affect the supply of crime.

B. The Production Functions of the Police and Court System

The probability of arrest and the probability of conviction given arrest represent the activities of the police and prosecutors as they protect the public from criminals. In the economic model of crime, the relationship between the activities of the criminal justice system and the supply of crime is summarized via a production function.[32] The production function that represents the activities of the police identifies the probability of arrest, while the production function that represents the activities of prosecutors identifies the probability of conviction given arrest. The production functions are

$$Pa = Pa(C, \text{PE}, \text{PW}, \text{TIS}, \text{TD}, \xi) \tag{7}$$

and

$$Pc|a = Pc|a(C, JE, PI, \text{TIS}, TD, \zeta). \tag{8}$$

The TIS dummy variable captures the effect of TIS laws on the probabilities of arrest and conviction given arrest. The coefficient's sign will depend on whether states and counties counteract or promote the TIS laws' additional deterrence.

If police and prosecutors attempt to minimize the social costs of crime, they must balance the marginal costs of enforcement with the marginal benefits of crime prevention. Police and judicial/legal expenditure variables, PE and JE, represent marginal costs of enforcement. Increases in crime will increase the demand for protection and the resources allocated to crime

[31] Lott & Mustard, *supra* note 17; John R. Lott, Jr., & William M. Landes, Multiple Victim Public Shootings, Bombings, and Right-to-Carry Concealed Handgun Laws: Contrasting Private and Public Law Enforcement (John M. Olin L. & Econ. Working Paper No. 73, Univ. Chicago L. Sch. 1999); David B. Mustard, Reexamining Criminal Behavior: The Importance of Omitted Variable Bias, Rev. Econ. & Stat. (forthcoming); Earl L. Grinols, David B. Mustard, & Cynthia H. Dilley, Casinos, Crime and Community Costs (Working paper, Univ. Ill. & Univ. Georgia 2000); Hashem Dezhbakhsh, Paul Rubin, & Joanna M. Shepherd, Does Capital Punishment Have a Deterrent Effect? New Evidence from Post-moratorium Panel Data (Working paper, Emory Univ., Dep't Econ. 2001); Shepherd, *supra* note 10.

[32] See generally Becker, *supra* note 15; Ehrlich, *supra* note 29.

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prevention. More expenditure should increase the productivity of law enforcement, or increase the probabilities of arrest and conviction given arrest. The crime rate, C, represents a marginal benefit of enforcement. The police and court systems may respond to increases in crime by increasing their own efforts to combat crime; thus, we would expect an increase in crime rates to be accompanied by increases in the probability of arrest and conviction given arrest.

The partisan influence variable, PI, represents any partisan influence on the makeup of the court system such as the appointment of new judges or prosecutors who are "tough on crime." The number of police officers, PW, captures the effect of the number of police on arrest rates. We would expect this variable to have a positive impact on arrest rates as increases in the number of police allow each officer to devote more effort to each case. Once again, TD is a set of time dummies that captures trends and influences in attitudes, crime, or police and prosecutor efforts that impact all counties but vary over time. County dummies are included to control for unobservable variables that differ among counties, and ξ and ζ represent other unobservable influences on the probabilities of arrest and conviction given arrest.

The supply-of-crime function in equation (6) and the production of public enforcement functions in equations (7) and (8) are the fundamental components of the market for offenses.[33]

C. Public Demand for Truth-in-Sentencing Legislation

A fourth equation represents the public demand for TIS laws that increase the incarceration period for violent offenders. The equation measuring the influences on the passage of TIS laws is

$$\text{TIS} = \text{TIS}(C, \text{MAX}, \text{PI}, \text{TD}, v). \tag{9}$$

[33] According to the standard market model, the supply of crime depends on the efforts of police and prosecutors, the efforts of police and prosecutors depend on the level of police and judicial resources, and the level of police and judicial resources depend on the supply of crime. Ehrlich, *supra* note 29. The third equation, the police and judicial resources equation, represents society's demand for protection. However, many studies do not specify an endogenous resources equation (Isaac Ehrlich, The Deterrent Effect of Capital Punishment: A Question of Life and Death, 65 Am. Econ. Rev. 397 (1975); Isaac Ehrlich, Capital Punishment and Deterrence: Some Further Thoughts and Additional Evidence, 85 J. Pol. Econ. 741 (1977); Lott & Mustard, *supra* note 17; Dezhbakhsh, Rubin, & Shepherd, *supra* note 31; Shepherd, *supra* note 10) because tests indicate that police variables are exogenous. William N. Trumbull, Estimations of the Economic Model of Crime Using Aggregate and Individual Data, 56 S. Econ. J. 423, 428 (1989). My own tests for exogeneity confirm that the police and judicial resources are exogenous. The exogeneity may be the result of a lack of data and a misunderstanding of the actual allocation of criminal justice resources and the incentives of the bureaucrats who decide how to allocate the resources. Bruce L. Benson, Iljoong Kim, & David W. Rasmussen, Estimating Deterrence Effects: A Public Choice Prospective on the Economics of Crime Literature, 61 S. Econ. J. 161, 162 (1994). Because the police and judicial resources are exogenous to the system of equations, but still affect the efforts of police and prosecutors, they enter in the production function equations.

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The crime rate, *C*, is included to test the effect of crime rates on the public's demand for TIS laws. High violent crime rates may increase the public's demand for longer sentences and lead to the adoption of TIS laws. The partisan influence variable, PI, captures any "get tough on crime" attitude that could result in the passage of TIS legislation. Maximum sentence lengths, MAX, represent the public belief that prison sentences were previously too short and, thus, public demand for TIS legislation.

Again, TD is a set of time dummies that captures trends in attitudes toward crime and imprisonment that are constant across counties but vary over time. County dummies are also included to control for unobservable variables that differ among counties, and *v* represents other unobservable influences on the passage of TIS laws.

D. Behavior of Courts and Apprehended Criminals

Another equation represents the behavior of the court system and apprehended criminals.[34] As discussed in Section III, theory suggests that both the court system and apprehended criminals influence the maximum sentence imposed in each case. The equation measuring the effects on maximum imposed prison sentences is

$$\mathrm{MAX} = \mathrm{MAX}(\mathrm{TIS},\ \mathrm{CE},\ \mathrm{PI},\ \mathrm{TD},\ \varepsilon), \tag{10}$$

where MAX represents measures of the maximum imposed prison sentence (both mean and median maximum sentence are estimated). The TIS dummy variable is included to test the effect of more trials on maximum imposed prison sentences. The maximum sentence imposed on convicted offenders depends in part on whether the offender accepted a plea bargain or went to trial. Theory has shown that a TIS law that increases the time served in prison will induce some offenders to go to trial instead of accepting a plea bargain. An increase in the proportion of cases resolved by trial should increase average and median maximum imposed prison sentences because offenders do not receive the plea-discounted sentence and instead either receive longer sentences from trial convictions or are acquitted, which does not affect the sentence length calculations.

Expenditure on the correctional system, CE, captures the effect of limited resources on sentence lengths. We would expect sentence lengths to decrease when there are insufficient funds devoted to prisons. The partisan influence variable, PI, captures public pressure to get tough on crime and increase sentence lengths.

Again, TD is a set of time dummies that captures trends in attitudes toward crime and imprisonment that are constant across counties but vary through

[34] Hausman and Lagrange Multipler tests confirm the endogeneity of the TIS and MAX variables. Russell Davidson & James G. MacKinnon, Estimation and Inference in Econometrics 237–42 (1993); Jack Johnston & John DiNardo, Econometric Methods 256 (1997).

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time. County dummy variables are included to capture county differences in attitudes toward crime and imprisonment that are constant over time. The error term, ε, represents other unobservable influences on prison sentences.

E. System of Equations

The estimable system of equations that represents the market for offenses based on equations (6)–(10) is then[35,36,37]

$$C_{i,t} = \alpha_{1,i} + \alpha_2 Pa_{i,t} + \alpha_3 Pc|a_{i,t} + \alpha_4 \mathrm{TIS}_{i,t} + \alpha_5 Z_{i,t} + \alpha_6 \mathrm{TD}_t + u_{i,t}, \quad (11)$$

$$Pa_{i,t} = \beta_{1,i} + \beta_2 C_{i,t} + \beta_3 \mathrm{TIS}_{i,t} + \beta_4 \mathrm{PE}_{i,t} + \beta_5 \mathrm{PW}_{i,t} + \beta_6 \mathrm{TD}_t + \xi_{i,t}, \quad (12)$$

$$Pc|a_{i,t} = \theta_{1,i} + \theta_2 C_{i,t} + \theta_3 \mathrm{TIS}_{i,t} + \theta_4 \mathrm{JE}_{i,t} + \theta_5 \mathrm{PI}_{i,t} + \theta_6 \mathrm{TD}_t + \zeta_{i,t}, \quad (13)$$

$$\mathrm{TIS}_{i,t} = \eta_{1,i} + \eta_2 C_{i,t} + \eta_3 \mathrm{MAX}_{i,t} + \eta_4 \mathrm{PI}_{i,t} + \eta_5 \mathrm{TD}_t + \upsilon_{i,t}, \quad (14)$$

and

$$\mathrm{MAX}_{i,t} = \psi_{1,i} + \psi_2 \mathrm{TIS}_{i,t} + \psi_3 \mathrm{CE}_{i,t} + \psi_4 \mathrm{PI}_{i,t} + \psi_5 \mathrm{TD}_t + \varepsilon_{i,t}. \quad (15)$$

The subscript i denotes county i, the subscript t denotes year t, and $Pc|a$—the probability of conviction given arrest—is approximated by the probability of imprisonment once arrested, $Pi|a$.[38] I estimate the simultaneous system

[35] In the estimation of the murder rate, an additional probability, the conditional probability of execution given sentencing, is included in equation (11).

[36] I am able to eliminate some of the measurement error in the murder arrest and conviction rates by specifying these probabilities as endogenous and using their predicted values. Many small counties do not have any murders. This would generate an undefined arrest rate because the number of murders is the denominator in the arrest rate. Similarly, if a county had no murder arrests, the conviction rate would be undefined. However, I create predicted arrest and conviction rates for the missing observations using equations (12) and (13) and then use the predicted values in the second stage of my regressions. This eliminates the measurement error in my estimation of crime and maximum sentences but not in my estimation of arrest rates. However, studies have found that measurement error in crime and arrest data has little effect on results. Levitt, *supra* note 22, at 354. In addition, the problem is eliminated when I reestimate the model using state-level data.

[37] Another possible specification would include MAX and $Pi|a$ in the probability-of-arrest equation (12) and MAX in the supply-of-offenses equation (11). This alternative specification yields very similar results; the TIS variable is similar in magnitude and significance to the primary specification across all crimes.

[38] The term $Pi|a$ is a proxy for probability of conviction given arrest, $Pc|a$. Conviction data have not been collected at the state or county level for a number of years, so the probability of imprisonment given arrest is the closest probability available. However, omitting the conviction probability may underestimate the true effect of arrest rates on crime. Studies have found that the omitted variable bias resulting from the exclusion of the probability of conviction may understate the true impacts of the arrest rate on crime by 11–43 percent. Mustard, *supra* note 31, at 16.

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of equations (11)–(15) with a two-stage least squares regression.[39] The estimation is weighted to correct for the heteroskedasticity of the error term.[40]

To test the theoretical predictions discussed above, I use a county-level data set covering all 3,054 counties in the United States for the period 1984–96. The time dimension of the data set is used to estimate county fixed effects, and I condition the estimation on these effects. County-specific characteristics could be correlated with the justice system variables and result in biased estimation. However, a county-level data set allows me to control for any unobservable heterogeneity and better isolate the effects of the TIS laws.

The data include county-level crime and arrest data for the violent crimes of murder, aggravated assault, robbery, and rape and the property crimes of larceny, burglary, and auto theft.[41] Also included are various sentencing var-

[39] I chose a single-equation method, two-stage least squares, over a systems method because in a systems method any specification error in one equation is propagated throughout the system, which can lead to inconsistency. William H. Greene, Econometric Analysis 616 (1993). Single-equation methods, such as two-stage least squares, confine the error to the particular equation in which it appears.

[40] These equations represent the aggregation of an individual's equations. In the individual equations, the error terms are stochastic with mean 0 and variance σ^2. Because of this, when the error terms are summed over n (the number of people in the county), the new error terms are heteroskedastic because their variances (σ^2/n) are proportional to county population. Tests for heteroskedasticity indicate that the error term in the unweighted regression is indeed heteroskedastic. Greene, *supra* note 39, at 395. Tests indicate that the heteroskedasticity has been corrected after weighting by the square root of the county population. In addition, tests for overidentification indicate that the model is correctly specified and employs valid instruments. Davidson & MacKinnon, *supra* note 34, at 235–36.

[41] Although the FBI Uniform Crime Report Data are the best county-level crime data currently available, there are some potential issues associated with the measurement error from underreporting and the estimation of missing data. Federal Bureau of Investigation, Uniform Crime Reports for the United States (1984–96). Nevertheless, many studies use the FBI county-level crime and arrest data. Lott & Mustard, *supra* note 17; Lott & Landes, *supra* note 31; Mustard, *supra* note 31; Gould, Mustard, & Weinberg, *supra* note 30; Grinols, Mustard, & Dilley, *supra* note 31; Dezhbakhsh, Rubin, & Shepherd, *supra* note 31; Shepherd, *supra* note 10. The FBI data include only reported crime data. Because not all crimes are reported to the police, there may be a difference between committed and reported crimes. This measurement error could vary by county or crime. However, studies have found that measurement error in crime and arrest data has little effect on results. Levitt, *supra* note 22, at 354. The inclusion of county fixed effects eliminates the effects of time-invariant differences in reporting methods across counties, and estimates of trends in crime should be accurate as long as reporting methods are not correlated across counties or time. Gould, Mustard, & Weinberg, *supra* note 30. Moreover, one way to address the problem of underreporting is to use the logarithms of crime rates, which are usually proportional to true crime rates. Ehrlich, *supra* note 29, at 57. Although my primary model is in linear form, the results are robust to a log specification. Another potential issue is that the manner in which the missing data are estimated changed in 1994, possibly leading to data that are incomparable with earlier years. In my 3 years of data following the change in estimation procedure (1994–96), over 70 percent of the counties in my sample reported 100 percent of the crimes committed and thus required no estimation of missing data. Over 85 percent of the counties reported at least 90 percent of crimes and thus required very little estimation. Similarly, over 50 percent of the counties reported 100 percent of arrests made, requiring no estimation; over 98 percent of counties reported at least 70 percent of arrests, requiring very little estimation. In addition, dropping the counties that did not have 100 percent reporting from my estimation did not affect my results.

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iables compiled from individual inmate records for prison admissions and releases and parole discharges.[42] The definitions and sources of all variables are discussed in Table 2.[43]

V. Empirical Results

I present the results from the estimation of equations (11)–(15) on county-level data in Tables 3–6.[44] I estimate the simultaneous system of equations with a two-stage weighted least squares regression and control for county-level fixed effects.[45]

[42] The sentencing variables are estimated with data from the BJS National Corrections Reporting Program (NCRP). Since 1983, BJS has compiled the NCRP data series. It is the only national-level database that is collected annually at the county level with information on prison population movement data and parole population data and provides a comprehensive description of offenders as they enter and leave correctional custody and supervision. During the 1990s, between 35 and 41 states have participated in the NCRP. In 1996, 37 states and the California Youth Authority reported 469,650 admissions that represented 91 percent of all admissions to state prisons based on data from the BJS National Prisoner Statistics data collection. Although this sample is not exhaustive across the nation, it represents a large percentage of the population of prison admissions and provides complete information on each state that participates. In the regressions that use variables from the NCRP data, I include only the 35 states for which there is NCRP reporting over the entire period. These states include 19 of the 25 TIS states.

[43] I have used the crime and arrest data and several other variables in previous papers. Dezhbakhsh, Rubin, & Shepherd, *supra* note 31; Shepherd, *supra* note 10. I am grateful to John Lott and David Mustard for providing me with the original data from their paper. Lott & Mustard, *supra* note 17.

[44] I will report only the results for the supply-of-crime equation (11), the probability-of-arrest equation (12), and the maximum-sentence equation (15). These are the only variables relevant to the theory discussed in Section III. I do not report results from the probability of imprisonment given arrest because this variable is only a proxy for the probability of conviction given arrest (see *supra* note 38) and is not the true variable I am interested in. Nevertheless, the first stage does produce some interesting results. In equation (14), the demand for TIS legislation equation, violent crimes have a positive and significant effect on the passage of TIS legislation, which suggests that high violent crime rates increase the demand for strict sentencing policies. The average maximum prison sentence has a negative and significant impact on the passage of TIS legislation for the majority of the crimes. This suggests that longer prison sentences satisfy the public demand for tougher sentencing and thus reduce demand for TIS legislation. Also in this equation, partisan influence has a consistently positive and significant impact on the passage of TIS laws. This result indicates that the more Republican the state, the more likely the enactment of TIS legislation. The partisan influence variable also has a consistently positive and significant impact on the probability of imprisonment given arrest in equation (13). This suggests that the more Republican the state, the more likely prosecutors and courts are to imprison offenders.

[45] The results are robust when the TIS variable is treated as exogeneous rather than endogeneous to the system of equations and when the model is estimated without variables from the NCRP data to include all states in my sample. As a check, I also estimated equations (11)–(15) with state-level data. I use the FBI's state-level crime data rather than data aggregated from my county-level data set. The FBI uses the same method across states to estimate the degree of underreporting and takes that into account when assigning state crime rates. However, state-level estimation may be subject to aggregation bias because the researcher cannot control for criminal, demographic, economic, and jurisdictional differences among counties; when data are averaged across counties, a high level in one county may obscure a low level in another county. Results with state data are similar to the results with county-level data. The coefficients

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TABLE 2

VARIABLES AND DATA SOURCES

Variable Name	Definition	Source
Dependent variables:		
TIS law	Dummy variable indicating year that state has TIS law on the books	GAO
Crime rates	Number of each crime in each county/(county population/100,000)	UCR
Probability of arrest	Number of arrests for each crime in each county/number of crimes in each county	UCR
Conditional probability of imprisonment given arrest	Number of people sentenced to prison for each crime/number of people arrested for that crime in each county	NCRP
Maximum imposed prison sentences	Mean and median maximum sentence imposed in each county for each of the crime categories	NCRP
Variables in *Z*:		
Real per capita personal income	Income in each county/population in each county	REIS
Real per capita unemployment insurance payments[a]	Unemployment insurance payments in each county/population in each county	REIS
Real per capita income maintenance payments[b]	Income maintenance payments in each county/population in each county	REIS
% population aged 10–19	(Number of people age 10–19 in each county/population in each county) × 100	CPR
% population aged 20–29	(Number of people age 20–29 in each county/population in each county) × 100	CPR
% African-American population	(Number of African-American people in each county/population in each county) × 100	CPR
% nonwhite and non-African-American population	(Number of people that are not white or African-American in each county/population in each county) × 100	CPR
% male population	(Number of males in each county/population in each county) × 100	CPR
Population density	Population in each county/square mile of each county	CPR
NRA membership rate (%)	(Number of NRA members in each state/population in each state) × 100	NRA
Crime rate of other-category crimes	Crime rate of all property crimes when a violent crime rate is estimated and vice versa	UCR

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TABLE 2 (*Continued*)

Variable Name	Definition	Source
Instrumental variables:		
Police expenditure	Real expenditure on the police in each state (includes current operating expenses and capital outlay on construction, land, and equipment)	EED
Judicial and legal expenditure	Real expenditure on the judicial and legal systems in each state (includes current operating expenses and capital outlay on construction, land, and equipment)	EED
Corrections expenditure	Real expenditure on the correctional system in each state (includes current operating expenses and capital outlay on construction, land, and equipment)	EED
Number of police officers	Number of employed police officers with arrest rights in each state	EED
Partisan influence variable[c]	(Number of people in each state voting Republican in the most recent presidential election/population in each state) × 100	CPR

SOURCES.—GAO: U.S. General Accounting Office, Truth in Sentencing: Availability of Federal Grants Influenced Laws in Some States 2 (GAO/GGD-98-42, 1998). UCR: U.S. Department of Justice, Federal Bureau of Investigation, Uniform Crime Reports for the United States (1984–96). NCRP: U.S. Department of Justice, National Corrections Reporting Program, Bureau of Justice Statistics (1984–96). REIS: U.S. Department of Commerce, Bureau of Economic Analysis, Regional Economic Information System (1984–96). CPR: U.S. Department of Commerce, U.S. Bureau of the Census, Current Population Reports (1984–96). EED: U.S. Department of Justice, Bureau of Justice Statistics, Expenditure and Employment Data for the Criminal Justice System (1984–96).

NOTE.—NRA: National Rifle Association; TIS: truth in sentencing.

[a] Unemployment insurance payments include state unemployment insurance compensation, unemployment for federal employees, unemployment for railroad employees, and unemployment for veterans.

[b] Income maintenance payments include Supplemental Security Insurance, Aid to Families with Dependent Children, and food stamps.

[c] There is one partisan influence variable for each 4-year presidential term during the time period.

A. *Crime*

The regression results for violent crime rates, equation (11), are presented in Table 3. The coefficients of TIS legislation are negative and significant

(t-statistics) on the TIS variable in the supply-of-crime equation (11) are murder, −1.13 (2.21) [$p > .05$]; aggravated assault, −46.21 (2.65) [$p > .05$]; robbery, −57.42 (5.88) [$p > .05$]; rape, −3.36 (2.31) [$p > .05$]; burglary, 122.61 (2.59) [$p > .05$]; larceny, −74.27 (.98); and auto theft, 138.64 (4.83) [$p > .05$]. The coefficients (t-statistics) on the TIS variable in the probability-of-arrest equation (12) are murder, 11.94 (1.66) [$p > .10$]; aggravated assault, 10.86 (2.56) [$p > .05$]; robbery, 3.88 (2.07) [$p > .05$]; and rape, .46 (.19). The coefficients (t-statistics) on the TIS variable in the median maximum sentences equation (15) are murder, −39,706.3 (.94); aggravated assault, −6,697.9 (3.21) [$p > .05$]; robbery, −1,395.8 (.26); and rape, 2,929.0 (.22). Aggregation bias may be the cause of the primarily insignificant coefficients in the maximum sentences equation: a high maximum sentence in one county may obscure a low maximum in another county.

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TABLE 3

TWO-STAGE LEAST SQUARES REGRESSION RESULTS FOR VIOLENT CRIME RATES

Regressors	Murder	Aggravated Assault	Robbery	Rape
Deterrent variables:				
Truth-in-sentencing legislation	−1.178	−44.809	−39.615	−4.226
	(3.14)*	(5.81)*	(7.46)*	(5.12)*
Probability of arrest	−.003	−.504	−.291	.030
	(.59)	(3.00)*	(3.35)*	(.94)
Conditional probability of imprisonment	.012	−4.549	.082	−.105
	(2.47)*	(11.29)*	(1.26)	(5.60)*
Economic variables:				
Real per capita personal income	.0001	−.008	.003	−.001
	(3.45)*	(5.07)*	(3.14)*	(4.10)*
Real per capita unemployment insurance payments	.001	−.349	.174	−.034
	(.22)	(6.63)*	(4.41)*	(5.37)*
Real per capita income maintenance payments	.008	−.079	−.264	−.020
	(4.56)*	(2.17)*	(9.96)*	(4.46)*
Demographic variables:				
% population aged 10–19	.992	43.301	20.487	.950
	(7.71)*	(14.89)*	(8.92)*	(2.78)*
% population aged 20–29	.328	11.194	11.719	−3.064
	(3.12)*	(4.27)*	(6.07)*	(9.61)*
% African-American population	.702	1.589	−9.068	−1.750
	(7.65)*	(.85)	(5.79)*	(8.55)*
% nonwhite and non-African-American population	.029	1.588	.527	−.196
	(3.67)*	(7.72)*	(3.27)*	(7.73)*
% male population	.027	−8.956	−.298	.481
	(.28)	(4.06)*	(.18)	(1.84)+
Population density	−.001	−.030	−.106	.002
	(1.62)	(3.22)*	(16.25)*	(1.88)+
NRA membership rate	.003	.121	.015	.001
	(3.31)*	(7.75)*	(1.35)	(.18)
Crime rate of property crimes	.002	.025	.061	.004
	(17.07)*	(8.05)*	(24.99)*	(12.88)*
Intercept	−38.869	−246.185	−211.666	76.055
	(8.68)*	(2.50)*	(2.83)	(6.02)*
N	14,205	26,083	17,473	19,213
F-statistic	89.27	262.46	401.22	84.22
Adjusted R^2	.8775	.9025	.9591	.8482

NOTE.—The dependent variable is the crime rate (crimes/100,000 population). Absolute values of t-statistics are in parentheses. The estimated coefficients for year and county dummies are not shown. The conditional probability of execution is a regressor in the murder equation and has a coefficient of −10.458 and a t-statistic of 8.34, which is significant at the 5 percent level. NRA = National Rifle Association.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

for murder, aggravated assault, robbery, and rape, which indicates that TIS legislation deters the violent crimes that it covers.

The coefficients in Table 3 suggest the number of crimes deterred. In 1996, TIS laws had not been adopted in 25 states and Washington, D.C., an area with a population of approximately 89,668,000 people. In 1996, had these states enacted TIS laws, there would have been 1,056 fewer murders, a 16 percent decrease; 40,179 fewer aggravated assaults, a 12 percent decrease;

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TABLE 4

TWO-STAGE LEAST SQUARES REGRESSION RESULTS FOR PROPERTY CRIME RATES

Regressors	Burglary	Larceny	Auto Theft
Deterrent variables:			
Truth-in-sentencing legislation	174.721	−89.486	70.252
	(11.73)*	(2.80)*	(3.95)*
Probability of arrest	6.288	16.060	9.419
	(3.47)*	(6.75)*	(5.52)*
Conditional probability of imprisonment	.794	−2.663	5.253
	(1.60)	(2.96)*	(3.64)*
Economic variables:			
Real per capita personal income	−.001	−.024	−.003
	(.50)	(4.09)*	(.68)
Real per capita unemployment insurance payments	.574	−.733	1.610
	(6.09)*	(3.49)*	(9.45)*
Real per capita income maintenance payments	.204	.216	.377
	(2.92)*	(1.62)	(3.52)*
Demographic variables:			
% population aged 10–19	−114.465	−63.773	39.904
	(19.89)*	(5.98)*	(4.79)*
% population aged 20–29	−1.237	−19.063	27.359
	(.22)	(2.08)*	(2.88)*
% African-American population	−41.020	41.889	51.080
	(10.40)*	(6.24)*	(7.78)*
% nonwhite and non-African-American population	−8.833	−4.746	−.814
	(26.60)*	(4.44)*	(1.13)
% male population	19.548	−36.967	−4.547
	(5.30)*	(3.60)*	(.60)
Population density	−.140	.061	.248
	(8.40)*	(1.12)	(6.38)*
NRA membership rate	−.203	−.095	−.045
	(7.52)*	(1.66)+	(.98)
Crime rate of violent crimes	.704	1.544	.842
	(30.06)*	(27.39)*	(23.51)*
Intercept	2,843.616	4,334.782	−2,730.190
	(15.93)*	(11.95)*	(8.00)*
N	26,736	26,966	24,413
F-statistic	625.36	274.72	157.65
Adjusted R^2	.8890	.9197	.9191

NOTE.—The dependent variable is the crime rate (crimes/100,000 population). Absolute values of *t*-statistics are in parentheses. The estimated coefficients for year and county dummies are not shown. NRA = National Rifle Association.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

35,522 fewer robberies, a 24 percent decrease; and 3,789 fewer rapes, a 12 percent decrease.[46]

Alternatively, TIS laws tend to increase some property crimes. As Table 4 shows, the coefficients on the TIS variable are positive and significant for

[46] The 95 percent confidence intervals for the violent crimes deterred in 1996 are murders, [397–1,715]; aggravated assaults, [26,626–53,733]; robberies, [26,190–44,854]; and rapes, [2,339–5,239].

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burglary and auto theft. This is consistent with the theoretical predictions that the laws' increased penalty for violent crimes causes offenders to substitute into property crimes. This result confirms that TIS deters, not just incapacitates. If the deterrent effect is stronger than the incapacitation effect, we would expect an increase in the expected penalty for one crime to cause substitution into other crimes.[47]

However, the results confirm that TIS laws also have an incapacitation effect. The TIS coefficient is negative and significant for the crime of larceny. The higher sentences for violent crimes also reduce larcenies as some people who would otherwise commit both crimes remain in jail.[48]

The sizes of the changes in property crimes are large. In 1996, adoption of TIS legislation by the 25 non-TIS states and Washington, D.C., would have increased burglaries by 156,669, or 20 percent, and auto thefts by 62,994, up to 15 percent. Larcenies would have declined by 80,240, or 3 percent.[49]

A recent National Institute of Justice study estimates the costs of victimization for different crimes based on tangible losses such as lost productivity, medical expenses, and property damage and intangible losses such as pain, suffering, and lost quality of life.[50] Using the coefficients from Tables 3 and 4, TIS laws in 1996 saved victims a net amount of approximately $4.5 billion. The reduction in violent crimes and larcenies represents a gain of $5 billion, while the increase in burglaries and auto thefts represents a loss of $481 million. The $4.5 billion saved by TIS in 1996 exceeds the $195.8 million that TIS legislation cost the federal government in 1996,[51] which makes this an efficient federal program, with each federal dollar creating over $23 of benefits.

Coefficients for the other variables vary among crimes. The probabilities of arrest and imprisonment are positive for some crimes and negative for others.[52] The greater the percentage of the population aged 10–19 and the greater the percentage minority other than African-American, the greater the violent crimes and the fewer the property crimes. The NRA membership

[47] Levitt, *supra* note 22, at 354.

[48] *Id*. at 354.

[49] The 95 percent confidence intervals are burglaries, [130,491–182,847]; auto thefts, [31,737–94,251]; and larcenies, [24,073–136,408].

[50] Ted R. Miller, Mark A. Cohen, & Brian Wiersema, Victim Costs and Consequences: A New Look 9 (1996).

[51] U.S. General Accounting Office, *supra* note 12, at 4. This cost excludes funds that the TIS legislation induces states to spend.

[52] The presence of positive coefficients for certain crimes may indicate that the arrest and imprisonment rates are not good measures of the probabilities of arrest and imprisonment given arrest. Nevertheless, these measures are most likely closer to what potential criminals view as the "correct" measure; there is evidence that offenders form perceptions based on what they observe happening to other offenders. Raaj K. Sah, Social Osmosis and Patterns of Crime, 99 J. Pol. Econ. 1272, 1273 (1991).

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TABLE 5

TWO-STAGE LEAST SQUARES REGRESSION RESULTS FOR PROBABILITY OF ARREST

Regressors	Murder	Aggravated Assault	Robbery	Rape
Truth-in-sentencing legislation				
	18.077	9.985	7.376	12.266
	(1.87)+	(1.87)+	(.99)	(2.63)*
Crime rate	−9.009	−.156	−.167	−2.098
	(11.29)*	(13.34)*	(10.75)*	(13.68)*
Police expenditure	.001	−.001	−.001	.001
	(3.03)*	(1.11)	(.54)	(6.57)*
Police employment	−.002	.001	−.001	.001
	(1.68)+	(1.26)	(2.10)*	(3.28)*
Intercept	238.696	94.574	112.524	130.284
	(9.89)*	(9.03)*	(7.30)*	(10.09)*
N	13,978	26,083	17,473	19,213
F-statistic	16.21	30.48	11.84	21.13
Adjusted R^2	.1579	.3223	.1397	.1290

NOTE.—The dependent variable is the arrest rate ([arrests/crimes] × 100). Absolute values of *t*-statistics are in parentheses. The estimated coefficients for year and county dummies are not shown.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

variable is also positively related to all violent crimes and negatively related to all property crimes. Finally, violent and property crime rates tend to move in the same direction.

B. Probability of Arrest

The results in Table 5 for equation (12) indicate that TIS increases the probability of arrest. All of the coefficients on the TIS variables are positive, and the coefficients for the crimes of murder, aggravated assault, and rape are positive and significant.[53] The results suggest that, instead of trying to counteract the laws' impacts, law enforcement shares the goals of the TIS legislation.

As expected, the arrest rate is positively related to the expenditure on police. The coefficients on expenditures are positive and significant for two of the crimes. Additional resources increase the productivity of the police.[54]

[53] The probability of arrest is defined as each county's number of arrests for each crime divided by the number of crimes and multiplied by 100. I report only the results for the violent crimes because theory predicts that the probability of arrest should be affected only for the crimes covered by TIS legislation. My results confirm this prediction. There is no significant impact of TIS laws on arrest rates for two of the three property crimes. Only for the crime of burglary did TIS laws have a very small positive effect on arrest rates.

[54] The other interesting result in Table 5 is that crime rates appear to be negatively related to arrest rates. An increase in crime should increase society's demand for protection and result in more productive enforcement (higher probabilities of apprehension) as more resources are devoted to the criminal justice system. This process, however, will not occur instantly. Because

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TABLE 6

TWO-STAGE LEAST SQUARES REGRESSION RESULTS FOR MAXIMUM IMPOSED PRISON SENTENCES

Regressors	Murder	Aggravated Assault	Robbery	Rape
Truth-in-sentencing legislation				
	2,162.082	195.316	656.576	758.923
	(4.28)*	(3.02)*	(5.71)*	(3.32)*
Corrections expenditure	.002	.001	.001 (6.87)*	.001
	(13.08)*	(5.17)*		(2.54)*
% Republican in 1984	−365.899	−28.273	−68.637	−115.831
	(8.27)*	(5.84)*	(7.87)*	(6.57)*
% Republican in 1988	−32.699	9.254	7.313	−24.980
	(.86)	(2.13)*	(.95)	(1.67)+
% Republican in 1992	−65.468	−4.505	−16.477	−63.845
	(1.88)+	(1.14)	(2.32)*	(4.58)*
% Republican in 1996	−194.736	−.966	−8.101	−34.940
	(5.54)*	(.27)	(1.27)	(2.83)*
Intercept	29,253.000	2,240.068	5,402.703	8,524.235
	(11.33)*	(7.87)*	(10.58)*	(8.28)*
N	12,748	16,795	15,308	11,404
F-statistic	32.58	25.11	50.61	20.74
R^2	.3259	.1439	.1020	.2889

NOTE.—The dependent variable is the median maximum sentence in days imposed for each crime. Absolute values of t-statistics are in parentheses. The estimated coefficients for year and county dummies are not shown.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

C. *Maximum Prison Sentences*

As Table 6 indicates in its results for the estimation of equation (15), TIS legislation increases the median imposed maximum sentences: the coefficients on the TIS variable are positive and significant for all four violent crimes.[55] This supports the theory that longer time served will result in more trials and higher maximum imposed prison sentences.

Maximum sentences are also significantly influenced by other variables. For example, expenditure on the correctional system is positively related to maximum sentences for all violent crimes. Increases in prison funding may

equation (12) estimates arrests in year t and crimes in year t, it may be too soon to see any increase in the demand for enforcement and productivity of police that are attributed to rising crime rates. As a result, any increase in crime in year t could cause police resources in year t to be stretched too thinly and thus result in lower police productivity as seen by decreasing probabilities of arrest. Isaac Ehrlich, Participation in Illegitimate Activities: A Theoretical and Empirical Investigation, 81 J. Pol. Econ. 521, 541 (1973).

[55] For conciseness, I report results only for median sentences. Results were similar for the mean sentence. I report the results only for violent crimes because theory predicts that TIS will affect the sentences only for these crimes. Unreported results confirm this. The maximum sentences of property crimes were, for the most part, unaffected by TIS laws. Again, only for the crime of burglary did TIS laws have a small positive impact on the maximum sentences.

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induce prosecutors and the courts to impose longer prison sentences for violent crimes. In addition, the justice system responds to the desires of conservative voters, not by increasing maximum prison sentences, but by increasing the probability of imprisonment and the percentage of sentences served. In the estimation for maximum sentences, the coefficients on the percentage of the state voting Republican are primarily negative and significant. In contrast, the results from first-stage regressions of equations (13) and (14) indicate that the more Republican the state, the higher the imprisonment rate and the more likely it is to pass a TIS law.[56]

VI. Conclusions

This paper is the first comprehensive theoretical and empirical analysis of one of the most significant recent crime interventions: TIS legislation. The results from my empirical estimation support many of the predictions of the economic model of crime: a TIS law that increases the penalties for certain crimes deters the crimes covered by the law but causes substitution into crimes not covered by the law. The probability of arrest increases on the passage of TIS legislation, which suggests that, instead of attempting to counteract them, police and prosecutors approve TIS laws and are inspired by them. In addition, the empirical results support my theoretical model; determinate sentencing policies that increase prison time will tend to increase maximum imposed prison sentences as offenders go to trial in hopes of avoiding higher penalties.

The conclusions of this paper are relevant in the debate over this and other "tough on crime" policies. Although there are substantial benefits of these laws, there may also be large costs. The policies do appear to deter covered crimes; TIS laws reduce victim costs by $5 billion per year. However, they also cause substitution into crimes not covered by the laws, burglaries and auto thefts increase, causing $481 million in additional victim costs. Furthermore, the costs of imprisoning people for long periods is substantial, not only to the correctional system, which must build more prisons and hire more guards, but also to the families and communities of incarcerated offenders.

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[56] See *supra* note 44.

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