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The Impact of Incentives on Human Behavior
Can We Make It Disappear? The Case of the Death Penalty

Naci Mocan and Kaj Gittings

11.1 Introduction

Economists are interested in the investigation of human behavior and how individuals respond to prices and incentives. Economic theory, which demonstrates an inverse relationship between the price of a commodity and its consumption, suggests that an increase in the price or cost of a behavior leads to a reduction in the intensity of that behavior. Therefore, as economic analysis of consumer behavior is applicable to any commodity ranging from apples to cars, it is also applicable to any type of human behavior, ranging from drunk driving to sexual activity to marital dissolution. Based on economic theory, an immense amount of empirical research has investigated the extent to which individuals alter their behavior in response to increases in the relevant "prices" that may impact that behavior.

11.1.1 Rationality and Reaction to Incentives

One common argument made by noneconomists against the economic approach to human behavior is that people are not *rational enough* to behave according to the predictions of economic theory when it comes to behaviors such as smoking, consumption of alcohol and illicit drugs, sexual activity, and crime. However, an enormous empirical literature in economics has

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demonstrated that even these behaviors are responsive to prices and incentives. For example, consumption of cigarettes declines when cigarette prices rise (e.g., Becker, Grossman, and Murphy 1994; Yurekli and Zhang 2000; Gruber, Sen, and Stabile 2003), alcohol consumption is curtailed when alcohol prices are increased (e.g., Farrell, Manning, and Finch 2003; Manning, Blumberg, and Moulton 1995), drug use responds to variations in drug prices (e.g., Van Ours 1995; Saffer and Chaloupka 1999; Grossman 2005), pregnancies and childbearing are influenced by state and federal policies that alter the costs (e.g., Mellor 1998; Lundberg and Plotnick 1995), and the timing of births within a year is responsive to the tax benefit of having a child (Dickert-Conlin and Chandra 1999). Such results hold true even in subpopulations such as adolescents, who are thought to be present-oriented and less rational (e.g., Pacula et al. 2001; Gruber and Zinman 2001; Grossman and Chaloupka 1998; Grossman et al. 1994; Lundberg and Plotnick 1990), and among individuals with mental health problems (Tekin, Mocan, and Liang, forthcoming; Saffer and Dave 2005). In a different vein, research in experimental economics has demonstrated that individuals respond to changes in prices as predicted by economic theory, and even children behave rationally when modifying their behavior in response to variations in prices (Harbaugh, Krause, and Berry 2001).

The same results are obtained from analyses of the response of criminal activity to the relevant costs and benefits. The pioneering work of Becker (1968) indicated that criminal activity should decline as the "price" of such activity increases. Empirical analyses testing the economic model of crime have demonstrated that illicit behavior indeed responds to incentives and sanctions. For example, Jacob and Levitt (2003) showed that incentives for high test scores motivate teachers and administrators to cheat on standardized tests in Chicago public schools. Corman and Mocan (2000, 2005) and DiTella and Schargrodsky (2004) demonstrated that increased arrests and more police officers reduce crime. Levitt (1998a) showed that juvenile crime goes down when punishment gets stiffer. Grogger (1998) and Mocan and Rees (2005) found that the extent of criminal involvement among high school students is influenced by both economic conditions and deterrence. Corman and Mocan (2005) and Hansen and Machin (2002) showed that criminal activity reacts to increases in the minimum wage. Similarly, it has been shown that prison crowding, which generates early release of prisoners, has a significant impact on crime rates (Levitt 1996).

One specific subanalysis in this domain has received significant attention. Specifically, the extent to which murder rates respond to deterrence was first investigated theoretically and empirically by Ehrlich (1973, 1975, 1977a), who found a deterrent effect of capital punishment. Some analysts questioned the robustness of the results (Hoenack and Weiler 1980; Passell and Taylor 1977), and Ehrlich and others responded to these criticisms (Ehrlich 1977b; Ehrlich and Mark 1977; Ehrlich and Brower 1987; Ehrlich and Liu

1999). In a recent article, Donohue and Wolfers (2005) focused on a number of recent papers that reported a deterrent effect of death penalty on murder and stated that the findings of these papers were not robust. The purpose of this paper is to provide a new and detailed analysis of the impact of leaving death row (executions, commutations, and other removals from death row) on state murder rates. Specifically, we make various attempts to eliminate the deterrent effect of capital punishment and investigate if and under what conditions one succeeds in eliminating the impact of leaving death row on the murder rate.

As we demonstrate in detail in the following, the signaling effect of leaving death row and its impact on murder is robust. Although the impact of executions sometimes disappears when one estimates specifications, which are inconsistent with theory, the impact of commutations remains significant even in those models. Furthermore, as summarized in table 11.13 and detailed in the chapter, in many cases the deterrence results *do not* disappear even under many specifications that have been tried out in the literature that have no theoretical foundation.

11.2 Data and the Empirical Model

The data set used in the chapter is the same one as employed by Mocan and Gittings (2003) and Donohue and Wolfers (2006). One distinguishing feature of the data set is that it contains the entire history of death sentences between 1977 and 1997, including the exact month of removal from death row and the reason for it (execution, commutation, etc.), for each death row inmate. The data on state-level crimes, arrests, prison population, prison deaths, and other state characteristics such as the unemployment rate, urbanization rate, racial composition of the state, and other attributes are compiled from various sources (see Mocan and Gittings 2003, 474–76).

The investigation of the impact of deterrence on murder is carried out by estimating models of the following form:

$$M_{it} = \mathbf{D}_{it-1}\,\alpha + \mathbf{X}_{it}\beta + \mu_i + \eta_t + \psi_{it} + \varepsilon_{it}, \tag{1}$$

where M_{it} is the murder rate in state i and year t. The vector $\mathbf{X}$ contains state characteristics that may be correlated with criminal activity, including the unemployment rate, real per capita income, the proportion of the state population in the following age groups: twenty to thirty-four, thirty-five to forty-four, forty-five to fifty-four and fifty-five and over, the proportion of the state population in urban areas, the proportion that is black, the infant mortality rate, the party affiliation of the governor, and the legal drinking age in the state. Theoretical and empirical justification for the inclusion of these variables can be found in Levitt (1998a) and Lott and Mustard (1997). Following Levitt (1998a) and Katz, Levitt, and Shustorovich (2003), we also control for the number of prisoners per violent crime and the prison death rate (a measure of prison conditions) as two additional measures of deterrence.

The variable μ_i represents unobserved state-specific characteristics that impact the murder rate, which are controlled for by state-fixed effects, η_t stands for common year effects, and the models also include state-specific time trends represented by ψ_{it}. To control for the impact of the 1995 Oklahoma City bombing, a dummy variable is included that takes the value of one in Oklahoma in 1995 and zero elsewhere.

11.2.1 Measurement of Risks (Increase and Decrease in the Cost of Murder)

The vector D represents deterrence variables and includes the probability of apprehension, the probability of sentencing given apprehension, as well as various probabilities pertaining to leaving death row, conditional on sentencing. It also includes the incarceration rate and the prison death rate. Note that execution is not the only outcome for prisoners on death row. During the period of 1977 to 1997 (the time period analyzed in this paper), 17 percent of inmates who completed their duration on death row were executed, while the other 83 percent left for other reasons (e.g., commutation of the sentence, sentence or conviction being overturned, sentence being found unconstitutional). This information allows for an investigation as to how the murder rate reacts to an increase in the price of crime (executions) as well as a decrease in the price of crime (commutation and all removals other than executions and deaths).

From a theoretical point of view, it is important to carefully consider the timing of events. The probability of apprehension is a measure of the risk of getting caught, given that a murder is committed. Because the unit of analysis is state-year, this probability is measured as the proportion of murders cleared by an arrest in a particular state and year; that is, $ARRATE_t = (AR_t/MUR_t)$, where AR_t is the number of murder arrests in a state in year t (state subscript is dropped for ease of exposition), and MUR_t stands for the number of murders in year t. The second risk variable is the probability of receiving a death sentence given that a murder arrest took place. After a person is arrested for murder, he or she does not automatically end up on death row; instead, a trial takes place in which not all defendants are found guilty nor do they all receive a capital sentence. Therefore, one can calculate the probability of being found guilty and sentenced to death, conditional on being arrested for murder. The average length of time between the date of a murder arrest and the date on which an inmate is sentenced to death is more than one year.[1] Thus, the risk of receiving the death sentence is defined as the number of death sentences handed out in a year divided

1. For example, a person who is arrested in October 1990, is likely to receive a death sentence after February 1992.

by the number of murder arrests two years prior. That is, $\text{SENTRATE}_t = (\text{SENT}_t/\text{AR}_{t-2})$, where SENT_t represents the number of death sentences handed out in year *t*.

Following Mocan and Gittings (2003), three death penalty–related deterrence variables are created. When constructing the capital punishment variables, it is useful to realize that if a person receives the death sentence, he or she is not executed instantly; instead, it has been demonstrated that the average duration from sentencing to execution (across states) is about six years during the period studied in this paper (Bedau 1997; Dezhbakhsh, Rubin, and Shepherd 2003; Mocan and Gittings 2003; Argys and Mocan 2004). As was done in Mocan and Gittings (2003), this information suggests that the risk of execution should be calculated as the number of executions divided by the proper cohort of death sentences six years earlier; that is, $\text{EXEC}_t/\text{SENT}_{t-6}$. Also, about 83 percent of the inmates are removed from death row for reasons other than execution. One such reason is commutation, where the inmate is granted clemency and the sentence is changed to a prison term, typically life. Because commutation implies a reduced risk of death and, therefore, a reduced cost of committing murder, an increase in the probability of commutations should theoretically increase the murder rate. The same argument is true for all removals from death row (other than executions and other deaths while on death row). Figure 11.7 displays the average duration on death row by execution, commutation, and other removals from death row and shows that the proper cohort to use in calculating the risk of commutation and risk of removal is about the same as that for executions.[2]

Not all previous research has considered the relevant cohorts when calculating these risk variables. For example, Donohue and Wolfers (2005) employ the data and methods of Mocan and Gittings (2003), but they create these variables as the ratio of executions (or removals) in a given year to the number of death sentences *in that same year,* that is, as $(\text{EXEC}_t/\text{SENT}_t)$ or $(\text{REMOVE}_t/\text{SENT}_t)$. These variables have no real meaning because the numerator and denominator of the ratio have no connection to each other: employing the ratio of executions in year *t* to the death sentences in year *t* incorrectly assumes that execution of each inmate takes place in the same year of sentencing.

Although calculating the risks this way is not sensible, it would be reasonable to ask if the results were sensitive to variations in their proper measurement. Specifically, we consider variations in the probability of execution, the probability of commutation, and the probability of removal from death row in three different dimensions and investigate if these variations

2. Note that the duration on death row for removals other than execution is less than that for executions and approximately five years, on average. For this reason, Mocan and Gittings (2003) used the sentencing cohort five years ago in models that include removals; that is, $(\text{EXEC}_t/\text{SENT}_{t-5})$, or $(\text{REMOVE}_t/\text{SENT}_{t-5})$.

make the deterrence results disappear. We deviate from the existing analyses of Mocan and Gittings (2003), who used $EXEC_t/SENT_{t-6}$, and Donohue and Wolfers (2005), who used $EXEC_t/SENT_t$, and vary the sentencing cohort of the risk variables. For this exercise, we calculate the risks of execution, commutation and removals as $(EXEC_t/SENT_{t-5})$, $(COMM_t/SENT_{t-5})$, $(REMOVE_t/SENT_{t-5})$, assuming a five-year wait on death row, and $(EXEC_t/SENT_{t-4})$, $(COMM_t/SENT_{t-4})$, $(REMOVE_t/SENT_{t-4})$, assuming a four-year wait.[3]

The preceding discussion concerns variations in the denominator of the risk variable, but proper measurement of the numerator is important as well. If executions, commutations, or removals from death row send signals to potential criminals, then the timing of the signal needs to be addressed. An advantage of these data is the availability of the date of each execution and removal, which enables one to create execution, commutation, and removal measures that are consistent with theory. Mocan and Gittings (2003) considered a monthly adjustment to the capital punishment events where executions, commutations, and removals are prorated based on the month in which they occurred. For example, an execution that took place in January of 1980 can have an impact on the murder rate for the full year of 1980. However, if the execution took place in November 1980, it will have a trivial impact on the 1980 murder rate. Rather, the impact of this November execution on murder will primarily be felt in 1981. Thus, this November execution counts as 2/12 of an execution for 1980 and 10/12 of an execution for 1981. The same algorithms are applied for commutations, and removals. We call these the first measure of executions, commutations, and removals (EXEC, COMM, REMOVE). This is the measure employed by Mocan and Gittings (2003) and also by Donohue and Wolfers (2005).

The second dimension to vary the measurement of the risk variables is through the numerator. We consider a means of allocating the capital punishment events that uses a coarser algorithm than described in the preceding: if an execution took place within the first three quarters of a year, we attributed that execution to the same year. If the execution took place in the last quarter of a year (October to December), we attributed that execution to the following year under the assumption that the relative impact on

3. The issue here is how potential criminals measure risks. Assume that the true risk of execution conditional upon sentencing is 0.20. Specifically, assume that in a given state, each year ten people receive the death sentence, they stay on death row for four years, and at the end of the fourth year, two of them get executed. Thus, in each year, the risk of execution is, $(EXEC_t/SENT_{t-4}) = 2/10$. Now assume that in one particular year, the number of death sentences goes down to five. Would the criminal believe that the risk of execution doubled this year because only five people got sentenced this year instead of the usual ten (the thesis by Donohue and Wolfers 2005), or would the criminal's expected risk of execution given sentencing not change if the criminal knows that executions today pertain to sentences in the past (more closely estimating the true risk)? If criminals are utilizing information to form expectations about the true risk, the latter more likely approximates the behavior.

murders would be felt in the following year. The same was done for removals and commutations. We name these the second measures of executions, commutations, and removals (EXEC2, COMM2, and REMOVE2).[4]

The third dimension in which we vary the risk measures is by experimenting with the wide range of other denominators to calculate the risk of leaving death row. Some of these measures have been used previously in the literature (e.g., executions per state population, executions per prison population), while others have not, such as the total number of inmates on death row. Despite the fact that the measurement of these particular risk variables is inherently flawed, we incorporate them into the analysis to further examine the robustness of the results. Beyond measurement issues associated with the risk probabilities, we push the robustness check further by estimating these models across different samples (e.g., dropping various states) and using alternative weighting schemes.

Note that the models include a number of state-specific variables, ranging from the governor's party affiliation to the unemployment rate to socioeconomic controls that aim to capture time varying factors that may impact the homicide rate in the state. Also included are state-specific time trends (in addition to the year-fixed effects and state-fixed effects) to capture the impact of residual time varying unobservables. In addition to the homicide arrest rate, sentencing rate, and the execution, commutation, and removal rates that are in the models, it would be desirable to include additional measures of the severity of punishment, such as median time served for murder in each state and year. Although there is some information based on prison releases, these data are spotty and, therefore, not feasible to use. However, as was done in Mocan and Gittings (2003), the models we estimate also include prisoners per violent crime and the prison death rate as additional controls for the certainty and severity of punishment.

Donohue and Wolfers (2005) claim that the deterrence results reported in Mocan and Gittings (2003) disappear when coding errors are corrected, and they put forth two issues. The first issue pertains to dropping those observations where the denominator of the risk variable (SENT) is zero. The second issue is the lag length in the models, but in this regard, they simply estimate a different specification than Mocan and Gittings (2003).[5] While the first issue changes the sample slightly, this adjustment alone has no meaningful impact on the results. Changing the model specification (which is not a coding error correction), implemented by Donohue and Wolfers (2005), alters the significance of the execution coefficient, but not its magnitude. Their specification decision reduces the sample size (which they object elsewhere), diminishes the statistical power by definition and, thus, the statistical signifi-

4. In the following sensitivity tests, we also employ other measures, including raw *counts* of executions and commutations as pure signals to criminals.

5. See note 2 and panel B of table 6 in Donohue and Wolfers (2005).

cance of the execution coefficient. However, even this model alteration does not eliminate the significance of the commutations and removals from death row (see panel B, table 6 of Donohue and Wolfers 2005).

We estimate each specification using the exact same data set and the exact same programming code written by Donohue and Wolfers (2005) that addresses the division by zero issue. This allows us to produce a transparent picture as to how the murder rate reacts to alterations in two key deterrence variables: the risk of execution and the risk or commutation (or removal from death row), keeping *all else the same* in the specification.

11.3 Results

We estimate various versions of equation (1). Following Corman and Mocan (2000), Levitt (1998a), Katz, Levitt, and Shistorovich (2003), and Mocan and Gittings (2003), the deterrence variables are lagged by one year to minimize the concerns of simultaneity. For example, if the risk variable is ($EXEC_t/SENT_{t-5}$), its lagged value is employed in the regressions (i.e., $[EXEC_t/SENT_{t-5}]_{-1} = [EXEC_{t-1}/SENT_{t-6}]$). The models are estimated by weighted least squares, where the weights are state's share in the U.S. population. Later in the paper, we report and discuss results obtained without weighting. Robust standard errors, which are clustered at the state level, are reported in parentheses under the coefficients. In the interest of space, only the coefficients and standard errors pertaining to executions, commutations, and removals are reported.

Table 11.1 displays the results where the first measures of execution, commutation, and removal are employed. The top panel of table 11.1 measures the relevant risks as ($EXEC_t/SENT_{t-5}$), ($COMM_t/SENT_{t-5}$), ($REMOVE_t/SENT_{t-5}$). That is, it calculates the rates of execution, commutation, and removal per death sentences imposed five years earlier (assuming that the average duration on death row is five years). The models presented in the middle panel of table 11.1 are identical, except, the average duration on death row is assumed to be four years. Thus, the variables are calculated as ($EXEC_t/SENT_{t-4}$), ($COMM_t/SENT_{t-4}$), and ($REMOVE_t/SENT_{t-4}$).[6]

A number of aspects of the results in table 11.1 are noteworthy. First, the point estimates are very robust between specifications reported in the top two panels. Second, the execution rate has a negative and statistically significant impact on the murder rate. Third, the commutation and removal rates have positive impacts on the murder rate. Fourth, these results are consistent

6. Mocan and Gittings (2003) employed risk variables that take the average duration on death row as six years (denominator SENT lagged six years) in models for executions and commutations. Because the time between sentencing and REMOVE from death row is about five years, they employed SENT lagged five years in the denominator when the model included removals. Dohonue and Wolfers (2006), on the other hand, prefer zero lags of SENT in the denominator (as we replicated in the bottom panel of table 11.1).

Table 11.1 **Determinants of the murder rate: the first measure of execution, commutation, and removal**

	Duration on death row: 5 years				
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0056**			–0.0058**	–0.0066**
	(0.0027)			(0.0028)	(0.0029)
$(COMM_t/SENT_{t-5})_{-1}$		0.0065		0.0070	
		(0.0047)		(0.0046)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0024***		0.0027***
			(0.0008)		(0.0009)
n	734	743	691	733	688
	Duration on death row: 4 years				
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0054**			–0.0055**	–0.0047**
	(0.0022)			(0.0022)	(0.0021)
$(COMM_t/SENT_{t-4})_{-1}$		0.0036*		0.0038**	
		(0.0021)		(0.0019)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0004		0.0005
			(0.0007)		(0.0007)
n	785	790	744	781	741
	Duration on death row: 0 years; time between arrest and death sentence: 0 years[a]				
$(EXEC_t/SENT_t)_{-1}$	0.0003			0.0001	0.0001
	(0.0014)			(0.0013)	(0.0014)
$(COMM_t/SENT_t)_{-1}$		0.0041***		0.0041***	
		(0.0013)		(0.0013)	
$(REMOVE_t/SENT_t)_{-1}$			0.0002		0.0002
			(0.0003)		(0.0003)
n	986	984	921	977	918

Notes: See section 11.2 for the explanation of the measurement of variables. Each model includes the following variables: murder arrest rate, sentencing rate, unemployment rate, real per capita income, proportion of the state population, in the following age groups: twenty to thirty-four, thirty-five to forty-four, forty-five to fifty-four, and fifty-five and over, proportion of the state population in urban areas, proportion that is black, infant mortality rate, legal drinking age in the state, number of prisoners per violent crime, and prison death rate. Also included in each model are state-fixed effects, a time trend, state-specific time trends, a dummy variable to control for the impact of the 1995 Oklahoma City bombing, and a dummy variable to indicate if the governor is a Republican. Robust and clustered standard errors are in parentheses.

[a]Specification estimated by Donohue and Wolfers (2006).

***Statistical significance at the 1 percent level or better.

**Statistical significance between 5 and 1 percent.

*Statistical significance between 10 and 5 percent.

with the specifications reported in Mocan and Gittings (2003), despite utilizing different sentencing cohorts as the denominator.

The bottom panel of table 11.1 displays the results of the model estimated by Donohue and Wolfers (2005) using the same data. In this specification, the execution, commutation, and removal rates are calculated by dividing executions, commutations, and removals in a year to the number of death sentences *in that same year.* Thus, it is assumed that the duration on death row is less than one year. Similarly, in this specification, the sentencing rate

Table 11.2 Determinants of the murder rate: the second measure of execution, commutation, and removal

	Duration on death row: 5 years				
$(\text{EXEC2}_t/\text{SENT}_{t-5})_{-1}$	–0.0058***			–0.0062***	–0.0073***
	(0.0020)			(0.0022)	(0.0022)
$(\text{COMM2}_t/\text{SENT}_{t-5})_{-1}$		0.0044		0.0056	
		(0.0047)		(0.0040)	
$(\text{REMOVE2}_t/\text{SENT}_{t-5})_{-1}$			0.0018***		0.0021***
			(0.0007)		(0.0007)
n	737	743	712	736	709
	Duration on death row: 4 years				
$(\text{EXEC2}_t/\text{SENT}_{t-4})_{-1}$	–0.0069*			–0.0070**	–0.0063*
	(0.0035)			(0.0035)	(0.0033)
$(\text{COMM2}_t/\text{SENT}_{t-4})_{-1}$		0.0034*		0.0036**	
		(0.0019)		(0.0016)	
$(\text{REMOVE2}_t/\text{SENT}_{t-4})_{-1}$			0.0002		0.0005
			(0.0008)		(0.0007)
n	785	792	761	783	758
	Duration on death row: 0 years; time between arrest and death sentence: 0 years[a]				
$(\text{EXEC2}_t/\text{SENT}_t)_{-1}$	–0.0002			–0.0001	–0.00004
	(0.0020)			(0.0019)	(0.0019)
$(\text{COMM2}_t/\text{SENT}_t)_{-1}$		0.0039***		0.0039***	
		(0.0010)		(0.0001)	
$(\text{REMOVE2}_t/\text{SENT}_t)_{-1}$			–0.0002		–0.0002
			(0.0006)		(0.0006)
n	989	990	952	984	949

Note: See table 11.1 notes.

is calculated as the ratio of death sentences in a year to murder arrests *in that same year,* assuming that the time length from arrest-to-trial-to-sentencing is also less than one year. Consequently, measuring the risk variables this way allows the execution result disappear, but the misspecification cannot eliminate the impact of commutations on the murder rate.[7]

Table 11.2 reports results obtained from models where the executions,

7. Note that the equation on page 816 of Donohue and Wolfers (2005) includes a variable called Pardons(t–1)/DeathSentences(t–7). Donohue and Wolfers (2005) write that Mocan and Gittings (2003) estimate that particular regression although Mocan and Gittings (2003) do not employ pardons in their paper. Similarly, table 6 of Donohue and Wolfers (2005 contains specifications in which a variable named "Pardons" is included, and a discussion is provided about pardons. For example, Donohue and Wolfers (2005) state on page 818 that "the two related measures of the porosity of the death sentence now yield sharply different results, with the *pardon rate* [emphasis added] robustly and positively associated with homicide . . ." Mocan and Gittings (2003) employ commutations in their regressions, not pardons. Commutations and pardons are two different events. A pardon, which is an extremely rare event, invalidates the guilt the punishment of the inmate. In fact, the official death row data we are using from the Bureau of Justice Statistics do not even identify a "pardon" as a type of removal from death row, unlike a sentence being commuted. A commutation reduces the severity of punishment; it is clemency, in which the sentence is reduced, typically to life in prison.

commutations, and removals are measured using the second set of variables that allocates events by the quarter in which they occur as described in section 11.2. In other words, the only difference between results reported in table 11.1 and table 11.2 is the measurement of the numerator of the execution, commutation, and removal rates. Once again, the impact of the execution rates does not disappear, unless one estimates the specification promoted by Donohue and Wolfers (2005). And, even in that case, similar to table 11.1, the impact of the commutation rate on the murder rate remains positive and statistically significant.

11.3.1 All Executions Are in Texas!

It can be argued that California and Texas are interesting states that contain potentially useful information for establishing the deterrent effect of the death penalty, and it could be that the deterrence results in the literature may be sensitive to exclusion of Texas and California from the analysis.[8] Table 11.3 is comparable to the top two panels in tables 11.1 and 11.2 with one difference: Texas and California are omitted from the models. As the table demonstrates, the impact of executions and commutations or removals are still significant when Texas and California are omitted from analysis.[9]

11.3.2 The Importance of the Denominator Once Again

Why is it the case that omitting Texas does not make the results disappear despite the fact that Texas executes a disproportionately large number of death row inmates? One explanation is that it is incorrect to focus on execution counts (to be included as an explanatory variable) when the correct measure is not the *number* of executions, but the *risk of the execution.* Despite the fact that a particular state has a large number of executions, the execution risk may not be high if the cohort of inmates that was sentenced to death is also large. Put differently, the number of executions needs to be adjusted by the appropriate denominator to obtain an actual measure of risk.

Table 11.4 summarizes the number of executions, commutation, and removals from death row between 1977 and 1997 for selected states; it also presents the average execution risk in each state during that period. The first measure is the number of executions in year t divided by the number of death sentences four years earlier. The second measure deflates the number of executions by death sentences five years prior. The third measure displayed in the table is a measure of risk previously used in the literature: the number of executions divided by prison population ($\text{EXEC}_t/\text{PRISON}_t$), and the fourth measure is the number of executions deflated by the number of inmates on death row in the same year ($\text{EXEC}_t/\text{ROW}_t$). While Texas executes

8. See Donahue and Wolfers (2005, 826).

9. We also omitted Texas and California individually. In neither case could we make the results disappear. See Mocan and Gittings (2006, 38–39).

Table 11.3 **Determinants of the murder rate (excluding Texas and California)**

The first measure of executions, commutations, and removals					
Duration on death row: 5 years					
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0029			–0.0030**	–0.0041*
	(0.0019)			(0.0020)	(0.0023)
$(COMM_t/SENT_{t-5})_{-1}$		0.0048		0.0051	
		(0.0043)		(0.0042)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0024***		0.0026***
			(0.0008)		(0.0009)
n	704	713	662	703	659
Duration on death row: 4 years					
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0041**			–0.0042**	–0.0036*
	(0.0019)			(0.0019)	(0.0018)
$(COMM_t/SENT_{t-4})_{-1}$		0.0042***		0.0043**	
		(0.0011)		(0.0019)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0007		0.0008
			(0.0007)		(0.0007)
n	753	758	713	749	710
The second measure of executions, commutations, and removals					
Duration on death row: 5 years					
$(EXEC2_t/SENT_{t-4})_{-1}$	–0.0039**			–0.0042**	–0.0054***
	(0.0016)			(0.0017)	(0.0019)
$(COMM2_t/SENT_{t-4})_{-1}$		0.0037		0.0046	
		(0.0040)		(0.0034)	
$(REMOVE2_t/SENT_{t-4})_{-1}$			0.0018***		0.0020***
			(0.0006)		(0.0007)
n	707	713	682	706	679
Duration on death row: 4 years					
$(EXEC2_t/SENT_{t-4})_{-1}$	–0.0055			–0.0056*	–0.0051
	(0.0034)			(0.0033)	(0.0031)
$(COMM2_t/SENT_{t-4})_{-1}$		0.0039***		0.0040***	
		(0.0011)		(0.0010)	
$(REMOVE2_t/SENT_{t-4})_{-1}$			0.0004		0.0006
			(0.0008)		(0.0007)
n	753	760	730	751	727

Note: See table 11.1 notes.

a large number of inmates annually, it is not the highest ranked state by any of these measures of execution risk. It is ranked fourth or fifth, depending on the risk measure, behind Virginia, Arkansas, and Louisiana. Missouri is generally ranked as the fifth. Therefore, the attempts to make the deterrence results disappear might be more productive if one were to omit high risk states rather than states with large absolute counts of executions.

Table 11.5 presents the results obtained from models when Virginia is dropped. Mocan and Gittings (2006) report the results when Arkansas or

Table 11.4 Execution risk by state

State	No. of exits from death row			Execution risk				Execution risk ranking			
	Executions	Commutations	Removals	$\frac{EXEC_t}{SENT_{t-4}}$	$\frac{EXEC_t}{SENT_{t-5}}$	$\frac{EXEC_t}{PRISON_t}$	$\frac{EXEC_t}{ROW_t}$	$\frac{EXEC_t}{SENT_{t-4}}$	$\frac{EXEC_t}{SENT_{t-5}}$	$\frac{EXEC_t}{PRISON_t}$	$\frac{EXEC_t}{ROW_t}$
Alabama	16	1	130	0.116	0.099	0.072	0.009	8	8	7	8
Arkansas	16	1	46	0.49	0.327	0.157	0.031	2	2	3	3
Georgia	22	6	150	0.136	0.127	0.057	0.012	7	7	8	7
Louisiana	24	2	78	0.345	0.315	0.226	0.056	3	3	1	2
Missouri	29	1	30	0.301	0.245	0.114	0.023	5	6	5	5
Nevada	6	3	32	0.079	0.08	0.072	0.007	10	9	6	9
Oklahoma	9	1	95	0.082	0.074	0.053	0.005	9	10	9	12
South Carolina	13	3	49	0.28	0.31	0.05	0.014	6	4	10	6
Texas	144	44	166	0.307	0.304	0.135	0.026	4	5	4	4
Virginia	46	5	15	0.612	0.652	0.162	0.059	1	1	2	1

Notes: PRISON is the total number of prisoners in the state. ROW is the number of death row inmates. The numbers in the execution risk columns are average annual values for the states.

Table 11.5 Determinants of the murder rate (excluding Virginia)

The first measure of execution, commutation, and removal					
Duration on death row: 5 years					
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0066*			–0.0068*	–0.0084**
	(0.0035)			(0.0037)	(0.0036)
$(COMM_t/SENT_{t-5})_{-1}$		0.0087**		0.0091**	
		(0.0038)		(0.0039)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0025***		0.0029***
			(0.0008)		(0.0010)
n	719	728	676	718	673
Duration on death row: 4 years					
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0052**			–0.0052**	–0.0045*
	(0.0025)			(0.0025)	(0.0024)
$(COMM_t/SENT_{t-4})_{-1}$		0.0044***		0.0045***	
		(0.0016)		(0.0015)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0004		0.0005
			(0.0007)		(0.0007)
n	769	774	728	765	725
The second measure of execution, commutation, and removal					
Duration on death row: 5 years					
$(EXEC2_t/SENT_{t-5})_{-1}$	–0.0063**			–0.0061**	–0.0083***
	(0.0026)			(0.0026)	(0.0024)
$(COMM2_t/SENT_{t-5})_{-1}$		0.0083***		0.0083***	
		(0.0030)		(0.0031)	
$(REMOVE2_t/SENT_{t-5})_{-1}$			0.0019***		0.0023***
			(0.0007)		(0.0008)
n	722	728	697	721	694
Duration on death row: 4 years					
$(EXEC2_t/SENT_{t-4})_{-1}$	–0.0066			–0.0067	–0.0060
	(0.0040)			(0.0040)	(0.0037)
$(COMM2_t/SENT_{t-4})_{-1}$		0.0043***		0.0044***	
		(0.0013)		(0.0012)	
$(REMOVE2_t/SENT_{t-4})_{-1}$			0.0003		0.0005
			(0.0008)		(0.0007)
n	769	776	745	767	742

Note: See table 11.1 notes.

Louisiana are dropped, respectively. In each case, dropping these states does not influence the results. That is, even when we remove the high-risk execution states from the analysis, the results are still robust. This may not be all that surprising as the coefficients are estimated through within state variation when including state-fixed effects.

This analysis shows that attempts to make the deterrence results disappear are ineffective. Even if one estimates an unusual specification that takes the numerator and denominator of the risk variables contemporaneously (in the bottom panels of table 11.1 and table 11.2), the estimated impact of executions becomes statistically insignificant, but the positive impact of commutations on the murder rate *does not disappear.*

11.4 The Impact of Death Penalty Laws

Donohue and Wolfers (2005) argued that the murder rates were *higher* in Kansas and New Hampshire after these states adopted the death penalty, were lower in New York and New Jersey after their adoption of the death penalty, and that murder rates *declined* in Massachusetts and Rhode Island after these states abolished the death penalty. We estimated various models in an effort to substantiate this statement. Because they indicate the impact of the death penalty laws are estimated separately for each of the mentioned states while controlling for the same variables as in the main specification, we estimated models separately for Kansas, New Hampshire, New York, New Jersey, Massachusetts, and Rhode Island.

For each state, a dummy variable is created that takes the value of one if the death penalty is legal and zero otherwise. Kansas legalized the death penalty in 1994. New Hampshire legalized it in 1991. Legalization took place in 1982 and 1995 for New Jersey and New York, respectively. Massachusetts and Rhode Island abolished the death penalty in 1984.[10] Because the sample runs from 1977 to 1997, estimating regressions for each state separately is complicated by a degrees-of-freedom problem. The results are summarized in table 11.6. The reported coefficients pertain to a lagged dummy variable indicating the legality of the death penalty.[11]

As the table shows, inclusion or exclusion of control variables has no substantial impact on the estimated coefficients of legal death penalty indicator. In these regressions, the coefficient of the death penalty indicator is not statistically different from zero in Rhode Island and New York. It is negative and significant in New Hampshire and New Jersey. In Kansas and Massachusetts, the coefficients are always negative and significant in one specification for each state.

As an alternative method to investigate the impact of each state's death penalty laws, we performed an interrupted time series analysis. To investigate

10. Massachusetts abolished the death penalty in October 1984. Thus, 1985 is the first year with no death penalty in Massachusetts in the data since abolishment took place. Similarly, 1985 is the first full year where the death penalty is illegal in Rhode Island.

11. The complete set of results can be found in Mocan and Gittings (2006). The number of control variables differs between the specifications to investigate the sensitivity. The sentencing rate could only be included in the regressions for New Jersey because there is no variation in the number of death sentences in the five other states. Similarly, the drinking age cannot be included in the models.

Table 11.6 The impact of the death penalty on the murder rate

	The coefficient of Death Penalty Legal ($t-1$)				
State	(1)	(2)	(3)	(4)	(5)
Kansas	–0.0214	–0.0044	–0.0007	–0.008*	–0.0011
	(0.0220)	(0.0183)	(0.0061)	(0.0040)	(0.0033)
New Hampshire	–0.0226	–0.0253**	–0.0125	–0.0206**	–0.0213**
	(0.0119)	(0.0099)	(0.0105)	(0.0080)	(0.0078)
Massachusetts	–0.0055	–0.0059	–0.0082*	–0.0075	–0.0066
	(0.0060)	(0.0048)	(0.0045)	(0.0065)	(0.0051)
Rhode Island	–0.0087	–0.0051	–0.0043	–0.0034	–0.0063
	(0.0046)	(0.0096)	(0.0070)	(0.0076)	(0.0067)
New York	0.0087	0.0165	0.0113	0.0119	0.0145
	(0.0183)	(0.0122)	(0.0125)	(0.0108)	(0.0194)
New Jersey	–0.0101	–0.009*	–0.0085***	–0.0132**	–0.0132**
	(0.0140)	(0.0037)	(0.0017)	(0.0036)	(0.0030)

Notes: Each cell reports the coefficient (standard error) of Death Penalty Legal ($t-1$) variable in the murder rate regressions for the corresponding state. This variable takes the value of 1 if death penalty is legal in the state and zero otherwise. Models in column (1) include murder arrest rate ($t-1$), sentencing rate, prisoners per violent crime ($t-1$), prison death rate ($t-1$), percent black, Republican governor, unemployment rate, per capita income, infant mortality rate, urbanization, percent aged twenty–thirty-four, percent aged thirty-five–forty-four, percent aged forty-five–fifty-four, percent aged fifty-five+, and time trend. Models in column (2) omit the unemployment rate, infant mortality rate, and urbanization. Models in column (3) omit the unemployment rate, infant mortality rate, urbanization, murder arrest rate ($t-1$), sentencing rate, prisoners per violent crime ($t-1$), and prison death rate ($t-1$). Models in column (4) omit percent black, Republican governor, unemployment rate, infant mortality rate, urbanization, percent aged twenty–thirty-four, percent aged thirty-five–forty-four, percent aged forty-five–fifty-four, and percent aged fifty-five+. Models in column (5) omit prison death rate ($t-1$), percent black, Republican governor, unemployment rate, per capita income, infant mortality rate, urbanization, percent aged twenty–thirty-four, percent aged thirty-five–forty-four, percent aged forty-five–fifty-four, and percent aged fifty-five+. Robust and clustered standard errors in parentheses.

***Statistical significance at the 1 percent level or better.

**Statistical significance between 5 and 1 percent.

*Statistical significance between 10 and 5 percent.

if the enactment or abolishment of the death penalty in a state has altered the behavior of the murder rate in that state over time, time series dynamics of the murder rate of each state can be modeled separately, and intervention variables can be added to investigate if the change in the death penalty law in that state in a particular year has altered the time series dynamics of the murder rate in that state. Following Mocan and Topyan (1993), Mocan (1994), and Harvey and Durbin (1986), let M_t stand for the murder rate in a particular state in year t. The dynamics of M_t over time can be expressed by equation (2), where μ_t represents slowly-evolving trend component of the murder rate, Ω_t stands for the cycle-component, and ε_t is regular random component.

(2) $$M_t = \mu_t + \Omega_t + \varepsilon_t$$

The trend in the murder rate, μ_t, is determined by its level and the slope in each time period, which can be written in general as random walks as in equation (3).

(3) $$\begin{aligned} \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\ \beta_t &= \beta_{t-1} + \xi_t \end{aligned}$$

A flexible method to model the cyclical behavior of the murder rate, represented by Ω in equation (2), is to assume a stochastic trigonometric process, which is depicted by equation (4).

(4) $$\begin{aligned} \Omega_t &= \rho \cos \lambda_c \Omega_{t-1} + \rho \sin \lambda_c \Omega^*_{t-1} + \tau_t \\ \Omega^*_t &= -\rho \sin \lambda_c \Omega_{t-1} + \rho \cos \lambda_c \Omega^*_{t-1} + \tau^*_t, \end{aligned}$$

where ρ is a damping factor with $0 \leq \rho \leq 1$, λ_c is the frequency of the cycle in radians, and τ_t and τ^*_t are independently, identically distributed disturbances with mean zero and variance σ^2_t.

The model can be extended by adding an intervention variable to investigate the impact of an event that took place in period k. The immediate pulse effect of the intervention can be modeled by employing the variable ω_t defined as $\omega_t = 0$ if $t \neq k$, and $\omega_t = 1$ if $t = k$. If the intervention shifts the level of the variable, then the intervention variable ω_t is defined as $\omega_t = 0$ if $t \neq k$, and $\omega_t = 1$ if $t \geq k$, and $\mu_t = \mu_{t-1} + \beta_{t-1} + \delta\omega_t + \eta_t$.

We estimated the model, depicted by equations (2) to (4) by including the intervention variables. The models are first estimated from 1977 forward to be consistent with the time period used in the earlier analyses. The estimated trend values (depicted by the dashed lines) along with actual data are displayed in figures 11.1 to 11.6.

The solid lines in figures 11.1 and 11.2 present the time series behavior of the murder rates in Kansas and New Hampshire since 1960. These states legalized the death penalty in 1994 and in 1991, respectively. Although it was asserted by Donohue and Wolfers (2005) that the murder rate went up in these states after the legalization, figures 11.1 and 11.2 show that the opposite is the case. It was also claimed that the murder rates went down in the states of New York and New Jersey after legalization (figures 11.3 and 11.4) and that murder rates fell in Massachusetts and Rhode Island (presented in figures 11.5 and 11.6) due to the abolishment of the death penalty. The evidence in figures 11.3 and 11.4 indeed indicate that murder rates fell in New York and New Jersey after these states legalized death penalty. Figure 11.5 shows that there was an increase in the level of the murder rate in Massachusetts after this state abolished the death penalty followed by a drop in 1997, but it is uncertain whether this drop in 1997 can be attributed to the change in law twelve years prior. In the case of Rhode Island (figure 11.6), the

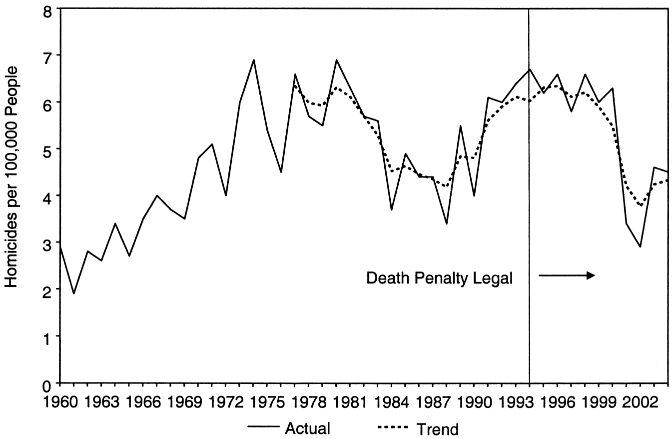

Fig. 11.1 Kansas murder rate and fitted trend

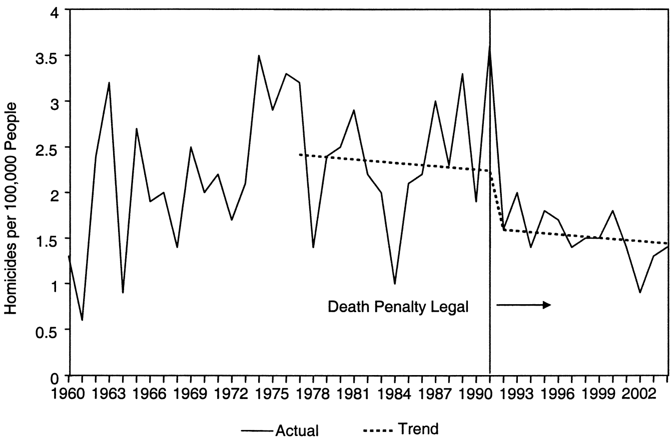

Fig. 11.2 New Hampshire murder rate and fitted trend

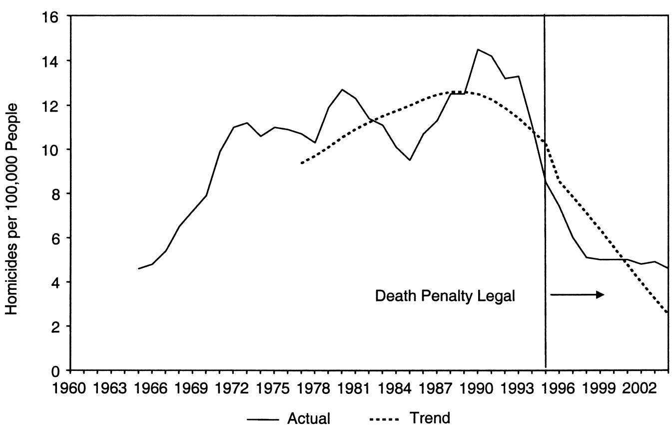

Fig. 11.3 New York murder rate and fitted trend

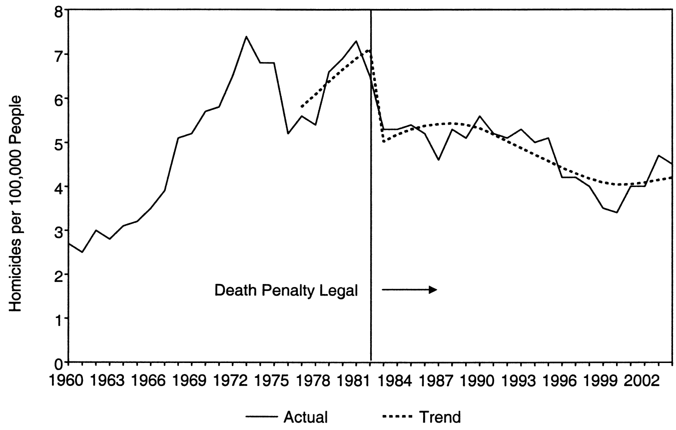

Fig. 11.4 New Jersey murder rate and fitted trend

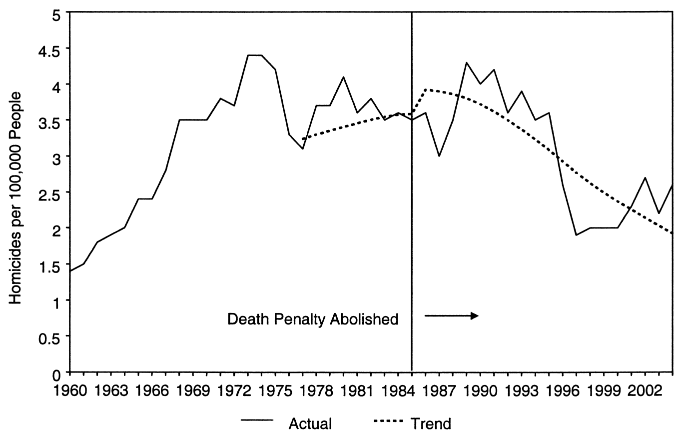

Fig. 11.5 Massachusetts murder rate and fitted trend

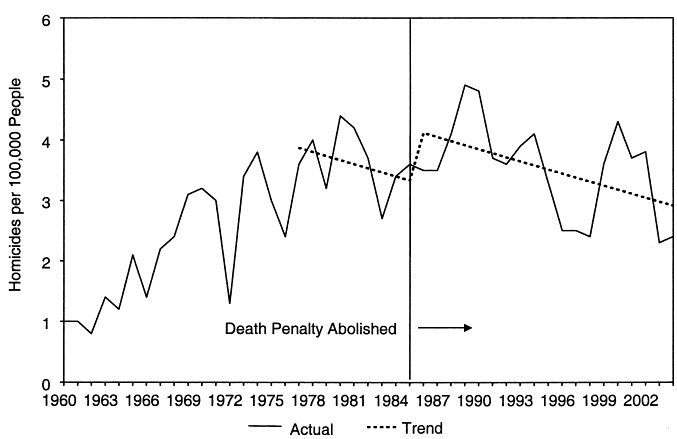

Fig. 11.6 Rhode Island murder rate and fitted trend

murder rate is fluctuating around a quadratic trend, and the level of the murder rate seems to have increased, rather than decreased, after the abolition.

As can be seen, in the four states that adopted the death penalty, the murder rate went down. In the two states that abolished the death penalty, on the other hand, the level of the murder rate has increased.[12]

As another set of analyses, we estimated the models starting in 1960, except for New York, where the data are available starting in 1965. This allowed us to investigate the impact of the adoption of the death penalty in South Dakota (in 1979), New Mexico (in 1979), and in Oregon (in 1978). Furthermore, we also jointly investigated the impact of the 1972 Supreme Court moratorium after the Furman decision.[13] In each case, the Furman decision is associated with an increase in the level of the murder rate. Consistent with the dynamics presented in figures 11.1 to 11.6, adoption of the death penalty generated declines in the murder trends, and abolition in Massachusetts and Rhode Island is associated with immediate increases in the murder rate although long-run trends in these series generated subsequent declines.[14]

11.4.1 Death Penalty Laws: Panel Data

In this section, we investigate whether the existence of the death penalty in a state has a separate impact on the murder rate in addition to the risks associated with being on the death row. To that end, we estimated the same models as those presented in tables 11.1 and 11.2, but we added a dichotomous indicator if death penalty is legal in a given state in a particular year. Furthermore, we interacted this dummy variable with the execution rate, commutation rate, and removal rate variables.

The results are displayed in tables 11.7 and 11.8, where the two alternative measures of execution, commutation, and removal risks are employed, except in column (1), which includes only the death penalty legality variable. In each case, models are estimated with 4 and 5 lags of the death sentences in

12. Although the death penalty was legal during the period before 1984 in Massachusetts, the 1970s and 1980s witnessed a series of legislation and judicial rulings regarding the death penalty. Identifying these time intervals and considering interventions associated with them did not alter the picture depicted in figure 11.5. The same, to a lesser degree, is true for Rhode Island, where the death penalty was reenacted in 1977, but in 1979 the Rhode Island Supreme Court issued the opinion of the violation of the prohibitions of the 8th amendment of the U.S. Constitution (Rhode Island Secretary of State Web site). Adding this potential intervention did not alter the picture depicted in figure 11.6.

13. In 1972, in case of *Furman v. the state of Georgia,* the Supreme Court of the United States struck down federal and state laws that allowed wide discretion that resulted in arbitrary and capricious application of the death penalty. As a result, executions were halted, and inmates had their death sentences lifted. Starting in mid-1970s, many states reacted by adopting new legislation to address the issues raised by the Supreme Court (see Mocan and Gittings [2003] for additional details).

14. These graphs, which are not reported in the interest of space, can be seen in Mocan and Gittings (2006).

Table 11.7 **Determinants of the murder rate: Models with deterrence variables and the death penalty indicator—the first measure of execution, commutation, and removal**

		$SENT_{t-4}$		$SENT_{t-5}$	
	(1)	(2)	(3)	(4)	(5)
Death Penalty Legal (–1)	–0.0152**	–0.0148**	–0.0123**	–0.0135**	–0.0116**
	(0.0063)	(0.0060)	(0.0056)	(0.0064)	(0.0056)
Murder Arrest Rate (–1)	–0.0009	–0.0019	–0.0020	–0.0028	–0.0021
	(0.0032)	(0.0026)	(0.0024)	(0.0026)	(0.0026)
Sentencing Rate (–1)	–0.0026	0.0093	0.0112	–0.0105	–0.0171
	(0.0216)	(0.0222)	(0.0236)	(0.0198)	(0.0198)
Prisoners per Violent Crime (–1)	–0.0401***	–0.0397***	–0.0378***	–0.0391***	–0.0375***
	(0.0087)	(0.0083)	(0.0085)	(0.0086)	(0.0087)
Death Penalty Legal (–1) × Execution Rate (–1)		–0.0056**	–0.0050**	–0.0061**	–0.0069**
		(0.0022)	(0.0020)	(0.0028)	(0.0029)
Death Penalty Legal (–1) × Commutation Rate (–1)		0.0038**		0.0067	
		(0.0019)		(0.0046)	
Death Penalty Legal (–1) × Removal Rate (–1)			0.0005		0.0028***
			(0.0007)		(0.0009)
n	894	781	741	733	688

Notes: The column headings $SENT_{t-4}$ and $SENT_{t-5}$ mean that execution, commutation, and removal rates are calculated by deflating $EXEC_t$, $COMM_t$, and $REMOVE_t$ by $SENT_{t-4}$ or $SENT_{t-5}$. Each model includes the following variables: murder arrest rate, sentencing rate, unemployment rate, real per capita income, proportion of the state population in the following age groups: twenty–thirty-four, thirty-five–forty-four, forty-five–fifty-four, and fifty-five and over, proportion of the state population in urban areas, proportion which is black, infant mortality rate, legal drinking age in the state, number of prisoners per violent crime, and prison death rate. Also included in each model are state-fixed effects, a time trend, state-specific time trends, a dummy variable to control for the impact of the 1995 Oklahoma City bombing, and a dummy variable to indicate is the governor is a Republican. Robust and clustered standard errors are in parentheses.

***Statistical significance at the 1 percent level or better.

**Statistical significance between 5 and 1 percent.

*Statistical significance between 10 and 5 percent.

Table 11.8 **Determinants of the murder rate: Models with deterrence variables and the death penalty indicator—the second measure of execution, commutation, and removal**

		$SENT_{t-4}$		$SENT_{t-5}$	
	(1)	(2)	(3)	(4)	(5)
Death Penalty Legal (–1)	–0.0152**	–0.0147**	–0.0126**	–0.0136**	–0.0131**
	(0.0063)	(0.0060)	(0.0056)	(0.0064)	(0.0057)
Murder Arrest Rate (–1)	–0.0009	–0.0018	–0.0028	–0.0029	–0.0028
	(0.0032)	(0.0026)	(0.0028)	(0.0026)	(0.0028)
Sentencing Rate (–1)	–0.0026	0.0092	0.0121	–0.0069	–0.0105
	(0.0216)	(0.0222)	(0.0237)	(0.0209)	(0.0199)
Prisoners per Violent Crime (–1)	–0.0401***	–0.0398***	–0.0387***	–0.0399***	–0.0388***
	(0.0087)	(0.0082)	(0.0082)	(0.0085)	(0.0085)
Death Penalty Legal (–1) × Execution Rate (–1)		–0.0070**	–0.0064*	–0.0064***	–0.0075***
		(0.0035)	(0.0032)	(0.0021)	(0.0022)
Death Penalty Legal (–1) × Commutation Rate (–1)		0.0036**		0.0054	
		(0.0016)		(0.0040)	
Death Penalty Legal (–1) × REMOVE Rate (–1)			0.0005		0.0022***
			(0.0007)		(0.0007)
n	894	783	758	736	709

Note: See table 11.7 notes.

the denominator of the risk variables as before. The results demonstrate that the existence of the death penalty in a state has a negative and statistically significant impact on the murder rate. In addition, the execution rate has a negative impact on the murder rate, and commutations and removals have a positive impact, although not always statistically significant.

11.5 The Denominator of the Risk Variables Again

Individuals do not exit the death row in the same year as they received the death sentence. To make the point more visible, the average duration on death row is calculated each year for those inmates who are removed that year and plotted in figure 11.7 by the reason of exit. As can be inferred, individuals who were commuted, executed, or otherwise removed from death row had spent an average of about six years on death row. On the other hand, those who were executed or commuted in 1997 had completed about eleven years on death row. Given this picture, one can use time varying durations on death row to calculate the risks of execution, commutation, or removals. For example, the execution risk in year 1981 can be calculated as the number of executions in 1981 divided by the number of death sentences in 1980 (because the duration on death row was one year in 1981). On the other hand, the risk of execution in 1990 can be measured as the number of executions in 1990 divided by the number of death sentences in 1982 (because the average duration on death row for those who were executed in 1990 was eight years. See figure 11.7). More generally, the execution, commutation, and removal rates are calculated as ($EXEC_t/SENT_{t-i}$), ($COMM_t/SENT_{t-j}$), and ($REMOVE_t/SENT_{t-k}$), where i, j, and k are average durations on death row for spells ending in year t for executions, commutations, and removals,

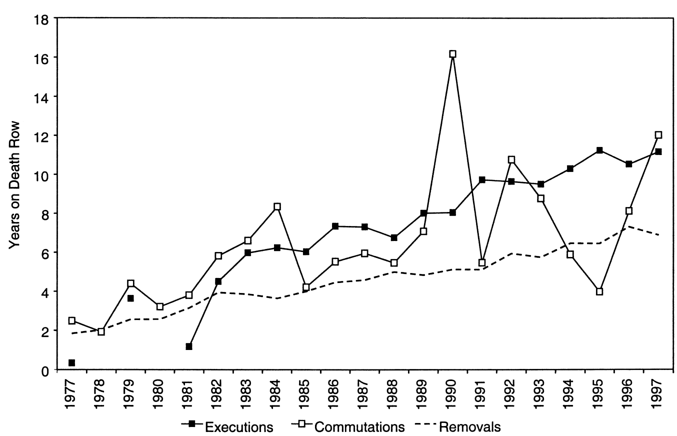

Fig. 11.7 Duration on death row from sentencing to exit

Table 11.9 **Determinants of the murder rate with time varying durations on death row**

	The first measure of execution, commutation, and removal				
$(EXEC_t/SENT_{t-i})_{-1}$	–0.0058*			–0.0058*	–0.0055*
	(0.0031)			(0.0034)	(0.0029)
$(COMM_t/SENT_{t-j})_{-1}$		0.0014		0.0009	
		(0.0064)		(0.0067)	
$(REMOVE_t/SENT_{t-k})_{-1}$			0.0003		0.0001
			(0.0008)		(0.0008)
n	830	642	784	629	773
	The second measure of execution, commutation, and removal				
$(EXEC2_t/SENT_{t-j})_{-1}$	–0.0049*			–0.0050	–0.0049*
	(0.0026)			(0.0032)	(0.0027)
$(COMM2_t/SENT_{t-j})_{-1}$		0.0009		0.0004	
		(0.0054)		(0.0059)	
$(REMOVE2_t/SENT_{t-k})_{-1}$			0.0007		0.0006
			(0.0007)		(0.0007)
n	833	643	806	632	797

Notes: See table 11.1 notes. *i*, *j*, and *k* are average durations on death row for spells ending in year *t* for executions, commutations and removals, respectively. For more details see section 11.5.

respectively. Calculating the risks this way produced the results displayed in table 11.9. Once again, we are unsuccessful in eliminating the impact of the execution risk on the murder rate.[15]

Some researchers calculated the execution risk as the number of executions in a year divided by the number of prisoners in that state in that year (e.g., Katz, Levitt, and Shustorovich 2003). This calculation assumes that every prisoner in state correctional facilities is at risk of being executed. This assumption has no validity as about 99.7 percent of the inmates in state prisons are incarcerated for noncapital offenses, and, therefore, they are not at risk of being executed. The difference is not simply a matter of scaling. The number of total prisoners to the number of death row inmates is not a constant proportion over time or across states.[16] Nevertheless, the results that use the total number of prisoners as the denominator is provided in table 11.10. Although this inaccurate measure makes the impact of commutations disappear, it cannot make the impact of executions go away.

A more appropriate way of calculating the risk of execution would be to

15. Another extreme is to uniformly increase the lag length of the denominator. For example, when lag-length seven is imposed, the same results are obtained, but not surprisingly, sample size and the statistical significance is reduced.

16. For example, in 1997, there were a total of 1,127,686 inmates in state prisons, and there were 3,328 death row inmates. The number of total prisoners was 1,316,302 in 2004, and the number of people on death row was 3,314 in the same year.

Table 11.10 Determinants of the murder rate: Deterrence variables deflated by total prisoners

The first measure of execution, commutation, and removal deflated by total prisoners/1,000					
$(\text{EXEC}_t/\text{PRIS}_t)_{-1}$	–0.0258**			–0.0255**	–0.0257**
	(0.0101)			(0.0102)	(0.0101)
$(\text{COMM}_t/\text{PRIS}_t)_{-1}$		0.0085		0.0075	
		(0.0077)		(0.0083)	
$(\text{REMOVE}_t/\text{PRIS}_t)_{-1}$			0.0007		0.0006
			(0.0008)		(0.0008)
n	894	894	894	894	894
The second measure of execution, commutation, and removal deflated by total prisoners/1,000					
$(\text{EXEC2}_t/\text{PRIS}_t)_{-1}$	–0.0208**			–0.0206**	–0.0208**
	(0.0083)			(0.0083)	(0.0083)
$(\text{COMM2}_t/\text{PRIS}_t)_{-1}$		0.0065		0.0056	
		(0.0067)		(0.0073)	
$(\text{REMOVE2}_t/\text{PRIS}_t)_{-1}$			0.0003		0.0028
			(0.0007)		(0.0007)
n	894	894	894	894	894

Notes: See table 11.1 notes. PRIS = prisoners per 1,000 population.

use the ratio of executions to the number of inmates on death row rather than deflating by the prison population in the state, although this measure is still inappropriate because a particular death row inmate is not at risk of execution if he just entered death row. Nevertheless, deflating by the stock of death row inmates is much more reasonable than deflating by total prisoners. Results obtained from this exercise are reported in table 11.11. Once again, executions have a negative impact on the murder rate in the state, and commutations are positively related to murder.

Two other denominators are promoted as deflators to the number of executions. For example, Donohue and Wolfers (2005, 815) write "A very simple alternative that avoids this scaling issue is measuring executions per 100,000 residents." They also write: "Another alternative scaling—and perhaps the one most directly suggested by the economic model of crime—is to analyze the ratio of the number of executions to the (lagged) homicide rate" (815). Although it is evident that these suggested measures are poor indicators of the relevant risks, we estimated the models with these denominators as well. The first panel of table 11.12 displays the results when the annual count of executions, commutations, and removals are deflated by state population, and the second panel presents the results when they are deflated by lagged homicide rate. The raw counts of executions, commutations and removals are denoted by #EX, #C, and #R, respectively.

Note that the dependent variable for the analysis is the murder rate, which is measured as murders deflated by population; thus, deflating executions by the state population means that population enters into the denominator of

Table 11.11 **Determinants of the murder rate: Determinance variables deflated by death row inmates**

The first measure of execution, commutation, and removal deflated by death row inmates					
$(\mathrm{EXEC}_t/\mathrm{ROW}_t)_{-1}$	–0.0465*			–0.0463*	–0.0466
	(0.0277)			(0.0276)	(0.0284)
$(\mathrm{COMM}_t/\mathrm{ROW}_t)_{-1}$		0.0098***		0.0097***	
		(0.0014)		(0.0015)	
$(\mathrm{REMOVE}_t/\mathrm{ROW}_t)_{-1}$			–0.0026		–0.0021
			(0.0062)		(0.0062)
n	894	894	890	894	890
The second measure of execution, commutation, and removal deflated by death row inmates					
$(\mathrm{EXEC2}_t/\mathrm{ROW}_t)_{-1}$	–0.0501*			–0.0500*	–0.0485
	(0.0287)			(0.0285)	(0.0298)
$(\mathrm{COMM2}_t/\mathrm{ROW}_t)_{-1}$		0.0084***		0.0083***	
		(0.0017)		(0.0017)	
$(\mathrm{REMOVE2}_t/\mathrm{ROW}_t)_{-1}$			–0.0043		–0.0039
			(0.0051)		(0.0052)
n	894	894	893	894	893

Notes: See table 11.1 notes. ROW = the number of death row inmates.

both the dependent and independent variables, inducing a positive bias in the estimated coefficient of the execution rate. Nevertheless, the coefficient of the execution rate remains negative and significant. Because the dependent variable of the analysis is the murder rate, to use the murder rate as the deflator of executions is not meaningful either.[17] However, as the second panel of table 11.12 demonstrates, using the lagged murder rate as the denominator did not make the results disappear.

What happens to the results if we go to the extreme and use the number of executions, commutations, and removals as measures of risk, without deflating by anything? Here, the level of executions, commutations, and removals are considered as appropriate signals to individuals, rather than the rates at which they occur (as defined by the correct denominator). Though we do not agree that this is the correct specification, the bottom panel of table 11.12 shows that even this modification does not eliminate the impact of prices on human behavior. Although the coefficients of commutations and removals are statistically insignificant, the coefficient of execution *remains significant even in this model.*

17. Donohue and Wolfers seem to recognize this and write that in their analysis they employ the lagged homicide rate as the deflator (Donohue and Wolfers 2005, footnote 63). However, if the homicide rate has any path-dependence, such as a simple AR(1) model, using the lagged-dependent variable in the denominator of the independent variable does not avoid a bias, and it creates a strange specification.

Table 11.12 Determinants of the murder rate deflated by population and lagged murder rate

The raw count of executions, commutations, and removals deflated by population/100,000					
$(\#EX_t/POP_t)_{-1}$	–0.055*			–0.0055*	–0.0051*
	(0.0281)			(0.028)	(0.0028)
$(\#C_t/POP_t)_{-1}$		0.0099		0.0011	
		(0.0212)		(0.020)	
$(\#R_t/POP_t)_{-1}$			0.0037		0.0037
			(0.0061)		(0.0063)
n	894	894	894	894	894
The raw count of executions, commutations, and removals deflated by lagged murder rate × 1,000					
$(\#EX_t/MURDER_{t-1})_{-1}$	–0.0543**			–0.0542**	–0.0543**
	(0.0251)			(0.0022)	(0.0021)
$(\#C_t/MURDER_{t-1})_{-1}$		–0.0120		–0.0098	
		(0.0254)		(0.0252)	
$(\#R_t/MURDER_{t-1})_{-1}$			–0.0004		0.0001
			(0.0122)		(0.0127)
n	894	894	894	894	894
The raw counts of executions, commutations and removals as risk variables (no deflator: denominator = 1)					
$\#EX_{t-1}$	–0.0007***			–0.0007***	–0.0007***
	(0.0002)			(0.0002)	(0.0002)
$\#C_{t-1}$		–0.00008		–0.00009	
		(0.0002)		(0.0002)	
$\#R_{t-1}$			0.00004		0.00005
			(0.0001)		(0.0001)
n	894	894	894	894	894

Notes: See table 11.1 notes. $\#EX_t$ = the raw counts of executions; $\#C_t$ = the raw counts of commutations; $\#R_t$ = the raw counts of death row removals; POP = the population in the state; MURDER = the murder rate.

11.6 Further Attempts to Make the Results Disappear

The risk measures employed in this paper are calculated such that if there is an execution in a given state in a given year, but if it so happens that no individual received a capital sentence five years prior, then the risk ($EXEC_t/SENT_{t-5}$) is set to missing because the denominator is zero. On the other hand, in cases where nobody was sentenced and nobody was executed, the execution risk was taken as zero.

One can adopt an algorithm where observations are dropped from the data when the corresponding executions and death sentences are both zero. This algorithm assumes that the risks cannot be calculated in situations when they should be zero, such as the cases where there is no legal death penalty. Even so, and despite the fact that this algorithm eliminates about half of the legitimate observations, the impact of the death penalty on the murder rate remains as shown in tables 11.13 and 11.14.

Table 11.13 Determinants of the murder rate: Alternative deflators for deterrence variables

	Duration on death row: 5 years				
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0043			–0.0045‡	–0.0061**
	(0.0027)			(0.0029)	(0.0026)
$(COMM_t/SENT_{t-5})_{-1}$		0.0057		0.0061	
		(0.0050)		(0.0050)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0022**		0.0025***
			(0.0008)		(0.0009)
n	398	398	398	398	398
	Duration on death row: 4 years				
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0053**			–0.0053**	–0.0054**
	(0.0022)			(0.0022)	(0.0021)
$(COMM_t/SENT_{t-4})_{-1}$		0.0018		0.0019	
		(0.0025)		(0.0023)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0002		0.0003
			(0.0006)		(0.0006)
n	426	426	426	426	426
Donohue III and Wolfers specification—duration on death row: 0 years; time between arrest and death sentence: 0 years					
$(EXEC_t/SENT_t)_{-1}$	0.00004			–0.0001	–0.0001
	(0.0012)			(0.0012)	(0.0013)
$(COMM_t/SENT_t)_{-1}$		0.0034*		0.0034*	
		(0.0019)		(0.0013)	
$(REMOVE_t/SENT_t)_{-1}$			0.0004		0.0004
			(0.0003)		(0.0003)
n	543	543	543	543	543

Notes: See table 11.1 notes. Observations are dropped when numerator = 0 and denominator = 0 when calculating the risk variable. Double dagger (‡) indicates p-value = 0.115.

It may be possible that the deterrent impact of the death penalty that exists in states with large populations such as New York and New Jersey exerts disproportionate influence in a population-weighted regression and overwhelms the no-deterrence result that would have been obtained in regressions with no weighting.[18] To investigate if the results are driven by this hypothesis, we take the models presented in tables 11.1 and 11.2 and reestimate them without population weights.[19] In models where the duration of death row is taken as five years, the results are actually stronger with the coefficients of the commutation rate being statistically significant. In the models where the duration of death row is taken as four years, the execution rate is insignificant, but the removal rate becomes significant when it was insignificant in the weighted regression displayed in tables 11.1 and

18. This hypothesis is developed by Donohue and Wolfers (2005, footnote 50).

19. The results, which are not reported in the interest of space, can be found in Mocan and Gittings (2006, 60–61).

Table 11.14 **Determinants of the murder rate dropping observations where risk is not well defined: the second measure of execution, commutation, and removal**

	Duration on death row: 5 years				
$(\text{EXEC2}_t/\text{SENT}_{t-5})_{-1}$	–0.0052**			–0.0058**	–0.0068***
	(0.0022)			(0.0023)	(0.0024)
$(\text{COMM2}_t/\text{SENT}_{t-5})_{-1}$		0.0041		0.0054	
		(0.0045)		(0.0037)	
$(\text{REMOVE2}_t/\text{SENT}_{t-5})_{-1}$			0.0017**		0.0020***
			(0.0006)		(0.0007)
n	398	398	398	398	398
	Duration on death row: 4 years				
$(\text{EXEC2}_t/\text{SENT}_{t-4})_{-1}$	–0.0069*			–0.0069*	–0.0071**
	(0.0035)			(0.0036)	(0.0034)
$(\text{COMM2}_t/\text{SENT}_{t-4})_{-1}$		0.0019		0.0021	
		(0.0021)		(0.0019)	
$(\text{REMOVE2}_t/\text{SENT}_{t-4})_{-1}$			0.00002		0.0003
			(0.0007)		(0.0006)
n	426	426	426	426	426
	Donohue III and Wolfers specification—duration on death row: 0 years; time between arrest and death sentence: 0 years				
$(\text{EXEC2}_t/\text{SENT}_t)_{-1}$	–0.0006			–0.0007	–0.00005
	(0.0020)			(0.0020)	(0.0019)
$(\text{COMM2}_t/\text{SENT}_t)_{-1}$		0.0034**		0.0034**	
		(0.0013)		(0.0013)	
$(\text{REMOVE2}_t/\text{SENT}_t)_{-1}$			–0.0005		–0.0005
			(0.0005)		(0.0005)
n	543	543	543	543	543

Note: See table 11.13 notes.

11.2. Finally, the results of the regression estimated by Donohue and Wolfers (2005) using contemporaneous numerators and denominators remain unchanged whether the regressions are weighted.

In table 11.15 we present the results obtained from the models that exclude New York and New Jersey and estimate the models without weighting. As can be seen, the impact of leaving the death row on the murder rate cannot be eliminated by dropping New York and New Jersey from the analysis and running the regressions with no weighting. The same conclusion is obtained when we ran the models displayed in tables 11.3 to 11.8 with no weights. Thus, the results are not an artifact of weighting.[20]

20. Dezhbakhsh and Rubin (2007) conduct extensive analyses on similar issues as well as others to investigate the sensitivity of deterrence results to model specification.

Table 11.15 Determinants of the murder rate (excluding New York and New Jersey): unweighted regressions

	The first measure of execution, commutation, and removal				
	Duration on death row: 5 years				
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0043**			–0.0044**	–0.0056**
	(0.0022)			(0.0021)	(0.0025)
$(COMM_t/SENT_{t-5})_{-1}$		0.0077***		0.0079***	
		(0.0022)		(0.0021)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0027***		0.0030***
			(0.0008)		(0.0009)
n	704	713	665	703	662
	Duration on death row: 4 years				
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0038			–0.0036	–0.0033*
	(0.0023)			(0.0023)	(0.0022)
$(COMM_t/SENT_{t-4})_{-1}$		0.0050***		0.0049***	
		(0.0007)		(0.0007)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0017**		0.0018**
			(0.0008)		(0.0008)
n	753	758	716	749	713
	The second measure of execution, commutation, and removal				
	Duration on death row: 5 years				
$(EXEC_t/SENT_{t-5})_{-1}$	–0.0044**			–0.0046**	–0.0054**
	(0.0022)			(0.0022)	(0.0027)
$(COMM_t/SENT_{t-5})_{-1}$		0.0064**		0.0068***	
		(0.0026)		(0.0022)	
$(REMOVE_t/SENT_{t-5})_{-1}$			0.0019***		0.0021***
			(0.0006)		(0.0007)
n	707	713	685	706	682
	Duration on death row: 4 years				
$(EXEC_t/SENT_{t-4})_{-1}$	–0.0048			–0.0048	–0.0049
	(0.0038)			(0.0038)	(0.0036)
$(COMM_t/SENT_{t-4})_{-1}$		0.0046***		0.0045***	
		(0.0008)		(0.0009)	
$(REMOVE_t/SENT_{t-4})_{-1}$			0.0013*		0.0015**
			(0.0007)		(0.0007)
n	753	760	732	751	729

Note: See table 11.1 notes.

11.7 Ph.D. Economists versus Criminals

In his Nobel lecture, Gary Becker (1992, 42) described his inspiration for modeling economic behavior of crime as follows:

> I began to think about crime in the 1960s after driving to Columbia University for an oral examination of a student in economic theory. I was late and had to decide quickly whether to put the car in a parking lot or risk

> getting a ticket for parking illegally on the street. I calculated the likelihood of getting a ticket, the size of the penalty, and the cost of putting the car in a lot. I decided it paid to take the risk and park on the street. (I did not get a ticket.)
>
> As I walked the few blocks to the examination room, it occurred to me that the city authorities had probably gone through a similar analysis. The frequency of their inspection of parked vehicles and the size of the penalty imposed on violators should depend on their estimates of the type of calculations potential violators like me would make.

One standard objection to economic analysis of crime is whether potential criminals are as astute as PhD economists to evaluate these probabilities accurately. This objection is invalid so long as the researcher believes that empirical research should be conceptually consistent with the underlying theory. If one assumes a priori that individuals are incapable of calculating the risks as they are defined by theory, then there is no room to conduct proper empirical research. For example, if one rejects the theoretically proper measure of the execution risk as executions within a cohort of death row inmates in a given year divided by death sentences handed out to that cohort in some earlier year (because one believes that potential criminals do not observe either the executions or the death sentences), then one ought to claim that they cannot observe and evaluate other variables either, including the arrest rates, the size of the police force, or police spending. Thus, there would be no need to conduct research investigating whether people react to deterrence, under the belief that people could not evaluate variations in deterrence risks to begin with.

Furthermore, attempts to justify the use of inappropriate variables based on the claim that individuals cannot observe, measure, or determine the values of decision parameters will produce peculiar analyses that cannot be defended theoretically.[21] For example, if the theory indicates that the real wages should matter in a particular context, it would be silly to suggest the use of nominal wages in a regression (instead of real wages) on the grounds that people cannot observe and predict accurately the level of the consumer price index. If the theory indicates that the accident risk in a state is best measured by the number of accidents per vehicle miles traveled, it would be incorrect to promote deflating accidents by other measures, such as the

21. In general, the manner in which individuals use information to determine the values of decision variables and whether these calculations are unbiased estimates of the true values has been investigated in a variety of context ranging from financial analysts (Keane and Runkle 1998) to parents as child care consumers (Mocan 2007). In the context of criminal activity, it has been acknowledged that the media coverage of the death penalty provides strong signals for potential criminals. For example, some papers investigated if media coverage of executions itself is a deterrent to murder (Bailey 1990; Stack 1987; Phillips 1980). Rincke and Traxler (2009) show that information on law enforcement is transmitted through word of mouth, which serves as a significant deterrent.

square miles of the state or the number of car dealerships, on the grounds that vehicle miles traveled is difficult to observe.

It should be noted that the deterrence results are robust even to the use of measures that are inconsistent with theory. A summary of the findings is provided in table 11.16, which displays the results obtained from estimating various versions of equation (1) along with the description of the measurement of the execution, commutation, and removal rates in each specification. The table displays results that are obtained from specifications where the key variables (execution, commutation, and removal risks) are measured as dictated by theory. The table also presents results from the models where they are measured incorrectly. Examples are the specifications where executions, commutations, and removals are deflated by lagged murder rate, by population; where the raw count of executions, commutations, and removals are used; or the specifications promoted by Donohue and Wolfers (2005, reported in rows [5] and [6] of table 11.16). As the table demonstrates, the results are remarkably stable even across models that substantially deviate from theory.

11.8 Conclusion and Discussion

Do people respond to incentives? An economist's answer to this question is a resounding "yes," not only because economic theory indicates that incentives matter, but also because an enormous empirical literature shows that they do. An especially confusing dimension for noneconomists is the behavior of individuals in such domains as the consumption of addictive substances, sexual activity, and criminal behavior. In the case of criminal behavior, noneconomists frequently express the belief that human beings are not rational enough to make calculated decisions about the costs and benefits of engaging in crime and that criminal activity cannot be altered by incentives. Of course, personal beliefs should not determine the answers to scientific questions. Rather, answers should be provided by careful and objective scientific inquiry.

In the economic approach to crime, decades of empirical research has demonstrated that potential criminals indeed respond to incentives. It has been documented that improved labor market conditions reduce the extent of criminal activity (recent examples include Grogger 1998; Freeman and Rodgers 2000; Gould et al. 2002), and criminal activity reacts to deterrence (e.g., Ehrlich 1975; Levitt 1998b; Kessler and Levitt 1999; Corman and Mocan 2000; Mustard 2003; Corman and Mocan 2005). For example, Levitt (1998b) shows that deterrence is empirically more important than incapacitation in explaining crime and that increases in arrest rates deter criminal activity. Kessler and Levitt (1999) show that Proposition 8 in California, which introduced sentence enhancements for certain crimes, reduced eligible crimes by 4 percent in the year following its passage and 8 percent

Table 11.16 **Summary of the results**

Risk Measures in the Analysis (A/B)			Impact on the murder rate of the:		
A	B	(A/B)	Execution rate	Commutation rate	Removal rate
First measures of executions, commutations, and removals	Death sentences handed out 5 years prior (duration on death row = 5 years)	$(EXEC_t/SENT_{t-5})$, $(COMM_t/SENT_{t-5})$, $(REMOVE_t/SENT_{t-5})$	–*	+	+*
	Death sentences handed out 4 years prior (duration on death row = 4 years)	$(EXEC_t/SENT_{t-4})$, $(COMM_t/SENT_{t-4})$, $(REMOVE_t/SENT_{t-4})$	–*	+*	+
Second measures of executions, commutations, and removals	Death sentences handed out 5 years prior (duration on death row = 5 years)	$(EXEC2_t/SENT_{t-5})$, $(COMM2_t/SENT_{t-5})$, $(REMOVE2_t/SENT_{t-5})$	–*	+	+*
	Death sentences handed out 4 years prior (duration on death row = 4 years)	$(EXEC2_t/SENT_{t-4})$, $(COMM2_t/SENT_{t-4})$, $(REMOVE2_t/SENT_{t-4})$	–*	+*	+
First measures of executions, commutations, and removals (D-III and W specification)	Death sentences handed out the same year (duration on death row = 0 years)	$(EXEC_t/SENT_t)$, $(COMM_t/SENT_t)$, $(REMOVE_t/SENT_t)$	–	+*	+
Second measures of executions, commutations, and removals (D-III and W specification)	Death sentences handed out the same year (duration on death row = 0 years)	$(EXEC2_t/SENT_t)$, $(COMM2_t/SENT_t)$, $(REMOVE2_t/SENT_t)$	–	+*	+
First or second measures of executions, commutations, and removals	Death sentences handed out *i*, *j*, or *k* years prior for spells ending in year *t* (duration on death row = changes by year)	$(EXEC_t/SENT_{t-i})$, $(COMM_t/SENT_{t-j})$, $(REMOVE_t/SENT_{t-k})$	–*	+	+
First measures of executions, commutations, and removals	Death row inmates (ROW)	$(EXEC_t/ROW_t)$, $(COMM_t/ROW_t)$, $(REMOVE_t/ROW_t)$	–*	+*	–
Second measures of executions, commutations, and removals	Death row inmates (ROW)	$(EXEC2_t/ROW_t)$, $(COMM2_t/ROW_t)$, $(REMOVE2_t/ROW_t)$	–*	+*	–
First measures of executions, commutations, and removals	Total prisoners (PRIS)	$(EXEC_t/PRIS_t)$, $(COMM_t/PRIS_t)$, $(REMOVE_t/PRIS_t)$	–*	+	+

(*continued*)

Table 11.16 (continued)

Risk Measures in the Analysis (A/B)			Impact on the murder rate of the:		
A	B	(A/B)	Execution rate	Commutation rate	Removal rate
Second measures of executions, commutations, and removals	Total prisoners (PRIS)	$(EXEC2_t/PRIS_t)$, $(COMM2_t/PRIS_t)$, $(REMOVE2_t/PRIS_t)$	–*	+	+
The raw count of executions (#EX), commutations (#C), removals (#R)	Population (POP)	$(\#EX_t/POP_t)$, $(\#C_t/POP_t)$, $(\#R_t/POP_t)$	–*	+	+
	Lagged murder rate (MURDER)	$(\#EX_t/MURDER_{t-1})$, $(\#C_t/MURDER_{t-1})$, $(\#R_t/MURDER_{t-1})$	–*	–	+
		$(\#EX_t)$, $(\#C_t)$, $(\#R_t)$	–*	–	+
First measures of executions, commutations, and removals (unweighted regression)	Death sentences handed out 5 years prior (duration on death row = 5 years)	$(EXEC_t/SENT_{t-5})$, $(COMM_t/SENT_{t-5})$, $(REMOVE_t/SENT_{t-5})$	–*	+*	+*
	Death sentences handed out 4 years prior (duration on death row = 4 years)	$(EXEC_t/SENT_{t-4})$, $(COMM_t/SENT_{t-4})$, $(REMOVE_t/SENT_{t-4})$	–	+*	+*
Second measures of executions, commutations, and removals (unweighted regression)	Death sentences handed out 5 years prior (duration on death row = 5 years)	$(EXEC2_t/SENT_{t-5})$, $(COMM2_t/SENT_{t-5})$, $(REMOVE2_t/SENT_{t-5})$	–*	+*	+*
	Death sentences handed out 4 years prior (duration on death row = 4 years)	$(EXEC2_t/SENT_{t-4})$, $(COMM2_t/SENT_{t-4})$, $(REMOVE2_t/SENT_{t-4})$	–	+*	+
First measures of executions, commutations, and removals	Death sentences handed out 7 years prior (duration on death row = 7 years)	$(EXEC_t/SENT_{t-7})$, $(COMM_t/SENT_{t-7})$, $(REMOVE_t/SENT_{t-7})$	–	+	+
Second measures of executions, commutations, and removals	Death sentences handed out 7 years prior (duration on death row = 7 years)	$(EXEC2_t/SENT_{t-7})$, $(COMM2_t/SENT_{t-7})$, $(REMOVE2_t/SENT_{t-7})$	–	+	–

Notes: + (–) indicates that the coefficient is positive (negative) in at least two of the three regressions pertinent to that specification. * indicates that the coefficient is statistically significant in at least two of the three specifications. The details are reported in various tables in the paper. Note that a number of specifications summarized in this table are inconsistent with theory. They are estimated and reported here as part of sensitivity analysis. Note also that this table is not an exhaustive summary of the models estimated in the paper. Other models, which are not reported in the interest of space in this table, are consistent with the pattern displayed here. Those results are presented in previous tables.

three years after the passage, providing strong evidence that crime rates react to the severity of punishment. In an analysis of the relationship between crime and punishment for juveniles, Levitt (1998a) finds that changes in relative punishment between juveniles and adults explain 60 percent of the differential growth rates in juvenile and adult crime, and that abrupt changes in criminal involvement with the transition from juvenile to adult courts indicate that individuals do respond to the expected punishment (as economic theory suggests). Corman and Mocan (2005, 2000) and Di Tella and Schargrodsky (2004) show that criminal activity responds to variations in arrests and the size of the police force.

As discussed in the introduction, the signal provided by leaving death row is no different from any other change in expected punishment. That is, an execution is a signal of an increase in expected punishment, and a commutation represents a decrease in expected punishment. However, it is sometimes claimed that because executions are infrequent events, they cannot possibly be a strong enough signals to alter the behavior of people. Yet the same analysts have no difficulty in believing that a prospective criminal observes correctly and accurately the extent of the increase in the number of arrests, and coupled with the information about the level of crime, he calculates the enhanced risk of getting caught, and changes his behavior. Similarly, the suggestion that if the local authority hires twenty new police officers, the associated increase in the risk of getting caught by this move is properly evaluated by potential criminals does not raise objections. Even prison deaths are believed to provide signals to people who are not in prison. Katz, Levitt, and Shustorovich (2003) find that the death rate in prisons constitutes deterrence, and an increase in prison deaths has a negative impact on crime rates. It is very difficult to argue that an increase in prison deaths would be a signal of deterrence, but an increase in the executions would not.

Clearly, analysts' personal beliefs regarding what should and should not constitute a strong signal are irrelevant. Whether police, arrests, prison deaths, executions, or commutations provide signals to people about the extent of expected punishment is an empirical question. In this chapter, we estimate a large number of models in an effort to make the relationship between murder rates and death penalty related outcomes (executions, commutations, and removals) disappear. We change the measurement of the risk variables by altering the numerator and the denominator of the variables in a variety of ways (see table 11.16 for a summary); we also investigate how the results change when we exclude various states from the analysis. The basic results are insensitive to these and a variety of other specification tests performed in the chapter.

It is understandable that the death penalty evokes strong feelings that could be due to political, ideological, religious, or other personal beliefs. It could also be because of the fear that a scientific paper that identifies a deterrent effect could be taken as an endorsement or justification of the death penalty. This fear seems to be powerful especially when there are recent efforts to abolish the death penalty in the United States, while some other countries, such as Mexico, are entertaining the possibility of introducing the death penalty. However, such fears should not be relevant for any scientific research. This point is highlighted by Mocan and Gittings (2003) and Katz, Levitt, and Shustorovich (2003). For example, Katz, Levitt, and Shustorovich (2003) find that the death rate among prisoners (a proxy for prison conditions) deters crime and state the obvious that this finding does not suggest that the society should increase the death rate of the prisoners by worsening the prison conditions to reduce the crime rate. Similarly, Mocan and Gittings (2003, 474) write that the fact that there exists a deterrent effect of capital punishment should not imply a position on death penalty. There are a number of significant issues surrounding the death penalty, ranging from potential racial discrimination in the imposition of the death penalty (Baldus et al. 1998) to discrimination regarding who is executed and who is commuted once the death penalty is received (Argys and Mocan 2004).

Given these concerns, it is critically important to preserve objectivity in scientific research on a subject matter in which opinions may have been formed without, or sometimes despite, the empirical evidence. This unfortunate phenomenon is described succinctly by Sunstein and Vermeule (2005), where they write in their reply to Donohue and Wolfers (2005):

> We cannot help but add that as new entrants into the death penalty debate, we are struck by the intensity of people's beliefs on the empirical issues, and the extent to which their empirical judgments seem to be driven by their moral commitments. Those who oppose the death penalty on moral grounds often seem entirely unwilling to consider apparent evidence of deterrence and are happy to dismiss such evidence whenever even modest questions are raised about it. Those who accept the death penalty on moral grounds often seem to accept the claim of deterrence whether or not good evidence has been provided on its behalf. (848)

In summary, the detailed analysis in this chapter demonstrates the deterrent effect of capital punishment. Yet this finding does not imply that capital punishment is good or bad, nor does it provide any judgment about whether capital punishment should be implemented or abolished. It is just a scientific finding that demonstrates that people react to incentives.

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Comment Lucía Quesada

The objective of the chapter is to show that the death penalty works as crime deterrent, specifically to show that potential murderers respond to incentives in such a way that when the probability of being executed increases, the homicide rate decreases.

This idea is based on an economic approach to crime in which the probability of being punished is interpreted as the "price" of crime. Thus, when its price increases, crime should decrease.

A model of individual decision making indicates that individual *i* commits a crime if his or her expected utility with crime is greater than his/her expected utility without crime:

$$EU_i(\text{crime}) > EU_i(\text{no crime})$$

Thus, the probability that a crime is committed by individual *i* is

$$\Pr_i(\text{crime}) = \Pr[EU_i(\text{crime}) > EU_i(\text{no crime})].$$

Hence, the determinants of the probability of committing a crime are the determinants of the expected utility with and without crime for individual *i*. Among these, the punishment and the probability of being punished are of interest for this chapter. Of course, an increase in any of those variables decreases the expected utility with crime, which implies, according to the theory, that it should also decrease the probability of committing a crime. This is the basic idea behind the economic theory of crime, which the authors intend to test empirically for the particular case of the death penalty.

The main question here is how to do the empirical work.

The probability of being punished that is used in the theoretical model of individual choice depends on individual characteristics like age, race, and income level and is an estimation individuals make based on available information like the existing law, the perceived efficiency of the judicial system, and maybe learning from own experience. Hence, the theoretical model is

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