American Economic Review: Papers and Proceedings 2012, 102(3): 487–492
http://dx.doi.org/10.1257/aer.102.3.487

Assumptions Matter: Model Uncertainty and the Deterrent Effect of Capital Punishment[†]

By Steven N. Durlauf, Chao Fu, and Salvador Navarro*

The effectiveness of capital punishment in deterring homicides has remained unclear despite the fact that the Supreme Court's moratorium on capital punishment and the subsequent adoption of capital punishment by a subset of states, combined with very different rates of execution across polities, would appear to be an ideal environment for revealing deterrence effects using panel data methods. One can find papers that argue that postmoratorium data reveal large deterrent effects (Dezhbakhsh, Rubin, and Shepherd 2003 (DRS hereafter); Zimmerman 2004), fail to provide evidence of a deterrent effect (Donohue and Wolfers 2005; Durlauf, Navarro, and Rivers 2010 (DNR hereafter)), or provide a mixture of positive deterrence and negative deterrence (brutalization) effects depending on the frequency of execution (Shepherd 2005).

The presence of disparate results on the deterrent effect of capital punishment is not, by itself, surprising. Social scientists have long understood that the data "do not speak for themselves," and so empirical analyses that involve substantive social science questions, such as the measurement of deterrence, can do so only conditional on the choice of a statistical model. The disparate findings in the capital punishment literature reflect this model dependence. This is true even when one conditions on the modern panel literature in which the various models typically represent statistical instantiations of Becker's (1968) rational choice model of crime. Thus, a common basis for understanding criminal behavior, in this case murder, is compatible with contradictory empirical findings because of the nonuniqueness of the mapping of the underlying behavioral theory to a statistical representation suitable for data analysis.

This article is designed to understand the sources of the disparate literature findings. Specifically, we consider how different substantive assumptions about the homicide process affect deterrence effect estimates. Since there is no a priori reason to assign probability 1 to any of the models we study, we constructively address the fact that one must account for the presence model uncertainty in the evaluation of the deterrent effect of capital punishment. Durlauf, Fu, and Navarro (forthcoming) (DFN hereafter) elaborate the analysis presented here.

Section I of the article outlines the way we think about model uncertainty. Section II describes the model space we employ to evaluate deterrence effects to capital punishment. Section III describes the data. Section IV provides our empirical results. Section V concludes.

I. Model Uncertainty

The importance of model uncertainty has been understood throughout the history of statistics, but our treatment follows Leamer (1978, 1983) in systematically exploring how different assumptions affect deterrence estimates. Suppose one wants to calculate a deterrence measure D. Conventional approaches to empirical work produce estimates of this measure given available data d and the choice of a model m:

$$\hat{D}(d,m). \quad (1)$$

Accounting for model uncertainty is, thus, no deeper than understanding the role of m in (1).

* Durlauf: University of Wisconsin, 1180 Observatory Drive, Madison, WI 53706 (e-mail: sdurlauf@ssc.wisc.edu); Fu: University of Wisconsin, 1180 Observatory Drive, Madison, WI 53706 (e-mail: cfu@ssc.wisc.edu); Navarro: University of Western Ontario, Social Science Centre, London, Ontario, Canada, N6A 5C2 (e-mail: snavarr@uwo.ca). We thank Timothy Conley and David Rivers for many insights. Hon Ho Kwok and Xiangrong Yu have provided outstanding research assistance.

† To view additional materials, visit the article page at http://dx.doi.org/10.1257/aer.102.3.487.

This article is not interested in resolving the differences between pairs of deterrence papers, as was the objective in Cohen-Cole et al. (2009). Our objective is to understand how different substantive assumptions about the homicide process affect deterrence estimates. We do not make the assumption that the "true" homicide process is part of the model space. While its absence would produce interpretation issues as to what the deterrence estimates mean, it does not preclude the exploration of the sensitivity of estimates to alternative modeling assumptions.

We eschew an emphasis on model averaging as a mechanism for reconciling different model-specific estimates. Our reason for this is that our goal is to understand how these assumptions determine deterrence findings. Given our focus on substantive differences, one can well imagine strong disagreements on the choice of a prior by either analysts or policymakers. We do report averaged estimates under a uniform model prior assumption to provide a summary statistic.

II. Model Space

The elements of our model space are outcome equations for murder rates, each of which is a modification of the baseline regression in DRS:

$$(2)\quad M_{c,t} = P_{c,t}(A)\beta_A + P_{c,t}(S|A)\beta_S + P_{c,t}(E|S)\beta_E + X_{c,t}\gamma + \theta_c + \theta_t + \xi_{c,t},$$

where $M_{c,t}$ is a measure of the murder rate in county c at time t, $P_{c,t}(A)$ is the probability that a murderer is caught, i.e., the apprehension rate for murders. $P_{c,t}(S|A)$ is the probability that an apprehended murderer is sentenced to death. $P_{c,t}(E|S)$ is the probability that a death sentence is carried out given a death sentence. $X_{c,t}$ are demographic and economic characteristics of the county. θ_c and θ_t are county and time fixed effects. $\xi_{c,t}$ is a zero mean residual that is assumed to be independent of $X_{c,t}$ but not of $P_{c,t}(A)$, $P_{c,t}(S|A)$, and $P_{c,t}(E|S)$.

We construct a model space by considering four distinct sources of model uncertainty. It is appropriate to think of our analysis as forming models by the resolution of the model uncertainty from each of these sources. The first source of model uncertainty is generated by alternative assumptions on the underlying probability model generating equation (2). As shown in DNR, justifying the linear structure in (2) as the aggregation of individual decisions requires that the binary choices of the individuals obey a linear probability model.

Linear probability models impose very stringent assumptions on the individual-level analogs of $\xi_{c,t}$ in order to ensure that probabilities are always bounded between 0 and 1. For this reason, we contrast (2) with a model in which the individual murder choices obey the standard logit model. DNR show that these aggregate murder rates will follow

$$(3)\quad \ln\left(\frac{M_{c,t}}{(1 - M_{c,t})}\right) = P_{c,t}(A)\beta_A + P_{c,t}(S|A)\beta_S + P_{c,t}(E|S)\beta_E + X_{c,t}\gamma + \theta_c + \theta_t + \xi_{c,t}.$$

Our second source of model uncertainty involves the choice of probabilities employed in equations (2) and (3). We refer to this as model uncertainty about the determinants of choice under uncertainty. The conditional probabilities that appear in equation (2) represent an assumption about how the likelihood of punishment affects individual choices. Although used in the empirical literature, these are *not* the appropriate probabilities to employ if potential murders obey the rational choice model of crime. DNR show that, under the linear probability model assumption, the probabilities that derive from utility maximization produce the aggregate murder equation

$$(4)\quad M_{c,t} = P_{c,t}(A)\beta_A + P_{c,t}(A, S)\beta_S + P_{c,t}(A, S, E)\beta_E + X_{c,t}\gamma + \theta_c + \theta_t + \xi_{c,t}.$$

The differences between (4) and (2) are immediate when one notes that $P_{c,t}(A, S) = P_{c,t}(S|A)P_{c,t}(A)$ and $P_{c,t}(A, S, E) = P_{c,t}(E|S) \times P_{c,t}(S|A)P_{c,t}(A)$, so that the probabilities in (2) interact to produce the regressors in (4). We are unaware of any formal justification for the use of conditional probabilities as appears in (2).

Our third source of model uncertainty, following Shepherd (2005), allows for state-specific coefficients in the probability of execution. We call this model uncertainty about state-level heterogeneity. Formally, if one defines an indicator variable $\delta_{s,c}$ which equals 1 if county c is in state s and 0 otherwise, Shepherd replaces $\underline{P_{c,t}}(\underline{E}|S)\beta_E$ with $\sum_s \delta_{s,c} P_{c,t}(E|S)\beta_{E,s}$ in equation (2). While Shepherd does not motivate her decision to introduce state-level heterogeneity only for this conditional probability, we restrict ourselves to the narrow form of heterogeneity considered by Shepherd in order to maintain closer touch to the existing literature.

Our final source of model uncertainty arises as a consequence of the murder rate being zero in many county-time observations in our data. For models based on the logistic probability model, the left-hand-side variable is a log transformation of the murder rate; thus, this variable is not defined for those county-time pairs for which the murder rate is zero. One possibility is to follow DNR and drop observations for which the murder rate is zero. This is a valid approach if the county-time pairs with zero murder rates are a random subsample of the data *given the observable characteristics*. However, there is no good reason to think that the zero-murder-rate observations are random. We therefore introduce a fourth form of model uncertainty: model uncertainty about exchangeability of county-time pairs with no murders and those with murders. While we refer to this as uncertainty about exchangeability between subsets of observations, it also encompasses issues normally associated with selection on unobservables. In order to account for the potential endogeneity of the zero murder county-time pairs, we employ control functions. Details may be found in DFN.

Together, these four sources of uncertainty generate 20 distinct models. Figure 1 illustrates our four sources of model uncertainty using a tree structure.

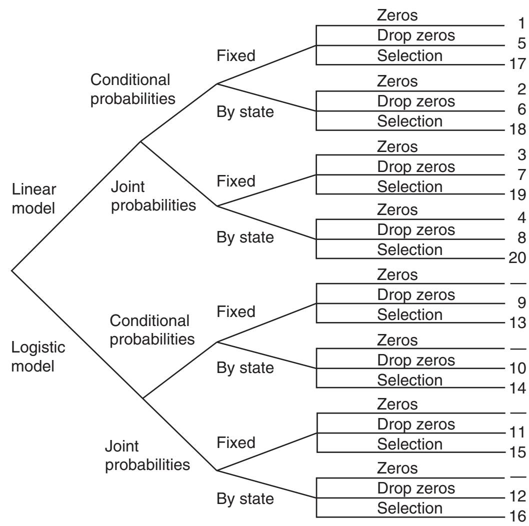

FIGURE 1. MODEL SPACE

III. Data

The data we use come from DRS, where sources and a complete description can be found. The dataset includes the murder rates for a panel of 3,054 counties for the 1977–1996 period. It also includes data on county assault and robbery rates, NRA state-level membership, data on population distribution by age, gender, and race as well as population density and data on per-capita income, income maintenance, and unemployment insurance payments.

We also use county-level data on murder arrests and murder sentencing as well as state-level data on executions of death-penalty inmates to estimate the probabilities of arrest, sentencing, and execution. We follow DRS in construction of probabilities. The probability of arrest is formed as the ratio of arrests to murders at time t. The lag between arrest and sentencing is reflected by constructing the probability of sentencing conditional on arrest as the ratio of death sentences at t over arrest for murder at $t - 2$. Since the average lag between sentencing and execution is six years, the execution probability is constructed as the ratio of executions at t to sentences at $t - 6$.

Finally, the dataset also includes data on expenditures on police and judicial legal system, prison admissions, as well as percentage of the state population who vote Republican in presidential elections. These variables represent exclusion restrictions with respect to the murder equation, i.e., they are variables that help predict the probability of punishment but that are not included in the equation relating murders to these probabilities. As such, these variables may be used to instrument for the endogenous probabilities of arrest, sentencing, and execution.

IV. Results

The exact specification for the baseline model we estimate is given by

$$(5)\quad \frac{Murders_{c,s,t}}{(Population_{c,s,t}/100{,}000)}$$
$$= \beta_1\left(\frac{HomicideArrests_{c,s,t}}{Murders_{c,s,t}}\right)$$
$$+ \beta_2\left(\frac{DeathSentences_{s,t}}{Arrests_{s,t-2}}\right)$$
$$+ \beta_3\left(\frac{Executions_{s,t}}{DeathSentences_{s,t-6}}\right)$$
$$+ \gamma_1\left(\frac{Assaults_{c,s,t}}{Population_{c,s,t}}\right)$$
$$+ \gamma_2\left(\frac{Robberies_{c,s,t}}{Population_{c,s,t}}\right)$$
$$+ \gamma_3 CountyDemographics_{c,s,t}$$
$$+ \gamma_4 CountyEconomy_{c,s,t}$$
$$+ \gamma_5\left(\frac{NRAmembers_{s,t}}{Population_{s,t}}\right)$$
$$+ \sum_c CountyEffects_c + \sum_t TimeEffects_t$$
$$+ \eta_{c,s,t}.$$

The other elements of the model space are variations of this baseline model as described in Section III. DFN contains details on estimation, which is based on the use of two-stage least squares to address endogeneity of the punishment probabilities.

In evaluating deterrence effects, the literature emphasizes the number of net lives saved per execution. For any model for the murder rate $M(e)$, where e is the number of executions, net lives saved is calculated as

$$(6)\quad Net\ Lives\ Saved = -\left(\frac{(\partial M(e))}{(\partial e)}\right) \times Population - 1,$$

where $((\partial M(e))/(\partial e))$ is the derivative of the murder rate with respect to the number of executions implied by each model. We calculate net lives saved by evaluating the formula in (6) at the average values for states having the death penalty in 1996 as in DRS.

Table 1 presents our estimated measures of net lives saved. In all cases, the confidence intervals are such that we cannot reject the hypothesis of zero deterrence effects. Our confidence intervals are wider than those in DRS because we follow Donohue and Wolfers (2005) and obtain them using the nonparametric bootstrap, clustering at the state level. Figure 2 provides a visual summary of how model assumptions determine estimates of the net lives saved per execution based on using the average characteristics of a 1996 death penalty state.

What do our findings show? First, the estimates exhibit great dispersion across models. Depending on the model, one can claim that an additional criminal executed induces 63 additional murders or that it saves 21 lives. This demonstrates the ease with which a researcher can, through choice of modeling assumptions, produce evidence that each execution either costs many lives or saves many lives.

Second, a particular subset of models—linear models with constant coefficients—always predict positive net lives saved (i.e., a deterrence effect). This subset contains all cases in which a marginal execution saves lives. All other models predict negative net lives saved for an additional execution. The linearity and constant coefficient assumptions thus are critical in the determination of the sign of the deterrence effect.

Third, the magnitudes of the point estimates of net lives saved, given a stance on whether the deterrent effect is constant across states, differ mainly because of the choice of linear versus logistic specifications. Controlling for the other three sources of model uncertainty, the magnitudes of the point estimates from the linear

TABLE 1

Net lives saved at avg. X			Model type			
Estimate	SE	Selection corrected	Linear or logistic	Conditional or joint probabilities	Fixed or state specific deterrence	Include zeros
18.45	43.53	No	Linear	Conditional	Fixed	Include
−51.71	45.65	No	Linear	Conditional	State	Include
16.6	44.73	No	Linear	Joint	Fixed	Include
−41.33	32.73	No	Linear	Joint	State	Include
16.51	45.74	No	Linear	Conditional	Fixed	Drop
−63.57	49.75	No	Linear	Conditional	State	Drop
14.98	48.16	No	Linear	Joint	Fixed	Drop
−45.04	35.23	No	Linear	Joint	State	Drop
−1.73	20.87	No	Logistic	Conditional	Fixed	Drop
−16.54	26.18	No	Logistic	Conditional	State	Drop
−2.71	22.14	No	Logistic	Joint	Fixed	Drop
−14.55	12.34	No	Logistic	Joint	State	Drop
−2.74	20.48	Yes	Logistic	Conditional	Fixed	
−11.62	19.41	Yes	Logistic	Conditional	State	
−5.33	21.14	Yes	Logistic	Joint	Fixed	
−15.25	12.48	Yes	Logistic	Joint	State	
20.88	27.37	Yes	Linear	Conditional	Fixed	
−23.47	37.81	Yes	Linear	Conditional	State	
20.15	28.76	Yes	Linear	Joint	Fixed	
−39.01	28.55	Yes	Linear	Joint	State	

models are almost always larger (in absolute value) than those from the corresponding logistic models.

How might information be aggregated across the model space to draw overall conclusions on deterrence? Because one of the sources of uncertainty we consider involves different sample sizes (i.e., sometimes dropping the county-time pairs with zero murder rate), standard model averaging techniques cannot be employed. Instead, we separate our model space into two subspaces, one containing all eight models that drop the county-time pairs with zero murder rate, and another containing the 12 models that include all observations. For each subspace we calculate the posterior probability that m is the correct model given the data d. That is, we calculate:

$$\Pr(m \mid d) \propto \Pr(d \mid m)\Pr(m). \tag{7}$$

Hence, the data and the substantive a priori theoretical commitments matter in determining the weights assigned to each model. We employ uniform priors in the calculation of (7) to reflect our lack of substantive prior knowledge about the models. We follow Eicher, Lenkoski, and Raftery (2009) to approximate $\Pr(d \mid m)$.

In each of our two model subspaces the logistic model, with joint probabilities employed to measure deterrent effects, and with constant coefficients, possesses a posterior probability of one (where in one case we drop the county-time pairs with zero murder rate and in the other we control for selection on unobservables). This is interesting, since the joint probability specification is the one suggested by the appropriate decision problem facing a potential murderer, and because the logistic specification has more appealing statistical properties than the linear probability model. The failure of the state-specific coefficients models to receive any posterior weight suggests little evidentiary support in the data for Shepherd's generalization.

For both of our model subspaces, the estimates suggest that an additional execution leads to approximately 15 more murders being committed. Hence, based on averaging, the marginal effect of an execution on the number of murders is *positive*. However, the standard errors of the estimates are large enough that the evidence for this conclusion is quite weak.

V. Conclusions

In this paper, we examine how four different types of model uncertainty affect deterrent effect estimates of capital punishment. We find that the choice of constant coefficients and a

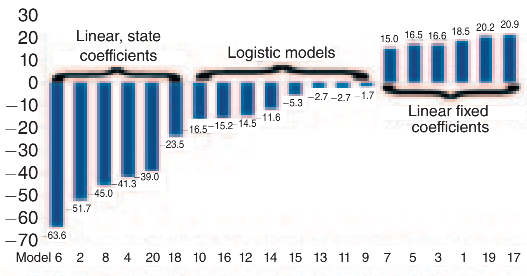

Figure 2. Net Lives Saved at Mean Characteristics of 1996 Death Penalty State

linear probability model are required to produce a positive deterrent effect. We further find that the magnitudes of the coefficients are sensitive to whether a logistic or linear probability model is assumed for unobserved heterogeneity. In contrast, neither the use of joint probabilities versus the conditional probabilities, nor the restriction of the analysis to county-time pairs with positive numbers of murders, have a first-order effect on deterrence estimates. Our results reinforce the message of Heckman (2005): questions such as the deterrence effect of capital punishment cannot be understood outside the prism of models, and it is illusory to think that they can be answered independently of substantive assumptions on the determinants of individual behavior.

REFERENCES

Becker, G. S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76 (2): 169–217.

Cohen-Cole, Ethan, Steven Durlauf, Jeffrey Fagan, and Daniel Nagin. 2009. "Model Uncertainty and the Deterrent Effect of Capital Punishment." *American Law and Economics Review* 11 (2): 335–69.

Dezhbakhsh, Hashem, Paul H. Rubin, and Joanna M. Shepherd. 2003. "Does Capital Punishment Have a Deterrent Effect? New Evidence from Postmoratorium Panel Data." *American Law and Economics Review* 5 (2): 344–76.

Donohue, John J., and Justin Wolfers. 2005. "Uses and Abuses of Empirical Evidence in the Death Penalty Debate." *Stanford Law Review* 58 (3): 791–846.

Durlauf, Steven, Chao Fu, and Salvador Navarro. Forthcoming. "Capital Punishment and Deterrence: Understanding Disparate Results." *Journal of Quantitative Criminology.*

Durlauf, Steven N., Salvador Navarro, and David A. Rivers. 2010. "Understanding Aggregate Crime Regressions." *Journal of Econometrics* 158 (2): 306–17.

Eicher, Theo S., Alex Lenkoski, and Adrian E. Raftery. 2009. "Bayesian Model Averaging and Endogeneity under Model Uncertainty: An Application to Development Determinants." Unpublished.

Heckman, James J. 2005. "The Scientific Model of Causality." *Sociological Methodology* 35 (1): 1–97.

Leamer, Edward E. 1978. *Specification Searches: Ad Hoc Inference with Nonexperimental Data.* New York: Wiley.

Leamer, Edward E. 1983. "Let's Take the Con Out of Econometrics." *American Economic Review* 73 (1): 31–43.

Shepherd, Joanna M. 2005. "Deterrence versus Brutalization: Capital Punishment's Differing Impacts among States." *Michigan Law Review* 104 (2): 203–55.

Zimmerman, Paul R. 2004. "State Executions, Deterrence, and the Incidence of Murder." *Journal of Applied Economics* 7 (1): 163–93.