DISCUSSION PAPER NO. 509

DETERRENCE AND DELINQUENCY: An Analysis of Individual Data*

by

Claude Montmarquette
Université de Montréal

and

Marc Nerlove
Northwestern University

November 1981

with the assistance of

Paul Forest
Université de Montréal

* Our research has been supported by a CAFIR Grant, the Centre de recherche en developpement economique, Université de Montréal, and by the U.S. National Science Foundation. A part of Nerlove's contribution was undertaken during his tenure as a Fellow of the Woodrow Wilson International Center for Scholars of the Smithsonian Institution, Washington, D.C.

We take this opportunity to thank Louise Biron and the Groupe de Recherche sur l'Inadaptation Juvénile for making available to us the data on which this paper is based.

We are indebted for editorial assistance and numerous substantive comments to Eugenia Grohman, Assembly of Behavioral and Social Sciences of the U.S. National Academy of Sciences.

ABSTRACT

This paper tests the hypothesis that the commission of crime is deterred by fear of arrest. We analyze individual data on the frequency of commission of three crimes (shoplifting, drug use, and stealing an item worth more than $50.00) and on perceptions of the probabilities of arrest. The data used in our study come from a survey of more than 3000 French-speaking teenagers from the Montreal school population in 1974. The questions also permit an analysis of the relation between age, sex, previous arrest record and both the frequencies of crime commission and perceived probabilities of arrest. The data are all categorical and require special techniques for their analysis. We estimate a multivariate log-linear probability model in order to test hypotheses concerning the direction and magnitude of bivariate associations among types of crimes and perceptions of the probability of arrest and the socioeconomic and demographic characteristics of respondents.

In Section I, we present an overview and an evaluation of the literature on deterrence. In Section II, we discuss the data set used in this study and introduce the basic elements of the multivariate log-linear probability model. The statistical results and their interpretation are presented in Section III. We present our conclusions in Section IV.

I. INTRODUCTION: DETERRENCE

As James Q. Wilson (1980) emphasizes in his recent survey of research on criminal rehabilitation, "If explaining individual differences is our object, then studying individuals should be our method." A panel of the National Research Council (NRC) on deterrent and incapacitative effects (Blumstein, et al., 1978 p. 11) also stresses the importance of analyzing individual behavior:

> "As an alternative to the aggregate studies that constitute the bulk of the deterrence literature, a fruitful approach might focus on the effects of sanctions on individual criminal be-behavior. Increased attention should be given to developing both methods and data bases that would make the study of individual criminal behavior possible."

And Manski (1978, p. 400) points out in a study paper prepared for the NRC panel:

> "While society's ultimate interest in deterrence policies may be in their impact on aggregate crime rates, such policies directly influence individual criminal behavior. To study deterrence at the level of individual decision making is therefore natural."

This paper focuses specifically on individual behavior and individual perceptions of the risks of criminal behavior for a population of juveniles that contains both those who have engaged in criminal activities and those who have not.

Theories of deterrence rest on a negative association between crime rates, or illegal behavior, and sanctions, measured by the certainty of sanctions, the severity of sanctions, or both. For deterrence to operate, however, objective reality must be translated into individuals' perceptions; in turn, perceptions of sanctions must be reflected in individual behavior. Without such links, one cannot conclude, as does Tullock (1974), that deterrence works. Policies designed to affect criminal behavior through deterrence must rest on measurement of the quantitative effects of various sanctions and on perceptions of those effects on individual behavior.

In recent years, many attempts have been made to measure deterrent effects using aggregate data.[1] Use of aggregate data results from a nearly total lack of individual data on criminal activities, on alternative choices among criminal activities and other activities, and on perceptions of sanctions and the probabilities of their being applied. Bailey and Lott (1976) note, for example, that " ... deterrence theory suggests that it is one's subjective perceptions of punishment that are important, not the objective probability and the actual sanctions that result." In addition, as Palmer (1977), Blumstein, et al., (1978), and others have pointed out, use of nonexperimental aggregate data across jurisdictions or over time contains a number of important sources of bias, such as: (1) a common third cause may exist, e.g., the proportion of juveniles in the population may influence both crime rates and sanction levels across units of observation; (2) measurement errors may be introduced in both crime rates and risks of apprehension by reporting errors that tend to produce a (spurious) negative association between the two variables; (3) the deterrent and incapacitative effects of prison may be confounded; and (4) the operation of the criminal justice system may be affected by crime rates and, in turn, affect the extent to which sanctions are applied.[2]

Such potential biases raise serious questions about results concerning deterrence based on aggregate data, and they direct attention to alternate sources of data and, in particular, to the individual self-reports of criminal behavior, of prime interest to sociologists for some time. If the credibility of self-reported data is accepted, such data may yield information directly an individual's subjective probability of apprehension and perceptions of punishment. Also, such data provide a way around some of the problems mentioned above, since any individual's choices most likely have a negligible effect on aggregate crime rates or on the operation of the criminal justice system. Finally, and perhaps even more importantly, self-reported data may yield information on noncriminals as well as on criminals, thus permitting analysis of the behavior of those who are completely ("absolutely" in Gibbs' (1975) terminology) deterred from crime or illegal behavior. This dimension of the problem has been largely ignored in the literature on deterrence since, with aggregate data across jurisdictions, only the variation of crime rates, and thus "relative deterrence," can be analyzed.

Reviewing the literature on deterrence using self-reported data, Saltzman-Anderson (1977) notes that most studies use college or high school students and are therefore more concerned with delinquency than criminality.[3] For the most common offenses examined in these studies, e.g., marijuana use, petty theft, and shoplifting, she notes important variations in the coefficients measuring the association between perceptions of the probability of sanctions and self-reported deviant behaviors. She attributes the discrepancies in the results to the timing of the study, the use of different measures of association (gamma coefficients, Pearson's product-moment correlation, and derivatives) or to the length of the recall period in which self-reported behavior may have occurred. Earlier studies with a shorter length of recall period and the use of gamma coefficients provided the strongest support for the deterrence hypothesis.

What is striking in this literature, however, including the longitudinal study of the deterrence model of Saltzman-Anderson (1977) and the work by Erikson, Gibbs, and Jensen (1977), is either the small number of observations on which these studies are based or the inappropriateness of the statistical techniques. For example, sample sizes are as low as 140 observations (Claster, 1967; Erickson, 1976) and more generally around 300 observations (Bailey and Lott, 1976; Waldo and Chiricos, 1972; Minor, 1976; and Saltzman-Anderson, 1977). With respect to statistical technique, we note the use of simple correlation coefficients, collapsing of the data into median-mean comparisons, or inappropriate application of ordinary least squares to a regression with a categorical dependent variable. The literature reflects the surprisingly widespread view expressed by Bailey and Lott (1976, p. 103) that: "Unfortunately, no well-developed multiple correlation technique is available for ordinal data that would allow an examination of the effects of three independent variables, with a total of nine sub-dimensions"; yet appropriate methods for the analysis of categorical data from surveys have existed for some time and have been a source of considerable discussion in journals of sociology.[4] One such technique appropriate to the analysis of self-reported individual data on criminal behavior is the so-called log-linear probability model, discussed in the next section.[5]

II. THE DATA AND THE STATISTICAL MODEL

The three types of juvenile crime we analyze in this paper may be related to one another in a complex way. In particular, all three types of crime might be positively associated in the sense that the same individual is likely to commit more than one type. However, stealing an item worth more than \$50.00 is more serious than either drug use or shoplifting, so the latter two crimes might be expected to be both more widespread and more closely associated. We should therefore analyze the joint relation among all three crimes, perceptions of the probabilities of arrest for each, and other variables. Because we have information on perceptions of arrest probabilities for each crime, we can test various hypotheses concerning the absolute and relative deterrence of each individual crime and on the cross-effects of perceptions of arrest probabilities for one crime on the frequency of commission of another.

In 1974, the GRIJ conducted a major survey on the behavior of adolescents (sexual habits, criminal background, drug abuse, family life, etc.); the survey included more than 3000 students aged 11 to 17.[6] The survey was carefully designed to be representative of the total Montreal francophone population of that age group. Of particular interest to our study, the questionnaire contained self-reported information for each individual on drug use, stealing (an item worth more than \$50.00), and shoplifting during the previous 12 months and on the perceived probability of arrest in each case, supposing he or she committed such offenses, and on arrest records. All questions asked for categorical answers (see the appendix).

One limitation of the data is already apparent. We do not know from the questionnaire whether shoplifting and stealing are mutually exclusive categories since shoplifting may involve an item worth more than \$50. Consequently, we expect, and indeed find, a strong positive association between the frequency of commission of the two crimes. This limitation of the data underscores the need for a joint analysis.

Clearly, the self-reported nature of the data and the truncation of the sample through truancy and school drop-out represent potential sources of bias in our investigation.[7] With respect to self-reporting, systematic understating of criminal activity by respondents may, but need not, bias the association between frequency of commission of crimes and perceptions of sanctions. However, differential under-reporting is likely to bias the associations among different types of crimes and any cross effects of perceptions of sanctions, i.e., the effect of perceptions related to one crime on commission of another crime. Sample truncation is also serious since dropping out of school may be systematically related not only to the level of delinquent behavior but also to relationships among crimes and to perceptions about the probabilities of arrest. Both limitations should be kept in mind in interpreting our results.

With the GRIJ survey, the questions of absolute and relative deterrence can be investigated in ways that avoid most of the pitfalls encountered in previous studies: namely, the problem of aggregate data and the difficulties associated with small sample sizes in self-reported data. To deal adequately with categorical data, we make use of the multivariate log-linear probability model.

Goodman (1970, 1971), Haberman (1974a,b), Nerlove and Press (1976) and others show how to parameterize contingency tables to represent the directions and the magnitudes of probabilistic relations among categorical variables.[8] Many choices are possible for parameterization of the joint probabilities of, say, q categorical random variables, A_1, ..., A_q, which may take on, respectively, $I_1, \ldots, I_q$, possible values. One possibility is by a traditional analysis-of-variance (ANOVA) format for the logarithms of the probabilities:

$$
\begin{aligned}
\log P_{i_1,\ldots,i_q} &= \mu + \alpha_1(i_1) + \ldots + \alpha_q(i_q) \\
&\quad + \beta_{1,2}(i_1, i_2) + \ldots + \beta_{q-1,q}(i_{q-1},i_q) \\
&\quad + \ldots \\
&\quad + \omega_{1,\ldots,q}(i_1,\ldots,i_q) \quad ,
\end{aligned} \tag{1}
$$

with $i_1 = 1,\ldots,I_1$, $i_2 = 1,\ldots,I_2,\ldots,$ $i_q = 1,\ldots I_q$, and imposing the usual ANOVA constraints,

$$
\begin{aligned}
\alpha_1(.) = \alpha_2(.) = \ldots = \alpha_q(.) \quad &= 0, \\
\beta_{1,2}(i_1,.) = 0, \beta_{1,2}(.,i_2) = 0,\ldots,\beta_{q-1,q}(.,i_q) \quad &= 0, \\
&\vdots \\
\omega_{1,\ldots,q}(i_1,\ldots,i_{q-1},.) = 0,\ldots,\omega_{1,\ldots,q}(.,i_2,\ldots,i_q) \quad &= 0.
\end{aligned} \tag{2}
$$

The dot used in place of an index denotes summation over that index. The parameters μ, $\alpha_1(i_1),\ldots,\omega_{1,\ldots,q}(i_1,\ldots,i_q)$ have the usual ANOVA interpretation: μ denotes an overall effect; $\alpha_1(i_1)$ denotes an effect due to A_1 (at "level" i_1); $\beta_{1,2}(i_1,i_2)$ denotes a second-order interaction effect between A_1 and A_2 (at "levels" i_1 and i_2, respectively); and $\omega_{1,\ldots,q}(i_1,\ldots,i_q)$ denotes a q-order intraction among $A_1,\ldots,A_q$ (at "levels" $i_1,\ldots,i_q$, respectively); etc. Although $\log P_{i_1,\ldots,i_q}$ is constrained to be negative, μ is not so fixed and, as a result, the effects themselves are unconstrained in sign.

When all effects or interaction configurations are assumed to be present the model is called saturated. Other models may be derived by deleting some of the interaction configurations.

Note that the condition that the probabilities sum to 1 requires that

$$(3) \quad \mu = -\log \sum_{i_1,\ldots,i_q} \{\alpha_1(i_1) + \ldots + \omega_{1,\ldots,q}(i_1,\ldots,i_q)\}$$

Substituting (3) into (1) shows that the log-linear probability model is equivalent to the multivariate generalization of the discrete logistic distribution by Mantel (1966).

Equations (1) and (3) and the constraints (2) for the saturated model correspond to a particular choice of basis for the vector space in which the Q-tuples of the log $P_{i_1,\ldots,i_q}$, arranged in some order, are elements, where $Q = \prod_{i=1}^{q} I_i$.[9] This basis is called the deviation-contrast basis. Examples are given in Koenig, Nerlove, and Oudiz (1982) and Kawasaki (1979, Chapter 2). For example, in the case of the bivariate dichotomy (2x2 case), the representation for log P = (log P_{11}, log P_{12}, log P_{21}, log P_{22})′ is

$$\log P = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \begin{bmatrix} \mu \\ \alpha_1(1) \\ \alpha_2(1) \\ \beta_{12}(1,1) \end{bmatrix} .$$ [10]

This parameterization makes no use of any order among the categories of a categorical variable. However, measures of association among the variables are possible with the frequently used Goodman-Kruskal gamma coefficient, γ , and with the Kawasaki component gamma coefficient, γ_c , which measures partial association between pairs of variables in a multivariate analysis.[11]

Although it would be tempting to structure our statistical analysis to correspond to a dynamic random utility model of criminal choice behavior along the lines suggested by Manski (1978), we limit our discussion here to a more descriptive approach based on the joint conditional probabilities of certain types of delinquent behavior.[12] We estimate the joint probabilities of stealing, shoplifting, and drug use, conditional on the reported subjective probabilities of arrest for each of the three crimes, arrest record, age and sex.

Ideally, we would like to proceed from estimation of a saturated model to a more parsimonious formulation, albeit with equivalent explanatory power. Unfortunately, as is the case in most social surveys, even when the sample size is large, there are empty cells when any significant number of variables are considered jointly. Such empty cells introduce numerous complications in the estimation and interpretation of the parameters, which we do not discuss fully here.[13] Because of the presence of empty cells we have found it necessary to combine some categories of answers.[14] And, finally, we have restricted our specification to models containing only some trivariate interactions. Our empirical results are presented in the next section.

III. EMPIRICAL RESULTS

Table 1 lists symbolic designations, variables, and aggregate categories for the questions from the GRIJ survey used in this study. (These questions are given in English translation in the appendix.) The questions referring to delinquent behavior have four categories of response; we have aggregated the last two, "several times" and "very often," to form a trichotomous variable for shoplifting and drug use. For stealing, we formed a dichotomous variable by aggregating into a single category "one or two times," "several times" and "very often." The questions referring to the probability of arrest have five categories of response; we have aggregated the first two, "none" and "a slight chance," and the second two, "a fair chance" and "a good chance," to form a trichotomous variable.

The estimated log-linear probability model relates stealing (St), shoplifting (Sh), and drug use (D) to the following conditioning variables: subjective probability of arrest if stealing (PSt), subjective probability of arrest if shoplifting (PSh), subjective probability of arrest if using drugs (PD), age (A), sex (S), and arrest record (ARR).[15]

The specification of the conditional model $\{St, Sh, D \mid PSt, PSh, PD, ARR, A, S\}$ includes an overall effect, all main effects, all second-order or bivariate

TABLE 1

List of symbols, variables and ordinal categories of answers

Symbols	Variables	Ordinal categories of answers
St	Stealing (item worth more than $50.00)	Never; one or two times; several times and very often
Sh	Shoplifting	Never; one or two times; several times and very often
D	Drug use	
PSt	Subjective probability of arrest if stealing	-- None to slight chance (0-25%) -- Fair to good chance (26-75%) -- Strong chance (76-100%)
PSh	Subjective probability of arrest if shoplifting	
PD	Subjective probability of arrest if taking drugs	
ARR	Arrest record	No; yes
A	Age	11 to 13; 14 to 17
S	Sex	Male; female

interaction effects, and third order interaction effects for the following 17 configurations:

St x D x ARR	Sh x D x ARR	St x Sh x A
Sh x D x A	Sh x D x S	St x PSt x ARR
Sh x PSh x ARR	D x PD x ARR	St x PSt x A
Sh x PSh x A	D x PD x A	St x PSt x S
D x PD x S	Sh x PSt x PSh	St x PSt x PD
Sh x PSh x PSt	D x PD x PSh	

To include all the 64 configurations with third order effects was beyond the limit of our computer program and would have used more memory space than available in our computer.

Furthermore, because each computer run to estimate a log-linear model of this size turned out to be very costly, we decided on the following procedure to determine those configurations to be retained.[16] Configurations with empty cells were left out as in the case, for example, of the configuration Sh x PSh x S; we estimated sequences of block configurations including the configuration St x Sh x D, and pairs of crimes with the conditioning variables record of arrest, sex, and age, each crime paired with its subjective probability of arrest against the same previous conditioning variables and finally each crime against a pair of subjective probability of arrest; and when <u>all</u> coefficient estimates of a configuration were small and with t-statistics smaller than one, the configuration was dropped from the model.[17]

Compared to a log-likelihood value of -16165.09 of the saturated model and the value of -25177.27 of the zero-parameter model (model of equiprobabilities), the former computed from the observed contingency table, our estimated model fits the data rather well, with a log-likelihood value of -16653.36 and a Goodman "coefficient of determination" (R^2) of .946.[18] Strictly speaking, the saturated model is not estimable because of the large number of zeros in the full contingency table; thus, the high R^2 may be somewhat misleading.

Tables 2A, 2B, and 2C exhibit the estimated bivariate and conditional bivariate component gamma coefficients associated with our model. The component gammas reported differ from the measure developed by Goodman and Kruskal (1979) in that the component gamma depends on a decomposition of the joint probability into components, each of which depends on a single main effect or a single bivariate interaction configuration, and so forth; the component gamma is defined for the component-bivariate probability estimates after account has been taken of main effects and other bivariate (and higher-order) interactions; conditional bivariate component gammas from trivariate configurations are for two of the variables conditional on the third. The careful reader will note that the component gammas conditional on dichotomous variables are exactly or nearly equal but opposite in sign. It can be shown that this relationship is exact; when exact equality of the absolute values is not obtained it is the result of rounding errors, which are all the more pronounced in the calculation of t-statistics. A more comlicated relation holds among the component gammas conditional on a trichotomous variable.

Examining the relationships among the crimes in Table 2A, we observe that pairs of crimes, particularly shoplifting and stealing, are significantly positively associated. The component gamma of those two crimes based on the trivariate configuration St x Sh x A goes from a significantly negative value of -.386 to a positive value of the same magnitude as A increases, showing that the relationship between stealing and shoplifting increases with the age of the

TABLE 2A

Estimated Component Gammas for the Conditional Model

[St, Sh, D | PSt, PSh, PD, ARR, A, S]

The Relations among the Crimes						
Configuration	Bivariate Component Gamma	Conditional Bivariate Component Gammas from Trivariate Configuration				
St x Sh	.624 (6.28)	given A = 11 to 13:	-.386 (-2.93)	;	14 to 17:	.386 (2.93)
St x D	.268 (2.36)	given ARR = No:	-.210 (-1.91)	;	Yes:	.210 (1.91)
Sh x D	.280 (2.91)	given ARR = No:	-.103 (2.13)	;	Yes:	-.117 (-1.94)
		given A = 11 to 13:	-.052 (-.611)	; ;	14 to 17:	.044 (.605)
		given S = Male:	-.094 (-1.81)	;	Female:	.089 (1.79)

Values in parentheses are t-statistics

TABLE 2B

Estimated Component Gammas for the Conditional Model
[St, Sh, D | PSt, PSh, PD, ARR, A, S]

		The Deterrence Factor					
Configuration	Bivariate Component Gammas	Conditional Bivariate Component Gammas from Trivariate Configuration					
St x PSt	-.336 (-1.61)	given PSh=slight:	.470; (2.94)	good:	.161 ; (.674)	strong:	-.588 (-3.87)
		given PD=slight:	-.288; (-1.40)	good:	.297 ; (1.45)	strong:	-.012 (-.046)
		given ARR=No:	-.130; (-.887)			Yes:	.130 (.887)
		given A=11 to 13:	.070; (.463)			14 to 17:	-.070 (-.463)
		given S=Male:	.247; (1.35)			Female:	-.247 (-1.35)
St x PSh	.193 (.139)	given PSt=slight:	.569; (4.44)	good:	-.109 ; (-.542)	strong:	-.490 -(2.92)
St x PD	-.068 (-.397)	given PSt=slight:	-.176; (-.808)	good:	.071 ; (.339)	strong:	.104 (.41)
Sh x PSh	-.305 (-3.03)	given PSt=slight:	.224; (1.61)	good:	-.025 ; (-.181)	strong:	-.202 (-1.67)
		given ARR=No:	-.077; (-.808)			Yes:	.077 (.790)
		given A=11 to 13:	.091; (.922)			14 to 17:	.087 (.950)
Sh x PSt	-.043 (-.457)	given PSh=slight:	.179; (1.69)	good:	.086 ; (.719)	strong:	-.245 (-1.74)

Table 2B (continued):

The Deterrence Factors								
Configuration	Bivariate Component Gammas	Conditional Bivariate Component Gammas from Trivariate Configuration						
Sh x PD	-.059 (-.769)							
D x PD	-.309 (-3.44)	given PSh=slight:	-.030; (-.282)	good:	-.123 (-.858)	;	strong:	.160 (1.26)
		given ARR=No:	-.275; (-3.30)				yes:	.278 (3.00)
		given A=11 to 13:	.250; (2.82)				14 to 17:	-.232 (-3.02)
		given S=Male:	-.026; (-.322)				Female:	.028 (.305)
D x PSt	-.101 (-1.92)							
D x PSh	.147 (1.69)	given PD=slight:	-.028; (-.303)	good:	-.155 (-1.30)	;	Strong:	.145 (1.20)

Values in parentheses are t-statistics

TABLE 2C

Estimated Component Gammas for the Conditional Model

[St, Sh, D | PSt, PSh, PD, ARR, A, S]

Configuration	Bivariate Components Gammas	Other Conditioning Variables: Conditional Bivariate Component Gammas from Trivariate Configuration
St x ARR	.725 (7.23)	given D=never: -.346 (-1.69) ; once or twice: .080 (.257) ; often: .273 (1.26)
		given PSt=slight: -.058 (-.286) ; good: -.269 (-1.34) ; strong: .323 (1.25)
Sh x ARR	.216 (1.40)	given D=never : .429 (3.55) ; once or twice: -.515 (-2.86) ; often: .116 (.774)
		given PSh=slight: -.145 (-1.24) ; good: .060 (.446) ; often: .085 (.447)
D x ARR	.742 (11.4)	given St=never: -.210 (-1.91) ; once or more: .210 (1.91)
		given Sh=never: .194 (2.56) ; once or twice: -.056 (-.683) ; often: -.134 (-1.37)
		given PD=slight: -.345 (-3.45) ; good: -.127 (-.894) ; strong: .452 (3.02)
St x A	.078 (.395)	given Sh=never: -.509 (-2.96) ; once or twice: -.096 (-.393) ; often: .577 (2.99)
		given PSt=never: .086 (.373) ; good: .036 (.152) ; strong: -.122 (-.447)
Sh x A	.273 (1.40)	given St=never: -.386 (-2.93) ; once or more: .386 (2.93)
		given D=never: -.049 (-.328) ; once or twice: -.045 (-.178) ; often: .095 (.491)
		given PSh=slight: .079 (.660) ; once or twice: .109 (.763) ; strong: -.187 (-1.00)

Table 2C (continued):

Other Conditioning Variables

Configuration	Bivariate Component Gammas	Conditional Bivariate Component Gammas from Trivariate Configuration
D x A	.286 (2.57)	given Sh=never: -.030 (-.286) ; once or twice: -.083; (-.742) strong: .114 (.751)
		given PD=slight: .298 (2.73) ; good: .123; (.821) strong: -.406 (-2.75)
St x S	-.534 (-3.38)	given PSt=slight: .362 (1.67) ; good: -.0003; (-.0001) strong: -.362 (-1.09)
Sh x S	-.241 (-2.85)	given D=never: -.108 (-1.05) ; once or twice: -.058; (-.383) often: .165 (1.52)
D x S	.241 (2.36)	given Sh=never: .168 (2.61) ; good: .064; (.894) strong: .105 1.06)
		given PD=slight: -.046 (-.445) ; good: .011; (.838) strong: .035 (.198)

Values in parentheses are t-statistics

juveniles in the sample. An increase in the conditional gamma coefficient is also observed between stealing and drug use for those with an arrest record. However, being a male or not having been arrested decreases the positive relationship between shoplifting and drug use.[19]

Results associated with deterrence are presented in Table 2B. Deterrence is clearly operative for both shoplifting and drug use in the sense that we observe a significant negative association between the perceived probabilities of arrest and the offense. For stealing, the gamma coefficient for the configuration St x PSt is also negative and of the same orders as for the other crimes, but a little less significant with a t-statistic of -1.61. Furthermore, statistically significant conditional gamma coefficients for some trivariate configuration indicate that those deterrent effects are influenced by other conditioning variables of the model. For example, the deterrent effect on stealing of a perception of a high probability of arrest for stealing increases as the perception of the probability of arrest for shoplifting increases (see St x PSt x PSh). The same result is also observed for the deterrent effect of the perception of the probability of arrest for shoplifting given an increase in the probability of arrest for stealing (Sh x PSh x PSt). For drug use, the deterrent effect of the perception of the probability of arrest for drug use increases with age, but somewhat surprisingly decreases with an arrest record (D x PD x A and D x PD x ARR). Cross effects between crimes and alternate perceptions of the probabilities of arrest are generally not significant or mixed in sign. Drug use, for example, is deterred by an increase in the perception of the probability of arrest for stealing (D x PSt), but an increase in the perception of the probability of arrest for shoplifting is associated with higher drug use (D x PSh). As in the previous case, these cross effects are also influenced by third variables.

One particularly interesting case is the configuration St x PSh x PSt in which the effect of the probability of arrest for shoplifting on stealing, initially positive but not significant (the gamma for St x PSh is .193 with a t-statistic of .139), stays positive and turns significant negative, given a perception of a slight probability of arrest for stealing (the conditional gamma in .569 with a t-statistic of 4.44), and becomes significantly negative when the perception of a strong probability of arrest for stealing is recorded (the conditional gamma is -.490 with a t-statistic of -2.92).

A similar situation also exists for the configuration Sh x PSt x PSh on which the conditional gamma for Sh x PSt given PSh is positive for a perception of a slight probability of arrest for shoplifting but negative if the perception of the probability of arrest is strong.

Although these examples reflect on the complexity of deterrence, it is clear nevertheless that an increase in the perception of the probability of arrest for any one crime deters directly or by cross effect the committment of all three crimes.

In table 2C, we present additional information on delinquent behavior associated with other conditioning variables of the model. Bivariate component gammas indicate that stealing and drug use are significantly positively associated with a previous arrest record. Drug use appears as the only crime that significantly varies positively with age, whereas, given the coding of the variables, boys steal and shop-lift more than girls, but girls are more prone to use drugs than boys.

IV. CONCLUSIONS

Despite data limitations, we find significant evidence for the deterrence hypothesis in the case of shoplifting and drug use and, to a lesser degree, for stealing: in all cases, the perception of probability of arrest is significantly negatively associated with the commission of the crime. Cross effects are generally not significant and are mixed in sign. Stealing is clearly a different order of seriousness than either shoplifting or drug abuse. While it might be tempting to suppose that a perception of a high probability of arrest for one crime would lead a criminally inclined teenager to commit another instead, such is unlikely to be the case in general. Except for the bivariate configurations of drug use or stealing and perceived probability of arrest for shoplifting (D x PSh and St x PSh), all cross effects are negative. Moreover, evidence from the third-order interaction configurations suggests that high perceptions of arrest probabilities for one crime enhance the deterrent effect of high perceptions of arrest for another crime.

While the literature on deterrence refers mostly to aggregate crime rates and not to individual crimes, we may, following the literature, distinguish between <u>absolute</u> and <u>relative</u> deterrence of a specific crime.[20] We also introduce the term <u>cross</u> deterrence: <u>absolute</u> deterrence refers to whether a specific crime is committed or not committed, not to the frequency with which it is committed, if committed; <u>relative</u> deterrence refers to the frequency with which a crime is committed; <u>cross</u> deterrence refers to the effect, or lack of effect, of deterrence for one crime on commission of another. As noted, cross-deterrence is a complex phenomenon; our results are not easily summarized. We can, however, recapitulate those of our results bearing on the nature of absolute and relative deterrence by an interesting and novel device based on the decomposition of probabilities permitted by the log-linear probability model (Kawasaki, 1979).

To draw some conclusions for our sample about the extent of different types of deterrence, we have computed the bivariate component probabilities for

TABLE 3

Component Probability
(observed marginal frequency)

	Crime							
	Stealing		Shoplifting			Drug Use		
Corresponding subjective probability of arrest	Never	One or two times and several times or very often	Never	One or two times	Several times and very often	Never	One or two times	Several times and very often
None to slight chance	.121 (.279)	.219 (.013)	.071 (.284)	.105 (.109)	.168 (.037)	.046 (.329)	.169 (.069)	.137 (.090)
Fair to good chance	.174 (.456)	.152 (.008)	.123 (.329)	.115 (.068)	.088 (.010)	.138 .312)	.103 (.011)	.075 (.008)
Strong chance	.205 (.241)	.129 (.003)	.143 (.143)	.104 (.018)	.084 (.003)	.167 (.176)	.062 (.003)	.103 (.003)
Totals	.500 (.976)	.500 (.024)	.337 (.756)	.324 (.195)	.336 (.050)	.351 (.817)	.334 (.083)	.315 (.101)

the configurations St x PSt, Sh x PSh, and D x PD from the estimated model

$$\{St,\ Sh,\ D \mid PSt,\ PSh,\ PD,\ ARR,\ A,\ S\}.$$ [21]

Table 3 reports these results together with the observed marginal frequencies. It should be emphased that no additional information is contained in Table 3 than has already been presented in Table 2B; it is just presented differently.

Essentially the component probabilities adjust the marginal table for the preponderance of individuals who never commit the crimes in question (main effects) and for the effects of the other variables included in the analysis. The result is that the component probabilities for shoplifting and drug use almost sum to one-third across categories of perceived probability of arrest. If only the main effects were removed the component probabilities would sum to exactly one-third across categories of perceived probability. For stealing, this sum is one-half since St is a dichotomous variable in our analysis.

Note that, although most individuals never commit the crimes in question, they hold widely differing beliefs about the probability of arrest; moreover, the perceptions of probability of arrest are quite similar for those who commit it frequently. One might be tempted to conclude that neither absolute nor relative deterrence works--at least in terms of subjective probabilities of arrest. However, the component probabilities tell quite a different story: a much larger proportion of the component probability is concentrated in the "fair to good chance" and "strong chance" categories of the subjective probabilities of arrest for those who never commit the crimes in question. A greater proportion of the component probability is concentrated in the "none to slight chance" category for those who frequently commit the crimes of stealing, shoplifting, and drug use. In the case of infrequent drug use, the component probability uniformly declines with increasing subjective probability of arrest. These results based on the component probabilities are simply a reflection of our finding of negative partial bivariate associations between the subjective probability of arrest for each crime and the frequency of commission of that crime. Use of the estimated bivariate interaction configurations to construct artificial marginal tables cross-classifying subjective probability of arrest and frequency of commission of a crime shows that both absolute and relative deterrence operate.

One must be cautious in interpreting these results in terms of the effects of criminal sanctions on criminal activity. Our results shed no light on factors affecting the perceived probabilities of arrest for the crimes considered or of the penalties that might be imposed on offenders if arrested.

While we have clear evidence of deterrence in both absolute and relative terms, our data yield no results on how such deterrence might be achieved. A more detailed series of questions related to perceived probabilities of arrest and the possibilities of punishment and to various factors affecting those perceptions would be necessary before such conclusions could be drawn.

FOOTNOTES

1 For a comprehensive review, see Nagin (1978).

2 See Blumstein, et al. (1978, pp. 23-30), Taylor (1978, 1976b), Meier and Johnson (1977), and Tittle (1977).

3 Her survey includes 11 major studies: Jensen (1969), Waldo and Chiricos (1972), Burkett and Jensen (1975), Bailey and Lott (1976), Kraut (1976), Minor (1976), Silberman (1976), Teevan (1976a and 1976b), Meier and Johnson (1977), and Tittle (1977).

4 See Goodman (1972, 1973), Gillespie (1978).

5 See Nerlove and Press (1976), Swafford (1980).

6 Groupe de recherche sur l'inadaptation juvénile of the Université de Montréal. Complete details about the construction of the survey and data preparation are presented in Biron, L., A. Caplan and M. Leblanc, La construction de l'échantillon, la cueillette des données et leur préparation, GRIJ, Université de Montréal, February 1975.

7 School is mandatory up to 16 years of age in the province of Quebec.

8 The discussion here follows Nerlove and Press (1978).

9 For a proof see Nerlove and Press (1978).

10 Only some of the parameters of the main and bivariate interactions appear; the remainder may be recovered from the constraints (2).

11 See Goodman and Kruskal (1979) and Kawasaki (1979). An alternative parameterization that is especially useful when the categorical variables are ordinal is scoring; see Haberman (1974b), Vuong (1979, 1980) and Koenig, Nerlove, and Oudiz (1981).

12 In general a joint or conditional log-linear probability model cannot be used to infer the parameters of a structural model, although log-linear probability models can be derived from structural models.

13 See Bishop, Fienberg and Holland (1976) and Kawasaki (1979). It can be shown that, for a particular class of models called hierarchical, it is a necessary condition for the existence of the maximum-likelihood estimates that the marginal tables corresponding to the highest-order interaction configurations included in the model contain no sampling zeros.

14 Table 1, below, shows how we aggregate responses.

15 Note that in principle by treating all variables as joint we can derive the corresponding conditional model from the estimates of the joint model; however such a procedure is correct only if all configurations among the conditioning variables are included in the joint model; see Link (1980).

16 The program used was developed at Northwestern University by John Link; our model, for example, filled 80256 memory units and took 11700 CP seconds execution time on our CDC 173 computer.

17 A chi-square test for the entire configuration based on the variance-covariance matrix for the parameters in the configuration gave similar results.

18 As defined by Goodman: R^2 = (log likelihood of the equiprobability model - log likelihood of the estimated model) / (log likelihood of the equiprobability model - log likelihood of the saturated model).

19 As seen in the Appendix, question 3 of the survey unfortunately does not ask the cause of arrest.

20 One could argue that both relative and absolute deterrence are special cases of one and the same concept, absolute deterrence being the limiting case of zero frequency.

21 Let $\beta(i_1,i_2)$, $i_1 = 1, \ldots, I_1$, $i_2 = 1, \ldots, I_2$, be the estimated bivariate interaction configuration; then the component probabilities are

$$P_c(i_1,i_2) = \frac{\exp \beta(i_1,i_2)}{\sum_{j_1 = 1}^{I_1} \sum_{j_2 = 1}^{I_2} \exp \beta(j_1,j_2)}$$

APPENDIX

Question and answer formats submitted to each respondent and used in this study

1. Q. - During the past 12 months, have you taken something of large value (worth $50.00 or more) that did not belong to you?

   - During the past 12 months, have you used marijuana or hashish?

   - During the past 12 months, have you taken something from a store a store without paying?

   A. - Never; once or twice; several times; very often.

2. Q. - Suppose you take something of large value (worth $50.00 or more) that does not belong to you, what are your chances of being picked up and brought to the police station?

   - Suppose you use marijuana or hashish, what are your chances of being picked up and brought to the police station?

   - Suppose you take something from a store with paying, what are your chances of being picked up and brought to the police station?

   A. - None (0%); a slight chance (1% to 25%); a fair chance (26% to 50%); a good chance (51% to 75%); a strong chance (76% to 100%).

3. Q. - Have you ever been picked up and brought to the police station?

   A. - Never; yes, before the past 12 months; yes, during the past 12 months; yes, before and during the past 12 months.

4. Q. - What is your date of birth? What is your sex?

REFERENCES

Bailey, W. C. and R. P. Lott, "Crime, Punishment and Personality: An Examination of the Deterrence Question," The Journal of Criminal Law and Criminology, 67: 99-109, 1976.

Biron, L., A. Caplan and M. Leblanc, La construction de l'échantillon, la cueillette des données et leur préparation, GRIJ, Université de Montréal, February 1975.

Bishop, Y.M.M., S.E. Fienberg and P.W. Holland with the collaboration of R.J. Light and F. Mosteller, Discrete Multivariate Analysis: Theory and Practice, MIT Press, Cambridge, Massachusetts, 1976.

Blumstein, A., J. Cohen and D. Nagin (eds.), Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates, National Academy of Sciences, Washington, D.C., 1978.

Burkett, S.R. and E.L. Jensen, "Conventional Ties, Peer Influence, and the Fear of Apprehension: A Study of Adolescent Marijuna Use," Sociological Quarterly, 16: 522-33, 1975.

Claster, D.S., "Comparison of Risk Perception between Delinquents and Non-Delinquents," Journal of Criminal Law, Criminology and Police Science, 58: 180-86, 1967.

Erickson, P.G., "Deterrence and Deviance: The Example of Cannabis Prohibition," Journal of Criminal Law and Criminology, 67: 222-32, 1976.

__________, J.P. Gibbs and G.F. Jensen, "The Deterrence Doctrine and the Perceived Certainty of Legal Punishment," American Sociology Review, 42: 305-17, 1977.

Gibbs, J.P., Crime, Punishment and Deterrence, Elsevier, New York, 1975.

Gillespie, M.W., "The Application of Log-Linear Techniques to Recursive Models: Comment on Reynolds," American Journal of Sociology, 84(3): 718-22, 1978.

Goodman, L.A., "The Multivariate Analysis of Qualitative Data: Interaction among Multiple Classifications," American Statistical Association, 65: 226-56, 1970.

__________, "The Analysis of Multidimensional Contingency Tables: Stepwise Procedures and Direct Estimation Methods for Building Models for Multiple Classifications," Technometrics, 13: 33-61, 1971.

__________, "A Modified Multiple Regression Approach to the Analysis of Dichotomous Variables," American Sociological Review, 37: 28-46, 1972.

__________, "Causal Analysis of Data From Panel Studies and Other Kinds of Survey," American Journal of Sociology, 28: 1135-191, 1973.

__________ and W. H. Kruskal, "Measures of Association for Cross-Classifications," J. American Statistical Association, 49: 732-64, 1954.

__________ and W. H. Kruskal, "Measures of Association for Cross-Classifications II: Further Discussion and References," J.American Statistical Association, 54: 23-63, 1959.

__________ and W. H. Kruskal, "Measures of Association for Cross-Classifications III: Approximate Sampling Theory," J. American Statistical Association, 58: 310-64, 1963.

__________ amd W. H. Kruskal, "Measures of Association for Cross-Classifications IV: Simplification of Asymptotic Variance," J. American Statistical Association, 67: 415-21, 1972.

________ and W. H. Kruskal, Measures of Association for Cross-Classifications, New York: Springer-Verlag, 1979. Collected papers: Goodman and Kruskal (1954, 1959, 1963, 1972).

Haberman, S.J., The Analysis of Frequency Data, University of Chicago Press, Chicago, Illinois, 1974a.

____________, "Log-linear models for frequency tables with ordered classifications," Biometrics, 30: 589-600, 1974b.

Jensen, G.F., "Crime Doesn't Pay: Correlates of a Shared Misunderstanding," Social Problems, 17: 189-201, 1969.

Kawasaki, S., Application of Log-Linear Probability Models in Econometrics, unpublished Ph.D. dissertation. Department of Economics, Northwestern University, Evanston, Illinois, June 1979.

Koenig, H., M. Nerlove and G. Oudiz, "Die Analyse Microökomisches von Konjunkturtest-Daten mit log-linearen Wahrschieinlichkeits-Modellen: ein Einfuhrung," Ifo-Studien, forthcoming.

Kraut, R.E., "Deterrent and Definitional Influences on Shoplifting," Social Problems, 23: 358-68, 1967.

Link, J.P., "The Equivalence between the Estimation of Joint and Conditional Log-Linear Probability Models," unpublished manuscript, Northwestern University, 1980.

Manski, C.F., "Prospects for Inference on Deterrence through Empirical Analysis of Individual Criminal Behavior," Pp. 400-24. In Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates, Blumstein, A., J. Cohen and D. Nagin, (eds.), National Academy of Sciences, Washington, D.C., 1978.

Mantel, N., "Models for Complex Contingency Tables and Polychotomous Responses Curves," Biometrica, 22, 83-110, 1969.

Meier, R.F. and W.T. Johnson, "Deterrence as Social Control: the Legal and Extralegal Production of Conformity," American Sociological Review, 42: 298-304, 1977.

Minor, W.W., A Deterrence-Control Theory of Crime, unpublished paper presented at the annual meetings of the American Society of Criminology, Tucson, 1976.

Nagin, D., "General Deterrence: A Review of the Empirical Evidence." Pp. 95-140 in Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates, Blumstein, A., J. Cohen and D. Nagin (eds.), National Academy of Sciences, Washington, D.C., 1978, 95-140.

Nerlove, M. and S.J. Press, Book Review of Bishop, Fienberg and Holland: Discrete Multivariate Analysis: Theory and Practice, MIT Press, Cambridge, Massachusetts, 1976, in Bulletin of the American Mathematical Society, 84: 470-80, 1978.

__________, "Multivariate Log-Linear Probability Models in Econometrics "Discussion Paper No. 47, Center for Statistics and Probability,Northwestern University, August 1980.

Palmer, J., "Economic Analyses of the Deterrent Effect of Punishment: A Review," Journal of Research in Crime and Delinquency, 14: 4-21, 1977.

Saltzman-Anderson, L., A Longitudinal Study of the Deterrence Model, Ph.D. dissertation, School of Criminology, The Florida State University, December 1977.

Silberman, M., "Toward a Theory of Criminal Deterrence," American Sociological Review, 41: 442-61, 1976.

Swafford, M., "Three Parametric Techniques for Contingency Table Analysis: A Nontechnical Commentary," American Sociological Review, 45: 664-90, 1980.

Taylor, J.B., "Econometric Models of Criminal Behavior: A Review," in Econometric Models of Criminal Behavior, Heineke, G.M. (ed.) North-Holland Publishing Co., Amsterdam, 1978.

Teevan, J.J., Jr., "Subjective Perception of Deterrence (continued),"Journal of Research in Crime and Delinquency, 13, 155-64. 1976.

__________, "Deterrent Effects of Punishment: Subjective Measures Continued," Canadian Journal of Criminology and Corrections, 18: 1976.

Tittle, C.R., "Sanction Fear and the Maintenance of Social Order," Social Forces, 55: 579-96, 1977.

Tullock, G., "Does Punishment Deter Crime?," Public Interest, 30: 103-11, 1974.

Vuong, Q.H., "A Note on Conditional Log-Linear Probability Models," unpublished manuscript, Northwestern University, 1979a.

__________, "A Further Note on Conditional Log-Linear Probability Models," unpublished manuscript, Northwestern University, 1979b.

__________, "Some Results on the SCORE parametrization," unpublished manuscript, Northwestern University, 1980.

Waldo, G.P. and T.G. Chiricos, "Perceived Penal Sanctions and Self-Reported Criminality: A Neglected Approach to Deterrence Research, Socal Problems, 19: 522-40, 1972.

Wilson, J.Q., "'What Works?' Revisited: New Findings on Criminal Rehabilitation," The Public Interest, 61: 3-17, 1980.

DISCUSSION PAPER NO. 509

DETERRENCE AND DELINQUENCY: An Analysis of Individual Data*

by Claude Montmarquette and Marc Nerlove

Errata Sheet

Page 14 -- line 19 -- A more complicated ...

14d table 2C St x A -- given PSt--never:

should be -- slight

D x S given Sh=never: .168 (2.61)

should be -.168 (-2.61)

Page 16 -- line 4 -- delete negative

line 6 -- should be -- is...

Page 17a Table 3 -- line in wrong place

short line separating Never and One or two times

long line separating Shoplifting and Drug Use

should be between Several Time and Never

Page 20 -- FN 2 -- Delete everything after Taylor (1978).

FN 3 -- Kraut (1975)

Page 24 -- Reference 5 -- Marijuana misspelled

26 " 5 -- 1967 should be 1975

27 " 1 -- delete page numbers after 1978.

27 " 5 -- delete December

27 " 9 -- 13: should be 13: