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Deterrence and Delinquency: An Analysis of Individual Data

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Is commission of crime deterred by fear of arrest? Individual self-reported data on the commission of three crimes are analyzed in relation to perceived probabilities of arrest for more than 3000 French-speaking teenagers of the Montreal school population in 1974. The crimes are shoplifting, drug use, and stealing an item worth more than $50.00. In addition to the effect of the individuals' perceptions of the probability of arrest for the three crimes, age, sex, and previous arrest record are also taken into account. The data are all categorical. A multivariate log-linear probability model is estimated in order to test hypotheses concerning the direction and magnitude of bivariate associations among the variables. We conclude that there is clear evidence of a negative association between the subjective probability of arrest for each crime and the frequency of commission of that crime. We also find some negative cross-effects of the perceptions of the probability of arrest for one type of crime on the commission of another, holding constant the direct effects.

KEY WORDS: deterrence; delinquency; individual data; categorical data; log-linear probability models.

1. INTRODUCTION

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 or, in the words of Layson (1983, p. 70), "that even

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potential murderers obey the law of demand". 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 by economists and others to measure deterrent effects using aggregate data.[3] However, as Palmer (1977), Blumstein *et al.* (1978), Greenberg *et al.* (1981), and others have pointed out, the use of nonexperimental aggregate data across jurisdictions or over time contains a number of important sources of bias, such as the following: (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.[4]

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 individual self-reports of criminal behavior.[5] If the credibility of self-reported data is accepted, such data may yield information directly on an individual's subjective probability of apprehension and perceptions of punishment.[6] 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 or over time, only the variation of crime rates, and thus "relative deterrence", can be analyzed.

Reviewing 11 major studies 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 criminal-

[3]For a comprehensive review, see Nagin (1978) and Brier and Fienberg (1980).

[4]See Blumstein *et al.* (1978, pp. 23–30) and Taylor (1978).

[5]Many authors have raised that point, but very few economic studies of criminal behavior have relied on individual data. Two recent exceptions are Witte (1980) and Myers (1983), who used, however, nonrandom samples of prison releases.

[6]Supporting the validity of the self-report method, see Hardt and Peterson (1977) and the comprehensive reference book by Hindelang *et al.* (1981).

ity. For the most common offences 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 the 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 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 *et al.* (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 and, more generally, about 300 observations; with respect to statistical technique, we note the use of simple correlations coefficients, collapsing of the data into median-mean comparisons, or inappropriate application of ordinary least squares to a regression with a categorical dependent variable. An important exception, however, is the recent study by Jensen *et al.* (1978), who apply statistical procedures developed by Goodman (1972, 1973) to a large sample of students in Arizona high schools and conclude that their data are consistent with deterrence theory. Even more recently, Saltzman *et al.* (1982) and Minor and Harry (1982) have referred to Goodman's techniques to discuss the fundamental problem of causal order in perceptual deterrence research. Unfortunately, this problem requires a longitudinal design sample not easily available for a large set of data.

In this paper, individual self-reported data on the commission of three crimes are analyzed in relation to perceived probabilities of arrest for more than 3000 French-speaking teenagers of the Montreal school population in 1974. In addition to the effect of the individuals' perceptions of the probability of arrest for shoplifting, drug use, and stealing an item worth more than $50.00, age, sex and previous arrest record are also taken into account. In accord with what Witte (1983, p. 173) considers an important contribution by economists to the study of criminal behavior, that is, the reference to appropriate statistical techniques and the provision of sophisticated and systematic statistical tests, a multivariate log-linear probability model is estimated in order to test hypotheses concerning the direction and magnitude of bivariate association among the variables. The model, briefly discussed in the next section, is appropriate to the analysis of categorical data and permits a complex modeling of delinquent behavior.[7] Our results add

[7]See Nerlove and Press (1976, 1980).

precision and insight with respect to two questions raised by Jensen *et al.* (1978). The first question concerns the problem of absolute and relative deterrence, and the second question relates to Teevan's (1975, 1976a, b) assertion that only act-specific measures of perceived risk are relevant in deterrence research, contrary to the findings of Silberman (1976) and Jensen *et al.* (1978). We conclude that there is clear evidence of a negative association between the subjective probability of arrest for each crime and the commission and frequency of commission of that crime. We also find some negative cross-effects of the perceptions of the probability of arrest for one type of crime on the commission of another, holding constant the direct effects.

2. THE DATA AND THE ECONOMETRIC 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.[8]

In 1974, the GRIJ (Groupe de recherche sur l'inadaptation juvénile) 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 11–17 years.[9] 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, on the perceived probability of arrest in each case, supposing that he or she committed such offenses, and on arrest records. All questions asked for categorical answers (see the Appendix).

[8]As for most studies on delinquency behavior, the problem of deterrence from the severity of sanctions is ignored in the present study.

[9]Complete details on the construction of the survey and data preparation are presented by Biron *et al.* (1975).

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 dropout represent potential sources of bias in our investigation.[10] With respect to self-reporting, systematic understating of criminal activity by respondents may, but need not, bias the association between the frequency of commission of crimes and perceptions of the probability of arrest. However, differential underreporting is likely to bias the associations among different types of crimes and any cross-effects of perceptions of probability of arrest, i.e., the effect of perceptions related to one crime on the 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.[11] Many choices are possible for parameterization of the joint probabilities of, say, q categorical random variables, $A_1, \ldots, A_q$, which may take on, respectively, $I_1, \ldots, I_q$, possible values. One possibility is by a traditional analysis-of-variance (ANOVA) decomposition for the logarithms of the probabilities:

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

[10]School is mandatory up to 16 years of age in the Province of Quebec.

[11]The discussion here follows Nerlove and Press (1978).

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

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

The dot used in place of an index denotes summation over that index. The parameters μ, $\alpha_1(i_1),\ldots$, and $\omega_{1,\ldots,q}(i_1,\ldots,i_q)$ 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 interaction 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 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

$$\mu=-\log\sum_{i_1,\ldots,i_q}\exp[\alpha_1(i_1)+\cdots+\omega_{1,\ldots,q}(i_1,\ldots,i_q)] \tag{3}$$

Substituting Eq. (3) into Eq. (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 $Q=\prod_{i=1} I_i$.[12] This basis is called the *deviation-contrast basis.* Examples are given by Koenig *et al.* (1982) and Kawasaki (1979, Chap. 2). For example, in the case of the bivariate dichotomy (2×2 case), the representation for $\log P=(\log P_{11}, \log P_{12}, \log P_{21}, \log P_{22})$ is[13]

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

[12]For a proof see Nerlove and Press (1978).

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

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.[14]

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.[15] 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. Our consideration of a wide range of joint and interaction effects among those variables should hopefully compensate for the omission in the model of variables such as the perceptions of expected sanctions, the family situation, the age at first arrest, etc.

Ideally, we would like to proceed from the estimation of a saturated model to a more parsimonious formulation, albeit with equivalent explanatory power. Unfortunately, as is the case in most socioeconomic surveys, even when the sample size is large, there are empty cells when any significant number of variables is considered jointly. Such empty cells introduce numerous complications in the estimation and interpretation of the parameters, which we do not discuss fully here.[16] Because of the presence of empty cells, we have found it necessary to combine some categories of answers.[17] And finally, we have restricted our specification to models containing only some trivariate interactions. Our empirical results are presented in the next section.

3. EMPIRICAL RESULTS

Table I lists symbolic designations, variables, and aggregate categories for the questions from the GRIJ survey used in this study. (These questions

[14]See Goodman and Kruskal (1979), Kawasaki (1979), and Nerlove (1983). An alternative parameterization that is especially useful when the categorical variables are ordinal is scoring; see Haberman (1974b), Vuong (1979a, b, 1980), and Koenig *et al.* (1982).

[15]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.

[16]See Bishop *et al.* (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.

[17]Table I shows how we aggregate responses.

are given in English 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).[18]

The specification of the conditional model [St, Sh, D|PSt, PSh, PD, ARR, A, S] includes an overall effect, all main effects, all second-order or bivariate interaction effects, and third-order interaction effects for the following 17 configurations:

$$\begin{aligned}
&\mathrm{ST} \times \mathrm{D} \times \mathrm{ARR},\\
&\mathrm{Sh} \times \mathrm{D} \times \mathrm{A},\\
&\mathrm{Sh} \times \mathrm{PSh} \times \mathrm{ARR},\\
&\mathrm{Sh} \times \mathrm{PSh} \times \mathrm{A},\\
&\mathrm{D} \times \mathrm{PD} \times \mathrm{S},\\
&\mathrm{St} \times \mathrm{PSt} \times \mathrm{PSh},\\
&\mathrm{Sh} \times \mathrm{D} \times \mathrm{ARR},\\
&\mathrm{Sh} \times \mathrm{D} \times \mathrm{S},\\
&\mathrm{D} \times \mathrm{PD} \times \mathrm{ARR},\\
&\mathrm{D} \times \mathrm{PD} \times \mathrm{A},\\
&\mathrm{Sh} \times \mathrm{PSt} \times \mathrm{PSh},\\
&\mathrm{D} \times \mathrm{PSh} \times \mathrm{PD},\\
&\mathrm{St} \times \mathrm{Sh} \times \mathrm{A},\\
&\mathrm{St} \times \mathrm{PSt} \times \mathrm{ARR},\\
&\mathrm{St} \times \mathrm{PSt} \times \mathrm{A},\\
&\mathrm{St} \times \mathrm{PSt} \times \mathrm{S}, \text{ and}\\
&\mathrm{St} \times \mathrm{PSt} \times \mathrm{PD}.
\end{aligned}$$

[18]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).

Table I. 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 years; 14 to 17 years
S	Sex	Male; female

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.[19] Configurations with empty cells were left out, as in the case, for example, of the configuration $\mathrm{Sh} \times \mathrm{PSh} \times \mathrm{S}$; we estimated sequences of block configurations including the configuration $\mathrm{St} \times \mathrm{Sh} \times \mathrm{D}$ 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 *all* coefficient estimates of a configuration were small and with t-statistics smaller than one, the configuration was dropped from the model.[20]

Compared to a log-likelihood value of $-16{,}165.09$ of the saturated model and the value of $-25{,}177.27$ 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 $-16{,}653.36$ and a Goodman "coefficient of determination" (R^2)

[19]The program used was developed at Northwestern University by John Link; our model, for example, filled 80,256 memory units and took 11,700 CP sec of execution time on our CDC 173 computer.

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

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

Relations among the crimes					
Configuration	Bivariate component gamma	Conditional bivariate component gamma from trivariate configuration			
St × Sh	0.624	Given A = 11 to 13:	−0.386	14 to 17:	0.386
	(6.28)[a]		(−2.93)		(2.93)
St × D	0.268	Given ARR = no:	−0.210	Yes:	0.210
	(2.36)		(−1.91)		(1.91)
Sh × D	0.280	Given ARR = no:	−0.103	Yes:	−0.117
	(2.91)		(2.13)		(−1.94)
		Given A = 11 to 13:	−0.052	14 to 17:	0.044
			(−0.611)		(0.605)
		Given S = male:	−0.094;	Female:	0.089
			(−1.81)		(1.79)

[a]Values in parentheses are t statistics.

of 0.946.[21] 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 II, III, and IV 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 variables conditional on the third. Note that the component gammas conditional on dichotomous variables are exactly equal, 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 more pronounced in the calculation of t statistics. A more complicated relation holds among the component gammas conditional on a trichotomous variable.

Examining the relationships among the crimes in Table II, we observe that pairs of crimes, particularly shoplifting and stealing, are significantly

[21]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).

positively associated. The component gamma of those two crimes based on the trivariate configuration St × Sh × A goes from a significantly negative value of −0.386 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 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.[22]

Results associated with deterrence are presented in Table III. 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 × PSt is also negative and of the same order 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 × PSt × 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 × PSh × 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 × PD × A and D × PD × ARR). Bivariate 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 × PSt), but an increase in the perception of the probability of arrest for shoplifting is associated with higher drug use (D × PSh). As in the previous case, these cross-effects are also influenced by third variables.

One particularly interesting case is the configuration St × PSh × PSt, in which the effect of the probability of arrest for shoplifting on stealing, initially positive but not significant (the gamma for St × PSh is 0.193, with a *t* statistic of 0.139), stays positive and turns significant, given a perception of slight probability of arrest for stealing (the conditional gamma is 0.569, 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 −0.490, with a *t* statistic of −2.92).

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

Table III. Estimated Component Gammas for the Conditional Model [St, Sh, D | PSt, PSh, PD, Arr, A, S]

Configuration	Bivariate component gamma	Deterrence factor: Conditional bivariate component gamma from trivariate configuration					
St × PSt	−0.336	Given PSh = slight:	0.470	Good:	0.161	Strong:	−0.588
	(−1.61)[a]		(2.94)		(0.674)		(−3.87)
		Given PD = slight:	−0.288	Good:	0.297	Strong:	−0.012
			(−1.40)		(1.45)		(−0.046)
		Given ARR = no:	−0.130			Yes:	0.130
			(−0.887)				(0.887)
		Given A = 11 to 13:	0.070			14 to 17:	−0.070
			(0.463)				(−0.463)
		Given S = male:	0.247			Female:	−0.247
			(1.35)				(−1.35)
St × PSh	0.193	Given PSt = slight:	0.569	Good:	−0.109	Strong:	−0.490
	(0.139)		(4.44)		(−0.542)		(−2.92)
St × PD	−0.068	Given PSt = slight:	−0.176	Good:	0.071	Strong:	0.104
	(−0.397)		(−0.808)		(0.339)		(0.41)
Sh × PSh	−0.305	Given PSt = slight:	0.224	Good:	−0.025	Strong:	−0.202
	(−3.03)		(1.61)		(−0.181)		(−1.67)
		Given ARR = no:	−0.077			Yes:	0.077
			(−0.808)				(0.790)
		Given A = 11 to 13:	0.091			14 to 17:	0.087
			(0.922)				(0.950)

Sh × PSt	−0.043	Given PSh = slight:	0.179	Good:	0.086	Strong:	−0.245
	(−0.457)		(1.69)		(0.719)		(−1.74)
Sh × PD	−0.059						
	(−7.69)						
D × PD	−0.309	Given PSh = slight:	−0.030	Good:	−0.123	Strong:	0.160
	(−3.44)		(−0.282)		(−0.858)		(1.26)
		Given ARR = no:	−0.275			Yes:	0.278
			(−3.30)				(3.00)
		Given A = 11 to 13:	0.250			14 to 17:	−0.232
			(2.82)				(−3.02)
		Given S = male:	−0.026			Female:	0.028
			(−0.322)				(0.305)
D × PSt	−0.101						
	(−1.92)						
D × PSh	0.147	Given PD = slight:	−0.028	Good:	−0.155	Strong:	0.145
	(1.69)		(−0.303)		(−1.30)		(1.20)

[a]Values in parentheses are t statistics.

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

		Deterrence factor					
Configuration	Bivariate component gamma	Conditional bivariate component gamma from trivariate configuration					
St × ARR	0.725 (7.23)[a]	Given D = never:	−0.346 (−1.69)	Once or twice:	0.080 (0.257)	Often:	0.273 (1.26)
		Given PSt = slight:	−0.058 (−0.286)	Good:	−0.269 (−1.34)	Strong:	0.323 (1.25)
Sh × ARR	0.216 (1.40)	Given D = never:	0.429 (3.55)	Once or twice:	−0.515 (−2.86)	Often:	0.116 (0.774)
		Given PSh = slight:	−0.145 (−1.24)	Good:	0.060 (0.446)	Often:	0.085 (0.447)
D × ARR	0.742 (11.4)	Given St = never:	−0.210 (−1.91)	Once or more:	0.210 (1.91)		
		Given Sh = never;	0.194 (2.56)	Once or twice;	−0.056 (−0.683)	Often;	−0.134 (−1.37)
		Given Pd = slight;	−0.345 (−3.45)	Good;	−0.127 (−0.894)	Strong;	0.452 (3.02)
St × A	0.078 (0.395)	Given Sh = never;	−0.509 (−2.96)	Once or twice;	−0.096 (−0.393)	Often;	0.577 (2.99)
		Given Pst = slight;	0.086 (0.373)	Good;	0.036 (0.152)	Strong;	−0.122 (−0.447)

Sh × A	0.273	Given St = never;	−0.386	Once or more;	0.386		
	(1.40)		(−2.93)		(2.93)		
		Given D = never:	−0.049	Once or twice:	−0.045	Often:	0.095
			(−0.328)		(−0.178)		(0.491)
		Given PSh = slight:	0.079	Once or twice:	0.109	Strong:	−0.187
			(0.660)		(0.763)		(−1.00)
D × A	0.286	Given Sh = never:	−0.030	Once or twice:	−0.083	Strong:	0.114
	(2.57)		(−0.286)		(−0.742)		(0.751)
		Given PD = slight:	0.298	Good:	0.123	Strong:	−0.406
			(2.73)		(0.821)		(−2.75)
St × S	−0.534	Given PSt = slight:	0.362	Good:	−0.0003	Strong:	−0.362
	(−3.38)		(1.67)		(−0.0001)		(−1.09)
Sh × S	−0.241	Given D = never:	−0.108	Once or twice:	−0.058	Often:	0.165
	(−2.85)		(−1.05)		(−0.383)		(1.52)
D × S	0.241	Given Sh = never:	0.168	Once or twice:	0.064	Often:	0.105
	(2.36)		(2.61)		(0.894)		(1.06)
		Given PD = slight:	−0.046	Good:	0.011	Strong:	0.035
			(−0.445)		(0.838)		(0.198)

[a]Value in parentheses are t statistics.

A similar situation also exists for the configuration Sh × PSt × PSh, in which the conditional gamma for Sh × 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 commitment of all three crimes, as Silberman (1976) and Jensen *et al.* (1978) found and in contrast to Teevan (1975, 1976a, b).

In Table IV, 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 shoplift more than girls, but girls are more prone to use drugs than boys.

4. CONCLUSION

Despite data limitation, we find significant evidence for the deterrence hypothesis in the case of shoplifting, drug use, and, to a lesser degree, stealing: in all cases, the perception of probability of arrest is significantly negatively associated with the commission of the crime. 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 aprobability of arrest for shoplifting (D × PSh and St × 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 *absolute* and *relative* deterrence of a specific crime.[23] We also introduce the term *cross*-deterrence: absolute deterrence refers to whether a specific crime is committed or not committed, not to the frequency at which it is committed, if committed; relative deterrence refers to the

[23]One could argue that both relative deterrence and absolute deterrence are special cases of one and the same concept, absolute deterrence being the limiting case of zero frequency. Jensen *et al.* (1978, p. 76) recognized that there are a number of different ways to examine relative deterrability.

frequency at which a crime is committed; cross deterrence refers to the effect, or lack of effect, of deterrence for one crime on the 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 the configurations St × PSt, Sh × PSh, and D × PD from the estimated model [St, Sh, D | PSt, PSh, PD, ARR, A, S].[24] Table V reports these results together with the observed marginal frequencies. It should be emphasized that no additional information is contained in Table V than has already been presented in Table III; it is simply 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

[24]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 $P_c(i_1, i_2) = \exp \beta(i_1, i_2) / \sum_{j_1=1}^{I_1} \sum_{j_2=1}^{I_2} \exp \beta(j_1, j_2)$.

Table V. 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	0.121 (0.279)	0.219 (0.013)	0.071 (0.284)	0.105 (0.109)	0.168 (0.037)	0.046 (0.329)	0.169 (0.069)	0.137 (0.090)
Fair to good chance	0.174 (0.456)	0.152 (0.008)	0.123 (0.329)	0.115 (0.068)	0.088 (0.010)	0.138 (0.312)	0.103 (0.011)	0.075 (0.008)
Strong chance	0.205 (0.241)	0.129 (0.003)	0.143 (0.143)	0.104 (0.018)	0.084 (0.003)	0.167 (0.176)	0.062 (0.003)	0.103 (0.003)
Total	0.500 (0.976)	0.500 (0.024)	0.337 (0.756)	0.324 (0.195)	0.336 (0.050)	0.351 (0.817)	0.334 (0.083)	0.315 (0.101)

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 as well as a longitudinal sample would be necessary before such conclusions could be drawn.

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 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 without 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?

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