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*Professor Greenberg is responding to an earlier article by Grasmick and Green, "Legal Punishment, Social Disapproval, and Internalization as Inhibitors of Illegal Behavior," 71 J. Crim. L. & C. 325 (1980). Professor Grasmick then offers a rejoinder to Professor Greenberg's critique.*

THE EDITORS

## METHODOLOGICAL ISSUES IN SURVEY RESEARCH ON THE INHIBITION OF CRIME\*

DAVID F. GREENBERG\*\*

In a recent article, Grasmick and Green<sup>1</sup> analyze the relationships they observe in their sample between scales for L = threat of legal punishment, S = threat of social disapproval, M = moral commitment to legal norms, I<sub>p</sub> = self-reported past involvement in illegal behavior, and I<sub>f</sub> = estimated future involvement in illegal behavior. The authors interpret their data on the basis of an assumed underlying causal model in which L, S, and M each influence I<sub>p</sub> and I<sub>f</sub>. Their findings are consistent with the proposition that each of the independent variables inhibits participation in crime.

Before these findings are accepted, other possible interpretations of the data must be ruled out. Grasmick and Green make no attempt to do this. Excluding correlated measurement errors, there are two rival interpretations to consider. The first is that L, S, and M are not causes of involvement in illegal behavior, but rather, are consequences of such involvement. The second is that the relationships are spurious, with nonvanishing correlations being produced by unmeasured exogenous causes of the observed variables. Each of these possibilities will be considered in turn.

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<sup>1</sup> Grasmick & Green, *Legal Punishment, Social Disapproval, and Internalization as Inhibitors of Illegal Behavior*, 71 J. CRIM. L. & C. 325 (1980).

## REVERSE CAUSAL ORDER

As operationalized in Grasmick and Green's study, L and S do not refer to objective features of the threats from legal punishment or social disapproval, but refer, instead, to subjective appraisals of these threats. That is quite appropriate in a study of this sort, since it is these subjective appraisals that are presumed to influence behavior. Yet it is by no means implausible that these appraisals should be influenced by subjects' participation in illegal activities. Should participants discover on the basis of their experiences that the consequences of involvement and apprehension are not as serious as they had previously thought, they would revise their estimates of L and S downward, producing a negative correlation between  $I_p$  on the one hand, and L and S on the other. Moreover, participation in illegal activity could cause people to reassess their moral standards. Perhaps this happens through psychological mechanisms for reducing guilt. After-the-fact rationalizations of this kind are a reasonably familiar phenomenon in everyday life.

Participation may also entail association with others whose values and beliefs about morality "rub off," leading to a higher tolerance or even approval of previously disapproved activities. This is the sort of process postulated by Edwin Sutherland in his famous "differential association" hypothesis,<sup>2</sup> but the process can occur as well following involvement in crime as before it. Still another possibility is that moral commitment to legal norms is eroded when participants learn on the basis of their experience that the social consequences of their involvement (such as harm to victims) are not as serious as they had previously believed. The positive reinforcement provided by the violations themselves (pleasure from participation) could have the same effect. It is more difficult to think of a plausible reason why a prediction of future involvement in crime would be a cause of current assessments of L, S, and M, and so we will not consider this possibility.

Figure 1 displays a path diagram for a model in which  $I_p$  influences L, S, and M, but is not influenced by them. Using the conventional rules for path analysis, we can derive consistency conditions that should hold if the postulated model is correct. These conditions are:

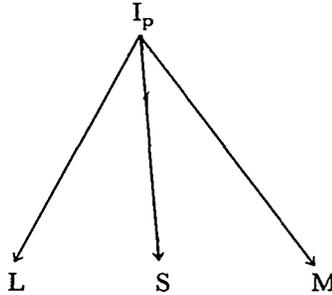
$r_{LI_p}r_{SI_p} = r_{LS}$ ,  $r_{SI_p}r_{MI_p} = r_{SM}$ , and  $r_{LI_p}r_{I_pM} = r_{LM}$ . Comparing these predictions with the correlations given in Grasmick and Green's Table 2, we find that none of them are well-obeyed. The three "equalities" we obtain when we substitute the observed correlations into these three equations are  $.236 = .370$ ,  $.248 = .420$ , and  $.168 = .290$ . Although the discrepancies are not enormous, they are substantial enough to indicate that the entire pattern of relationships is not due to the effect of  $I_p$

<sup>2</sup> E.H. SUTHERLAND & D.R. CRESSEY, *CRIMINOLOGY* 77-98 (10th ed. 1978).

on L, S, and M. We cannot, however, exclude the possibility that *some part* of the relationships originate in this way.

**FIGURE 1**

INVOLVEMENT IN CRIME AS A CAUSE OF  
INHIBITION INDICATORS



SPURIOUSNESS

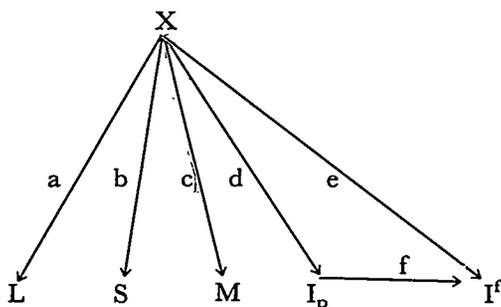
The second possibility we must consider is that the relationships observed are spurious. If this is so, the observed pattern does not reflect the causal influence of observed variables on one another. Rather, it reflects the influence of one or more unobserved variables on the measured variables. It is plausible that spuriousness of this kind should exist. Variation in participation in illegal activity can reflect variability in the strength of motivation and in differential opportunities, as well as in control factors. It does not seem unlikely that some of the personal characteristics that influence motivation and opportunity should also influence perceived risk and strength of moral inhibitions. We would expect members of a simple random sample drawn from a city directory (as was Grasmick and Green's sample) to differ on a number of variables (such as age, sex, race, and class) that would influence L, S, M, and  $I_p$ . These same variables would also plausibly influence one's predicted future involvement in crime. If, for example, low income causes a person to steal right now, and he thinks his impoverished economic status is likely to persist, he would probably predict that he will continue to steal in the future.

Apart from L, S, and M, we would expect  $I_p$  to influence  $I_f$ , simply because people are likely to estimate their future behavior by assuming that they will continue to do what they are now doing. Social scientists are generally aware that there is some tendency for involvement in crime to be consistent; that is, that current violators are more likely to be violators in the future than are current nonviolators. Lay persons are

also likely to believe this. The path model corresponding to these assumptions is displayed in Figure 2.

FIGURE 2

A MODEL OF PARTIAL SPURIOUSNESS AMONG OBSERVED VARIABLES<sup>a</sup>



<sup>a</sup> The variable *X* is unmeasured; the remaining variables are defined in the text.

Let us first consider the relationships among the variables *L*, *S*, and *M*, and *I<sub>p</sub>*. There are four parameters (*a*, *b*, *c*, and *d*) to be estimated from the six independent correlations among the variables. These parameters are the standardized path coefficients (regression coefficients) for the influence of a postulated single exogenous variable that causes all four observed variables.<sup>3</sup> We will thus have two consistency conditions that can be used to check the model.

A useful way to carry out these checks is to derive expressions for each of the parameters. We can derive two such expressions for each parameter, and can then compare the two estimates. This gives us four tests, since the two estimates of each parameter should be similar. Only two of these four tests will be independent. The tests are as follows:

1. We compare  $a^2 = r_{LS}r_{LI_p}/r_{SI_p} = .251$  with  $a^2 = r_{LS}r_{LM}/r_{SM} = .255$ .
2. We compare  $b^2 = r_{LS}r_{SM}/r_{LM} = .536$  with  $b^2 = r_{SM}r_{SI_p}/r_{MI_p} = .590$ .
3. We compare  $c^2 = r_{SM}r_{LM}/r_{LS} = .329$  with  $c^2 = r_{SM}r_{MI_p}/r_{SI_p} = .300$ .
4. We compare  $d^2 = r_{SI_p}r_{LI_p}/r_{LS} = .638$  with  $d^2 = r_{MI_p}r_{LI_p}/r_{LM} = .579$ .

Here we find the consistency to be quite good. The discrepancies are all small, well within the magnitude that might be expected on the basis of

<sup>3</sup> This single variable can be a composite of the conceptual variables that enter our theories. Moreover, no special assumption about the functional form of this composite need be made; in particular, it need not be linear.

sampling fluctuations. This evidence is consistent with there being no influence of L, S, M on  $I_p$ .

Now let us consider the relationships involving  $I_f$ . We have two additional parameters to estimate (e and f), and four correlations to use in estimation. Thus there are two consistency conditions. These can be taken to be

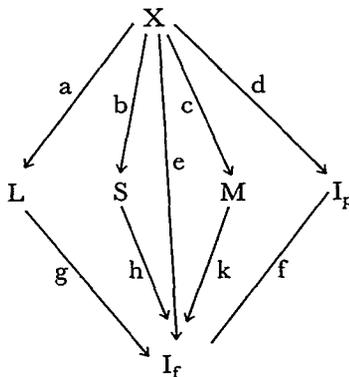
$$r_{LI_f}/r_{SI_f} = a(e+df)/b(e+df) = a/b,$$

$$r_{SI_f}/r_{MI_f} = b(e+df)/c(e+df) = b/c.$$

To check these equations, we use the mean values of the estimates for a, b, and c obtained earlier, and the observed values of the correlations. The first equation proves to be extremely well-obeyed, but the second equality is substantially violated. This tells us that the model is inadequate and must be revised.

A parsimonious revision of the model will leave the relationships among L, S, M, and  $I_p$  intact, but alter the relationships among these variables and  $I_f$ . We can do this by permitting L, S, and M to influence  $I_f$  with respective path coefficients g, h, and k (assuming that the reverse causal ordering is substantively implausible). The path diagram for this model is displayed in Figure 3. With five coefficients (e, f, g, h, and k) to be estimated on the basis of four correlations, the coefficients are under-identified. Unless additional information is brought to bear, we cannot obtain unique estimates of the parameters.

**FIGURE 3**  
COMPLEX CAUSAL MODEL FOR CRIME INVOLVEMENT  
AND INHIBITORS



Perhaps the most plausible identifying restriction we can make would be that  $e = d$ . This says that the effect of omitted exogenous variables on future involvement in crime is the same as their effect on present involvement in crime. On the basis of this assumption we can

use the expressions  $r_{LI_f} = ae+g$ ,  $r_{SI_f} = eb+h$ ,  $r_{MI_f} = ec+k$ ,  $r_{PI_f} = ed+f$  to estimate  $g = .05$ ,  $h = .075$ ,  $k = -.11$  and  $f = .10$ . Only moral commitment to legal norms reduces anticipated future involvement in crime, and its effect is quite small. Although it is counter-intuitive to find that the threat of legal punishment and of social disapproval increase anticipated involvement in illegal behavior, the effects are extremely small and could represent sampling error.

The sensitivity of these estimates to the assumption that  $e = d$  can be ascertained by making alternative assumptions about the value of  $e$ . Since it is highly unlikely that instantaneous exogenous variables would affect anticipated future involvement in crime more strongly than present involvement, we can restrict ourselves to the range between 0 and  $d$ . When  $e = -.6$  instead of  $-.78$  (the value of  $d$ ), we find  $g = -.04$ ,  $h = -.06$ ,  $k = -.21$  and  $f = .25$ . Here, legal threat, social disapproval, and moral commitment all have the expected sign, but only the latter is nontrivial in magnitude. In the extreme (and implausible) case where we set  $e = 0$ , we find  $g = -.34$ ,  $h = -.51$ ,  $k = -.55$  and  $f = .71$ . Here the estimates are more substantial. We note that in all instances the threat of legal punishment is a less effective inhibitor of anticipated future illegality than the threat of social disapproval or moral commitment to legal norms. The magnitude of these influences, as estimated from this model, though, is somewhat sensitive to the assumptions made about the relative magnitude of the parameters  $d$  and  $e$ . Some estimates are miniscule while others are more substantial. The data themselves provide no way of checking these assumptions, leaving the question of crime inhibition up in the air.

### CONCLUSION

Our re-analysis of Grasmick and Green's data makes clear that their conclusions about the inhibition of illegal behavior are not warranted. Their data do not establish that the threats of legal punishment or of social disapproval inhibit self-reported illegal behavior. Nor do they demonstrate that moral commitment to legal norms discourages illegality. Although the data are certainly consistent with the interpretation Grasmick and Green have given them, they are also consistent with plausible rival hypotheses.

Our examination of these rival hypotheses showed that the only one which could be ruled out as inconsistent with the data was the hypothesis that involvement in crime is the sole systematic cause of the various inhibition variables. The data were consistent with the assumption that an omitted exogenous variable influences these inhibition variables and

past criminality, with no causal influences among these measured variables.

The situation with regard to predicted future involvement in illegality proved to be more complex. Here a model of complete spuriousness due to an omitted exogenous variable was inconsistent with the data, even when past criminal involvement was utilized to predict future involvement. When the model was revised to allow for the possible influence of the supposed inhibiting variables on future involvement in crime, the model proved to be under-identified. Precise values of the parameters representing the strength of these influences could not be obtained without using ad hoc assumptions.

This inability to identify the model means that we were not able to establish that any appreciable degree of crime inhibition originates with the variables Grasmick and Green set out to study. Nor were we able to exclude such inhibition. The precise nature of the relationship between past involvement in crime, anticipated future involvement, and the presumed inhibiting variables cannot be determined on the basis of the sort of data Grasmick and Green have collected (that is, cross-sectional data) without ad hoc assumptions which come from outside the data themselves. At present there is no sound theoretical or empirical basis for such assumptions. Under these circumstances no statistical sleight-of-hand can answer the question Grasmick and Green believe they have answered. For this purpose, longitudinal data are needed.

Several years ago, the problems with dealing with spuriousness and uncertainty in causal direction among variables in deterrence research were highlighted by Nagin, and Fisher and Nagin.<sup>4</sup> Although these authors discussed these problems in the context of geographically aggregated official data, they are no less relevant to the analysis of unaggregated survey data. While Grasmick and Green have moved the study of the social control of crime forward by refining the indicators used in this sort of research, their inattention to plausible alternative interpretations of their data, and methods for distinguishing among them, render their work methodologically primitive, and its conclusions suspect.

Since the issues raised here have been generally neglected in survey research on crime deterrence,<sup>5</sup> the thrust of the Nagin-Fisher analysis is

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<sup>4</sup> Nagin, *General Deterrence: A Review of the Empirical Evidence*, in DETERRENCE AND INCAPACITATION: ESTIMATING THE EFFECTS OF CRIMINAL SANCTIONS ON CRIME RATES 95 (A. Blumstein, J. Cohen & D. Nagin eds. 1978) [hereinafter cited as DETERRENCE AND INCAPACITATION]; Fisher & Nagin, *On the Feasibility of Identifying the Crime Function in a Simultaneous Model of Crime Rates and Sanction Levels*, in DETERRENCE AND INCAPACITATION, *supra*, at 361.

<sup>5</sup> See Anderson, Chiricos & Waldo, *Formal and Informal Sanctions: A Comparison of Deterrent Effects*, 25 SOC. PROB. 103 (1977); Meier & Johnson, *Deterrence as Social Control: The Legal and*

worth underscoring here. In the absence of a model that includes all appreciable influences on crime and social control variables, estimates for the effect of social control variables on crime will be biased. When models of this kind embody reciprocal causal relationships, as they generally will, ordinary least squares regression estimates will also be biased, and simultaneous equation methods must be employed. The parameter restrictions needed to carry out such methods on the basis of cross-sectional data will frequently be implausible. I have argued elsewhere that multiwave panel data will permit such simultaneous equations to be estimated on the basis of far less restrictive assumptions.<sup>6</sup>

Thus, what is needed in survey research on the subjective aspects of the social control of illegality is clear: the formulation of causal models that incorporate *all* relevant variables, not just control variables, and a data-collection design that will permit these models to be estimated without specification bias. It will rarely be possible to do this with cross-sectional data.

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*Extralegal Production of Conformity*, 42 AM. SOC. REV. 292 (1977); Silberman, *Toward a Theory of Criminal Deterrence*, 41 AM. SOC. REV. 442 (1976).

<sup>6</sup> GREENBERG & KESSLER, *LINEAR PANEL ANALYSIS: QUANTITATIVE MODELS OF CHANGE* (1981); Greenberg & Kessler, *Panel Models in Criminology*, in *MATHEMATICAL METHODS IN CRIMINOLOGY 1* (J. Fox ed. 1981); Greenberg, Kessler & Logan, *A Panel Model of Crime Rates and Arrest Rates*, 44 AM. SOC. REV. 843 (1979).