COMMISSIONED PAPERS

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The processes underlying the generation of data on crimes and sanctions offer alternative explanations for the observed inverse association between crime and sanctions. Variations, either across jurisdictions or over time, in police practices in the recording of offenses reported to them by the public or in the subsequent unfoundings of recorded offenses may in themselves generate an inverse association between published crime rates and any sanction variable using published counts of crime in its denominator (e.g., clearance rate, prison commitments per crime). Jurisdictions that record fewer reported crimes and/or unfound more recorded crimes will tend to have lower crime rates and higher measures of such sanction rates. Overt manipulation of clearance and crime reports will serve to generate an even larger negative association between crime rates and the clearance rate. High clearance rates and low crime rates are used as indicators of an effective police department. Police departments may use their discretion not to record or to undefund a reported offense to manipulate reductions in published crime rates. Concurrently, by offering suspects leniency if they admit to previously unsolved crimes, the police can also inflate clearance rates. The negative association between clearance rates and crime rates may simply reflect the varying intensity across jurisdictions with which such practices occur.

Similarly, the observed inverse association between prison commitments per crime and the crime rate may also be a reflection of the plea bargaining process. Plea bargaining will have the effect of understating in published statistics the actual number of prison commitments for crimes and/or convictions. Jurisdictions that record fewer reported crimes and/or over time, in police practices in the recording of offenses reported to them by the public or in the subsequent unfoundings of recorded offenses may in themselves generate an inverse association between published crime rates and any sanction variable using published counts of crime in its denominator (e.g., clearance rate, prison commitments per crime). Jurisdictions that record fewer reported crimes and/or unfound more recorded crimes will tend to have lower crime rates and higher measures of such sanction rates. Overt manipulation of clearance and crime reports will serve to generate an even larger negative association between crime rates and the clearance rate. High clearance rates and low crime rates are used as indicators of an effective police department. Police departments may use their discretion not to record or to undefund a reported offense to manipulate reductions in published crime rates. Concurrently, by offering suspects leniency if they admit to previously unsolved crimes, the police can also inflate clearance rates. The negative association between clearance rates and crime rates may simply reflect the varying intensity across jurisdictions with which such practices occur.

The purpose of this paper is to raise the issue of whether the processes underlying the generation of data on crimes and sanctions offer alternative explanations for the observed inverse association between crime and sanctions. Variations, either across jurisdictions or over time, in police practices in the recording of offenses reported to them by the public or in the subsequent unfoundings of recorded offenses may in themselves generate an inverse association between published crime rates and any sanction variable using published counts of crime in its denominator (e.g., clearance rate, prison commitments per crime). Jurisdictions that record fewer reported crimes and/or unfound more recorded crimes will tend to have lower crime rates and higher measures of such sanction rates. Overt manipulation of clearance and crime reports will serve to generate an even larger negative association between crime rates and the clearance rate. High clearance rates and low crime rates are used as indicators of an effective police department. Police departments may use their discretion not to record or to undefund a reported offense to manipulate reductions in published crime rates. Concurrently, by offering suspects leniency if they admit to previously unsolved crimes, the police can also inflate clearance rates. The negative association between clearance rates and crime rates may simply reflect the varying intensity across jurisdictions with which such practices occur.

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genetation of data on crimes and sanctions observed in the private sector. A recent study has shown that insurance companies use their own crime data to adjust premiums, which is now being investigated by the authorities.

In sum, the rationale for the statistical approach is that crime affects sanctions as well as that sanctions affect crime. The econometric models used to estimate these effects are designed to control for the endogeneity of crime and sanctions, which is achieved by using instrumental variables. The results suggest that increases in crime lead to higher sanction levels, and vice versa.

In the next section, the identifications of the sanction functions (in addition to those related to the identification of the crime function) are based on making the following assumptions:

1. There is a causal relationship between crime and sanctions.
2. The impact of crime on sanctions is not influenced by unobserved factors.
3. The impact of sanctions on crime is not influenced by unobserved factors.
4. The impact of sanctions on crime is not influenced by the same unobserved factors that affect crime.

These assumptions are used to derive a set of simultaneous equations that are solved to estimate the crime function and the sanction function. The results are presented in the following section.
Identifying the Crime Function

Blumstein and Cohen (1973) and Blumstein et al. (1978) have offered still another reason for believing that crime rates will negatively affect sanctions. They have hypothesized that society is willing to deliver sanctions as well as that sanctions level of resources devoted increased rate saturate the over-utilization of the sanction E, then the resource saturation over-utilization of In lr more crimes in absolute terms E

The resource saturation hypothesis is a priori hypothesis, their empirical support for the "limits on punishment" hypothesis, their empirical results are also tentative and require further investigation.

Both the "resource saturation" and "limits on punishment" hypotheses predict a negative effect of crime on sanctions. Some have argued that the plausibility of increased crime rates causing a saturation of sanctions. This hypothesis is raised, for example, by Forst and Avio (1974). Empirical evidence supporting this position is also observed a positive association between crime rate and sentence length. The emicent of the New York Repeat Offender Law and the Massachusetts Gun Law also support the "toughening" position.

The possibility of simultaneity between crime and sanctions, no matter what its cause, raises serious obstacles to empirical analysis and requires that simultaneous equations be used to estimate the deterrent impact of sanctions in the simultaneous association of crime and sanctions. The separation of the two effects cannot be achieved under a priori assumptions about the specific nature of the simultaneous relationship is invoked. These assumptions, which are called "identification restrictions," are the keystones of simultaneous equation estimation, for data alone are not sufficient for estimating the structural parameters of a simultaneous system "no matter how extensive and complete those observations may be" (Fisher 1966, p. 33).

In the next section, the identification problem will be discussed and its basic role in simultaneous equation estimation illustrated.

Identifying the Crime Function

The regression coefficients are not consistent estimates of the structural parameters b and d because the mutual interaction of x and y makes it impossible to assume that either independent of the stochastic disturbances u and e. Since x influences y, and since y influences x, it cannot be the case that x and e are uncorrelated. Hence a regression of y on x will confound the effect of x on y, with that of e on y, and will not produce a consistent estimate of b.

An estimator is said to be consistent if its probability limit exists and is the true parameter value. Intuitively, this is similar to saying that with a sufficiently large sample the parameter can be estimated with high probability with any desired precision. An estimator that is inconsistent will also, generally, be biased. The converse is often not the case.

The respective covariances of a, with e, y, and with x, can be shown to be:

$$\gamma_{ae} = \frac{1}{1 - \rho^2} [\sigma_{ey}^2 - \rho \sigma_{xy} \sigma_{ey}]$$

$$\gamma_{ay} = \frac{1}{1 - \rho^2} [\sigma_{ey}^2 - \rho \sigma_{xy} \sigma_{ey}]$$

where:

- $\sigma_{xy}$ and $\sigma_{ey}$ are covariance of x and y, and y and e,
- $\sigma_{xy}^2$ and $\sigma_{ey}^2$ are variance of x and y, and e,
- $\rho$ is correlation of x and y, and e.

Since $\rho = 0$ and $\sigma_{xy} = \sigma_{ey} = 0$ are respectively necessary conditions for regression to produce consistent estimates of b and d, regression is an inappropriate estimation technique.
were developed because classical
methods produce inconsistent parameter estimates, but no consistent estimator of those parameters exists. There is no consistent way to estimate them from the data. The problem can be seen in Figure 2 which presents the non-stochastic components of equations (1a) and (1b). Because \( x_t \) and \( y_t \) mutually affect one another, we will observe only a single equilibrium point \((x^*_t, y^*_t)\). (If the stochastic terms were introduced, then the equilibrium points would be scattered about \((x^*_t, y^*_t)\).) This single equilibrium point does not provide sufficient information for estimating either of the two equations, (1a) and (1b), that produced it. For example, the equilibrium \((x^*_t, y^*_t)\) could just as well have been generated by the system shown in Figure 3.

Indeed, there are an infinite number of such systems that could have generated \((x^*_t, y^*_t)\). There is no way to use the data to distinguish the true system from the others. Algebraically, this amounts to observing that any linear combination of equations (1a) and (1b) will produce an identical equilibrium \((x^*_t, y^*_t)\). There is no way of distinguishing the true (1a) or (1b) from any such linear combination.

In Figure 4, the non-stochastic component of (1a) is presented as a function of \( T \), where \( (x^*_t, y^*_t) \) are the equilibrium values of \( x_t \) and \( y_t \) for the three equilibrium points \( T = T_1, T_2, T_3 \). The three points where (1a)'s equilibrium values of \( x_t \) and \( y_t \) are the same as \( T \) are shown in Figure 5. As the system is specified, neither equation is identified and neither can be estimated consistently by any method. As indicated earlier, the impossibility of estimating the system is a reflection of there being an infinite set of equation systems that could generate \((x^*_t, y^*_t)\). Suppose, however, that an exogenous variable, \( w_t \), is suspected to have an effect on \( x_t \), but is known to have no effect on \( y_t \). Eq. (1a) could then be re-specifed as:

\[
y_t = \alpha + \beta x_t + \gamma T + \epsilon_t
\]

Additionally, assume for concreteness that \( f < 0 \).

In Figure 4, the non-stochastic component of (1a) is presented as a function of \( T \), for three different values of \( T \). Consistent with the assumption that \( f < 0 \), Figure 4 shows that for any given value of \( x_t, y_t \) is smaller for larger values of \( T \).

| Ordinary least squares regression, however, remains inconsistent even though consistent estimators exist. |
| An assumption of \( f > 0 \) would do just as well; an assumption, however, of \( f = 0 \) would leave both equations unidentified as before. |
eral equations involving simultaneous causation is a difficult problem. Under certain conditions, estimation procedures do provide a consistent estimate of the system, provided that the true structural equations are specified. However, if these conditions are not satisfied, then the estimated parameters may be inconsistent even though consistent estimates of the coefficients may be obtained.

The equation is specified. and the coefficients are estimated. The equation is estimated. and the coefficients are consistent estimates. It is important to note that the estimated parameters may not be consistent even though consistent estimates of the coefficients are obtained.

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Identifying the Crime Function

In Figure 7, the crime rate is given in Figure 7.

Characterization of the unobserved crime rate (i.e., crime rate on clearance rates and not clearance rates) can be determined. (The crime function, however, remains unidentified and it will remain unknown and unknowable to us that, indeed, higher clearance rates do not deter crime. Suppose, however, it were arbitrarily assumed that sentence, $S_t$, affected clearance rates and not crime rates. Then the mechanics of simultaneous estimation would have allowed an equation for the crime rate to be estimated. That equation, however, would be identical to the one obtained by drawing a line through the equilibrium values of $s$ and $y$. Thus, the estimated relation would actually be the relationship describing the effect of crime rate on clearance rates and not crime rate on clearance rates, and so would be completely wrong. In this case, we would conclude that clearance rates have a direct effect on crime when in fact they have none.

The very real possibility of making erroneous causal inferences when a model is identified through erroneous assumptions underscores the point that identification is not a minor technical point of estimation. If an equation is not identified, one cannot estimate it. If one tries to do so

$$y_t = y_{t-1} + e_t$$

strated in Figure 8.

Identifying the Crime Function

In Figure 8, the crime rate as a function of the clearance rate and the average sentence ($T$).

In Figure 9, the clearance rate function is superimposed on the crime functions in Figure 8. As was shown previously, the clearance rate function is now identified. By connecting the observed intersections in Figure 9, the exact specification for the clearance rate function can be determined. The crime function, however, remains unidentified and it will remain unknown and unknowable to us that, indeed, higher clearance rates do not deter crime. Suppose, however, it were arbitrarily assumed that sentence, $S_t$, affected clearance rates and not crime rates. Then the mechanics of simultaneous estimation would have allowed an equation for the crime rate to be estimated. That equation, however, would be identical to the one obtained by drawing a line through the equilibrium values of $s$ and $y$. Thus, the estimated relation would actually be the relationship describing the effect of crime rate on clearance rates and not crime rate on clearance rates, and so would be completely wrong. In this case, we would conclude that clearance rates have a direct effect on crime when in fact they have none.

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$$y_t = y_{t-1} + e_t$$

Identifying the Crime Function

using false restrictions to identify the equation, one can draw completely erroneous conclusions from the estimated relationship.

It is thus essential that when exclusion restrictions are used for identification, the restrictions must be carefully justified on the a priori grounds that the excluded variables do not directly affect the value of the endogenous variable on the left side of the equation from which they are excluded. If a variable is excluded from an equation merely to facilitate estimation, then the coefficient estimates will remain inconsistent and thus unsuitable for inference about the behavior of the system. Moreover, identifying restrictions must be assumed a priori and the nature of the problem is such that restrictions needed to identify can never be tested using data generated by the model under investigation.

In analyzing the mutual association of crime and sanctions, the possibility of making erroneous causal inferences about the causal effect of sanctions on crime is particularly high. Since there are good reasons for believing that crime has a negative causal effect on sanctions, we would expect to observe a negative association in the data between crime and sanctions even if sanctions do not deter crime. Such negative associations are well documented in the deterrence literature (e.g., Ehrlich 1973; Sjoquist 1973; Tittle 1969). Having observed the negative association, we are left with the delicate problem of determining the extent to which it is produced by the negative deterrent effect of sanctions on crime as opposed to the negative effect of crime on sanctions (if the latter effect is indeed negative).

In view of the importance of the identification problem, we shall review some of the restrictions that have been used by some authors to identify the crime functions so that the validity of their findings on the deterrent effect of sanctions can be put into perspective. When evaluating the validity of such restrictions, one should keep in mind that crime-function restrictions presume that the variables involved affect either sanctions, police expenditures per capita (a variable commonly hypothesized to be simultaneously related to crime), or other endogenous variables included in the model, but do not directly affect the crime rate itself.

Ehrlich (1973) identified his crime function by excluding from it (but including elsewhere in his model) the following variables:

1. The crime rate lagged one period.
2. Police expenditures per capita.
3. Unemployment rate of civilian
4. Percent of males aged 14-24
5. Percent of population living in urban areas
6. Males per female
7. A southern regional variable
8. Mean years of schooling of post
9. Total population.

In Carr-Hill and Stern (1973), the excluding:
1. Total population
2. Proportion of reported crimes
3. A measure of the proportion of

Aivo and Clarke (1974) estimate a crime rates, and police expenditures terminated. The crime function is iden
tified in part by the exclusion of the remaining

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12Ehrlich (1973) identified his crime function by excluding from it (but including elsewhere in his model) the following variables:

13His Ph.D. dissertation, Ehrlich (1970) on above unemployment, age, and education vs. significant association between crime rate as
tified in part by the exclusion of the remaining

However, other data generated in other ways (by experiment, for example) can be so used.

Indeed, in a complex model, such an observed negative association could occur even if neither direct effect is negative because of relations among the disturbance terms. 

13Indeed, Ehrlich's own theoretical model does have such an effect.
Identifying the Crime Function

1. The crime rate lagged one period
2. Police expenditures per capita lagged one period
3. Unemployment rate of civilian males aged 35-39
4. Percent of males aged 14-24
5. Percent of population living in SMSAs
6. Males per female
7. A southern regional variable
8. Mean years of schooling of population over age 25
9. Total population.

In Carr-Hill and Stern (1973), the crime function is identified by excluding:
1. Total population
2. Proportion of reported crimes that are violent
3. A measure of the proportion of the population that is middle class.

Avio and Clarke (1974) estimate a model in which crime rates, clearance rates, and police expenditures per capita are simultaneously determined. The crime function is identified by excluding:
1. Population density
2. The total population
3. Police expenditures lagged one period
4. Motor vehicle registration per capita lagged one period
5. Crimes against persons lagged one period.

In all these papers, identification of the crime function relies on the exclusion of socioeconomic variables (SES) and lagged endogenous variables from the crime function. It is difficult to imagine any plausible argument for the exclusion of the SES variables. Intercorrelation among these SES and demographic correlates of crime makes it difficult to determine which among them do have a causal association with crime, but it is simply not plausible to assume that such SES variables do not have a direct effect on crime, while also assuming that each does directly affect either sanctions or police expenditures per capita.

Identification of the equation from which estimated sanctions must be assumed of crime and sanctions, the rate problem of determining the causal effect on sanctions, we legislate deterrent effect of crime on sanctions: Since crime and sanctions are simultaneously related, our conclusion is that it is most unlikely that the authors mentioned have successfully identified and consistently estimated the deterrent effect of sanctions. Consequently, one can have little confidence that the estimated sanctions coefficients are consistent. Moreover, the magnitude of the inconsistency seems likely to be substantial since the restrictions used to identify seem unlikely to be even approximately correct (see Fisher 1961). Consequently, the resulting parameter estimates cannot be used for causal interpretation.

A crucial question is then: Can the crime function ever plausibly be identified, i.e., can we ever hope to find variables that influence sanctions but have no direct effect on crimes? This question, which is the central topic of this paper, is the focus of the next section. The question of the feasibility of identifying the crime function requires an appreciation of some more generalized identification concepts. Thus, before we turn to the topic of feasibility, we shall develop these concepts.

III. SOME MORE GENERALIZED IDENTIFICATION CONCEPTS

The paper discussion has focused on the requirements for identifying the structural equations in a system where only two variables are simultaneously related. We shall now generalize to a situation where M variables simultaneously affect one another.

Suppose we specify the interrelationship of the M variables by:

\[ y_1 = a_{11}x_1 + a_{12}x_2 + \ldots + a_{1M}x_M + \epsilon_1 \]

\[ y_2 = a_{21}x_1 + a_{22}x_2 + \ldots + a_{2M}x_M + \epsilon_2 \]

\[ \vdots \]

\[ y_M = a_{M1}x_1 + a_{M2}x_2 + \ldots + a_{MM}x_M + \epsilon_M \]

where:

\[ y_j = \text{the } j\text{th endogenous variable} \]

\[ a_{ij} = \text{the coefficient defining } \epsilon_j \text{ on the } i\text{th variable} \]

\[ x_j = \text{the } j\text{th non-endogenous variable} \]

\[ b_j = \text{the coefficient defining \[ x_j \text{ on the } j\text{th endogenous variable}} \]

\[ \epsilon_i = \text{the stochastic component} \]

As was shown previously, without the empirical observations how well measured or extensive consistently estimating the structural equation in system (2), require generating \( M + 1 \) parameters of empirical information are of information can be obtained. \( N + M - 1 \) parameters of this ex that only the \( N \) non-endogenous parameters. The \( M \) endogenous variables for stochastic effects once the \( x_j \) effects, we could think of performing them for us) by setting the effect on the \( y_j \). There would be, in setting the \( N \) non-endogenous \( x_j \) redundant.

In the stochastic case, the error term \( \epsilon_i \text{ at most} \) that each of \( \epsilon_i \text{ with the disturbances, } \epsilon_i \text{ from the first equation} \epsilon_i \text{. The } y_j \text{ are} \]
Identifying the Crime Function

If $M = 1$ so that there were no simultaneity, then these $N$ zero correlations would suffice to allow the consistent estimation of the first (and only) equation by ordinary regression. In that case, only exogenous variables would appear on the right side of that equation and the $N$ zero correlations would satisfy the necessary conditions for ordinary regression to generate a consistent estimator—namely, that the regressors be uncorrelated with the disturbance. Where $M > 1$ and there is simultaneity, these $N$ zero correlations are not enough to recover the $M = 1 + N$ parameters of the first equation.

Another way of putting it is to say that analysis of the data can at most only tell us about the total effects (direct and indirect) of the $x_i$ on the $y_i$ (from the "reduced form" in which the equations are solved for the $y_i$ only in terms of the $x_i$ and $e_i'). The direct effects of the $x_i$ on the $y_i$ (the $b_{ik}$) and the direct effects of the $y_i$ on each other (the $a_{ik}$) cannot be recovered from the data without at least $M - 1$ additional independent pieces of information for each equation. Such additional information must come from outside, a priori considerations.

The situation is completely isomorphic to the logical impossibility of finding a unique solution to a system of linear equations in $M + N - 1$ unknowns, when only $N$ independent equations are available. A unique solution can only be obtained if $M - 1$ additional independent equations, comparable to our restrictions, are imposed. The identification restrictions in simultaneous equation estimation provide the $M - 1$ additional restrictions that sufficiently augment the empirical information to allow the estimation of the structural equation.

The $M - 1$ additional equations in the system of linear equations in $M + N - 1$ unknowns are as important in specifying a unique solution as the $N$ original equations. Similarly, the identification restrictions are as important in the determination of the coefficients as the observational information.

The additional $M - 1$ restrictions can be (but need not be) generated by assuming that $M - 1$ of the parameters in the equation are zero. The $M - 1$ restrictions could be generated if we assumed $a_{ik} = 0, (i = 2, \ldots , M)$, which is to assume that $y_i$ is not simultaneously related to any of the other $y_j$. Since the $x_i$'s are assumed to be uncorrelated with $e_i$, the coefficients of the first equation could then be consistently estimated by ordinary least squares.

Suppose, however, that we conclude that a priori considerations allow us only to assume that $(M - 1) - k$, where $0 \leq k < M - 1$, of the

$$a_{ik}$$

are zero. We must still estimate $k$ values on only the $N$ equation. The additional $k$ pieces of information would allow us to non-endogenous $x$ do not enter more of the other equations $(i \neq 1)$. By assuming that $k$ of the estimate them. Thus the $N$ equation to estimate the remaining $N - k$ plus, however, that the result plausibly if $M - 1 + k$ of the $a_{ik}$ rec. Thus, any empirical of those a priori premises.

When only $M - 1$ restriction is identified, it is said derives from the fact that if we then the equation will not be only a single restriction means general an infinite number of data. All such equations are ob. Thus, it must be remembered as a consistent estimator, one is than zero restrictions. In either and no causal inference can be 1 of the models to be examined to

We sometimes it is also possi- tions and to identify the equa- stances, the equation is said to 1 more than $N$ pieces of informa- estimation, of course, remains.

Before turning to the next se- crime function, several import- importance, they are: First, if restric- used to identify it analyzed. The unstability of a model cannot even be estin

9See Fisher (1966) for a complete discussion.

10This is a necessary but not sufficient condition for identification. For a full discussion see Fisher (1966).
Identifying the Crime Function

In this section, we shall examine the central issue of this paper: Can the crime function be plausibly identified? We shall proceed by first examining the simplest model in which a single crime type and sanction type are simultaneously related. Several categories of just-identifying restrictions, none of which are mutually exclusive, will be analyzed for their strengths and weaknesses. The single-crime-type, single-sanction-type model overly simplifies the real phenomenon of multiple crime types and multiple sanction types. However, to date no analyses have attempted to estimate models in which more than one crime and sanction type are simultaneously related. More important for our pur-

4. On the Feasibility of Identifying the Crime Function

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I multaneity, then these N zero consistent estimation of the first

definitions of the x's, on which the equations are solved for

e direct effects of the y's on each other (the a j) cannot be

additional independent

The logical impossibility of

in the equation are zero. The

assumed to be uncorrelated with

11 The additional k pieces of information can be generated if a priori

considerations would allow us to assume plausibly that k of the N

non-endogenous x's do not enter the first equation but do enter one or

more of the other equations (i.e., k of the b j = 0 but b j ≠ 0 for some j ≠ i).

By assuming that k of the b j's are zero, it becomes unnecessary to

Thus the N pieces of empirical information can be used to

estimate them. Thus the N pieces of empirical information can be

used to estimate the remaining N parameters consistently. It must be

emphasized, however, that the remaining N parameters will only be

consistently estimated if the a j (or b j) are unique. If two or more

parameters share the same value for a single equation, it is not

possible to separate them and estimate them independently.

Thus it must be remembered that from the perspective of the existence

of the restrictions follows from the fact that

there are alternative ways to just-identify it. One can estimate the

model under a variety of subsets of just-identifying restrictions, with

each of the resulting model estimates being contingent upon the valid-

ity of the just-identifying subset used. If one has little or no faith in

the validity of any one of the subsets, then even if one gets the same results

under each subset (for example, samplings do not deter crime), then

one cannot conclude that those results are valid.

Second, any additional restrictions beyond a set of M = 1 just-

identifying ones can be tested. Those tests are, however, contingent

upon the validity of the M = 1 just-identifying restrictions. If one has

faith in the validity of these M = 1 restrictions, then one can have faith

in the validity of the empirical tests of the additional over-identifying

restrictions. But, if one has little faith in the validity of the just-

identifying restrictions, one can have only little faith in the validity of the

test of the remaining restrictions. One implication of this point is

that if one generates a set of over-identifying restrictions—but in this

situation there does not exist a subset of just-identifying restrictions whose

validity is unquestionable (or nearly so)—one cannot gain a test of

the set of restrictions by exhaustively testing each restriction under

the assumption that the remaining ones are correct. 10

that a priori considerations k, where k < k - 1, of the

for identification. For a full discussion

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[e.g., the clearance rate's specification (1b) cannot be estimated unless

we assume that T j does not enter (1b). Since we cannot estimate (1b) if

T j does enter it, then we cannot test whether it should enter (1b)].

A related point follows when a model is over-identified, that is, when

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IV. ON THE FEASIBILITY OF IDENTIFYING THE CRIME FUNCTION

In this section, we shall examine the central issue of this paper: Can the crime function be plausibly identified? We shall proceed by first examining the simplest model in which a single crime type and sanction type are simultaneously related. Several categories of just-identifying restrictions, none of which are mutually exclusive, will be analyzed for their strengths and weaknesses. The single-crime-type, single-sanction-type model overly simplifies the real phenomenon of multiple crime types and multiple sanction types. However, to date no analyses have attempted to estimate models in which more than one crime and sanction type are simultaneously related. More important for our pur-

10 Naturally, no model is likely to include all possible factors, and some factors will be omitted, but this does not affect the generality of the results. The question of which factors are included in a model is important, but it is not the focus of this paper. It is beyond the scope of this paper to discuss the implications of excluding certain factors from a model.
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IDENTIFYING THE CRIME FUNCTION

entail issue of this paper: Can the crime of burglary be identified? We shall proceed by first examining the crime function, which is the real phenomenon of multiple crime and sanction types. The single-crime-type, crime (C), crime only insofar as it affects the capability of the criminal justice system (CJS) to detect crime, is predicated upon the theory that increased resources devoted to the CJS, as measured by CJS expenditures in time, will decrease the resource saturation effect of any given level of crime. For example, increased police expenditures will increase apprehension probability (which is estimated by clearance rate, because the clearance rate is defined as the number of crimes solved divided by the number of crimes reported). Perhaps this frequency can be used to provide the necessary single identifying restriction to estimate eq. (3a), is predicated upon the theory that CJS expenditures increase the probability of the CJS to deliver sanctions. For sanctions delivered by the courts (e.g., conviction, imprisonment) or regulated by bottom-up considerations, such as those in the case of burglary, the crime function is defined as the number of crimes solved divided by the number of crimes reported.

In this system, there are two endogenous variables, C and S. The crime equation includes one right-side endogenous variable, C; the estimation of eq. (3b) will thus require that one identification restriction be imposed. (Within the context of the identification rules laid out in the previous section, M = 2 and therefore we need M - 1 = 1 restriction to identify eq. (3b).)

In this paper, we have not included the crime function. This exclusion is based upon the necessity to provide the empirical evidence to support the single identifying restriction used in the crime function. However, the crime function is used to identify the crime equation. This exclusion is necessary to fit the identification rules laid out in the previous section, M = 2 and therefore we need M - 1 = 1 restriction to identify eq. (3b).

In conclusion, one can have faith that the crime function is identified. One must have faith beyond a set of just-identifying restrictions whose properties are to be discussed. In this model, which is also characterized by the flow chart in Figure 10, C is determined by S, and S is determined jointly by C and E. The tons expenditures variable, E, enters the equation for S, under the assumption that increased resources devoted to the CJS, as measured by E, will decrease the resource saturation effect of any given level of crime. For example, increased police expenditures will increase apprehension probability (which is estimated by clearance rate, because the clearance rate is defined as the number of crimes solved divided by the number of crimes reported). Perhaps this frequency can be used to provide the necessary single identifying restriction to estimate eq. (3a), is predicated upon the theory that E affects crime only insofar as it affects the capability of the CJS to deliver sanctions. For sanctions delivered by the courts (e.g., conviction, imprisonment) or regulated by bottom-up considerations, such as those in the case of burglary, the crime function is defined as the number of crimes solved divided by the number of crimes reported.

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identifying omitted variable

\[ E_t + e_t \]  
\[ (3a) \]
\[ E_t = \gamma + \beta C_t + \epsilon_t \]  
\[ (3b) \]

FIGURE 10 Diagram of model using expenditures as an identifying variable. The possibility that \( C_{t-1}, E_{t-1}, \) and other variables affect expenditure at \( t > 2 \) are not ruled out by the above equation does not aid in the identification of the latter. This is because these variables do not appear anywhere in the sanctions-cycles loop and have no effect captured beyond taking expenditures as exogenous to that loop. Another way of putting it is that the omission of such variables from the crime equation does not help to distinguish it from the sanctions equation since the variables do not appear in that equation either.

Identifying the Crime Function

\[
\begin{align*}
C_t &= v_1 - \gamma C_{t-1} \\
E_t &= v_2 - \gamma E_{t-1} \\
S_t &= \gamma + \beta C_t + \epsilon_t \\
\end{align*}
\]

Other Variables

The level of police expenditures is likely to influence the visibility of police, since in two identical communities, the one with greater expenditures is likely to have a larger police force. Police visibility may have an independent deterrent effect beyond \( S_t \), where \( S_t \) is measured by clearance rate, because the potential criminal's perception of apprehension probability (which is the "true" measure of \( S_t \)). For example, it is likely where they seek police when \( S_t \) refers to police-delivered sanctions that undeniably derives from the crime equation. A potential criminal cannot observe the actual apprehension probability, but rather can only measure it roughly. One such measure is the frequency with which he and his fellow criminals with whom he has contact experience apprehension.

Perhaps this frequency can be approximated by the clearance rate. The criminal's perception of apprehension probability, however, does not follow criminals with whom he has contact experience apprehension. Perhaps this frequency can be approximated by the clearance rate. The criminal's perception of apprehension probability, however, does not follow criminals with whom he has contact experience apprehension. Perhaps these criminals with whom he has contact experience apprehension may be made by the behavior of the stochastic components, \( e_t \). We must specify the behavior of these stochastic terms over time. We could assume that these errors are independent over time, or we could make a less restrictive assumption that they are serially correlated. For example, we might assume that they follow a first-order autoregressive process, characterized by:

\[ \epsilon_t = \varphi \epsilon_{t-1} + \xi_t \]  
\[ (4) \]

where:

- \( \varphi \) is a parameter
- \( \xi_t \) is non-serially correlated disturbance term.

Identifying the Crime Function

Such assumptions about \( \theta_t \) are critical for identification. In our empirical information in a situation where the maximum number of independent variables available for consistent estimation is \( N \), this was because of the assumption that \( \epsilon_t \) is not correlated with \( \theta_t \). This assumption is not unreasonable, since it is unlikely that the level of crime affects the level of expenditures, at least across jurisdictions and probably over time. The observed positive association between police expenditures per capita and crime rate provides some evidence for the likelihood of such an effect (see, for example, McPhers and Strong 1975).

2. Expenditures are influenced only by lagged crime rates and are therefore predetermined, although not fully exogenous. This seems more reasonable than does full exogeneity. Due to the government budgeting cycle, the level of \( E_t \) is specified before the beginning of a period. That level, although probably influenced by the crime rate, is influenced by rates in prior periods, for example, \( C_{t-1} \). Thus, \( E_t \) is a predetermined variable.\(^{11} \)

Granting that \( E_t \) is predetermined, a further crucial assumption must be made about the behavior of the stochastic components, \( e_t \). We must specify the behavior of these stochastic terms over time. We could assume that the errors are independent over time, or we could make a less restrictive assumption that they are serially correlated. For example, we might assume that they follow a first-order autoregressive process, characterized by:

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\[ (4) \]

where:

- \( \varphi \) is a parameter
- \( \xi_t \) is non-serially correlated disturbance term.

\^[11] It should be noted that if \( C_t \) does influence \( E_t \) directly, perhaps because the budget is adjusted or in reaction to \( C_t \), then \( E_t \) becomes determined simultaneously with \( C_t \) and \( S_t \) and the crime function is no longer identified even if \( E_t \) does not appear in it. Some additional restrictions involving a non-endogenous variable are necessary.\]
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Identifying the Crime Function

Such assumptions about the serial relationships among the εi are critical for identification. In our previous discussion on the limits of the empirical information in a simultaneous system, we stated that the maximum number of independent pieces of empirical information available for consistently estimating each structural equation was N, where N equals the number of non-endogenous variables in the system. This was because of the assumption that there are N non-endogenous variables that are uncorrelated with the stochastic disturbances and thus that can be varied independently. If that assumption fails for J, of the non-endogenous variables, then the number of pieces of empirical information for consistently estimating each structural equation is reduced to N-J. In effect, an additional J of the variables become endogenous.

When using predetermined variables for identification, the possibility that the disturbances are serially correlated must be given special consideration. If the εi are serially correlated (for example, a first-order autoregressive process as in eq. (4)), then the predetermined variables will necessarily be correlated with at least some of the stochastic components. In particular, Et will be correlated with εi because εi is correlated with ℓ-1, and Et is a function of ℓ-1, which is in turn a function of ℓ-2.

When serial correlation among the disturbances is thought to be present, estimation still remains possible if one correctly specifies the specific structure of the presumed serial correlation. If one is not certain of the specific structure of the serial correlation, and one rarely is, then the less restrictive the assumption the better. For example, the first-order autoregressive assumption is less restrictive than assuming no serial correlation because the latter will occur for the special case of all the μ zero. However, if the model is estimated under an assumption of no serial correlation, then the possibility of serial correlation of some specific type cannot be tested. Even less restrictive assumptions about the nature of the serial correlation (higher-order processes, for example) can be made, but some specific assumptions must be made.

Excluding a capital punishment analogy by Ehrlich (1975), all simultaneous analyses have employed estimation methods that generate consistent estimates only when there is no serial correlation of any kind among the disturbances. If the exclusion of a predetermined variable is used as an identification restriction, as with E in the model under consideration, the validity of using that restriction when using these methods turns on the assumption of no serial correlation. If the assumption is incorrect, then the parameter estimates will be inconsistent.

Combining the Crime Function

The assumption of no serial correlation among the disturbances is not only fundamental in cases like this; it reflects implicit assumption that are captured in the disturbances because they are not explicitly included in the model. Deciding whether the assumption of no serial correlation can plausibly be maintained thus requires consideration of such factors.

In the crime function shown in eq. (3a), the variables not explicitly included would include all the SES variables that affect crime. However, this is because of the simplistic nature of eq. (3a) adopted for expositional purposes. As already remarked, in practice, if eq. (3a) were to be estimated, some SES variables would be explicitly included. Nevertheless, some part of the stochastic disturbance, ε, would still consist of small effects. It is impossible to include all the SES variables influencing crime both because we do not know all of them or cannot measure them and because there are likely to be many of them, each with a small effect. In addition, if included SES variables affect crime in ways only approximated by our choice of functional form in eq. (3a), then departures from that approximation influence the disturbance term.

From this perspective on the factors generating ε, is it reasonable to assume no serial correlation of ε? The answer, we believe, is no. Many of the SES variables influencing ε change only gradually over time. Thus, if the realized values of these variables in period t are such that the disturbance is positive in period t, it is likely that their realized values in period t+1 will lead to a positive disturbance as well. Hence we should expect positive serial correlation in ε. One possible characterization might be the first-order autoregressive process shown in eq. (4), with α > 0.

When using data with a cross-sectional component, the most common type of data utilized in deterrence analyses, the likelihood of serial correlation is particularly high because there is likely to be particularly wide variation in the values of excluded variables across the sampling units (usually states). Put simply, locations whose actual crime rate is higher than predicted by the systematic part of the equation in one year are likely to remain so in the next year.

The implausibility of an assumption of no serial correlation requires that estimation be done under a less restrictive assumption about the serial correlation of the stochastic terms. If inconsistency is to be avoided. We shall not address the question of what sort of assumption can plausibly be maintained thus requires consideration of such factors.

2. Models Using Prison Cells

In the system shown below, let C, S, and X be determined simultaneously. The system under consideration, the validity of using that restriction when using these methods turns on the assumption of no serial correlation. If the assumption is incorrect, then the parameter estimates will be inconsistent.
Identifying the Crime Function

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assumption, the better. One possibility, given enough data, would be to allow for an autoregressive relationship of order \( \gamma \), where:

\[
d' = \sum_{i=1}^{\gamma} \beta_i x_{t-i} + \delta
\]  

(5)

Estimation under any assumption of serial dependence, however, requires the use of data with a time-series component. For example, the \( \gamma \)th order autoregressive assumption would require that the time-series data in the component be at least \( \gamma + 1 \) periods. Pure cross-sectional data cannot be used.

To summarize, we conclude that the exclusion of the expenditures variable cannot be used plausibly to identify the crime function, at least with cross-sectional data. To do so at all requires the very implausible assumption of serial independence in the stochastic components. To estimate a model under any assumption of serial dependence requires time-series data and thereby precludes the possibility of using only cross-sectional data.

Moreover, as we have seen, the use of the expenditures restriction, no matter what one assumes about the nature of the serial dependence, hinges upon the assumption that \( E_t \) does not directly affect crime. If \( S_t \) and \( E_t \) are defined in terms of court-related activities only, this seems plausible. If \( E_t \) and \( S_t \) pertain to the police, however, then the assumption that \( E_t \) does not directly influence \( C_t \) is questionable. Expenditures on police will be closely linked to the visibility of police in the community, and police visibility may indeed be a very important factor in deterrence crime. Further, if expenditures on courts and expenditures on police vary together, then one may simply be fooling oneself about identification in specifying and estimating a model in which \( E_t \) relates only to courts.

2. Models Using Prison Cell Utilization

In the system shown below, \( C_t \) is again a function of \( S_t \) and \( S_t \) is a function of \( F_t \). Additionally, \( S_t \) is specified to be a function of prison cell utilization, \( U_t \), defined to be the ratio of the prison population in period \( t \), \( P_t \), to total prison cells in \( t \), \( K_t \):

\[
C_t = \beta S_t + \epsilon
\]

(6a)

\[
S_t = \frac{M_s}{P_t} U_t + \epsilon
\]

(6b)

In addition, if we specifically define \( S_t \) to be the degree of imprisonment given a crime and assume that an imprisoned individual is incarcerated for a single period, then \( P_t \) will be:

\[
N_t = \text{total population in } t
\]

From eq. (6c) in eq. (6d)

(6b')

Where:

- \( P_t \) = prison population in period \( t \)
- \( K_t \) = prison cell capacity in period \( t \)
- \( U_t = P_t/K_t \)

As before, sex variables are omitted for expositional convenience. To our knowledge, no deterrence investigation has included \( U_t \) in the equation for sanctions. The rationale for its inclusion again involves a resource utilization argument and, indeed, this model can be taken as a simple example in which the resource saturation hypothesis is made explicit. As prisons become increasingly crowded, pressure will be exerted to reduce utilization. \( U_t \). In the short term (e.g., a year) this reduction can only be accomplished through a reduction in prison population, \( P_t \), since expansion of existing cell capacity, \( K_t \), would require considerably more time. 30

One recent example of this effect of resource saturation at work is Federal Judge Frank Johnson's order to the Alabama Corrections Department to release a sufficient number of prisoners to alleviate prison overcrowding (see Criminal Justice Bulletin 1976). Judge Johnson's order resulted in the reduction of both the probability of imprisonment given conviction and time served given imprisonment.

In this single-sanction and single-crime-type model with only two endogenous variables, identification of the crime function requires that one restriction be imposed; the absence of \( U_t \), prison cell utilization in \( t \), from eq. (6a) provides the necessary restriction. To see this, consider a log-linear specification of eqs. (6a-b):

\[
\ln C_t = \beta \ln S_t + \gamma \ln P_t + \delta
\]

(6a')

\[
\ln S_t = \gamma \ln C_t + \gamma \ln P_t + \epsilon
\]

(6b')

In addition, if we specifically define \( S_t \) to be the degree of imprisonment given a crime and assume that an imprisoned individual is incarcerated for a single period, then \( P_t \) will be:

\[
N_t = \text{total population in } t
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Substituting eq. (6c) in eq. (6d)

(6b')

Where:

- \( N_t \) = total population in \( t \)
- \( P_t \) = \( P_t \) in \( t \)

The exclusion of \( \ln (N/K) \) restriction for identification.

3. Inertia Model: Lagged Sanctions

In the system shown below, \( S_t \), the level of the unit, \( U_t \), is a partial cause, \( \text{is} \), it is likely that their realized crime rate is different than the overall rate. As before, the possibility of using only cross-sectional data is reasonable. One possible characteristic regression process shown in eq. (3a), then

then can be many of them, each with a distinct character, whose actual crime rate is plausible.

The validity of this identification that \( U_t \) does not directly influence \( C_t \), however, is questionable. As prisons become increasingly crowded, pressure will be exerted to reduce utilization. \( U_t \). In the short term (e.g., a year) this reduction can only be accomplished through a reduction in prison population, \( P_t \), since expansion of existing cell capacity, \( K_t \), requires considerably more time. 30

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(6b')

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\[
\text{Identifying the Crime Function}
\]

\[ Y_t = \sum_{i=1}^{\gamma} \beta_i x_{t-i} + \delta \] (5)

Estimation under any assumption of serial dependence, however, requires the use of data with a time-series component. For example, the \( \gamma \)th order autoregressive assumption would require that the time-series data in the component be at least \( \gamma + 1 \) periods. Pure cross-sectional data cannot be used.

To summarize, we conclude that the exclusion of the expenditures variable cannot be used plausibly to identify the crime function, at least with cross-sectional data. To do so at all requires the very implausible assumption of serial independence in the stochastic components. To estimate a model under any assumption of serial dependence requires time-series data and thereby precludes the possibility of using only cross-sectional data.

Moreover, as we have seen, the use of the expenditures restriction, no matter what one assumes about the nature of the serial dependence, hinges upon the assumption that \( E_t \) does not directly affect crime. If \( S_t \) and \( E_t \) are defined in terms of court-related activities only, this seems plausible. If \( E_t \) and \( S_t \) pertain to the police, however, then the assumption that \( E_t \) does not directly influence \( C_t \) is questionable. Expenditures on police will be closely linked to the visibility of police in the community, and police visibility may indeed be a very important factor in deterrence crime. Further, if expenditures on courts and expenditures on police vary together, then one may simply be fooling oneself about identification in specifying and estimating a model in which \( E_t \) relates only to courts.

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\[ C_t = \beta S_t + \epsilon \] (6a)

\[ S_t = \frac{M_s}{P_t} U_t + \epsilon \] (6b)

In addition, if we specifically define \( S_t \) to be the degree of imprisonment given a crime and assume that an imprisoned individual is incarcerated for a single period, then \( P_t \) will be:

\[ N_t = \text{total population in } t \]

Substituting eq. (6c) in eq. (6d)

(6b')

Where:

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The exclusion of \( \ln (N/K) \) restriction for identification.

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\[ P_t = C_s N_t \]

(6c)

\[ \ln P_t = \ln C_s + \ln N_t \]

(6c')

where:

\[ N_t = \text{total population in } t \]

Substituting eq. (6c') in eq. (6b') and rearranging terms:

\[ \ln S_t = \frac{\gamma}{1-\gamma} + \frac{\eta}{1-\gamma} \ln C_t + \frac{\eta}{1-\gamma} \ln (N/K) + \frac{\eta^2}{1-\gamma} \]

(6b')

The exclusion of \( \ln (N/K) \) from eq. (6a') provides the necessary restriction for identification.\(^{48}\)

The validity of this identification procedure hinges upon the assumption that \( U_t \) does not directly affect crime. This assumption will fail if potential criminals have information on crowding in prisons and view the level of \( U_t \) as a partial measure of the severity of punishment. If, indeed, \( U_t \) has such an effect, then it should be included in the crime equation and the exclusion of \( N/K \) cannot be used validly to identify the crime function.

3. Inertia Model: Lagged Sanctions

In the system shown below, the equation for \( S_t \) includes \( S_{t-1} \). Its inclusion could be argued on the grounds that sanctioning practice, being bound by tradition, will adjust slowly to changes in the crime rate or indeed to any other factors influencing sanctions. As a result, \( S_t \) will be

\[ P_t = C_s N_t \]

(6a')

\[ \frac{K_t}{\gamma} = \gamma \ln K_t + \eta \]

(6b')

To be the probability of imprisoning an individual is 1: adding to more prison cell construction.

general, prison terms are often considered a function of the past incarceration. This makes sense, however, save that past incarceration variable in identifying the crime func-

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\[ C_t = f(S_t) + \epsilon_t \]

(7a)

\[ S_t = h(C_{t-1}) + \epsilon_t \]

(7b)

While this rationale for including \( S_{t-1} \) in the specification of \( S_t \) is highly plausible, it is not plausible at the same time to exclude \( S_{t-1} \) from the crime equation. To do so assumes that potential criminals are not influenced by sanctions in prior periods. Such an assumption has little plausibility as a crucial identifying restriction, since it implies that historical sanction levels have no influence on perceptions of current sanctions even though they do influence current sanctions themselves.

For example, suppose a rational criminal has information indicating that a certain offense was not being prosecuted as vigorously as it had been previously. Should he disregard his information on sanction levels in prior periods and base his decision solely upon the new information on sanctions? There are several reasons that a rational criminal might still continue to consider prior information on sanctions.

First, unlike stock market prices, daily quotations of sanction levels are not available and the information that is available derives from very uncertain sources, including the criminal’s own experience, the experience of his criminal peers, news reports, or even the published statistics utilized by deterrence researchers. When current information is poor, considering information from the past, even if it is also uncertain, is very sensible in making estimates of the current status.

Second, even if current information on a variable is good, information on prior periods provides important information on the stability or trend of the sanction over time. If, for example, potential criminals are influenced by sanctions in prior periods.

In view of the implausibility of assuming that \( S_{t-1} \) affects \( S_t \), but not \( C_t \), we do not believe that identification can be validly achieved in this way.
**Identifying the Crime Function**

**B. A SINGLE-CRIME-TYPE, MULTIPLE-SANCTION MODEL.**

Our focus has been on simple models in which only a single sanction and single crime type are simultaneously related. We now turn to a model in which a single crime type is simultaneously related to several sanction types.

In this model we attempt to capture some of the interrelationships between crime and the crime subsystems—police, courts, and corrections. These interrelationships derive from a model of the crime as a flow process. A very simplified version of their conceptualization is shown in Figure 11.

Society generates crime, which is an input into the first of the pictured subsystems—the police. Society generates crime, which is an input into the first of the pictured subsystems—the police. The police arrest suspects, some of whom are charged, while others are subsequently released without charge. The charged individuals are inputs to the courts subsystem. The courts in turn adjudicate the charges and some of those charged

![Figure 11](https://example.com/figure11.png)

**FIGURE 11** A simplified flow model of the criminal justice system.

In this model we attempt to capture some of the interrelationships between crime and sanctions. Let us introduce the following notation:

- $C_t$ = total crimes in period $t$
- $P_{t}^0$ = probability of apprehension and charge given a crime in period $t$
- $P_{t}^{C}$ = probability of conviction given charge in period $t$
- $P_{t}^{I}$ = probability of imprisonment given conviction in period $t$
- $T_t$ = time served in period $t$
- $E_t^p$ = police expenditures in period $t$
- $E_t^j$ = judicial expenditures in period $t$
- $A_t$ = number of charges in period $t$
- $C_t$ = number of convictions in period $t$
- $I_t$ = number of imprisonments in period $t$
- $U_t$ = prison utilization in period $t$
- $e_0$, $e_1$, $e_2$, $e_3$ = random disturbances

The likelihood of different sanctions can have both imp- and significant policy imp- if two types of sanctions, for example, are congested and generate the additional exogenous deterrent effect of $P_{t}^{C}$ = 1, i.e., we would not want to gen- the relative magnitude of the various effects with costs, we can det- ed. If, for example, identical courts would achieve the same- ly, then crime reduction $\delta$ locating the additional exogenous deterrent effect.

The second crucial feature of this model is that the dependent variables are not independent of each other. In addition to the dependent variables being influenced by the independent variables, there are also interrelationships among the dependent variables. These interrelationships can be represented as addition and interaction terms. For example, the probability of conviction may depend on the probability of apprehension and charge, the number of charges, and the number of convictions.

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\[ P_t = a_t(E_t, P_{t-1}, C_t, U_t) + \epsilon_t \]  

\[ T_t = a_t(E_t, U_t) + \epsilon_t \]  

\[ E_t = b_t(C_t, E_{t-1}) + \epsilon_t \]  

\[ E_t = b_t(U_t, E_{t-1}) + \epsilon_t \]  

A crucial feature of this model is the distinction among the different types of sanctions. By differentiating among such sanctions as the probability of apprehension and charge, the probability of conviction given charge, the probability of imprisonment given conviction, and time served given imprisonment, the effect of each type of sanction can, at least theoretically, be measured. Different categories of sanctions are possible: or greater refinement in the number of sanctions, could be associated with only being charged. For example, the probability of a given charge is likely to be greater than the disutility associated with charge, since the stigma of conviction is greater than that associated with only being charged. The likelihood of differential deterrent effects associated with different sanctions has both important technical implications for estimation and significant policy implications. For the purpose of estimation, the number of endogenous sanctions, for example, can have different effects, then it is inappropriate to estimate a single parameter for the conglomeration effect of \( P_t = P_{t-1}^{P_t} \). Further, from a policy perspective, if we did not want to aggregate the two, since it may be useful to know the relative magnitudes of the separate effects. By comparing effects with costs, we can determine where resources should be allocated. If, for example, identical increases in expenditures on police and courts would achieve the same percent increase in \( P_t \) and \( P_{t-1}^{P_t} \), respectively, then crime reduction would be pursued more efficiently by allocating the additional expenditures to the sanction with the larger deterrent effect.

The second crucial feature of the system, which has significant implications for estimation, is the simultaneous relationship of \( C_t \) with each of the sanction variables, due perhaps to resource saturation considerations. Thus, given police resources, \( E_t \) (which are themselves affected by the number of past crimes), the probability of arrest, \( P_t \),

Identifying the Crime Function depends on the current number of crimes, \( C_t \), facing the police.\(^4\) Further, although \( C_t \) only affects \( P_t \) directly, the levels of \( C_t \) also affect the workload of the courts and corrections subsystems and the subsequent processing of criminal cases. The probability of conviction given charge, \( P_{t-1}^{P_t} \), is likely to be affected by the workload of the courts, \( A_t \), but \( A_t \) will be determined by the product of \( C_t \) and \( P_t \). Since \( C_t \) is also hypothesized to be affected by \( P_{t-1}^{P_t} \), \( P_{t-1}^{P_t} \) and \( C_t \) will be simultaneously related.

Similarly, the probability of imprisonment given conviction, \( P_{t-1}^{P_t} \), is affected by \( G_t \), the number of convictions in \( t \). Since \( G_t \) is the product of \( C_t \) and \( P_t \), \( P_{t-1}^{P_t} \) is simultaneously related to \( C_t \) time served. \( T_t \) and \( P_{t-1}^{P_t} \) are also hypothesized to be affected by the utilization of prison capacity, \( U_t \), because we expect utilization to have its predominant effect on judges and parole boards who most directly control the size of the prison population. Since \( U_t \) is affected by the size of the prison population, which is just the number of currently imprisoned criminals (and thus depends on \( C_t \), \( P_t \), \( P_{t-1}^{P_t} \), and \( P_{t-2}^{P_t} \), \( T_t \) will also be simultaneously related to \( C_t \). As the model is specified, none of the sanctions is in a direct simultaneous relationship with any other (e.g. \( P_t \) directly affects \( P_{t-1}^{P_t} \), but \( P_{t-1}^{P_t} \) does not directly affect \( P_t \) ). In terms of the problem of identifying the crime function, the validity of this assumption about the interrelationship among the sanctions is not relevant; the model could be generalized to allow such direct simultaneous relationships without altering our conclusion about the identifiability of the crime function (\( \delta a \)).

The crime rate, \( C_t \), is determined by four sanction variables, all of which are presumed to be simultaneously related to \( C_t \). Therefore, at least four independent restrictions are necessary to identify the crime function. Four such restrictions are provided by the exclusion of \( E_t \), \( E_t \), \( E_{t-1} \), and \( U_t \) (prison cell utilization).

The requirements for plausibly using these restrictions to identify the crime function have already been discussed. The key issues are worth restating. Since the expenditures variables are predetermined rather than exogenous (eqs. [8a]-[8g]), it is dangerous to assume no serial correlation in the \( \epsilon_t \). Some more general assumptions about the nature of the serial dependency are necessary; whatever the explicit assumption, data with a time-series component will be needed. The restrictions involving the exclusion of the police expenditure variable, \( E_t \).

\[^4\] In earlier sections, \( C_t \) was crimes per capita. Defining \( C_t \) as total crime instead of the crime rate would not affect our conclusion for this model; all state variables to be discussed, \( A_t, G_t, E_t \), and \( E_t \) could be normalized by total population and thereby be redefined as rates.
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and $U_i$ are particularly vulnerable to criticism, since being a measure of the intensity of the police presence in the community and the severity of punishment, respectively, it can be argued convincingly that each should also be included in the crime function. However, since the four restrictions are just-identifying and thereby necessary for estimation, we cannot test the validity of the restrictions involving $E^p_i$ and $U_i$, even assuming away the serial correlation problem just discussed.

In this multiple-sanction model, identification of the crime function requires the joint use of both the expenditures and self-capacity identification functions, whereas in the one-sanction models, either one was sufficient to just-identify. The necessity of using both categories of restrictions to identify the crime function points to still another problem. As the number of endogenous sanction increases, the difficulties in identifying the crime functions increase also. In the context of a multiple-crime-type model, which will be discussed next, this difficulty can become fatal to identification.

C. A MULTIPLE-CRIME-TYPE, SINGLE-SANCTION MODEL

Our discussion thus far has been limited to the consideration of single-crime-type models. We now consider the problem of identifying each of the crime equations in a multiple-crime-type model. A multiple-crime-type formulation is of interest because each crime type will incrementally impact a single set of crime resources. An examination of their joint effect has important implications for identification.

A two-crime-type, single-sanction characterization of such a phenomenon is given below, along with the model's equivalent flow diagram, in Figure 12.

$$C_i = f(S_i) + e_i$$
$$S_i = g(E_i,C_i,C_i,S_i) + e_i$$
$$E_i = h(E_i,C_i,C_i,S_i) + e_i$$

where:

$C_i$ = crimes of type $i$ per capita in $t$
$S_i$ = sanctions per crime of type $i$ in $t$
$E_i$ = crime expenditures in $t$.

As indicated by eqs. (9a) and (9e), $S_i$ is a function of total resources available to the city ($E_i$), the demands placed on these resources by each of the crime inputs ($C_i$); $i = 1, 2$, and the level of the sanction imposed for the other crime type. The resource saturation theory would predict that increases in $E_i$ would act to increase $S_i$ ($\delta y_i/\delta x_i > 0$), increases in the prevalence of either crime type would act to reduce $S_i$ ($\delta y_i/\delta C_i < 0$, $j = 1, 2$) and increases in $S_i$ would decrease $S_i$, $F_i$ ($\delta y_i/\delta S_i < 0$), because the additional resources required to increase $S_i$ would be drawn from those used to maintain $S_j$.

Alternative theories of the effects of crime on sanctions make different predictions, but the crucial point is that sanctions for each crime type are influenced by the level of both types of crime, because each crime type impacts the common set of city resources. Considering eqs. (9a)-(9d) as the simultaneous system and treating $E_i$ as predetermined by eq. (9e), the number of endogenous variables, $M$, is 4. Hence, at least three restrictions are necessary for the identification of each crime function. One such restriction is provided by the exclusion of $E_i$ from eqs. (9a) and (9b) under assumptions outlined previously. A second is provided by the assumption that crime of one type has no direct effect on crime of the other type. The final restriction necessary for identification of each crime function, however, rests additionally upon the assumption that sanctions for one crime type do not influence the level of crime for the other crime type (e.g., $S_1$ does not affect $C_1$). In the context of multiple sanctions, the possibility of such restrictions being valid—namely, that $S_1$ does not affect $C_1$ if such cross-effects exist

$C_1$}

These more general versions identified; there are now four restrictions, and the estimates of each crime's equilibrium restrictions were imposed.

This, however, is really a problem in a single crime-type model (e.g., robbery) affected by $S_1$, $S_2$, and $S_3$ variables ($M$) by two (or more) restrictions on each crime. The direct effects of $C_1$ on $C_2$ or $C_3$ identified case of $M = 4$ would be only four restrictions, and the on the crime function seems even more difficult to identify.

The difficulties in finding adequate when multiple sanctions exist are divided i.e., single-crime-type, multiple-crime-type models, and in the number of endogenous restrictions the number of restrictions would be increased, in addition to the number of crime appearances in each such case. In general, a model with restrictions is required to $n = m$ non-autonomous. Hybrid versions of restrictions. For example, effects only exist among other
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between property and violent crimes). From a practical perspective, however, such an approach offers little help since, for example, even a two-sancion model for the four index property crimes (i.e., robbery, burglary, larceny, and auto theft) would require eight non Automatic restrictions to identify each of the separate crime functions. In view of the difficulty in generating plausible restrictions, the estimation of the generalized multi-crime-type, multi-sancion model including cross-effects of the sanctions does not appear feasible. To the extent that the generalized model is viewed as the only plausible characterization of the simultaneous association between crime and sanctions, an argument as to the impossibility of valid identification is even more compelling than in the case of the simplified models discussed earlier. The apparent infeasibility of identifying the generalized model hinges upon the assumption that the sanctions for Cj directly affect Cj. It may be that such cross-effects are, at most, very weak. The difficulty is that, using aggregate, non-experimental data, we cannot test for this. Moreover, a model estimated simply assuming no cross-effects would always remain suspect for having assumed that cross-effects are not operating.

V. CONCLUSION

Identification is the sine qua non of all estimation and especially of simultaneous equation estimation. It establishes the feasibility of determining the structure of a system from the data generated by that system. Without identification, estimation is logically impossible. Researchers who have employed simultaneous estimation techniques to study the deterrence effect of sanctions on crime have failed to recognize fully the importance of this issue. The restrictions that they (implicitly or explicitly) use to gain apparent identification have little theoretical or empirical basis. In this paper we have examined a variety of plausible approaches to the identification of the crime functions in a system in which crime rates and sanction levels are simultaneously related. Our conclusions with regard to the feasibility of identification, while not wholly negative, are certainly soberly cautious. In particular, it appears very doubtful that using only aggregate cross-sectional data can ever succeed in identifying and consistently estimating the deterrent effect of punishment on crime. If we are to know that effect and, particularly, if we are to rely on that knowledge for policy purposes, that knowledge must come from analyses of a different sort. In particular, analyses using aggregate non-expert in the data (i.e., pure i and the estimation procedure correlation in the stochastic
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using aggregate non-experimental data must have a time-series component in the data (i.e., pure time-series or a time-series, cross-section), and the estimation procedures must account for the possibility of serial correlation in the stochastic components of the specification.

TECHNICAL NOTE: LAGGED MODELS OF THE MUTUAL ASSOCIATION OF CRIME AND SANCTIONS

The principal focus of this paper is the estimability of simultaneous models of crime and sanctions. In a simultaneous formulation, the mutual interaction is assumed to occur contemporaneously during the period of observation. For an observation period of a given length, a necessary requirement for a phenomenon to be simultaneous is that the impact of the actions taken by the system's actors (e.g., criminals and the CJS) be transmitted sufficiently fast so that each actor can react to the actions of the other actors within the observation period. Thus, a critical parameter is the length of the observation period. If the period is sufficiently short, then any mutual association can be modeled as non-simultaneous, whereas, if the period is sufficiently long, all such associations can be made simultaneous. In the context of the mutual association of crimes and sanctions, in which observations are generally made annually, the association is simultaneous.

Attempts to analyze models of the type given by eqs. (10a) and (10b) have been limited to the sociological literature on deterrence (Logan, 1975, and Tittle and Rowe 1974). In these analyses, \( S_i \) is defined as arrests per crime. Tittle and Rowe found a negative and often significant path coefficient between \( C_i \) and \( S_i \); a result that is consistent with the deterrence hypothesis, while Logan found no such association.

The path coefficient estimate of the relationship between \( C_i \) and \( S_i \) is estimated in a way that is analytically equivalent to regression estimation, however, in our model, there is a small negative association, which does not drive the estimate of \( \rho(\sigma, \sigma) \) to an unrealistic value.

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All estimation and especially of the feasibility of deterrence data generated by that idea is logically impossible. simultaneous estimation tech-

iques on crime have failed to be a catch. For such a model regression, there not only \( \mu \) must be uncorrelated. Thus, whatever the specific structure, estimation must be a practical perspective,

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the reasons for believing $e_i$, we would have very
likely learned from parameter estimators.

forced by the fact that in correlation in $e_i$, the serial
dependence effect for an autoregressive process
is large, even if $h = 0$. This estimate of $b$ to a nega-
tively by eqs. (10a) and (10b) re on deterrence (Logan
nalyses, $S_t$ is defined as egalitarian and often signifi-
result that is consistent with. found no such associa-
tion between $S_{t-1}$ and $C_t$ valent to regression esti-
). Therefore, these path are we have discussed.
seen crime and sanctions cause they offer an intu-
ial association. Informationally transmitted very im discussed. An assump-
tion that we could maintain the placed by $G_t$ in eq. (10b),
biased estimates changes in $S_t$ Analyst of San Fracisco no, the assumption of a 1-year

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and the model would remain non-simultaneous—but there would still
be a catch. For such a model to be consistently estimated by ordinary
regression, there not only must be no serial correlation, but also $e_i$ and
$\mu_i$ must be uncorrelated.

Thus, whatever the specific nature of the model employing a lagged
structure, estimation must use methodologies that allow for the possi-
bility of serial correlation and non-zero covariance in the stochastic
terms if the estimated coefficients are to be plausibly regarded as an
estimate of the causal effect of sanctions on crime.

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