PROPERTY CRIME AND THE RETURNS TO LEGITIMATE AND ILLEGITIMATE ACTIVITIES

Technical Report CERDCR-2-78

March 1978

Prepared under Grant No. 77-NI-99-0071 from the National Institute of Law Enforcement and Criminal Justice, Law Enforcement Assistance Administration, U.S. Department of Justice.

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I. Introduction

There appears to be widespread concern among policymakers today with the relationship between unemployment and crime.[1] We see this relationship, at least for property offenses, as a manisfestation of a more fundamental question. Specifically, what is the relationship between crime levels and the pecuniary returns to legitimate and illegitimate activities? After all, changes in employment opportunities will usually alter the expected monetary returns from both legitimate and illegitimate pursuits. Hence the concern about the effect of changes in the unemployment rates on property crime can be viewed as a specific question about the effect of changes in monetary returns on crime levels. Similarly, since changes in criminal justice policy variables, such as arrest rates, conviction rates, and sentencing practices, directly alter the expected monetary returns from criminal endeavors, questions regarding the effectiveness of these policy instru-

[1] The House Committee on the Judiciary's Subcommittee on Crime held hearings on unemployment and crime in Washington during September and October 1976, and in San Francisco and Los Angeles during December 1976. The Secretary of Labor has a continuing interest in this area, and the Law Enforcement Assistance Administration has recently expanded its research program to include the VERA Institute's investigation of the relationship between unemployment and crime.

ments can also be interpreted as specific questions concerning the impact of changes in monetary returns on crime levels.

While changes in employment opportunities and in the various criminal justice policy variables may have significantly different effects on monetary returns, evaluating their impact on the levels of specific property crimes can be accomplished using a common framework. In order to provide such a framework, the Center devoted considerable effort to the construction and estimation of an econometric model relating expected monetary returns, from both legitimate and illegitimate activities, to the supply of labor and the level of property crime.[2] This report summarizes the major findings of that work and presents a number of applications of this model that should be of special interest to criminal justice policymakers. Included in the latter category are estimates of the effect on the level of specific property crimes of changes in: 1) arrest rates, 2) prison sentences, and 3) unemployment rates.

The starting point for the formal modeling effort was the individual household.[3] Here it was assumed that the rational decision maker was faced with a more or less traditional time allocation problem. Income could be generated by spending time in the legitimate labor market and/or

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[2]The theoretical framework used in this report was developed by J.M. Heineke under a grant from the Center. The estimated model that appears in this report was performed by the Center's research staff. For a discussion of the theoretical formulation, see J.M. Heineke, "The Supply of Legal and Illegal Activity: An Econometric Model," Technical Report ESCD-1-78, Center for Econometric Studies of the Criminal Justice System, Hoover Institution, Stanford University, January 1978.

[3]See Heineke [1978] for a discussion of the choice model.

by devoting time to property crimes such as burglary, robbery or larceny.[4] Expected returns were considered in all cases and hence the "return" to a specific type of property crime was considered to be the gross return minus the probability of capture times the monetary equivalent of the punishment. The decision or the allocation of time to the "generic" legitimate activity and to burglary, robbery and larceny was then shown, in general, to depend on all expected returns and income. That is, the supply of legitimate time as well as the time devoted to burglary, robbery and larceny depend, in general, not only on their own expected returns but also on the expected returns to all income producing and time consuming activities. Incorporating this potential interdependence into the econometric model allowed us to estimate the degree of substitutability between the various income generating options.

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[4] We decided not to include a motor vehicle theft equation in this study because there is strong evidence indicating that many auto thefts are for "joy riding" rather than pecuniary gain. Approximately 85% of all auto thefts might be considered to be "consumption crimes" and not the "production crimes" that are the subject of this paper.

II. A Note on the Econometric Model

The theoretical model used in this study required the estimation of a system of four equations, one equation for each of the major property crimes (burglary, robbery and larceny) and one equation for the supply of legitimate effort. The actual system of market equations implied by the theoretical choice model is shown in Appendix Table 1.[5]

Two general points about the equations are worth noting. First, the specific, and somewhat complex, functional form of the equations is dictated by the approach taken in the model building stage. The actual econometric model used in this estimation was constructed by applying modern duality theory to the supply of legitimate and illegitimate activities. The specific functional form of the supply equation reflects the use of a transcendental logarithmic function to approximate the household's objective or utility function. Second, since the four supply equations were derived directly from a model of rational choice subject to a budget and time constraint, the equations have been estimated with all of the coefficient restrictions implied by such a model imposed on the system.[6]

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[5] The specific income measures used in these equations result from the aggregation assumptions in the theoretical model and are discussed in Heineke [1978].

[6] See Heineke for a discussion of these restrictions.

III. Data

The data used to estimate the model involved observations on selected SMSA's during the period 1966 to 1972. For the version of the estimated model discussed in the text the sample size was 121.[7] These observations were drawn from a potential sample of several thousand observations. The FBI data tapes used in this study contained some crime information on all reporting agencies over the period 1966 to 1972. However, the requirements for relatively complete FBI coverage in any year, and the necessity to mate the crime data with other data sources, drastically reduced the potential sample.

Of the approximately 1,700 SMSA observations that we were able to derive from the UCR data tape, only 910 were for SMSA's with populations over 250,000. Since detailed Census data is only available for large SMSA's, only these observations were considered candidates for inclusion in our sample. Unfortunately, UCR data on arrest, clearances and conviction is quite sparse and only 141 of the observations on large SMSA's met our coverage criterion, i.e., a minimum of 50% of the population, within an SMSA, covered by reported clearance and conviction data. Next, these observations had to be mated with sentence data, and such data was available for only 132 observations. Of these observations, the required earnings income and employment data we ultimately used in estimation was

[7] A list of the SMSA's by year of inclusion is given in Appendix Table 2 for this sample (Gross Returns 121) as well as for an alternative sample specification (Gross Returns 85). A discussion of the alternative sample specification appears below.

available for only 121 observations.[8]

a. Crime Rates and Value Transferred Data

Crime rate data, as was mentioned above, was obtained from a tape containing UCR crime data for all reporting agencies from 1966 to 1972. This tape was prepared for us on special request by the Federal Bureau of Investigation. Also taken from this tape were the figures for the total value of property stolen by type of property offenses: burglary, robbery, and larceny.[9] The UCR crime rate is, of course, based on crimes reported to police and hence understates the true crime rate to the extent that crimes are often not reported to the police.[10] Value transferred data is based on values reported or estimated by the various policy departments involved in recording crimes. This figure will be biased upward both by the purported tendency of victims to overvalue their losses and by the tendency of victims to more frequently report crimes involving large

[8]Even in this small sample we had to use an average employment rate for 16 observations.

[9]Without the cooperation of the FBI this project could not have been undertaken since only crime rate data is available in published form for SMSA's. The value transferred data, as well as the clearance and conviction data discussed below, is available for individual reporting agencies only on FBI tapes. Since this estimation was performed we have been supplied with UCR data tapes for 1973 to 1976. Copies of these FBI tapes as well as a special data tape containing the SMSA data set used for this study are available from the Center.

[10]The proportions of burglaries, robberies and larcenies reported to the police are .53, .44 and .43, respectively.

losses than those involving small losses.[11]

Using this crime rate and value of property transferred data, the following dependent variables were constructed:

1) BSHARE = (BURTOT/CPOP)(RETBUR/DFLAT)

2) RSHARE = (ROBTOT/CPOP)(RETROB/DFLAT)

3) LRSHAR = (LARTOT/CPOP)(RETLAR/DFLAT)

where BURTOT/CPOP, ROBTOT/CPOP and LARTOT/CPOP are the usual per capita burglary, robbery, and larceny rates and RETBUR/DFLAT, RETROB/DFLAT and RETLAR/DFLAT are the real or price adjusted gross returns per burglary, robbery and larceny.[12] The deflator in this case, DFLAT, adjusts for both intercity and intertemporal variation. This was accomplished by using published BLS data on intermediate budgets for a family of four for the specific cities and time periods involved.[13]

The dependent variables, BSHARE, RSHARE and LRSHAR, are interpreted as the per capita income transferred by burglary, robbery and larceny, respectively. These are the criminal activity variables in this

[11] For a discussion of the relationship between losses and reporting, see Goldberg and Nold, "Victimization and Reporting: A Microeconomic Analysis of Deterrence," Center for Econometric Studies of the Criminal Justice System, Hoover Institution, February 1978.

[12] The precise definitions of RETBUR, RETROB and RETLAR appear in the glossary.

[13] $DFLAT_{ij} = BUDJET_{ij}/9235$, where $BUDGET_{ij}$ is the intermediate for city i in year j and 9235 is BUDGET for Albuquerque in 1966.

model and each one is assumed to depend on the net returns to burglary, robbery, larceny, legitimate employment, wealth, and the distribution of wealth.

b. Legitimate Earnings

In addition to constructing variables measuring the supply of property crimes, it was also necessary to construct a variable that measured the supply of legitimate effort. The raw materials for this variable were obtained from BLS, Census and Internal Revenue Service publications.[14] Since Census income data was not available for individual SMSA's on a yearly basis, we constructed estimates of annual per capita income by using IRS data in conjunction with a 1969 Census benchmark for each SMSA. IRS income data was available biannually for each SMSA and annually for every state. This data was used to adjust the Census benchmark by constructing the following index:

4) INDEX = (EXINC/IRSPEG)(ADJINC)

where EXINC is per capita income calculated biannually for each SMSA from IRS data, IRSPEG is EXINC for 1969, and ADJINC is 1 in the years that EXINC is available and equal to the annual change in per capita IRS income for the state(s) in which the SMSA is located in the years that EXINC is not available.

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[14] See the glossary for a listing of the data used in constructing this activity measure.

A measure of the supply of legitimate effort, LSHARE, was then estimated by using the following formula:

5) LSHARE = (INDEX/DFLAT)(CENSUS)

where DFLAT is the same deflator as was discussed above and CENSUS is per capita Census income for a SMSA in 1969.[15] As is clear from expression (5), the dependent variable for the legitimate labor supply equation was an internally constructed annual estimate of SMSA-specific per capita Census income.

c. The Net Returns to Burglary, Robbery and Larceny

The level of each criminal activity, BSHARE, RSHARE, and LRSHAR, as well as the level of legitimate activity, LSHARE, depends on the expected net returns to the three property crimes; consequently we needed to produce estimates of these expected returns to implement the model. In actually constructing estimates of the net returns to burglary, robbery and larceny, we began with the UCR data on the value of property transferred. This data was obtained for each observation in our sample from the FBI data tape. As we mentioned above, the recorded value of property transferred will overstate the true value of property stolen to the extent that individuals: 1) have a tendency to report a higher proportion of crimes involving large losses, and 2) on balance, overestimate the

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[15]See the appendix for details on the construction of CENSUS.

value of their property losses. Of course, since the value of property transferred, except in the case of currency, is not the market value to the offender, even the true value of property stolen would overestimate the real returns to the various activities.[16]

Adjusting this gross return to reflect the expected costs of punishment proved to be one of the most troublesome tasks in the empirical implementation of this project. In general, the concept of net returns that we used was simply:

$$NR = GR - p_F LOSS$$

where NR is the net return to the activity, GR the gross return or average value transferred, p_F the probability of failure, and LOSS the monetary loss from punishment. While obtaining an estimate for GR was, as discussed above, relatively straightforward, obtaining estimates for p_F and LOSS proved very problematical.

Constructing p_F as a product of the probability of arrest and the probability of conviction, given arrest, turned out to be infeasible. Arrest data was not available on a consistent basis and hence we had to substitute clearances for arrest data. Next, although conviction data was supposedly available for all of the observations in our 121 observations sample, it evidenced very erratic behavior and we felt it prudent to estimate and use an average conviction probability over the

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[16] No attempt was made to deflate returns for their market or "fence" value to the offender since there is an offsetting overstatement of the expected punishment engendered by using UCR and not victimization clearance rates.

entire sample.[17] Hence we estimate the probability of failure in a given SMSA by multiplying the SMSA's clearance rate times an average conviction rate. It should be recognized that even if this produced an unbiased estimate of the UCR failure rate, it would overestimate the actual failure probability facing an offender. This is the case because a large number of crimes are never reported and thus the UCR conviction rate seriously overstates the actual conviction rate.

Generating an estimate of the monetary value of imprisonment proved even more troublesome. First, there were no National Prisoner Statistics prison data on average time served by specific crime that could be used for this sample. To compensate for this lack of punishment data, we requested a special compilation of Uniform Parole Reports data from the National Council on Crime and Delinquency's Research Office. After receiving individual releases from all of the states concerned, we were able to obatin data on average time to release on parole by crime, year and state for 39 states and the District of Columbia.[18, 19] These state figures were smoothed and extrapolated and

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[17]The actual probabilities ranged from zero to nearly one. We felt such disparities reflected different degrees of conscientiousness across police departments in following cases through the court system.

[18]A list of these states is given in the appendix.

[19]The research staff at NCCD was extremely cooperative and the estimates of time to parole could not have been obtained without their assistance.

then used as a proxy for time served in SMSA's within a given state.[20] We would have liked to add jail sentence information, since many individuals convicted of these crimes are sentenced to jail. However, such information is unavailable for all but a few large SMSA's.

We used per capita IRS income data as a proxy for an offender's sacrificed earnings. Using this income variable, the annual monetary loss from imprisonment, INCLOS, was derived as follows:

7) INCLOS = .37(.79ADJINC + EXINC - .5BUDGET)

where .37 is the factor that converts household to individual loss, .79 the factor that adjusts IRS income for non-wage income, and .5 the factor that adjusts BUDGET to a subsistence expenditure level. The logic of INCLOS is that it is intended as an estimate of the annual discretionary or non-subsistence loss imposed on an individual when he is imprisoned. Subsistence is subtracted because this is provided in prison.

Combining our estimates of the gross returns, failure probabilities and loss yielded an estimate of the net return based on the calculation below:

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[20] We performed the calculation outlined below for each crime in each state, and 117 models for extrapolation were developed in all. The number of individuals released for a given crime in a given year varies by year. Assuming that the variance for each mean sentence was inversely proportional to the number of individuals released, we used generalized least squares estimations to fit a time trend to the average prison sentences. We allowed up to second order terms to appear. Selecting a reasonable regression, we predicted sentences for 1964 and 1965 and any other year for which that state showed no releases in the crime. We then took as our average sentence a three year moving average of actual average sentences, substituting predicted values when actual values were unavailable.

8) $WBUR = RETBUR - CLRBUR \cdot (.092) \cdot INCLOS[1 - EXP(-.20 \cdot ASB)]/.20$

where WBUR is the net return to burglary, RETBUR the gross return, CLRBUR the clearance rate, .092 the estimated conviction as charged rate, ASB the average time served, .20 the discount rate, and EXP(·) the exponential function. The discount rate chosen represents the approximate market rate for totally unsecured consumer credit. Analogous calculations were performed for robbery and larceny. The net returns to these activities are referred to in the text as WROB and WLAR, respectively.

Using the formulation of INCLOS in (7) and applying the calcuation procedure in (8) to the 121 observations that met our data requirements resulted in an estimated negative expected net return for at least one crime in 20 cases. The crime most often containing the negative expected return was larceny. Burglary, on the other hand, did not have an estimated negative expected return for any of the observations.[21] However, since the equations were estimated as a system even one negative expected return in an SMSA would force us to drop the observation from the sample.

The implications of eliminating sample points because an estimate of at least one return was negative concerned us. An estimated negative expected return indicates that the activity is not very attractive relative to other income generating activities and we felt we might be losing important information by omitting these observations. Our approach to this

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[21]The expected return was negative for larceny in 13 observations and negative for robbery in 9 observations.

involved using all 121 observations and arbitrarily substituting a small but positive return ($1.00) for all of the estimated negative returns.[22] As an alternative to this arbitrary "fixing" of negative returns, we also estimated the model using only the 85 observations with estimated positive returns for all crimes and complete legal earnings information. The difference between the 121 observations and the 85 is that 20 are lost due to at least one negative return and 16 lost if average unemployment rates are not used when actual ones are not available. The sample implied by this restriction on the observations is given in Table 2 of the appendix under the title "Gross Returns 85."[23]

d. The Return to Legitimate Employment

Expected returns to legitimate activity were calculated by using SMSA-specific average hourly wages of production workers and an estimate of SMSA employment rates.[24] The calculations for expected legal returns, LEGW, was simply:

9) LEGW = (LEGALW/DFLAT)(NOLEMP/LFORCE)

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[22] Another approach to this problem of negative expected returns would be to use an approximation to the household's utility function that would yield demand and supply functions that could be estimated using negative returns. This would have resulted in a major change in model specification and was not attempted.

[23] Estimates of the coefficients of this model as well as estimates of the elasticities discussed in the text are given in Tables 3, 6, 7, 8, 9 in the appendix.

[24] All data for this calculation were obtained from published BLS sources. The specific hourly wage used was the Average Hourly Wages of Production or Nonsupervisory Workers on Private Nonagricultural Payrolls.

where LEGALW is the hourly wage, DFLAT the deflator, NOLEMP the number of employees, and LFORCE the number of individuals in the labor force. This estimate was used in the supply equations as an indicator of the expected return to all legitimate pursuits.

e. Wealth Levels

In addition to the returns to burglary, robbery, larceny, and legitimate effort, the levels of various illegal and legal activities depend on the individual's wealth level. When the individual supply equations are aggregated the market supply equations will, as is shown in Table 1 of the appendix, depend on some measure of the distribution of wealth in the population. Information on the actual distribution of wealth was not available for the observations in this sample. As a surrogate measure we used the income distribution implied by the biannual IRS income data. Actually included in the estimation of the supply equations were the income variables EXINC and EXILNI.[25]

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[25] EXILNI is the expected value of EXINC · LOG(EXINC). See Heineke [1978] for an explanation of why EXINC and EXILNI are included in the aggregate supply functions.

IV. Empirical Results

The primary purpose of this research project was to provide a framework within which to address a number of important policy issues. In order to accomplish this, a consistent econometric model was developed for the supply of selected legitimate and illegitimate income producing activities. This model was then estimated using the best available measures for the observable determinants of these activity levels: 1) expected net returns to major income producing property crimes, 2) expected returns to a "representative" or typical legitimate activity, and 3) the distribution of wealth in the population. The results of this estimation provide enough information for us to assess the likely qualitative and quantative effects, on property crime levels, of changes in net returns. By using the estimated effects of changes in net returns, it is then possible to directly address several important policy issues. For example, we are able to estimate the effect on specific property crimes of changes in the: 1) unemployment rate, 2) clearance rate, and 3) average time served.

a. Net Return Elasticities

As we have previously pointed out, one of the unique features of the model estimated in this study is that the level of each activity depends on the net returns to all activities. Specifically, the level of burglary activity (BSHARE), robbery activity (RSHARE), larceny activity (LRSHAR), and legitimate activity (LSHARE) all depend on the net returns to burglary (WBUR), robbery (WROB), larceny (WLAR) and legitimate effort (LEGW). The estimated relationships between the various activities and net returns are given in Table 3 of the appendix under the column heading 121 observations. Because of the complex functional form implied by the theoretical model, the individual coefficients in the equations for BSHARE, RSHARE, LRSHAR and LSHARE do not have a straightforward interpretation.[26] They can, however, by used to construct traditional elasticity measures.[27]

In Table 1 we present all of the statistically significant direct and cross supply elasticities for the four activities: burglary, robbery, larceny and legitimate work. Reading down a column, we have all of the statistically significant elasticities with respect to that return. For example, reading down the column labeled "legal," we find that a one percent increase in the expected wage leads to a .492 percent decrease in the aggregate burglary rate, and a .097 percent increase in legal earnings. Across a row in the table we have presented all of the statistically significant elasticities with respect to that activity. Here, if we select the row

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[26]The results are presented in the appendix primarily to provide the reader with some perspective on the "raw materials" used in deriving the results presented in this paper.

[27]In Appendix Table 4 we present two examples of how the coefficients are used to construct supply elasticities. The calculation for a direct elasticity is displayed first. Specifically, we show the derivation of the elasticity of the per capita burglary rate with respect to the net returns of burglary. This elasticity gives us a measure of the percentage change in the per capita burglary offense level due to a one percent change in the net returns to burglary. In the second calculation we show the derivation of the cross elasticity between burglary and the return to robbery (the percentage change in the burglary rate due to a one percent change in the return to robbery).

Table 1

Direct and Cross Return Elasticities

121 Observations

	Return			
	Burglary	Robbery	Larceny	Legal
Activity				
Burglary	.594	Ø	Ø	-.492
Robbery	Ø	.299	Ø	Ø
Larceny	Ø	Ø	.1ØØ	Ø
Legal	-.ØØ1	Ø	Ø	.Ø97

Note: All coefficients are significant at the 1% level.

labeled "legal," we find that a one percent increase in the net returns to burglary leads to decrease of approximately .001% in legitimate work and again a one percent increase in expected legal returns leads to a .097 percent increase in legitimate earnings. Reiterating, the main diagonal elements are the direct elasticities and the off diagonal elements are all cross elasticities of supply.[28]

All of the main diagonal elements in Table 1 are positive, indicating that own net expected returns and activity levels are positively related.[29] More significantly, all of the illegal activities are responsive to their own expected net returns, with burglary being the most responsive and larceny the least responsive. We find that a 1% increase in the net expected returns to burglary induces about a .6% increase in the burglary rate. For the crimes of robbery and larceny, the induced changes resulting from a similar increase in their net expected returns would be about .3% and .1%, respectively.[30]

The off diagonal elements have an interesting pattern. We would expect all off diagonal elements to be zero or negative. That is, an increase in the expected returns to an activity would either leave another

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[28]Table 5 in the appendix presents the complete set of estimated elasticities for this version of the model and Table 6 contains the same information for the 85 observations version.

[29]It should be noted that in the 85 observations version the direct return elasticity for legitimate activity is not statistically significant.

[30]All of the elasticities are evaluated at the means of the return and income variables.

activity unchanged or would lead to a decrease in the other activity. This turns out to be the case, at least for the statistically signifi- cross elasticities. What is surprising is the number of zero off diagonal elements. In this estimation we find no evidence of substitution between crimes.[31] There are no statistically significant cross elasticities between the various property crimes. In other words, we find no evidence that a change in the net expected returns to one major property crime affects the level of activity in other major property crimes. This has two rather straightforward and related implications:

1) Previous studies such as Ehrlich [1973] which include only one illegal return, own return, in the offense equation appear to contain an adequate specification of the offense functions.

2) Policy implications can be deduced directly from knowledge of direct return elasticities.

Increases in sanction probabilities and/or sanction levels for a specific property crime appear not to have significant "spillover" effects. Hence, our findings of positive direct return elasticities for all major crimes implies that a policy change that decreases the net expected re-

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[31]Using the 85 observations sample results in estimates of the off diagonal elements that are slightly different than those discussed above. Specifically, several of these estimated cross elasticities involving robbery are positive and significant. Complementarity between crimes is not what we would expect in this context. It is possible that this apparent relationship is a consequence of restricting the information on low value observations by dropping these sample points. See Appendix Table 6 for a complete listing of the direct and cross elasticities for this sample specification.

turns to one or all of these crimes will unambiguously reduce the property crime rate.

The two statistically significant off diagonal elements in Table 1 involve the legitimate alternatives.[32] We find that a 1% increase in the expected returns to legitimate activity decreases the burglary rate by about .5%. It is interesting to note that the supply of burglary is almost as responsive to changes in legal alternatives as it is to changes in its own return. While there is some symmetry in cross effects, burglary returns do influence the supply of legitimate effort; the effect is, as one would suspect, very small. A 1% increase in the net returns to burglary will reduce legitimate effort supplied by approximately .001%, and although it is esthetically pleasing to have symmetry in Table 1, this cross effect is of little practical significance.

The fact that there is only one significant cross effect involving the expected legitimate return in Table 1 is not very surprising. The question being asked here is limited. Essentially we are asking: what is the effect on illegitimate activities of changing <u>only</u> the expected return to legitimate employment? Holding the net expected returns to burglary, robbery and larceny constant amounts to ignoring the possible effect of changes in the expected legal returns on the opportunity cost of imprisonment. Hence the effect on relative returns of a change in

[32] In the estimation of the model using 85 observations, there is one additional significant cross effect involving the legitimate market. We find here that there is a significant but extremely small negative market effect of larceny returns on the supply of legitimate effort.

the expected legal returns is assumed to operate exclusively through legal returns. It we were to allow, as we do below for employment calculation, changes in the expected legal wage to affect the opportunity cost of imprisonment, we would automatically induce a cross effect of legitimate returns on all of the property crimes.

The present treatment of changes in expected returns to legitimate activity brings up an interesting question. What should one consider as the opportunity cost of imprisonment, and how should it behave with respect to changes in legal opportunities? If we assume that, at least for the class of offenders, legitimate activity is usually "mixed" with illegitimate income generating activity, then the use of the offender's expected legal income sets a lower bound to the income sacrificed by being imprisoned. After all, if working full time paid better than stealing, we would assume that most rational individuals would not be engaged in any criminal activities. Moreover, changes in legitimate opportunities that are considered "permanent" will increase the opportunity cost of imprisonment for current offenders and non-offenders alike and should be accounted for in assessing the cross effects of any change in the expected return to legitimate activity.[33] This calculation is accomplished for the specific case of unemployment effects in a subsequent section of this paper.

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[33]Only in the case where the offender specializes in crime is it possible for changes in the expected legal wage to leave the opportunity cost of imprisonment unaffected.

b. Sanction Elasticities

Using the definitions of expected net returns to the illegitimate activities (WBUR, WROB and WLAR) and the estimated direct return elasticities given in Table 1, we can calculate sanction elasticites for these property crimes. In Table 2 we present the clearance and punishment elasticities for burglary, robbery and larceny. The clearance elasticity gives us the percentage change in the specific crime rate due to a 1% change in the clearance rate.[34]

The estimated sanction elasticities all have rather modest magnitudes. For example, the largest sanction elasticity presented, the elasticity of robbery with respect to clearances, has a magnitude of approximately .15. Hence a 1% increase in the clearance probability for robbery (a one percent change corresponds to four more actual clearances given the mean number of robberies) reduces the robbery rate, but only by .15%. The clearance elasticities are all rather small relative to previously published estimates.[35] Likewise, the sentence or punishment elasticities, measuring the percentage change in a specific crime rate due to a 1% change in the average sentence

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[34]Note this is a 1% change in the clearance rate, not a 1 percentage point change in the clearance rate. This latter change would represent about a 3.7% change in the mean clearance rate. Thus increasing the clearance rate for robbery from .28 (current value at the mean) to .29 would reduce the robbery rate by .56%.

[35]See Ehrlich (1973).

Table 2

The Effect of Sanctions on Per Capita Crime Rates: Elasticities of Clearance Probabilities and Average Sentences:[1]

Deterence Variable	Clearance Probability[2]	Average Sentence[2]
Crime		
Burglary	-.053 (7.99)	-.042 (7.99)
Robbery	-.153 (4.26)	-.101 (4.26)
Larceny	-.068 (4.70)	-.057 (4.70)

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[1]Estimates which appear in this table are based on the model estimated with 121 observations.

[2]The estimated coefficient divided by its estimated standard error appears in parenthesis. This test statistic should be compared to the Standard Normal Density to determine significance levels. Note that the values of the test statistic are the same going across a row. This is because the same estimated coefficient enter both calculations with the differences caused by multiplication with the mean values of different independent variables. These different mean levels cancel when the ratio is taken to produce the test statistic.

for that crime, are also small relative to previous estimates.[36]

The policy implications here are clear: Changing sanction probabilities and/or levels will deter property crime, but the magnitude of the deterrent effects is small. A drastic reduction in property crime rates is likely to require substantial increases in expenditures for police, courts and prisons.

c. Employment Elasticities

Using the elasticities in Table 1 and the definitions of the variables, we have calculated the elasticities of the various crime rates to changes in the employment rate. Specifically, we have calculated the percentage change in each crime rate associated with a one percent change in the employment rate.[37] This is, as we mentioned above, a special case of a change in the expected returns to legitimate activity. The qualitative results presented below apply equally to changes in the wage rate.

Three calculations are given for each criminal activity. In Table 3, the first column gives the percent change in the specific crime rate, if we consider only the effect of changes in the employment rate on the expected legal wage. This is merely the estimated coefficient in column four of Table 1. In columns two and three, we give the effect of a one percent change in the employment rate considering both its direct effect

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[36] See Ehrlich [1973] but note that he obtains statistically significant results for only one of these property crimes.

[37] This converts to about a .9 percentage point change in the current unemployment rate. That is, a change from, say, 6% to 5.1% unemployment.

Table 3

Elasticities of Per Capita

Crime Rates: Changes in Employment[1, 2]

Crime	Direct Effect	Direct Plus Own Return	Direct Plus Imputed Loss
Burglary	-.492 (5.28)	-.517 (5.59)	-.746 (7.55)
Robbery	---	-.070 (1.86)	-.724 (4.26)
Larceny	---	-.032 (1.90)	-.324 (4.70)

[1]Estimates which appear in this table are based on the model estimated with 121 observations.

[2]Only effects which were judged significant at the ten percent level for Type One Error were used in these calculations. Test statistic suitable for determining the significance of the elasticities are presented beneath each elasticity in parenthesis.

on the expected legal wage and its indirect effect on the expected returns to criminal activity.[38] For example, the entry for burglary in column two represents the effect on the burglary rate of increases in the expected wage considering both its direct effect (increasing the attractiveness of legitimate pursuits) and its indirect effect of lowering the expected returns to burglary by increasing the penalty if caught. The difference between columns two and three is in the method by which increases in expected returns are translated into opportunity cost. Both versions, however, assume that the individual does not consider the change in employment opportunites to be transitory. The change in the employment rate is projected to be at least as long lasting as the prison term and is hence a rough version of a "permanent" employment effect.

In column two, we assume that the individual changes the monetary loss due to imprisonment by the amount implied by the direct elasticity term for legitimate activity. (See Table 1.) Since this elasticity term indicates that individuals respond to higher expected wages by taking a significant portion of their increased income in leisure, this calculation yields a very modest increase in the opportunity cost of imprisonment. Essentially, this calculation is based on a pure financial loss concept of the opportunity cost of imprisonment. While the effects

---

[38] Of course, if the individual spent all of his time at illegal pursuits, his alternative legal earnings would be a lower bound on the opportunity cost from imprisonment, but changes in expected legal earnings might have no effect on the "true" opportunity cost of imprisonment.

in column two of changes in employment opportunities on robbery and larceny are quite small, this tying of changes in legal opportunities to the opportunity cost of imprisonment obviously introduces direct interaction between all legitimate and illegitimate markets.

The elasticities in column three are computed under the assumption that the elasticity of income with respect to changes in expected returns is unity. Here we are using the unitary elasticity assumption to indicate the responsiveness of these crime rates to changes in "full income" opportunity costs. This approach prices changes in leisure at the expected legitimate wage rate. Changes in the opportunity cost of imprisonment due to a change in expected legitimate returns then include both the changes in direct pecuniary returns and the change in the value of leisure. While this approach to changes in expected legal returns is somewhat more comprehensive than our concept of INCLOS used in the estimation, it does illustrate the power of a broader definition of the opportunity cost of imprisonment. All of the elasticities derived by using this concept indicate a moderate level of responsiveness of crime rates to changes in the expected net return to legitimate activity.

Summarizing our employment elasticity calculations, we have seen that if changes in employment opportunities are considered transitory then, at best, these changes will affect only burglary and this crime level only modestly. On the other hand, if such changes are considered permanent, then they will affect all crime rates. Here, however, the effect of changes in employment opportunities on robbery and larceny rates will be comparable to the effect on burglary only if a "full income" concept of income is considered.

One policy implication of these results is immediate. Programs designed to increase employment will have a significant potential for decreasing all property crimes only if they affect the long term unemployment rate. Short term programs designed to provide temporary employment are likely to disappoint their supporters in terms of their effect on property crimes.

VI. Concluding Comments

The complex theoretical and empirical framework reported in this paper was designed to investigate the relationships between property crime rates and the returns to legitimate and illegitimate activity. In the process of applying this framework we addressed four main topics: 1) the degree to which property crimes are substitutes or complements to legal activity, 2) the degree to which substitution takes place among income generating crimes, 3) the effects of sanctions on property crime rates, and 4) the effect of legal employment opportunities on property crime rates.

This research indicates that legal and income generating criminal activities are either substitutes or independent. The strongest substitutability, measured with and without considering the effect of legal returns on imprisonment costs, is between burglary and legal activity. Without considering effects of legal opportunities on imprisonment costs, the other cross elasticities with respect to legal returns are also negative, indicating substitutes, but are not statistically significant. Regarding the second topic, we find that illegal income generating activities are independent; their levels appear insensitive to the expected returns in other property crimes.

The framework adopted in this research proved particularly useful for addressing these two questions since it explicitly allows for complementarity or substitutability among activities. However, our findings indicate that, in the range of variation we observe, approaches which focus on a single crime and legal activity would provide a sufficiently rich framework to address the effect of returns on activities. In addition, a consequence of the apparent independence of income generating criminal activities is that campaigns designed to suppress a specific type of crime by diminishing its expected return will not generally have the perverse effect of increasing other property crime rates.

On the third topic, results which are generally consonant with previous findings emerge. We have found a deterrent effect to the sanctions of clearance and prison sentences. These effects, at least at the sanction levels represented in this sample, were modest. So modest, in fact, that it appears as if very substantial expenditures of resources would be required to orchestrate a significant decline in property crime rates.

Finally, property crime rates are found to be moderately responsive to permanent changes in employment opportunities, with crime commission decreasing when there is a perceived permanent increase in the employment rate. Of course, the ability of policymakers, at least at an aggregate level, to significantly increase the employment rate is subject to some debate. In general, while we have found that property crime rates are moderately sensitive to net returns they appear to respond only very modestly to policy instruments affecting net returns.

APPENDICES

GLOSSARY OF VARIABLES

(Note: "LN" used as a prefix indicates that the log of the variable is being used. It should also alert the reader that the variable may have been deflated and/or transformed. Reference to the attached variable definitions should resolve any ambiguity.)

ADJINC: Index of year to year changes of average per capita taxable income for a given state.

ASB: Average sentence for burglary for a specific state and year. Calculated from Uniform Parole Reports.

ASL: Average sentence for larceny for a specific state and year. Calculated from Uniform Parole Reports.

ASR: Average sentence for robbery for a specific state and year. Calculated from Uniform Parole Reports.

AVHRW: Average hours worked in the manufacturing sector in a given SMSA and year.

BSHARE: Per capita income generated from burglary. A dependent variable.

BUDGET: Intermediate budget for a family of four in an SMSA for a given year.

BURTOT: Total number of burglaries reported to the FBI in an SMSA for a given year.

CPOP: Population by SMSA and year that is covered by FBI reports.

CLRBUR: Probability of a burglary being cleared in a given year and SMSA.

CLRLAR: Probability of a larceny being cleared in a given year and SMSA.

CLRROB: Probability of a robbery being cleared in a given year and SMSA.

DFLAT: Deflator based on BUDGET which uses Albuquerque, 1966 (9235) as its base.

EXILNI: A measure of income dispersion calculated from IRS tax returns. It is the expected value of EXINC · LOG(EXINC).

EXINC: Average per capita income calculated from IRS returns in each SMSA. Available every other year. Used in combination with ADJINC to produce a per capita income series.

FCINC: Income in 1969 by SMSA per earning age female.

FCPOP: Earning age female population in 1969 by SMSA.

INCLOS: "Discretionary" income per year of an average individual in an SMSA by year.

IRSPEG: Per capita income based on IRS figures for the SMSA in 1969. Used to produce an adjustment factor when used in combination with EXINC and ADJINC.

LARTOT: Total number of larcenies reported to the FBI.

LEGALW: Hourly wage in manufacturing for a given SMSA and year.

LFORCE: Labor force (employed plus those seeking work) in an SMSA for a given year.

LRSHAR: Per capita income generated from larceny. A dependent variable.

LSHARE: Per capita income generated from all legal activities. A dependent variable.

MCINC: Earning age male per capita income in 1969 by SMSA.

MCPOP: Population of earning age males in 1969 by SMSA.

NOLEMP: Number of employees for a given SMSA and year.

POP: Population by SMSA in 1969.

RETBUR: Gross average return per burglary by SMSA and year. Taken from UCR reports.

RETLAR: Gross average return per larceny by SMSA and year. Taken from UCR reports.

RETROB: Gross average return per robbery by SMSA and year. Taken from UCR reports.

REILNI: Deflated EXILNI.

REXINC: Deflated EXINC.

RSHARE: Per capita income generated from robbery. A dependent variable.

ROBTOT: Total number of robberies reported to the FBI.

WBUR: Expected net return to burglary by SMSA and year.

WLAR: Expected net return to larceny by SMSA and year.

WROB: Expected net return to robbery by SMSA and year.

CONSTRUCTION OF VARIABLES

```
DFLAT = BUDGET/9235

INCLOS=(.79*ADJINC*EXINC-.5*BUDGET)*.37

WROB=RETROB-CLRROB*.167502*INCLOS*(1-EXP(-.20*ASR))/.20

WBUR=RETBUR-CLRBUR*.091870*INCLOS*(1-EXP(-.20*ASB))/.20

WLAR=RETLAR-CLRLAR*.282221*INCLOS*(1-EXP(-.20*ASL))/.20

LNLEGW=LOG(LEGALW*NOLEMP/(LFORCE*DFLAT))

LNWROB=LOG(WROB/DFLAT)

LNWBUR=LOG(WBUR/DFLAT)

LNWLAR=LOG(WLAR/DFLAT)

REXINC=EXINC/DFLAT

REILNI=EXILNI/DFLAT-REXINC*LOG(DFLAT)

RSHARE=ROBTOT*RETROB/(CPOP*DFLAT)

BSHARE=BURTOT*RETBUR/(CPOP*DFLAT)

LRSHAR=LARTOT*RETLAR/(CPOP*DFLAT)

LSHARE=EXINC*ADJINC*(MCPOP*MCINC+FCPOP*FCINC)/(IRSPEG*POP*DFLAT)

CENSUS=(MCPOP*MCINC+FCPOP*FCINC)/POP
```

NOTE: THE FUNCTION EXP(.) IS EXPONENTIATION.

APPENDIX TABLE 1

SYSTEM OF ESTIMATED EQUATIONS

```
EQUATION 1:
BSHARE = 1/D * [-(A1 + BETA11*LNWBUR + BETA21*LNWROB + BETA31*LNWLAR + BETA41*LNLEGW)*REXINC - PI1*REILNI].


EQUATION 2:
RSHARE = 1/D * [-(A2 + BETA21*LNWBUR + BETA22*LNWROB + BETA32*LNWLAR + BETA42*LNLEGW)*REXINC - PI2*REILNI].


EQUATION 3:
LRSHARE = 1/D * [-(A3 + BETA31*LNWBUR + BETA32*LNWROB + BETA33*LNWLAR + BETA43*LNLEGW)*REXINC - PI3*REILNI].


EQUATION 4:
LSHARE = 1/D * [-(A4 + BETA41*LNWBUR + BETA42*LNWROB - BETA43*LNWLAR + BETA44*LNLEGW)*REXINC - PI4*REILNI].


          WHERE D      = -1 - PI1*LNWBUR - PI2*LNWROB - PI3*LNWLAR - PI4*LNLEGW,
                BETA11 = - BETA21 - BETA31 - BETA41 - GAMM11 - PI1,
                BETA22 = - BETA21 - BETA32 - BETA42 - GAMM21 - PI2,
                BETA33 = - BETA31 - BETA32 - BETA43 - GAMM31 - PI3,
                BETA44 = - BETA41 - BETA42 - BETA43 - GAMM41 - PI4.
```

APPENDIX TABLE 2

DESCRIPTION OF SAMPLE USED IN MODEL ESTIMATION

SMSA (Number)	1966	1967	1968	1969	1970	1971	1972	Total 85	Total 121
Akron (9)	–	–	B	B	B	B	B	5	5
Albuquerque (23)	B	B	B	B	B	B	B	7	7
Boston (105)	–	–	B	–	–	–	–	1	1
Buffalo (124)	–	–	B	–	–	–	–	1	1
Cincinnati (165)	–	–	–	–	X	X	–	0	2
Cleveland (170)	B	B	B	B	B	B	–	6	6
Columbus (188)	X	X	B	X	X	B	X	2	7
Ft. Wayne (289)	X	X	X	X	–	B	B	2	6
Fresno (299)	–	–	–	–	–	B	–	1	1
Grand Rapids (317)	B	B	B	B	–	B	–	5	5
Indianapolis (372)	B	B	–	–	–	–	–	2	2
Jackson (381)	X	X	X	X	B	B	B	3	7
Kansas City (404)	B	B	B	B	B	B	–	6	6
Louisville (483)	–	–	–	B	–	–	–	1	1

B: Sample point included in both Gross Return 85 and Gross Return 121 versions of the model.

X: Sample point included in only the Gross Return 121 version of the model.

SMSA (Number)	1966	1967	1968	1969	1970	1971	1972	Total 85	Total 121
Madison (506)	X	–	X	X	X	–	X	0	5
Miami (529)	B	X	–	–	–	–	–	1	2
Milwaukee (538)	B	B	B	B	B	B	B	7	7
Nashville (570)	B	–	B	–	–	–	–	2	2
Newport News (602)	X	–	–	X	B	–	–	1	3
New York (607)	–	B	–	–	–	–	–	1	1
Norfolk (611)	B	–	B	B	B	–	–	4	4
Omaha (634)	X	–	–	–	–	–	–	0	1
Philadelphia (657)	B	–	B	–	B	B	–	4	4
Phoenix (662)	B	B	B	B	X	–	–	4	5
Rockford (736)	X	–	X	B	B	–		2	4
San Diego (777)	B	B	B	B	B	B	B	7	7
South Bend (828)	B	B	B	B	–	B	B	6	6
Syracuse (869)	–	–	–	–	–	B	–	1	1
Tucson (906)	B	B	X	X	X	X	X	2	7
Wichita (956)	B	X	X	X	–	–	X	1	5
								85	121

B: Sample point included in both Gross Return 85 and Gross Return 121 versions of the model.

X: Sample point included in only the Gross Return 121 version of the model.

Appendix Table 3

Estimated Parameters:[1]

Explanatory Variables:	121 OBSERVATIONS Coefficient	121 OBSERVATIONS Test Statistic	85 OBSERVATIONS Coefficient	85 OBSERVATIONS Test Statistic
A1	-6.823	-2.807	-18.637	-5.960
BETA21	.032	.597	.264	4.176
BETA31	.068	.812	.269	1.613
BETA41	-2.659	-2.770	-4.313	-4.313
GAMM11	.409	.398	-.110	-.097
PI1	.260	1.386	.879	3.969
PI2	-.030	-0.468	.038	.981
PI3	.363	2.821	.754	4.605
PI4	76.98	1.727	122.544	2.288
A2	.040	.050	-2.751	-4.685
BETA32	.018	.659	.073	1.968
BETA42	-.104	-.313	.228	1.295
GAMM21	-.050	-.139	-.818	-3.952
A3	-1.766	-1.136	-7.876	-3.629
BETA43	-.289	-.441	-1.126	-1.524
GAMM31	-.440	-.635	-.767	-.927
A4	3570.2	7.916	3353.62	6.591
GAMM41	-573.82	-2.580	-421.847	-1.834

DEPENDENT VARIABLES:	R-SQUARED	STANDARD ERROR OF REGRESSION	MEAN	R-SQUARED	STANDARD ERROR OF REGRESSION	MEAN
BSHARE	.407	1.124	2.42	.572	.985	2.60
RSHARE	.145	.388	.34	.453	.171	.34
LRSHAR	.149	.772	2.13	.323	.728	2.21
LSHARE	.417	543.28	3647.47	.458	238.09	3625.75

[1] All coefficients have been multiplied by 10,000 to facilitate presentation.

Appendix Table 4

Typical Elasticity

Calculation:

```
ETA11 = BETA11/(( A1 + BETA11*5.12 + BETA21*4.29 + BETA31*3.31 +
        BETA41*.952) + PI1*73816.3/7691.7) + PI1/DENOM,

ETA21 = BETA21/(( A2 + BETA21*5.12 + BETA22*4.29 + BETA32*3.31 +
        BETA42*.952) + PI2*73816.3/7691.7) + PI1/DENOM,


Where DENOM  = -1 - PI1*LNWBUR - PI2*LNWROB - PI3*LNWLAR - PI4*LNLEGW,
      BETA11 = - BETA21 - BETA31 - BETA41 - GAMM11 - PI1,
      BETA22 = - BETA21 - BETA32 - BETA42 - GAMM21 - PI2.
```

The means at which the elasticities are evaluated have been substituted in the expressions. Those mean values are:

MEAN OF LNWBUR:	5.12
MEAN OF LNWROB:	4.29
MEAN OF LNWLAR:	3.31
MEAN OF LNLEGW:	Ø.952
MEAN OF REXINC:	7691.7Ø
MEAN OF REILNI:	73816.2

Appendix Table 5

Estimated Direct and Cross Elasticities[1]

121 OBSERVATIONS

	Estimated Coefficient	T-Statistic
ETA11	.594	7.99
ETA21	.071	.60
ETA31	.024	.811
ETA41	-.000	-2.86
ETA22	.299	4.26
ETA32	.006	.66
ETA42	-.000	-.27
ETA33	.100	4.70
ETA43	-.000	-.69
ETA12	.010	.60
ETA13	.021	.81
ETA14	-.492	-5.28
ETA23	.039	.66
ETA24	-.240	-.32
ETA34	-.111	-.47
ETA44	.097	2.08

[1]Examples of the formulae used to calculate these elasticities can be found in Appendix Table 4.

Appendix Table 6

Estimated Direct and Cross Elasticities[1]

85 OBSERVATIONS

	Estimated Coefficient	T-Statistic
ETA11	.873	9.24
ETA21	.568	4.06
ETA31	.092	1.61
ETA41	-.001	-4.61
ETA22	.466	7.18
ETA32	.025	1.96
ETA42	.000	1.16
ETA33	.272	5.71
ETA43	-.000	-1.95
ETA12	.076	4.12
ETA13	.078	1.60
ETA14	-.667	-8.74
ETA23	.156	1.96
ETA24	.479	1.26
ETA34	-.396	-1.57
ETA44	.052	1.05

[1] Examples of the formulae used to calculate these elasticities can be found in Appendix Table 4.

Appendix Table 7

Direct and Cross Return Elasticities

85 Observations

	Return			
	Burglary	Robbery	Larceny	Legal
Activity				
Burglary	.873	.076	0	-.667
Robbery	.568	.466	.156*	0
Larceny	0	.025*	.272	0
Legal	-.001	0	-.000*	0

Note: A "*" means the coefficient is significant at the 5% level. All other coefficients are significant at the 1% level.

Appendix Table 8

Elasticities of Per Capita

Crime Rates: Changes in Employment[1]

Crime	Direct Effect[2]	Direct Plus Own Return	Direct Plus Imputed Loss
Burglary	-.667 (8.74)	-.667 (8.74)	-1.04 (11.2)
Robbery	---	---	-1.13 (7.18)
Larceny	---	---	-1.28 (4.79)

[1]Estimates which appear in this table are based on the model estimated with 85 observations.
[2]Only effects which were judged significant at the ten percent level for Type One Error were used in these calculations. Test statistic suitable for determining the significance of the elasticities are presented beneath each elasticity in parenthesis.

Appendix Table 9

The Effect of Sanctions on Per Capita Crime Rates: Elasticities of Clearance Probabilities and Average Sentences[1]

Deterence Variable[2]	Clearance Probability	Average Sentence
Crime		
Burglary	-.078 (9.24)	-.062 (9.24)
Robbery	-.238 (7.18)	-.158 (7.18)
Larceny	-.186 (5.71)	-.154 (5.71)

[1]Estimates which appear in this table are based on the model estimated with 85 observations.

[2]The estimated coefficient divided by its estimated standard error appears in parenthesis. This test statistic should be compared to the Standard Normal Density to determine significance levels. Note that the values of the test statistic are the same going across a row. This is because the same estimated coefficient enter both calculations with the differences caused by multiplication with the mean values of different independent variables. These different mean levels cancel when the ratio is taken to produce the test statistic.

Appendix Table 10

STATES INCLUDED IN NCCD
TIME TO RELEASE DATA
1967-1974

Alabama
Arizona
Arkansas
California
Connecticut
Delaware
District of Columbia
Florida
Georgia
Idaho
Illinois
Indiana
Iowa
Kansas
Kentucky
Maine
Massachusetts
Michigan
Mississippi
Missouri
Nebraska
Nevada
New Mexico
New York
North Carolina
North Dakota
Ohio
Oregon
Pennsylvania
Rhode Island
South Carolina
South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
West Virginia
Wisconsin
Wyoming