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# Functional Substitution Among Crimes: Some Evidence

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Since Becker's 1968 paper on the economic model of criminal behavior, there has been a lot of empirical work to test the deterrence hypothesis [1, 3, 5, 15, 17]. These studies have looked at how punishment (certainty and severity) deters crime, and have concluded that deterrence works. However, these studies have looked at the supply of one type of crime in isolation without paying attention to the criminal's choices among crime types. Given that criminals seek to maximize the net returns to their activities, they are likely to respond in one of three possible ways to a relative decline in the net returns to a particular criminal activity. They would either withdraw completely from criminal activity, substitute one type of criminal activity for the one with decreased relative returns, or move to another jurisdiction where net returns to criminal activities are higher.

The movement from one jurisdiction to another in response to decreased returns to crime is described as spatial substitution of crime or the spillover effects while substitution among crime types is known as functional substitution. Withdrawal from criminal activity or the reduction of criminal activity in response to increased cost to the criminal is known as the deterrent effect. Spillover effects have been investigated by Hakim et al. (1979) and Hakim and Regent (1981), among others. Though spatial substitution of crime is of interest in its own right, especially its policy implication for collaboration of law enforcement agencies for crime prevention, it is not the focus of this study. The deterrence hypothesis has been extensively investigated by other researchers. In this study, we concern ourselves with the functional substitution among crimes.

The probable shift from one type of crime to another implies that though a deterrent policy that focuses on one type of crime may lead to a decrease in that particular crime type, such a policy may not have any effect on the overall crime rate because criminals may substitute one crime type for another. Such a change in the probability and severity of punishment associated with a particular crime type may only change the composition of crimes but not the total volume of crime.

Though there have been studies of spatial displacement of crime [9, 10, 11], as well as of the deterrence hypothesis [1, 2, 3, 4, 5, 6, 15, 16], there have been very few studies of the functional substitution among crime types. Yet studies of functional substitution among crime types could have interesting policy implications for crime prevention. For example, if all property crimes are found to be complements, then law enforcement agencies could concentrate on preventing a few types of property crimes instead of spreading their resources thinly over all property crime types.

The few studies of functional substitution among crime types have produced mixed results. Heineke (1978), using a translog utility function and data for SMSAs in the US from 1967 to 1972, finds no substitution among property crimes even though he finds a strong substitution between crime and legal activities. Witte and Schmidt (1984) find evidence of functional substitution of crime among recidivists in North Carolina. However, their sample may be a biased sample since the study considered only persons with a criminal history. It is therefore difficult to make any inference about the general population from their results. Hakim, Spiegel and Weinblatt (1984), using data from New Jersey, find that robbery, burglary and larceny are substitutes while auto theft is complementary to burglary and larceny though not to robbery. In addition to measuring functional substitution, Hakim, Spiegel and Weinblatt also estimated the effects of city size on the crime rate and found it to be significant. They use the arrest rate as the only

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measure of the probability of punishment. Though arrest is a necessary condition for punishment (sanctions), it is not a sufficient condition and therefore may not properly capture the deterrence effect.[1]

This paper uses data from the state of Florida to estimate functional substitution among crimes, employing the standard supply of crime approach that has been used by economists. Our approach differs from other studies of functional substitution among crimes. First, we use a different data set. By using data from one state, we would presumably avoid problems posed by institutional differences across states. Second, we estimate a standard supply of crime equations, but include the sanction variables of all crimes in each crime supply equation to capture substitution (complementarity). Third, we do not try to capture size effects; hence our crime variables are measured in rates rather than absolute numbers. This removes any scale factor that may affect our results. Fourth, our measure of sanction variable is more inclusive than has hitherto been used in studies of functional substitution among crimes. We believe that the measure of sanctions used here is more appropriate, and all things equal, will strengthen the results. Fifth, our study covers all seven Federal Bureau of Investigation (FBI) index crimes instead of only property crimes as in previous studies.

Finally, we explicitly test to find out if the model is correctly specified. Hakim, Spiegel and Wienblatt (1984) use the three stage least squares (3SLS) estimation procedure in their study. Though the 3SLS is more efficient than other systems regression procedures like the two stage least squares (2SLS) for example, if any of the equations in the system is misspecified, all parameters are inconsistent. One should therefore test for correct specification before using the 3SLS procedure. In an otherwise excellent study, Hakim, Spiegel and Wienblatt did not conduct this specification test. We provide such a specification test.

The rest of the paper is organized as follows: Section II presents the model while section III describes the data. Section IV presents and discusses the empirical results and section V concludes the paper.

## II. THE MODEL

In the simplest form of the economic model of criminal behavior, the potential criminal maximizes a Von Neumann utility index whose arguments are non income wealth (W), net income from criminal activity (Y) and the probability of punishment (p). The potential criminal decides to engage in criminal activity if the expected benefits from doing so exceed the expected cost. The criminal's Von Neuman utility index is given as

$$EU = pU(W + Y - F) + (1 - p)U(W + Y) \tag{1}$$
$$\partial EU/\partial(Y - F),\ \partial EU/\partial Y \geq 0,\ 1 \geq p \geq 0,\ (W + Y) \geq F, \quad \text{and } F \geq 0$$

where EU = expected utility index, F = size of punishment if caught, and other variables as defined above.

We assume that income, regardless of its source has a positive marginal utility. Differentiating (1) with respect to F or p shows that the Von Neumann utility index is decreasing in these variables.

$$\begin{aligned} \partial EU/\partial F &= -pU(W + Y - F) \leq 0 \\ \partial EU/\partial p &= U(W + Y - F) - U(W + Y) \leq 0 \end{aligned} \tag{2}$$

These equations indicate that, in order to maximize utility, the criminal decreases criminal activity in response to an increase in the probability or severity of punishment, all things equal. This is the deterrence hypothesis. From here, it is easy to specify the supply of crime as a function of net gains from criminal activity, the probability of punishment as well as the severity of punishment. Formally:

$$C = C(Y, F, p) \tag{3}$$

where C is the number of crimes committed by the criminal, all other variables as defined above.

In the above discussion, the criminal's choice is between legal and criminal activities. In this case, when the "cost" of criminal activity increases, the criminal substitutes away from crime to legal activity.



However, in the real world, the criminal is faced with a choice between several types of criminal activities and legal activity. When the cost of one type of criminal activity increases, all things equal, the criminal may substitute for another crime instead of legal activity. Total crime may rise, remain unchanged or decrease even though deterrence works for the particular crime type whose cost has increased. To illustrate this point, suppose the criminal's Von Neumann utility function is given as:

$$EU = \sum_i p_i U_i(W + Y_i - F_i) + \left(1 - \sum_i p_i\right) U_i\left(W + \sum_i Y_i\right) \tag{4}$$

where $p_i$ = probability of punishment associated with crime i, $Y_i$ is returns to crime i and $F_i$ is punishment associated with crime i. Differentiating (4) with respect to p gives:

$$\partial EU/\partial p_i = U_i(W + Y_i - F_i) - U_i(W + Y_i) + \sum_j p_j \partial U_j(W + Y_j - F_j)/\partial p_i, \quad \text{for } i \neq j \tag{5}$$

Clearly, the sign of (5) is indeterminate as it depends in part on the sign and magnitude of the last expression.[2] (5) is negative if the last expression is negative; otherwise the sign is indeterminate.

The last expression in (5) shows how the utility associated with income from other crime sources change in response to changes in the probability of punishment associated with crime i. It reflects the relationships among various crime types in a crime supply equation. The presence of this expression in the effects of punishment of crime i on the criminal's utility function implies that in order to fully assess the deterrent effects of punishment for a particular crime, one must account for the spillover effects of such punishment to other crime types. In light of this, the supply of crime function for any particular crime should include the probability of punishment of other crimes as arguments. A more complete crime supply equation is:

$$C_i = C_i\left(p_i, \sum_j p_j, (Y_i - F_i), \sum_j (Y_j - F_j)\right) \tag{6}$$

The nature of the relationship among crime types cannot be determined a priori: it is an empirical question. To investigate the relationship among crimes empirically, one could estimate equation (6) alone. However, previous research has shown that the probability of punishment is dependent on crime rate as well as resources devoted to fighting crime, which in turn depends in part on the crime rate. This implies that the appropriate approach to use to investigate functional substitution among crimes is a simultaneous equation framework. We therefore specify and estimate a three equation simultaneous equation model to investigate functional substitution among crimes.

In light of the discussion above, the model to test functional substitution among crime types consists of three simultaneous equations: a crime supply equation, a sanction probability equation and a demand for police protection equation. The theory underlying our model follows earlier researchers [1, 2, 3, 5, 6] and will not be repeated here. We only mention the essential characteristics here. Each crime equation depends upon its own sanction probability and the sanction probabilities of other crimes, the gains from that criminal activity and a vector of socioeconomic characteristics. Sanction probability for each crime depends on the crime rate, the amount of police resources available to fight crime, the allocation of police resources to that particular crime, as well as a vector of socioeconomic variables. These socioeconomic variables enhance the productivity of law enforcement agencies and can be thought of as nonpurchased inputs into the production of police protection. Demand for police protection will depend on total crime, average loss per crime, community resource base and a vector of socioeconomic characteristics. These socioeconomic characteristics represent the community's preference for police protection. The complete model is given in equations 7-9 below.

$$\begin{aligned} C_i = C_i(&\text{SANCR, SANCL, SANCB, SANCM, DENS, UNEMP, POOR, WAGE,} \\ &\text{RACE, LOOT}_i\text{, URB, YOU, MD}) \quad i = \text{ROB, LARC, BURG, MVTH} \end{aligned} \tag{7a}$$

(7b) $C_j = C_j(\text{SANCRAP, SANCAA, SANCMU, POOR, UNEMP, YOU, RACE, URB})$ $j$ = RAPE, ASSAULT, MURDER

(8) $\text{SANC}_{i(j)} = \text{SANC}_{i(j)}(C_{i(j)}, \text{POLEX}, \text{PLOOT}_i, \text{VC}, \text{OLD}, \text{YOU})$

(9) POLEX = POLEX (TOTCR, REV, VC, OLD, MLOOT, URB)

The variables in the model are defined as follows:

ENDOGENOUS VARIABLES: $C_{i(j)}$ = Reported crime rates per 10,000 people for the 7 FBI index crimes, ie robbery (ROB), burglary (BURG), larceny (LARC), motor vehicle theft (MVT), rape (RAPE), aggravated assault (AA), and criminal homicide (MUR). SANCR, SANCB, SANCL, SANCM, SANCRAP, SANCAA, SANCMU = sanctions probabilities for ROB, BURG, LARC, MVT, RAPE, AA and MUR respectively. These sanction probabilities are measured as the product of arrest rate and the probability of punishment given arrest. They therefore measure the true probability of punishment given that a crime has been committed. POLEX = per capita police expenditure.

EXOGENOUS VARIABLES: DENS = population density per square mile, UNEMP = unemployment rate of the total labor force in a jurisdiction. POOR = percent of families in a jurisdiction below the poverty line. WAGE = average manufacturing wage rate in a jurisdiction. RACE = percent of a jurisdiction's population that is nonwhite. VC = sum of RAPE, AA and MUR as a percentage of total crime index. $\text{LOOT}_i$ average value of property stolen for each occurance of crime i. YOU = percent of population between 16 and 24 years old. MD = number of motor vehicles per square mile. $\text{PLOOT}_i$ = percent of total value lost to property crime that is due to crime i. MLOOT = average value of property value lost to all property crimes. REV = per capita general revenue. OLD = percent of the population that is 65 years or older. TOTCR = total index crimes per 10,000 people.

The explanatory variables included in the equation system have been guided by the results of earlier research [1, 4, 6, 9, 10, 15] and are now standard in the literature. We therefore do not try to justify their inclusion here. Each crime equation includes its own sanctions probability, the sanction probabilities of other crimes, the average gain from that crime, and a vector of socioeconomic characteristics. Sanction probabilities are hypothesized to depend upon the crime rate, police resources to combat crime, the proportion of property loss that is attributable to that crime (PLOOT), and a vector of socioeconomic characteristics. PLOOT is intended to capture the proportion of total crime prevention resources that is allocated to fighting crime i. Demand for police protection depends upon the crime rate, the proportion of crimes that are considered violent, the average value of property stolen, percent of the population that is old, and an urban dummy variable. The urban dummy (URB) is intended to test whether demand for police protection in urban areas differ from that of nonurban areas. Presumably, the citizen-voter will demand more crime prevention the larger the proportion of crimes that are violent and the larger the average property loss due to crime. MD, the number of automobiles per square mile, is included in the MVT equation to capture the effect of opportunities available to the auto thief. It is possible, however, that this variable may capture the lack of need to steal an automobile.

Our specification follows Hakim, Spiegel and Weinblatt (1984) and other researchers [6, 15, 17]. There are only two differences between our specification and that of Hakim et al. First, we do not estimate size effects-we measure crime in rates, rather than in absolute numbers. Second, we use the probability of sanctions, measured as the arrest rate (proportion of reported crimes cleared by the police through arrest) multiplied by the probability of punishment given arrest, instead of only arrest rates, as the punishment variable. This measure of sanctions probability is different from those that have been used by earlier researchers. We believe that this is a more appropriate measure of sanctions probability since it reflects the probability that a criminal is punished given that he (she) has committed a crime.

We measure the probability of sanctions as the arrest rate multiplied by the probability of punishment, given arrest. In a simultaneous equation system, this would require us to model the police as well as the court system's production function. This would require data not available to us. We therefore assume that the probability of punishment, given arrest, is exogenous to the model. This exogenous variable is used to multiply the probability of arrest to obtain the sanctions probability we use here.



Though the probability of punishment given arrest is exogenous to the model, it corrects for wrongful and multiple arrests for the same crime.

The supply of each property crime is expected to be negatively related to its own sanctions probability and positively related to the value of stolen property (LOOT) for that crime. These variables measure the costs and benefits of criminal activity respectively to the criminal. DENS and UNEMP are expected to have positive association with crime rates. High concentration of population provides the criminal with more criminal opportunities than in less densely populated areas while unemployment decreases the opportunity cost of criminal activity. Previous research has found a positive association between crime rate on the one hand and RACE and YOU on the other. We expect to find such an association.[3] On the assumption that the opportunity cost of punishment is income forgone, WAGE is expected to be negatively associated with crime rates. However, it is possible that WAGE measures the potential opportunity available to the criminal, hence it may be positively related to the crime rate. In the same way, one may argue that POOR may be measuring lack of potentially profitable criminal opportunity to the criminal instead of measuring a decreased opportunity cost of criminal activity. In property crimes, therefore, one cannot sign these variables. Whether property crime rates are higher in urban areas than in non urban areas because of differences in population density or not is an empirical question. Therefore URB cannot be signed a priori.

In the sanctions probability equations, crime rates are expected to have a negative coefficient (capacity overload), while POLEX is expected to have a positive coefficient. PLOOT and VC are expected to have positive coefficients. The demand for police is hypothesized to be positively related to total crime (TOTCR), the proportion of total crime that is violent (VC), the average value of stolen property for all crimes (MLOOT), total resource base of the community measured by per capita general revenue (REV), and the proportion of the population that is OLD. URB cannot be signed a priori.

Substitution (complementarity) among crimes in any crime supply system is measured by the sign of the cross effects of the sanctions probabilities in a crime supply equation. A positive cross effect implies substitution between the two crimes while a negative coefficient implies a complementary relationship in the supply of the two crime types.

We recognize the differences in motivations for committing property crimes (economic gains) and those for committing crimes against the person (crimes of passion). Because of the differences in motivation, it may be wrong to use the same specification to estimate property crime and personal crime equations. We therefore assume functional separability in the supply of these two types of crime and estimate their supply separately.

## III. DATA

The model is estimated using 1980 cross-sectional data for the sixty seven counties for the state of Florida. The dependent variable in the crime equation is measured as the number of reported crimes per 10,000 people for the seven FBI index crimes. Sanction probabilities are measured as the arrest rates for each crime multiplied by the probability of punishment given arrest. The probability of punishment given arrest is measured as the number of punishments (jail sentences, fines, suspended sentences, probation, etc.) as a proportion of total arrests for a crime. $\text{LOOT}_i$ is calculated as total value of property lost to crime i divided by the number of crime i committed; PLOOT is calculated as the total value of property lost to crime i divided by total value of all property lost to all crimes, while MLOOT is a weighted average of LOOT with the proportions of property crimes accounted for by a particular crime type serving as the weights.

Data for various crime rates as well as arrest rates and URB were obtained from *Crime in Florida 1980*, (Tallahassee, Florida Department of Law Enforcement [FDLE] 1980). OLD, YOU, POOR, and MD were obtained from *Florida Statistical Abstract 1982*, (Gainesville, College of Business Administration, University of Florida, 1982). WAGE data were obtained from *Quarterly Report on Employment and Wages, 1982*, (Tallahassee, Florida Department of Labor and Employment Security). These sources were checked against data from the *1980 Census of Population*, (Washington D.C., U.S. Department of

Commerce, Bureau of the Census). Data for UNEMP and RACE were obtained from the *1980 Census of Population.* POLEX and REV data were obtained from *Local Government Financial Report, 1980–1981,* (Tallahassee, Florida Department of Banking and Finance). Data for MLOOT, LOOT, and PLOOT were obtained from unpublished sources at FDLE. Data for calculating probability of sanctions given arrests were obtained from the files of the Florida Department of Corrections (FDC), State Court Administrator's office and Office of the Governor. All nominal variables have been adjusted using Florida's relative price index. These data are therefore comparable across space.

It is well known that crimes are seriously underreported.[4] Researchers using national data have adjusted for underreporting using results from national victimization surveys. It is not clear whether reporting patterns in Florida counties follow the national trend. In the absence of any strong evidence, the Florida crime data is not adjusted for underreporting.[5]

There were some counties that reported no crimes of certain categories. Since the model was estimated in the double log form, these zero observations were treated as missing observations in those equations, hence they were deleted.[6] Of the sixty seven counties in Florida, an average of four observations were missing for each equation system, with the total number of missing observations not exceeding six in any equation.

We append multiplicative error terms, assumed to be normally distributed with zero means and unit variance and uncorrelated to the exogenous variables, to each of the equations in the system. This provides a stochastic framework for estimation of the system of equations.

## IV. ESTIMATION AND REGRESSION RESULTS

Each of the crime equations exclude the LOOT from other crimes, and all except the motor vehicle theft equation exclude MD. From each of the sanction probability equation, we exclude the PLOOT of other crimes and also exclude almost all the socioeconomic variables. All the sanction probabilities and socioeconomic variables are excluded from the police demand equation. These conditions make each equation in the system identified according to the order condition.

To take into account the correlation of residual errors across equations, we use the 3SLS estimation procedure to estimate the system. When all equations in the system are correctly specified, 3SLS estimates attain the Cramer-Rao bound. However, if any of the equations in the system is misspecified, the misspecification is spread to all equations in the system, producing inconsistent parameter estimates. One therefore has to test for correct specification before using the 3SLS procedure. We use Hausman's *m* statistic (Hausman: 1978) to test for correct specification.

The Hausman specification test (Hausman: 1978) is based on the difference between two estimators, both consistent under the null hypothesis of correct specification but only one attains the Cramer-Rao bound, and the other, though efficient, is not consistent under the alternative hypothesis. Under the null hypothesis of correct specification, both 2SLS estimator ($b_{2SLS}$) and 3SLS estimator ($b_{3SLS}$) are consistent but only $b_{3SLS}$ attains the Cramer-Rao bound while under the alternate hypothesis, only $b_{2SLS}$ is consistent. Defining $q = b_{2SLS} - b_{3SLS}$ and $V = (V_2 - V_3)$, where $V_2$ and $V_3$ are the asymptotic variances of $b_{2SLS}$ and $b_{3SLS}$ respectively, Hausman's specification test is based on the statistic:

$$m = q'(V)^{-1}q \tag{10}$$

This statistic is asymptotically distributed as chi-squared with degrees of freedom equal to the number of parameter estimates.

Three stage least squares parameter estimates, together with Hausman's *m* statistics for each equation are presented in Tables 1 and 2. Table 1 presents 3SLS coefficient estimates for crime supply equations while Table 2 presents the 3SLS coefficients for the sanctions probability equations and the demand for police equation. We find that the hypothesis of correct specification of each equation in the system cannot be rejected at the .01 significance level.

From Table 1, we find that the coefficient for LOOT is positive and significant in only the ROB equation; it is insignificant in all other equations. This is a rather surprising result given that the



**TABLE 1**
Three Stage Least Squares Coefficients of Crime Equations

| | ROB | BURG | LARC | MVT | RAPE | AA | MUR |
|---|---|---|---|---|---|---|---|
| Constant | 3.8146<br>(0.8964)† | 8.0860<br>(3.9440) | 9.8740<br>(7.9060) | 0.9380<br>(0.6380) | 0.6490<br>(0.3700) | 5.6870<br>(3.0220) | 3.1630<br>(2.2080) |
| SANCR | −0.9989<br>(1.7479) | −0.4379<br>(5.0510) | −0.3770<br>(4.1520) | −0.1160<br>(1.1360) | — | — | — |
| SANCB | −0.2039<br>(0.3772) | −1.5930<br>(5.7750) | −0.8450<br>(2.5410) | −0.6240<br>(4.9320) | — | — | — |
| SANCL | −0.4913<br>(2.1586) | −2.8700<br>(3.0630) | −4.6330<br>(5.0210) | −0.1670<br>(2.5520) | — | — | — |
| SANCM | 0.4859<br>(0.7148) | −0.3850<br>(0.9710) | −0.3660<br>(0.8650) | −0.2946<br>(2.2900) | — | — | — |
| SANCMU | — | — | — | — | 0.1840<br>(0.8590) | −0.2160<br>(1.1830) | −0.9540<br>(4.2770) |
| SANCRAP | — | — | — | — | −0.8645<br>(5.1250) | −0.0400<br>(0.5380) | −0.2160<br>(1.1830) |
| SANCAA | — | — | — | — | 0.0830<br>(0.4150) | −1.3130<br>(4.9500) | −0.0180<br>(0.1800) |
| YOU | 0.4080<br>(1.7910) | 0.2650<br>(0.8930) | 0.1620<br>(0.7060) | 0.6830<br>(2.4310) | 0.4160<br>(1.1100) | 0.0350<br>(0.1140) | — |
| DENS | 0.0810<br>(1.1690) | 0.0060<br>(0.2370) | 0.0130<br>(1.6930) | — | — | — | — |
| UNEMP | 0.2880<br>(0.9707) | 0.2424<br>(1.6130) | 0.2270<br>(1.4920) | 0.4270<br>(2.4360) | 0.3160<br>(1.1830) | 0.0310<br>(0.1440) | 0.3660<br>(1.5290) |
| POOR | −0.1503<br>(1.4370) | 0.1363<br>(0.9830) | 0.0310<br>(0.2020) | −0.5200<br>(3.2430) | −0.7080<br>(2.9420) | −0.0950<br>(0.5460) | 0.3390<br>(1.5780) |
| WAGE | 0.4829<br>(10.0810) | 0.2532<br>(0.7180) | 0.1780<br>(0.5060) | 1.0400<br>(2.8400) | — | — | — |
| RACE | 0.4847<br>(2.0443) | −0.1010<br>(0.9150) | 0.0080<br>(0.0640) | 0.2920<br>(2.0640) | 0.7390<br>(3.6030) | 0.2870<br>(2.0220) | 0.7030<br>(3.5940) |
| MD | — | — | — | 0.0651<br>(1.6950) | — | — | — |
| LOOT | 0.1234<br>(1.4440) | −0.0110<br>(0.1210) | −0.0280<br>(0.2830) | 0.1060<br>(0.6330) | — | — | — |
| m | 8.3214 | 4.8343 | 7.3845 | 4.3710 | 4.0220 | 5.7490 | 6.8330 |

†Absolute value of t statistics in parenthesis.

motivation behind property crime is economic gain. It is possible that poor quality data used to measure this variable accounts for this rather surprising result. There was little variation in this variable across counties, making the value of stolen goods less important in the estimated equation. However, we take consolidation in the fact that the signs were in the right direction.

The performance of the socioeconomic variables was mixed. YOU has a positive and significant coefficient in only the ROB and MVT equations, DENS is only significant in the LARC equations, while POOR has a negative and significant coefficient in the ROB, MVT, RAPE and MUR equations. These

**TABLE 2**
Three Stage Least Squares Estimates of Arrest Rates

| | SANCR | SANCB | SANCL | SANCM | SANCRAP | SANCAA | SANCMU |
|---|---|---|---|---|---|---|---|
| Constant | 2.212 (1.103)* | 8.330 (3.708) | 13.383 (1.431) | 5.630 (1.970) | 4.919 (4.528) | −4.129 (0.896) | 30.920 (2.140) |
| ROB | −.386 (1.772) | — | — | — | — | — | — |
| BURG | — | −.584 (3.532) | — | — | — | — | — |
| LARC | — | — | −.937 (1.165) | — | — | — | — |
| MVT | — | — | — | −.440 (1.442) | — | — | — |
| RAPE | — | — | — | — | −.345 (1.618) | — | — |
| AA | — | — | — | — | — | −2.635 (2.138) | — |
| MUR | — | — | — | — | — | — | −.213 (2.250) |
| POLEX | .220 (1.412) | .002 (0.014) | .146 (1.291) | .101 (.585) | .052 (1.459) | .177 (0.744) | .009 (.085) |
| VC | −.457 (1.929) | — | — | — | −.370 (1.383) | 2.099 (1.633) | −.213 (1.112) |
| OLD | −.203 (1.08) | .077 (.356) | −.018 | — | .880 (1.559) | .090 (1.112) | — |
| YOU | — | — | — | 0.431 (1.689) | 1.380 (1.488) | 0.280 (1.088) | — |
| m | 3.6006 | 4.1740 | 2.4720 | 5.3887 | 3.9340 | 3.7990 | 8.9160 |

Police Expenditure Equation:

POLEX 1.764 + .292 TOTCRIM + .116 REV + .236VC + .382 OLD + .048 MLOOT
(0.560) (3.054) (1.897) (1.107) (2.2410) (0.223)

− .071 URB
(0.381) m = 3.8060

*absolute value of t statistics in parentheses.

variables are all insignificant in the other crime equations. Apart from the rather surprising negative coefficient of POOR in the crimes against the person equations, these coefficients are consistent with the results of earlier researchers. WAGE has a positive coefficient in all the crime supply equations and is significant in the ROB and MVT equations. It seems that POOR and WAGE are measuring the opportunities available to the criminal.

RACE has a positive and, except for BURG and LARC, significant coefficient in all the crime supply equations. This, however, does not imply that nonwhites are more prone to criminal behavior than their white counterparts. It simply implies that some important explanatory variables that have been excluded from the equation may be correlated with RACE.[7] URB is significant in only the LARC and RAPE



equations. For other crimes, it apparently makes no difference whether one is in an urban setting or a rural setting.

As expected, all crime rates are negatively related to their sanction probabilities. All the own saction probabilities are significantly different from zero, at least, at the 5 percent level of significance. This result is similar to results obtained by other researchers [1, 3, 4, 5, 6, 9, 15] and provides further evidence that certainty of punishment deters crime.[8] The own sanctions elasticities, especially those for larceny and burglary, are relatively large, indicating that in Florida, the deterrent effect of certainty of punishment is very strong. The own sanction elasticities are largest for larceny and burglary and least for motor vehicle theft. Apart from the low ranking of the own sanction elasticity for motor vehicle theft, the rankings of the sizes of the own sanction elasticities are consistent with results obtained by earlier researchers [9, 15].

Substitution or complementarity among crimes in this model is captured by the cross effects of the sanction probability variables. In the property crime equations, we find that with the exception of SANCM in the ROB equation, all the cross sanction probability variables have negative coefficients. With the exception of SANCM in the ROB, BURG and LARC, and SANCR in the MVT equations, all the cross elasticities are significantly different from zero at any reasonable level of confidence. These coefficient estimates suggest that robbery, burglary, and larceny are complementary in supply: an increase in the probability of punishment in any of these crimes tends to reduce the incidence of other crimes. For example, a 1 percent increase in the sanctions probability of larceny not only leads to a 4.3 percent reduction in larceny rate, it also reduces the rates of robbery, burglary and motor vehicle theft by .49, 2.8 and .17 respectively. However, with the exception of larceny and burglary, the elasticities of complementarity are less than unity. The signs of the cross effect of SANCM in the BURG and LARC equations would seem to suggest that motor vehicle theft is a complement to burglary and larceny. However, because the coefficients are statistically insignificant, one cannot say anything about the relationship among those crimes. In the same way, one cannot say anything about the relationshnip between robbery and motor vehicle theft, even though the positive (but insignificant) cross effect indicates that they are substitutes.

From the estimated cross elasticities, it appears that larceny and burglary have the strongest complementarity with other crimes. This is not hard to explain. The two crime types are the most prevalent property crime types in our sample and may occur in conjunction with other crimes.

The complementary relationships found among property crimes in Florida is consistent with two hypotheses. The first hypothesis is that the same criminals commit most or all types of property crimes in Florida. There seems to be no specialization in any particular crime by these criminals. When these criminals are incarcerated or punished in some other form, they are not available to commit that or any other type of property crime (specific deterrence). The other hypothesis is that there is a large number of potential property crime offenders but punishment in Florida is so effective that it not only deters the offender, it also deters all potential property offenders regardless of what property crime they intended to commit (general deterrence). It is also possible that the complementary relationship reflects only the definitional relationships among property crimes. For example, a burglary turns into robbery when the criminal accidentally confronts the victim during a break-in.

The complementary relationship found among property crimes in this study is consistent with Myers (1982) who found burglary and larceny to be each complementary to legal work, implicitly suggesting a complementary relationship between burglary and larceny. The results of this study, however, contrast with the results obtained by Hakim, Spiegel and Weinblatt (1984) who found substitution among robbery, burglary and larceny while finding a complementary relationship between motor vehicle theft on the one hand and larceny and burglary on the other. Perhaps differences in model specification and data type accounts for the differences in results.

The results of the substitution (complementarity) tests are different when one looks at the supply of crimes against the person (MUR, RAPE and AA). The own sanction probabilities have negative and significant coefficients, supporting the deterrence hypothesis. However, none of the cross effects of the sanction probabilities is statistically significant in any of the equations, implying that there are no significant relationships among the supply of crimes against the person. This result may be explained by the fact that these crimes, unlike property crimes, are not motivated by economic and hence systematic, forces but by other factors that may be random. A potential criminal commits a crime against the person in isolation based on emotions without rational thought or planning, in most cases.

Table 2 presents the estimated coefficients for the sanction probabilities and the police demand equations.[9] With the exception of LARC, the crime rate in each sanction probability equation is negative and significantly different from zero. This indicates the existence of a capacity overload on the criminal justice system: as the volume of cases to be dealt with by the criminal justice system increases, the system's productivity declines. Of course, our results here follow similar results obtained by other researchers [1, 3, 6, 9, 15]. VC is negative in the SANCRAP, SANCR, and SANCMU equations, again a further indication of the capacity constraint. PLOOT is only significant in the SANCL equation.

As expected, POLEX has a positive coefficient in all the sanctions probability equations. However, it is significant in only two of these equations. The negative coefficient of VC in the SANCR, SANCRAP and SANCMU equations may at first appear rather surprising. However, if one considers the fact that VC will act as a capacity overload on the prevention of violent crimes, these coefficients are to be expected. The performance of the socioeconomic variables in the sanction probability equations are mixed. OLD is significant only in the SANCRAP equation while YOU has a positive and significant coefficient in only the SANCM and SANCRAP equations.

In the demand for police equation, TOTCRM, REV and OLD have positive coefficients. These coefficients are in accord with prior expectations. Old people are more likely to be victims of crime or they are more likely to have a greater aversion to crime and hence will demand more police protection than the general population. Two other indicators of the citizenry's aversion to crime, VC and MLOOT, have positive but statistically insignificant coefficients while URB has a negative and insignificant coefficient. Apparently, urbanities do not demand more police protection that nonurban dwellers.

The result of this study has some implications for crime prevention policy in Florida. For property crimes, an appropriate sentencing policy for each type of crime may involve the consideration of the effects that such punishment may have on the supply of other types of property crime. Another policy implication is in the area of law enforcement. Since most property crimes in Florida were found to be complementary, the police may do well to concentrate their attention on increasing the arrest rates of criminals who commit a particular type of property crime that is complementary to other property crimes rather than spreading their resources too thin over all property crimes. The specialization on a few types of property crimes will make the police more efficient in fighting that crime type and hence all property crimes indirectly. Specialization will allow the police to develop special expertise in fighting that property crime while the complementary relationship among crimes will ensure that success in fighting this particular crime type will spread to other crime types.

Efficient allocation of crime prevention resources under conditions where crime types are complementary indicate that deterrence efforts concentrate on increasing the probability of sanction with respect to a few specific crime types that are most complementary to other crimes. From the parameter estimates, it appears that a viable strategy for deterring property crimes in Florida may be to concentrate on increasing the punishment probabilities of larceny and burglary. This recommendation seems to imply that the present strategy of police department assigning low priorities to larceny in resource allocation may be inefficient. Of course, this recommendation does not rule out other methods, such as education, as tools for crime prevention. When it comes to crimes against the person, one will have to treat each type of crime against the person as an independent entity in policing as well as in sentencing.

## V. CONCLUSION

This paper investigated the functional relationship among the seven FBI index crimes using 1980 cross section data pertaining to Florida's counties. Using 3SLS procedure to estimate a system of crime supply functions, sanction probability functions and a demand for police function, we find complementary relationships among robbery burglary, larceny, and motor vehicle theft. We find no statistically significant relationship among crimes against the person (rape, aggravated assault and criminal homicide). These findings could have interesting policy implications for crime prevention in Florida and, possibly, elsewhere.



## FOOTNOTES

1. The fact that a person is arrested for a crime does not constitute punishment. Given the possibilities of wrongful or multiple arrests, arrest rates may be a poor proxy for the probability of punishment. Since punishment depends on arrest as well as successful prosecution, one must take into consideration the probability of punishment given arrest in constructing a punishment variable. We note, however, that other researchers besides Hakim et al have used arrest rates as a proxy for the probability of punishment. For example, se C.R. Title and A.R., Rowe, "Certainty of Arrest and Crime Rates: A Further Test of the Deterrence Hypothesis," *Social Forces*, Vol. 52, June 1974.
2. This formulation assumes that the probability of punishment for crime i and j are independent of each other even though the marginal (dis)utility of punishment from crime i is not independent of the utility of incomes from other crimes.
3. The fact that RACE is expected to be positively related to the crime rate does not imply that any particular racial group has a higher inherent propensity to commit crime than the general population. For more on the relationship between race and crime rates, see Gyimah-Brempong (1986).
4. See [18]
5. Myers (1980) has shown that, qualitatively, it makes no difference whether crime rates are adjusted for underreporting or not, though the magnitude of coefficients change when crime rates are adjusted for underreporting. Since we are only interested in the direction of the relationship among crime types, it will make very little difference whether we adjust for underreporting or not.
6. Apart from a better fit to the data, the double log specification allows us to interpret the coefficient estimates as elasticities.
7. See [8]
8. We are unable to assess the relative importance of certainty versus severity of punishment in deterring crime since our model does not account for the severity of punishment.
9. The dependent variable in the sanctions probability equation is the product of the police output and the exogenously determined (in this study) court output. One should therefore be very careful in interpreting these coefficients. They reflect police productivity only after the productivity of the court system has been considered.

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