Functional Substitution Among Crimes: Some Evidence

Kwabena Gyimah-Brempong

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, 2, 3, 4, 5, 6, 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 choice among crime types. Given that criminals seek to maximize the net returns to their activities, they are likely to respond to 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 splinter effect, 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 deterrence effect. Splitter 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 implications 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 complemented, 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. Heinske (1978), using a travel 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. Wittke and Schmidt (1984) find evidence of functional substitution of crime among neofascists 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 Weimert (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 Weimert 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

*Wright State University, Dayton, OH 45435.
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 equation, 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, Spiegler and Wiendblatt (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, Spiegler and Wiendblatt 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 Neumann utility index is given as

$EU = pU(W + Y - F) + (1 - p)U(W + Y)$

where $EU$ is expected utility index, $F$ is 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.

$$\frac{dEU}{dF} = -pU'(W + Y - F) < 0$$

$$\frac{dEU}{dp} = -U'(W + Y - F) - U(W + Y) < 0$$

These equations indicate that, in order to maximize utility, the criminal decreases criminal activity in response to an increase in the probability of arrest 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:

$$C = C(Y, F, p)$$

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.

$$EU = \sum p_i U(W + Y_i - F_i) + \left(1 - \sum p_i\right)U(W + \sum Y_i)$$

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

$$\frac{dEU}{dp_i} = p_i U'(W + Y_i - F_i) - U(W + Y_i) + \sum p_j U'(W + Y_j - F_j)$$

Clearly, the sign of (5) is indeterminate as it depends in part on the sign and magnitude of the last expression.3 (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 relative effects of changes 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:

$$C_i = C_i(p_i, \sum p_j(Y_j - F_j), \sum(Y_j - F_j))$$

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 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 crime 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 crimes, 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 purchased inputs into the production of police protection. Demands for police protection will depend on total crime, average loss per crime, community resources 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.

$$(7a) C_i = C_i(SANC, SANCL, SANC, SANC, DENS, UNEMP, POOR, WAGE, RACE, LOGT, URB, YOU, MD)$$
The variables in the model are defined as follows:

ENDOGENOUS VARIABLES: \( C_{it} =\) Reported crime rates per 10,000 people for the 7 FBI index crimes, i.e., robbery (BOB), burglary (BURG), larceny (LARC), motor vehicle theft (MVT), rape (RAPE), aggravated assault (AA), and criminal homicide (MUR).\( S_{it} =\) 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: DIENS = 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.

LOOT, average value of property stolen for each occurrence of crime. MD = number of motor vehicles per square mile. PLOOT, percent of total value lost to property crime that is due to crime. MLOOT, average value of property damage to all property crimes. REY, per capital general revenues. 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 non-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 response 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 are allocated to fighting crime). Demand for police protection depends upon the crime rate, the proportion of crime that is considered violent, the average value of property stolen, percent of the population that is old, and an urban dummy variable. The urban dummy (URE) is intended to test whether demand for police protection in urban areas differs 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 the effects of economic crime 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 crime 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. DIENS 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. 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 opportunities 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 (certainly in theory), 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), the resource base of the community measured by per capita general resources (REY), and the proportion of the population that is OLD. URB cannot be signed a priori.

Substitution (complementarily) 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 difference in motivations for committing property crimes (economic gain) 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 our model 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. LOOT is calculated as the total value of property lost to crime divided by the number of crime i committed; PLOOT is calculated as the total value of property lost to crime i divided by the total value of all property lost to all crimes, while MLOOT is a weighted average of TOTCR with the proportions of property crimes accounted for by the particular crime type serving as the weight.

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, (Tallahassee, 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 used to collect data from the 1980 Census of Population, (Washington, D.C., U.S. Department of
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 PLOT 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 SSLS estimation procedure to estimate the system. When all equations in the system are correctly specified, SSLS estimates attain the Cramer-Rao bound. However, if any of the equations in the system is misspecified, the misspecification is spread across the equations to the system, producing inconsistent parameter estimates. One therefore has to test for correct specification before using the SSLS 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 SSLS estimator (bSSLS) and SSLS estimator (bSSLS) are consistent but only $bSSLS$ attains the Cramer-Rao bound while under the alternative hypothesis, only $bSSLS$ is consistent. Defining $c = bSSLS - bMTE$ and $V = (V_1 - V_2)^2$, where $V_1$ and $V_2$ are the asymptotic variances of $bSSLS$ and $bMTE$ respectively, Hausman's specification test is based on the statistic:

$$m = q(V)^{-1}q$$

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 statistic for each equation are presented in Tables 1 and 2. Table 1 presents SSLS coefficient estimates for crime supply equations while Table 2 presents the SSLS 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 0.01 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 surprising result given that the 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 consolation in the fact that the signs were in the right direction.

The performance of the socioeconomic variables were raised. 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.
# Table 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>SANCR</th>
<th>SANC</th>
<th>SANCL</th>
<th>SANCM</th>
<th>SANCRAP</th>
<th>SANCAA</th>
<th>SANCMU</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROB</td>
<td>-0.386</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BURG</td>
<td>-0.584</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>LARC</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>MT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>RAP</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>AA</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>MUR</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POLEX</td>
<td>0.320</td>
<td>0.022</td>
<td>0.146</td>
<td>0.101</td>
<td>0.002</td>
<td>0.177</td>
<td>0.005</td>
</tr>
<tr>
<td>VC</td>
<td>-0.457</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLD</td>
<td>-0.303</td>
<td>0.077</td>
<td>0.018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>YOU</td>
<td></td>
<td>0.431</td>
<td>1.380</td>
<td>0.280</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>m</td>
<td>3.606</td>
<td>4.740</td>
<td>2.470</td>
<td>5.387</td>
<td>3.950</td>
<td>3.790</td>
<td>8.910</td>
</tr>
</tbody>
</table>

**Police Expenditures Equation:**

\[
\text{POLICE} = 1.764 + 0.292 \times \text{TOTCRIM} + 0.116 \times \text{REV} + 0.236 \times \text{CIV} + 0.328 \times \text{OLD} + 0.048 \times \text{MLOOT} \\
(0.500) \\
(0.054) \\
(1.073) \\
(2.414) \\
(0.323) \\
(0.931) \\
(3.040) \\
(0.006)
\]

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. The UR is significant in only the LARC and RAP 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 sanction 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, 13] and provides further evidence that certainty of punishment deters crime. The own sanction 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 size of the own sanction elasticities are consistent with results obtained by earlier researchers [9, 13].

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 sanction 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, .58, 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 relationship 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. This 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 tends to 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 such 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 Weinfield (1964) 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 systemic, forces but by other factors that may be random. A potential criminal commits a crime against the person in relation to emotions without rational thought or planning, in most cases.

Table 2 presents the estimated coefficients for the sanction probabilities and the police demand equations.* 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 SANCPR, SANC, and SANCX equations, again a further indication of the capacity constraint. PLOT is only significant in the SANCX 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 SANC, SANCPR, and SANCX equations may at first appear rather surprising. However, if one considers the fact that VC will set 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. OLQ is significant only in the SANCX and SANC equations.

In the demand for police expenditure, TOCTCM, REV, and OLQ have positive coefficients. These coefficients are in accord with prior expectations. Older 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 citizen's aversion to crime, VC and MLQOT, have positive but statistically insignificant coefficients while URB has a negative and insignificant coefficient.

Apparently, addicts do not demand more police protection that nonusers 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 of the 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 decreasing property crimes in Florida may be to concentrate on increasing the punishment probabilities of luxury and burglary. This recommendation seems to imply that the present strategy of police department assigning low priorities to luxury 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 ILSA's procedure to estimate a system of crime supply functions, sanction probability functions and a demand for police functions, 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. Gives 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 on successful prosecution, one must take into consideration the probability of punishment given arrest in construing a punishment variable. We note, however, that other researchers besides Haskin et al have used arrest rates as a proxy for the probability of punishment. For example, C.R. Fitis and A.R. Rowe, "Criminality of Arrest and Crime Rates: A Further Test of the Deterrence Hypothesis," Social Forces, Vol. 33, 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 returns 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 Gynther-Brenkoff (1986).

4. See [18]

5. More (1980) has shown that, qualitatively, it makes no difference whether crime rates are adjusted for underreporting or not, though the magnitude of coefficients changes 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 [18]

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) output quotient. One should therefore be very careful in interpreting these coefficients. They reflect police productivity only after the productivity of the output system has been considered.

REFERENCES


A Note On Some Theorems in the Theory of International Trade

Geoffrey A. Jehle*

The purpose of this note is to provide for pedagogical purposes a simple, unified set of diagrammatic proofs for several fundamental propositions in the standard, $2 \times 2$ Heckscher-Ohlin model of international trade. The Heckscher-Ohlin theorem and its two principal corollaries, the Factor Price Equalization theorem and the Stolper-Samuelson theorem, together constitute, "the central body of international trade theory" (Jones and Neary, 1984). However, proofs of these important theorems in the literature and in textbooks at any level typically proceed along different and often arcane mathematical or diagrammatic lines, and so tend to obscure the essential unity of this central body of the theory. Since these and many other propositions in the literature which address the income distributional aspects of international trade all rely on the same set of relationships between relative product prices, relative factor prices and real factor earnings, they may all be demonstrated by means of a simple diagrammatic device reflecting these basic relationships simultaneously.

Let the usual assumptions of the standard Heckscher-Ohlin trade model obtain. There are two countries ($I$ and $II$) with perfectly competitive economies, producing the same two final goods ($X$ and $Y$) with two internally mobile, inelastically supplied and fully employed factors ($L$ and $K$). Let the production of each good in each country take place in the absence of externalities and under conditions of constant returns to scale (CRS). Let the technologies for producing a given good be identical in both countries, but let capital intensities in production ($R_L$ and $R_K$) differ between goods. In particular, let good $X$ be capital intensive relative to good $Y$ at all relative prices of labor ($w = w')$. Then the relationships in Figure 1 between relative commodity prices ($P = p_X/p_Y$), relative factor prices, capital intensities in $X$ and $Y$ production, and real returns to labor ($w = w'$) and capital ($r = r'$) obtain in both countries.

Panels A and B of Figure 1 simply reproduce the familiar "Harrod-Johnson" diagram relating relative product prices, relative factor prices and capital intensities in production, and hardly require any comment or justification. Suffice it to point out that any given pair of CRS technologies gives rise to a set of such relationships in general competitive (product and factor market) equilibrium which is unique and which holds in the range of relative product prices, factor prices, and factor intensities consistent with incomplete specialization in production. If the production functions for $X$ and $Y$ are identical across countries, then the same set of relationships will obtain in each country within ranges consistent with incomplete specialization in both countries.

Figure 1 is completed by appending panels C and D which depict the necessary and corresponding relationships between the capital intensity, $R_K$, and the marginal productivity of labor and capital, respectively, in the production of good $X$ under conditions of CRS. It is, of course, well-known that when the technology exhibits constant returns to scale the marginal product of each factor depends systematically on the capital intensity in production, but is independent of the level of output. Thus, one need not be reluctant to depict such relationships diagrammatically.

The validity of the relationships depicted in panels A and B, though not disputable, depends nonetheless on some rather delicate reasoning on the subject of general competitive equilibrium in a constant returns to scale economy satisfying the Strong Factor Intensity Assumption. No such delicacy is involved in panels C and D, however, since they simply reflect properties of the assumed technology which are independent of the competitive structure of the economy. It is, of course, true that we are only able to make inferences about factors' real earnings from the marginal products of the underlying technology.

*Vassar College, Poughkeepsie, New York 12601.