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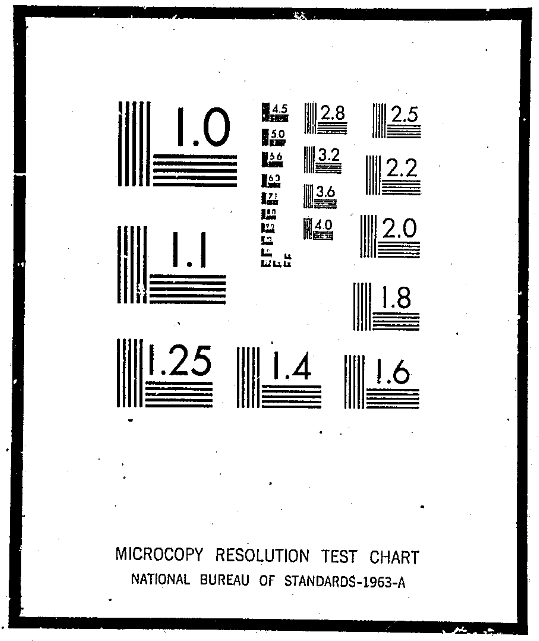

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AN ECONOMETRIC ANALYSIS OF PROPERTY CRIME: INTERACTION BETWEEN POLICE AND CRIMINALS

By

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ABSTRACT

The extent to which economic theory can explain variations in property crimes within the City of Rochester is tested with a four equation econometric model. The endogenous variables in the model are the property offense rate, the arrest rate, the clearance rate, and police density. One result of the analysis is that the incremental effect of additional police in a neighborhood is an increase in the reported crime rate, implying that any deterrent effect is outweighed by a reporting effect.

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This paper presents an econometric model of property crimes for Rochester, New York. To help place the problem in perspective, I will begin with a brief survey of three important predecessors of this particular project.

Interest in economics of crime, like so many other applied microeconomic problems, was greatly stimulated by the work of Gary Becker. In his now classic article [1], Becker presents a basic theoretical discussion of public policy toward law enforcement. Once society has decided on a set of laws and a definition of property rights, it must then decide how to enforce these rules. Becker postulates that society should equate (at the margin of course) the harm from illegal activity against the costs of control of such activities, namely the costs of apprehension, conviction and punishment. One important section of his paper is devoted to derivation of the supply of offenses. Becker assumes that criminals behave like rational economic men (preferring more to less). The supply of offenses then will be negatively related to the probability of detection and magnitude of the punishment, and positively related to the expected gains.

One of Becker's students, Isaac Ehrlich, has done a substantial amount of research attempting to empirically test Becker's supply of offenses equation. Ehrlich [2] tested the model with cross-sectional data for the United States, with states as the unit of observation. Ehrlich ran several different tests using various crime types and both single and simultaneous equation techniques. The results broadly confirmed Becker's hypotheses. Ehrlich also discussed adding two additional equations to his system: a police production function and a law enforcement expenditures function. The production function postulated that the clearance rate is positively related to expenditures of law enforcement per capita and negatively related to crimes per capita. Expenditures per capita was assumed to be positively related to crime rates and to average losses. These aspects of Ehrlich's model were not tested in any detail, perhaps because of the limitations of his state-wide data.

Roy Carr-Hill and Nick Stern [3] have performed another econometric analysis of crime, but in their case they draw on data for England and Wales. Unlike Ehrlich, whose primary emphasis was on his supply of offenses equation, Carr-Hill and Stern were equally interested in the control of offenses. Their model ends up looking much like Ehrlich's. The three endogenous variables are offenses committed, police expenditures per capita, and the clearance rate. The data are also similar to Ehrlich's as they are from a cross-section of police districts (what I take to be the equivalent to cities or counties in the U.S.). Again, the basic economic hypotheses are generally confirmed.

In this paper, I examine the same general problem from a slightly different point of view. Instead of looking at differences in crime rates among large geographic areas like states or police districts, I look at the distribution of crime within a city. The data used in this study are at the census tract level. This allows me to separate two factors which have been heretofore combined: the number of criminals residing in an area and the number of crimes committed in that area. If most crime is committed locally (as seems

to be true) then for a state (or police district) these two variables are indistinguishable. But at the neighborhood (tract) level it is quite possible to have high crime rates without having many <u>resident</u> criminals. This study also differs from previous work in that actual police deployment data are used rather than the less descriptive police expenditures data. The police data were obtained for the year 1972 from computer tapes provided by the Rochester, New York, Police Department. The demographic data used are from the 1970 Census.

The ultimate goal of this research is to explain the level of property crime[1] in a particular neighborhood (census tract)[2]. Property crime was selected because it was felt that an economic model would better explain property crimes than crimes against persons or so-called victimless crimes. It is obvious that any such explanation must model the behavior not only of criminals, but also the police. The model used has four endogenous variables: the number of arrests for property crimes per population, A; the police presence per acre, P; the "clearance rate" for property crimes, C; and the property offense rate per population, O. Section I will define each of these variables and will present a model in which they interact. Section II presents the empirical results.

I.1 Arrests

For every crime in which an arrest has been made, the police report two addresses: the address at which the crime took place, and

[1] In this analysis, the category of property crime includes burglary, larceny, and robbery, as defined by Articles 140, 155, and 160 of the Penal Law of the State of New York.

[2] All but two of the 89 census tracts in the City of Rochester were included. The two atypical tracts excluded from this analysis were those containing the airport and the University of Rochester.

the address at which the arrestee lives. The latter address is used to measure Ai which is defined as the number of residents of tract i arrested for committing property crimes divided by the population of tract i. I wish to use Ai as a proxy for the number of individuals engaged in property crime living in a given tract. This brings us quickly to an important limitation of all crime data: the only information available about criminals is for the ones who get caught. Thus Ai is only a good proxy for the true number of criminals in a neighborhood if the probability of getting caught is invariant with respect to the criminal's place of residence. (Note that this probability is different than the clearance rate used later which is defined by the location of the crime.) Unfortunately, there is no way to test the degree to which these probabilities differ, and so results involving Ai must be interpreted cautiously.

Before discussing how Ai will be modeled and used, I will explain one way in which it will not be used. Since for those crimes cleared by an arrest we know the location of the crime and the criminal's place of residence, a tempting research project was to examine the choice of crime sites in a manner similar to the shopping problem in marketing, deriving the implicit supply elasticity of criminals with respect to distance. However, the data limitations discussed in the previous paragraph present much more disturbing problems in this case. It is widely held that the probability of detection is inversely related to the distance traveled to commit the crime (perhaps because the chance of being recognized is greatest close to home). If this assumption is true, then we would observe that

those people who get caught live relatively close to where they committed their crime. But this is exactly the same result which one would expect to find if criminals treat distance traveled as a cost. (In fact, inspection of the data shows that a high proportion of those caught live in the same tract or an adjacent tract to the one in which they committed their crime.) This would make the interpretation of any distance elasticity estimate virtually impossible. Thus, distance traveled is not used explicitly in this model. I do present some evidence, however, related to the issues discussed in this paragraph.

The variable A will be used then, as a proxy for the number of criminals living in a tract. Three different models could be used to explain variations in A across tracts. Model I makes the implicit assumption that neighborhoods "produce" criminals. The argument would be that "ghetto" conditions such as poor housing, high unemployment, low education, high population density, many broken families, etc., would create many criminals. This could happen if the conditions of the neighborhood affected either the residents tastes for criminal activity or their alternative legal wage rates. The alternative Model II would then turn the problem around and try to explain where criminals choose to live. The explanatory variables in this equation might include factors assumed to be attractive to the "typical criminal". Such factors might include a high proportion of young people, single people, and perhaps night spots, etc. A third alternative, Model III, might be called the "where there's smoke, there's fire" theory. The idea here would be that some groups such as young single males are known to have higher participation in criminal activity than other groups so the best way to explain variations in A would be to use measures of the numbers of these high-crime groups.

Fortunately, for the purposes of this paper, it is not necessary to choose one of the above models over the other. We simply need a good predictive equation for A. Thus, the actual equation estimated contains variables consistent with all three models.

I.2 Police Density

Police density, Pi, is defined as the number of patrol car hours spent in tract i divided by the area of tract i in acres. The numerator of Pi, call it police presence, is really the combination of two activities: answering calls for service and preventive patrol. Data for hours spent answering calls for service were obtained by census tract by using a Rochester Police Department computer tape containing over 200,000 such calls. While a car was responding to a call, it was assumed that it was in the tract where the call was located. (This will be in error only for the amount of time spent going through other tracts on the way to the call, normally a relatively small amount of time.)

Measuring preventive patrol presented greater problems.[3] We began by defining preventive patrol for a car as the difference between the total time available and that time spent answering calls, going to

[3]The problems stem, of course, from the fact that cars report where they are going when answering a call, but not when cruising around. This also leads to the curious fact that the police dispatcher knows the precise location of all the cars not available to answer calls and just the general location of those cars available for calls.

lunch, and any other activities taking the car out of service. In other words, it is the time the car spends ready to answer calls. The problem comes in assigning this time across tracts. There are thirty-five car beats in Rochester, eighty-nine census tracts, and few common boundaries. Thus, a typical beat might have portions of five or six tracts in it, and conversely, a tract might be split within three different car beats. Since we had patrol time by car one possibility was to divide that time up among the relevant tracts in proportion to their geographic share of the beat's total area. Instead, we decided to allocate the patrol time in proportion to the shares of the time spent answering calls each tract received. The police felt that this assumption was reasonable. One difficulty of this method, however, is that the two components of police presence in a tract were fairly highly correlated and it was therefore concluded that it would not be possible to use both variables as explanatory variables in the same equation.

Police density is police presence divided by acres. Since both arrests (A) and offenses (0) are normalized by dividing by population this procedure probably needs some clarification. This variable is used to model the allocative decisions of the police department, and the criminals' reactions to those decisions. The police tend to think about patrol beats in terms of geographical areas so police per acre seemed more natural than police per population. Further, it is the geographic density that is observed by the criminals on the street. For both purposes then, acres seemed preferable to population.

P can be thought of as the supply of police services to a neighborhood. How is this determined? It is reasonable to assume that in the short-run the total supply of police services is fixed, i.e., $\sum_i Pi = P^T$ where P^T is the pre-determined supply of police for the city. The police must then allocate the Pi's to maximize some objective function. Different distributions of the Pi's will result in both different levels of total crime and different distributions of crime. Presumably the police department's objective function is to minimize some index of the social costs of crime. The cost of a particular crime might depend on the type of crime, the amount of property and physical damages if any, and the demographic and political makeup of the neighborhood. To optimize the department would also have to have an estimate of each tract's reaction function. Modeling this problem is beyond the scope of this paper.[4] I will settle for an equation for P which depends on O, non-property offenses and some other demographic factors. There is some temptation to refer to P as "almost exogenous." By this I mean that since P is not really modeled, and since property crimes represent only a small portion of the demand for police services, P can almost be thought of as a variable determined outside the system.

I.3 Clearance Rates

A clearance rate is usually defined as the proportion of crimes "solved" by the police. The definition of a "cleared" offense, however, is subject to considerable interpretation. Frequently an individual will be arrested for a particular crime, say a house burglary, and will "confess" to several other similar crimes. Even if he is only charged with one offense, the police will categorize all the crimes to which he confessed as "cleared". We will refer to the clearance rate generated in this manner as the police clearance rate, C. This is the clearance rate used by police departments both internally and externally (i.e., reports).

[4] I hope to be able to deal with this problem directly in future research.

However, the theory used to model the equation for the offense rate requires a measure of the probability of apprehension. To satisfy this need, we generated a second clearance rate which I will refer to as the arrest clearance rate, C'. For the purposes of generating C', a crime is only considered cleared if an individual was arrested and charged with that specific crime. We obtained this number by matching the arrest records with the offense records. Both variables are used in the analysis. My hypotheses were that in estimating the effect of P on C we would find that C would be more sensitive to P than would C' since the police have less incentive to increase C'. On the other hand, I felt that in estimating the offense rate we would find that the criminals would respond to C' more than C since C' is a better estimate of the marginal risk.

The clearance rate in a tract is a function of two of the other endogenous variables in the system, A and O. Remember that Ai is defined as the number of arrestees living in tract i. Now let us assume that there is some tendency for criminals to commit crimes close to home (i.e., traveling is costly). Also assume as discussed in Section I.1 that the probability of detection is inversely related to the distance traveled to commit the crime. The first assumption implies that tracts with many criminals living in them will have more crime committed domestically so to speak (i.e., by residents) than tracts with few criminals. When combined with the second assumption, this leads us to expect high clearance rates in those tracts with high A's.

There is some tendency to feel that Ci should be related to Ai positively by arithmetic! This is not true. Let Aij be the number of individuals who live in tract i and commit a crime in tract j. Let Oj be the number of offenses committed in tract j. Then $C'_j = (\sum_i A_{ij})/O_j$. When Ai is used in the regression it is not $\sum'_i A_{ij}$ but rather $\sum'_j A_{ij}$. C only differs from C' in that the Aij's are weighted by the number of offenses committed.

We include O in the system to allow for either increasing or decreasing returns to crime solving by putting the level of crime into the clearance rate equation. Ehrlich asserts that the sign of the coefficient for this variable should be negative, pointing out that relatively few people are arrested during a riot.

I.4 Property Offenses

The model driving the equation for the offense rate is the basic economic theory presented by Becker [1]. I assume that criminals maximize their expected gains from illicit activity.

The equation for O can be thought of as a reaction function of criminals which depends on the other three endogenous variables. It

is expected that A will have a positive effect on O because of the tendency to reduce costs by committing crimes close to home. The clearance rate C or C' should be negatively related to O because of the costs associated with getting caught.[5] This deterrence argument is well known and I should not have to elaborate here. Finally, the police density is included. The effect of added police, after controlling for any effect of increasing the clearance rate, is impossible to predict *a priori*. This is due to the fact that the offense rate used here and in all other crime research is the *reported* offense rate. The reported offense rate is only a fraction of the true, total offense rate. Now an increase in police density would be expected to have two effects. The true offense rate should *decrease* due to the "visible deterrence" effect of criminals simply seeing more policemen around. On the other hand, more policemen are likely to *increase* the reporting rate both by observing some crimes themselves and by making it easier or more worth-while for a citizen to report them. The net effect is ambiguous.[6]

I.5

The relationships between the endogenous variables can now be summarized in Figure 1. In the presentation, an X indicates that the variable is not included in that particular equation. Otherwise the +, -, or ? indicate the expected signs of an included variable.

[5] Actually these two variables should interact. If, as I have been arguing above, distance and probability of apprehension are negatively related, then the tendency to commit crimes close to home will be reduced. Of course it may not be *eliminated* if the effect is small relative to the costs of traveling.

[6] For a thorough explanation of this problem, see Stern and Carr-Hill [3].

Figure 1

	A	P	C	O
Equation 1 A		X	X	X
Equation 2 P	X		X	+
Equation 3 C	+	+		?
Equation 4 O	+	?	-	

II. Empirical Results

The variables used in the analysis are listed in Table 1 along with their means and standard deviations. The equations were estimated using two-stage-least-squares (TSLS). The reduced form and TSLS estimates are given in Tables 2 and 3. I will discuss the TSLS estimates of each equation in turn.

II.1 Equation 1: Arrests

The equation for the number of criminals living in a tract explains most of the variance (R^2 = .86) but does not confirm any particular model. The three most important independent variables are % male 15-24, number of unrelated individuals per population, and % families with both husband and wife living at home. All have coefficients with the expected signs and healthy t statistics. Population density has a negative coefficient which seems counterintuitive. The "economic" variables included in the equation (% homes greater than $20,000, median income, % unemployment, and median school years completed) do not perform very well. The only variable of the group with a signifcant coefficient

Table 1

Means and Standard Deviations

Variable Name	Mean	Standard Deviation
Arrests Per Population A	.0239	.0851
Police Presence Per Acre P	.0602	.0664
Police Clearance Rate (%) C	25.9	11.4
"Arrest" Clearance Rate C'	6.3	4.3
Property Offenses Per Population O	.0877	.182
Population Density X_1	19.7	9.5
% Male 15-24 X_2	6.2	1.4
% Male Married X_3	60.8	9.2
% Families With Both Husband and Wife X_4	76.6	8.4
# Unrelated Individuals Per Population X_5	.152	.148
% Negro X_6	19.6	27.2
Median School Years Completed X_7	10.6	1.3
% Unemployment X_8	4.6	3.2
% Houses Greater than $20,000 in Value X_9	11.4	14.5
Median Income X_{10}	9338.	2032.
Population X_{11}	3254.	1428.
Mean Reported Losses X_{12}	49.7	21.8
Mean Reported Losses Squared X_{13}	2949.	2657.
Average Response Time in Minutes X_{14}	10.5	2.7
Non-Property Offenses Per Population X_{15}	.0761	.104
% of Property Offenses Being Robberies X_{16}	4.8	6.1

Table 2

Reduced Form

	Eq. 1 Arrests	Eq. 2 Police Density	Eq. 3a Arrest Clearance	Eq. 3b Police Clearance	Eq. 4 Offenses O
α	-.085 (1.28)	.030 (.20)	24.3 (2.18)	9.3 (.37)	-.045 (.26)
X_1 Population Density	.00031 (.86)	.00081 (1.01)	-.061 (1.03)	.23 (1.73)	-.00088 (.93)
X_2 % Male 15-24	.018 (6.94)	.011 (1.87)	1.4 (3.08)	3.2 (3.24)	.049 (7.04)
X_3 % Male Married	.0015 (2.06)	-.0053 (3.25)	-.11 (.92)	.10 (.38)	.0013 (.67)
X_4 % Husb.-Wife	-.0026 (4.07)	.0061 (4.30)	-.16 (1.48)	-.14 (.61)	-.0059 (3.55)
X_5 # Unrelated	.18 (3.32)	-.071 (.59)	3.8 (.41)	6.2 (.30)	.42 (2.90)
X_6 % Negro	-.00016 (.96)	.00066 (1.82)	-.0093 (.34)	.18 (3.06)	-.0011 (2.43)
X_7 Median School Years	.00079 (.21)	-.010 (1.22)	-.18 (.27)	-.11 (.07)	-.0029 (.29)
X_8 % Unemployed	-.0017 (1.61)	.0014 (.58)	-.065 (.36)	.30 (.75)	-.0028 (.98)
X_9 % Houses > $20,000	-.00056 (2.54)	.00019 (.39)	-.065 (1.73)	-.12 (1.48)	-.0010 (1.78)
X_{10} Median Income	$.29\text{x}10^{-5}$ (1.29)	$-.13\text{x}10^{-4}$ (2.54)	-.00021 (.56)	-.00020 (.24)	$.81\text{x}10^{-5}$ (1.36)
X_{11} Population	$.85\text{x}10^{-5}$ (3.48)	$.14\text{x}10^{-5}$ (.26)	.00067 (1.60)	.00085 (.93)	$.23\text{x}10^{-4}$ (3.57)
X_{12} Losses	-.00036 (.84)	.00068 (.71)	-.14 (1.93)	-.25 (1.57)	-.0011 (.94)
X_{13} (Losses)^2	$.27\text{x}10^{-5}$ (.78)	$-.67\text{x}10^{-5}$ (.88)	.00097 (1.66)	.0019 (1.48)	$.76\text{x}10^{-5}$ (.84)
X_{14} Response Time	.0013 (1.29)	-.0015 (.70)	.083 (.49)	.10 (.38)	.0032 (1.21)
X_{15} Non-Property Offenses	.43 (7.48)	.38 (3.00)	-9.8 (1.01)	-22.5 (1.05)	1.1 (7.57)
X_{16} % Robberies	-.00036 (.44)	-.0018 (1.02)	.079 (.58)	.0030 (.75)	-.00049 (.23)
	R^2 = .93	R^2 = .78	R^2 = .50	R^2 = .65	R^2 = .93

Note: The numbers in parentheses are the absolute values of the coefficients' t-statistics.

Table 3

Two Stage Least Squares

		Eq. 1 A	Eq. 2 P	Eq. 3a C'	Eq. 3b C	Eq. 4a O	Eq. 4b O
Arrest Rate	- $\hat{A}$			15.1 (.24)	706. (4.80)	2.56 (13.5)	2.59 (19.6)
Police Density	- $\hat{P}$			3.0 (.27)	62.7 (2.39)	.22 (1.91)	.24 (2.14)
Police Clearance-Rate	$\hat{C}$						-.0017 (2.24)
Arrest Clearance-Rate	$\hat{C}'$					-.00064 (.165)	
Property Offense-Rate	$\hat{O}$		-.44 (3.46)	6.8 (.28)	-264. (4.59)		
Constant Term	- α	-.038 (.51)	.10 (1.62)	8.9 (3.51)	34. (5.64)	.022 (.72)	-.062 (2.49)
Population Density	- X_1	-.00091 (2.34)					
% Male 15-24	- X_2	.024 (7.82)	-.036 (3.87)				
% Male Married	- X_3	.0010 (1.04)	-.0054 (6.01)				
% Husb.-Wife	- X_4	-.0023 (2.77)					
# Unrelated	- X_5	.28 (4.21)					
% Negro	- X_6	.00019 (.97)					
Median School Years	- X_7	-.0027 (.65)					
% Unemployed	- X_8	-.0021 (1.55)					
% Houses > $20,000	- X_9	-.00060 (2.19)		-.051 (1.63)	-.084 (1.14)	.00059 (1.31)	$.82\text{x}10^{-4}$ (.18)
Median Income	- X_{10}	$.52\text{x}10^{-5}$ (1.78)					
Population	- X_{11}		$-.84\text{x}10^{-5}$ (1.68)				
Losses	- X_{12}			-.11 (1.61)	-.26 (1.59)	-.00025 (.86)	-.00015 (.59)
(Losses)^2	- X_{13}			.00079 (1.40)	.0021 (1.54)		
Response Time	- X_{14}			-.054 (.32)	-.13 (.33)		
Non-Property Offenses	- X_{15}		.88 (4.74)				
% Robberies	- X_{16}			.13 (.31)	.77 (2.73)		
		R^2 = .86	R^2 = .73	R^2 = .41	R^2 = .54	R^2 = .92	R^2 = .93

Note: The numbers in parentheses are the absolute values of the coefficients' t-statistics.

is % homes greater than $20,000 and it does have the expected negative sign. Median income and unemployment have coefficients barely significant at the 10% level but both are the "wrong" sign. The % Negro variable is not significant.

II.2 Equation 2: Police Density

Police density measures the supply of police per acre to the given census tract. Variables were included which were thought to be proxies for the "demand" for police services. Four census variables were used: population, % male 15-24, % male married and number of unrelated individuals per population. All had significant coefficients with the expected sign. The variable number of non-property crimes per population also had a significant coefficient with the expected positive sign, but O, property offenses, had a negative (significant) coefficient. Although this is a surprising result, it is not inconsistent with the model suggested in Section I.2. It might be rational to deploy police manpower to areas with low property crime levels. The fit for the equation is reasonably good ($R^2 = .73$).

II.3 Equations 3a and 3b: Clearance Rates

The clearance rate equations were run twice, once using the police clearance rate and once using our "arrest" clearance rate. The fit for the police rate is better ($R^2 = .54$ vs. $.41$). The results for the police density variable are consistent with the first hypothesis stated in Section I.3. More police have a positive significant effect on the police clearance rate, but an insignificant effect on the arrest clearance rate. There are at least two possible explanations for this

phenomenon. (1) The police report their clearance rate and so have an incentive to behave in ways which will increase this rate which is used as one measure of performance. This would induce them to try harder to solve crimes where they have reason to believe that one person was responsible for several crimes. (2) Even if the police clearance rate were not reported it might be rational to concentrate on those crimes which appear to be related on the theory that the value of arresting a man who committed ten crimes is greater than the value of arresting a man who committed only one crime, even if both are only charged with one offense. Since the results were uniformly better for C, the police clearance rate, I will limit the rest of my discussions to Equation 3a.

The coefficient for the arrest rate, A, is positive and highly significant. This result is consistent with the assumptions discussed in Section I.2. While this does not prove that the probability of getting caught is higher close to home, it certainly suggests that assumptions to the contrary should be avoided. Notice that it is neighborhoods with many resident criminals which yield the higher clearance rates, not neighborhoods with high crime rates. In fact, for crime rates, the relationship goes in the other direction. The coefficient for the property offense rates is negative and significant. This could reflect a greater degree of difficulty in solving crimes in high crime neighborhoods, and is consistent with Ehrlich's hypothesis.

There is a strong presumption that, *ceteris paribus*, the police would like to solve "important" crimes first. This argument was used above to explain why the police clearance rate is a meaningful performance measure. On the other hand, some crimes are easier to solve than others, and the police are sometimes faced with trading off the ease of solving the crime against the importance of the crime. Thus murders are always thoroughly investigated even if the probability of solution is very low while petty thefts are sometimes left uninvestigated even if a suspect is known. Robberies represent a class of property crimes which are both relatively important and easy to solve. The presence of a victim creates potential dangers (explaining its importance) but also guarantees the existence of a witness (making solution much more likely than an unseen bicycle theft for example). Thus it is reassuring that the variable % robberies has a positive significant coefficient.

Another measure of the importance of a crime is the value of the goods stolen. This variable (median losses) and its square were used to try to discover any relationship between clearance rate and amount stolen. Unfortunately, the results were inconclusive to interpret. The coefficient for the linear term was positive while the quadratic term's coefficient was negative, but neither was significant. A function of this form would imply low clearance rates in the tracts with the highest median losses.

Finally, the variable response time was included in the equation. The true measure of response time would be the time between when the call was received at the police department and when the car arrived on the scene of the crime. This measure, however, was not available since no record is kept of arrival time. Instead,

we used the time between when the call was received and when a car was dispatched. This will differ from the true measure by the amount of travel time. This variable did not prove to be a significant explanatory factor (t = .7).

II.4 Equations 4 a and 4 b: Property Offenses

We can now turn to the key variable in the system, the level of property offenses per capita. The coefficient for A was positive and highly significant. Again, the temptation is to conclude that this confirms the hypothesized tendency to commit crimes close to home. But this result, as explained above, can also be explained by the negative relationship between distance traveled and probability of detection if such a relationship exists.

The coefficient for P is also positive and significant. This implies that, with clearance rate held constant, the effect of more police increased reporting of crimes more than it deters the commission of crimes.

To test the second hypothesis stated in Section I.3, the offense equation was run twice using both clearance rate measures. In this case, the hypothesis was not confirmed. The coefficient for C was negative and significant while the coefficient for C' was insignificant. One possible explanation for this is that C' is measured badly. We had to generate this statistic ourselves and there may be idiosyncrasies in the reporting procedures which have prevented us from getting an accurate estimate of C'. Alternatively, it may be that the police clearance rate, C, is simply a better measure of risk.

Essentially, C is a weighted clearance rate where the weights are determined by the number of crimes the police can associate with a given arrestee. Perhaps arresting an individual who has committed many crimes will scare others who hear about it. At the least it takes one active criminal out of commission for a while!

Criminals should be attracted to neighborhoods where the expected gains are highest. Since expected gains are the product of the probability of success and the mean value of the goods stolen we included the latter variable in this equation. We also included % homes greater than $20,000 as another measure of potential gains. Neither variable was significant.

III. Conclusions

The conclusions of this research can be placed in two broad categories, those for researchers and those for policy makers. In the research category, it appears that the empirical results by and large are consistent with the economic approach espoused by Becker and others. Important work remains to be done, however, in modeling the allocation decision by the police department. In the area of policy, two results stand out. First, it does appear that criminals commit crimes close to home, and that the probability of detection is inversely related to distance traveled. The evidence is admittedly indirect and other research should be done on this issue. Second, the effect of increased police presence on reported crime is positive, even after controlling for the deterrent effect through an increase in the clearance rate. How much of this is due to reporting biases is unknown, but it

seems unlikely that there can be a large negative effect on actual crime. In other words, unless there is some reason to think that the reporting effect is very large, the deterrent effect of increased police must be small. This conclusion is consistent with those drawn in an experiment conducted in Kansas City where police patrol was experimentally varied and was found to have little effect. It would appear that for the crime rate to be reduced means will have to be found other than simply putting more police out on the beat.

References

[1] Gary S. Becker, "Crime and Punishment: An Economic Approach," Journal of Political Economy, March/April, 1968.

[2] Issac Ehrlich, "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation", Journal of Political Economy, May/June, 1973.

[3] R. A. Carr-Hill and N. H. Stern, "An Econometric Model of the Supply and Control of Recorded Offenses in England and Wales,", Journal of Public Economics, 1973.

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