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A THEORETICAL AND EMPIRICAL
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THE ECONOMICS OF LAW ENFORCEMENT:
A THEORETICAL AND EMPIRICAL INVESTIGATION

by

EMANUEL HAAS

A dissertation submitted to the graduate faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

1976

This manuscript has been read and accepted for Graduate Faculty in Economics in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Introduction

Over the past several years many attempts have been made by economists to analyze the economics of crime. Several recent articles have sought to establish the optimal rules that society should follow in combatting illegal behavior (Becker 1968; Stigler 1970). These policies depend on the extent of damages resulting from crime, the general effectiveness of detterence and the social cost of apprehension and punishment. A number of empirical studies dealing with the relationship between crime rates, conviction probabilities and environmental variables have also appeared recently (Fleisher 1966; Ehrlich 1973; Swimmer 1974). In developing a supply function for criminal activities, these studies provide testable empirical estimates of deterrence. Another avenue of research has been to investigate those factors that affect the productivity of police resources (Carr Hill and Stern 1973, Thaler 1974). By developing measures of the impact of police expenditures on conviction rates these studies have lead to estimates of the effectiveness of police expenditures on law enforcement in reducing the crime rate.

The underlying assumption that economists usually make is that the decision to engage in crime is, for the most part, a rational one. The potential offender considers both the benefit that he will derive if his crime is successful and the loss that he will suffer if he is apprehended and punished. In addition, he has some knowledge of the probability that exists for either of the above outcomes. Whether or not an individual will commit an offense is determined by the maximization of his expected utulity function. It follows that the supply of offenses that society faces, which is the summation of all individual criminal acts, depends on the expected net benefit of offenses, their expected net losses, and the risk preferences of offenders.

The net benefit of an illegal act consists of the monetary and psychic returns that the offender receives, minus the direct and indirect costs associated with the commission of the offense. For monetary crimes the returns vary directly with the wealth of the victim. The returns may also be a function of the offender's ability and experience in determining the method of the crime. As far as costs are concerned, a very important factor is the opportunity cost of the crime in terms of alternative earnings in the legal marketplace. The higher a person's legal income potential is, the greater the cost of an illegal act. If legal earnings depend in part on experience, it follows that an individual who has devoted all of his time and resources in the past in an illegal 'occupation' is likely to possess a lower cost per offense than someone who specializaed in legal activities.

The expected net loss of a crime is the loss sufferred by the offender once he is convicted,multiplied by the probability that he will be convicted. The monetary value of the loss is, first of all, a function of the penalty that is handed down. If the penalty involves incarceration for a period of time, then the earnings forgone during the period of incarceration must be considered. An employed person would, in such a case, face a greater loss than a person who is not employed. The monetary value of the loss is also a function of taste factors. While some would be willing to pay a great deal to avoid the stigma of conviction, others, (primarily those outside the middle class socio-economic pattern) may regard this stigma as a minor cost.

The probability of conviction is affected by the number of police, (i.e. the probability of apprehension), the attitudes of the courts, the resources available to the defendant during his trail, and, to some extent, the legal framework in which the accused is tried.[1] Clearly, not all offenders are equally capable of avoiding conviction . It is logical to assume, however, that the individual probability of conviction of each offender is directly related to the average probability of conviction of all offenders.

The assumption that most crimes are the result of private economic decisions, made by rational individuals, leads us to a number of implications that can be tested empirically. For example, the number of offenses commited by an individual should be inversly related to his legal earnings. This is because this variable reducesthe net benefit of an offense by incresing the offenders costs. In addition , communities with large numbers of very wealthy citizens, (who are potential victims), should attract a large number of offenders, because the returns from crime are high in those communities. Furthermore, the supply of crime should be inversly related to the probability and severity of punishment, since both of these factors increase the expected loss associated with illegal acts.

It should be noted, that it has nowhere been assumed that individuals necessarily specialize in either legal or illegal

[1] In an interesting study Landes suggests that releasing an offender on bail prior to his trail may reduce the probability of conviction, since the offender has a greater possibility to prepare his defense. He also has some empirical evidence to support this assertion. See William M. Landes, "An Economic Analysis of the Courts," Essays in the Economics of Crime and Punishment, NBER, New York, 1974

occupations. If, however, earnings are a function of experience, then the initial decision of an individual to partake in either legal or illegal activities will result in an increased cost of switching across occupations. For convicted offenders, in particular, the earnings potential in the legal marketplace is quite limited due not only to the depreciation of legal skills, but also due to employer reluctance to hire convicts. Thus, it is quite likely that most people will specialize in either the legal or illegal sector.

It is worthwhile to note, that most of the literature, to date, does not approach the question of the determination of illegal activity as simply a special case of the economic theory of choice. In particular, sociologists and criminologists tend to explain criminal activity as the result of social conditions and individual personality traits. These factors are affected by family background, psychological conditioning, and personal motivation. Economists, of course, recognize that the above considerations are valid and that economic analysis can not be used to explain all forms of criminal behavior. Becker, in a theoretical study, suggests that violent crimes such as murder and rape may be less responsive to changes in the probability and severity of punishment, since the former type offenses are often acts of passion.[2] With regard to such factors as personality, family, and society, economists usually consider the effects of those variables under the ambiguous category of 'personal tastes'. Thus, an individual's respect for legal authority and the distaste that he has for violence, are both factors that enter into his utility function. (To the extent

[2]Gary S. Becker, "Crime and Punishment: An Economic Approach," ibid. page 41.

that these unmeasurable variables are related to environmental factors, such as the social and economic variables reported by the census, they can be considered for empirical purposes.) Whatever an individual's personal tastes are, however, changes in the relative costs and benefits of a particular offense, can be expected to produce changes in the supply of those offenses. The concept that offenders act rationally by no means rejects the possibility of noneconomic causes of crime.

Thus far I have limited the discussion to the supply curve for criminal acts which can be viewed as a function of various environmental factors and of deterrence. But who decides upon the probability of conviction and the severity of punishment? Clearly, the degree of enforcement of the criminal law is a basic issue of social policy and is determined jointly by governments and by court systems. It is assumed that in order to increase the level of deterrence society must allocate more resources for that purpose. Therefore, a demand curve for crime elimination is necessary in order to understand how an equilibrium level of safety and deterrence is achieved.

The purpose of this study will be to examine actual variations in safety rates and deterrence expenditures across communities. On the one hand I shall try to estimate a demand curve for safety. This demand curve is derived as the result of the maximization of some utility function. The variables that are contained on the right hand side of the demand curve include the price (marginal cost) of safety and some exogenous factors that are related to the amount of loss that a victim suffers if he is victimized. The other aspect of the model involves the estimation of a safety production function which, as previously described, depends upon the level of deterrence and on several exogenous variables.

The reason for variations in safety rates can now be attributed to variations in two sets of exogenous variables. Firstly, some communities may suffer a greater average loss per crime due to differences in property values, income levels, education levels, etc... That, in turn, causes an outward shift in the demand curve for safety. The community responds by increasing enforcement which results in more safety at a higher price (assuming increasing marginal cost). Another cause for differences in crime rates across communities are the variables that affect the production of safety. Variations in such factors as unemployment and income distribution, enter into the safety production function and thereby alter the marginal cost of safety. The community responds by adjusting its level of safety. Thus, by estimating the safety production function together with the demand curve, one can explain the variation in crime rates. An important by product of this analysis will be the derivation of a derived demand curve for police expenditures. These expenditures can be viewed as an input that the municipality undertakes in achieving its equilibrium level of safety.

In recent years several important studies on the economics of crime have appeared. In a theoretical study, Becker set forth the optimal social policies towards law enforcement.[3] His approach was to minimize the social loss resulting from crime. One component of this loss is the net (social) cost of an offense, which consists of the harm that the victim suffers minus the gain that the offender achieves. In addition, society should take into account the cost of

[3]ibid

apprehension, conviction, and punishment. The more that is spent on the latter variables, the greater the deterrence and the fewer the number of offenses. The optimality condition requires that society spend for deterrence until that point where the gain from the marginal dollar of deterrence no longer exceeds the dollar cost.

In deriving the above conditions, Becker considered both victim and offender as members of society. In calculating the damage from an offense, he subtracted the gain that the offender receives, and in considering the social cost of punishment, Becker included the disutility that the criminal suffers. Included in the cost of apprehension were the efforts and expenses undertaken by the offender to avoid apprehension. The social cost of crime also took into account the effect on production and output that results from a reduction in an individual's effective ownership over his property. All of the above factors are difficult to measure. Becker's stated aim was to propose a theoretical demand (marginal revenue) and supply (marginal cost) curve of criminal activity in order to "demonstrate that optimal policies to combat illegal behavior are part of an optimal allocation of resources."[4]

In the present study my concern will not be to analyze the optimal social policies from the point of view of society in general, but rather to examine the actual policies that governments undertake based on their own incentives. Thus, for example, if a municipality does not pay for the marginal cost of court proceedings and corrections, (but rather the state and federal governments pay for it), I shall assume that these costs are not considered by the municipality. In addition,

[4]ibid. page 45.

since governments are generally elected by nonoffenders, I shall assume that the authorities consider the utility functions of law-abiding citizens. Therefore, a crime such as robbery will not be considered as a monetary transfer from the victim to the offender. Instead, the total amount of the robbery is counted as a social loss.

Another important study, that was undertaken by Ehrlich, was aimed at measuring the supply curve for illegitimate activities.[5] Ehrlich used regression analysis to estimate the elasticities of seven types of offenses with respect to variables measuring deterrence, and with respect to exogenous factors relating to the relative benefits of the offense. The seven offense categories included crimes against the person, (murder, rape, and assult) and crimes against property (robbery, burglary, larceny, and auto theft). The variables used to measure deterrence were the probability of conviction and the average time served by offenders. The exogenous factors included the median income of families, the number of nonwhites in the population, and the percentage of families below one half of the median income. Ehrlich's results were consistent with the hypothesis suggested here. In nearly all cases the elasticities obtained from the exogenous variables indicated that offenders do increase or decrease the number of crimes they commit in response to changes in pecuniary returns. In all cases the rate of crime varied inversly with the probability and severity of punishment.

This study goes beyond that of Ehrlich's in that a major emphasis

[4]Issac Ehrlich, "Participation in Illegitimate Activities: An Economic Analysis," ibid.

is placed here on the derivation and empirical formulation of a community demand curve for safety. Furthermore, I shall be dealing with a cross-section of municipalities within a single state, rather than a cross-section of states, as was used by Ehrlich. As a consequence I assume that the severity of punishment is not a variable, since it is determined wholly by state and federal authorities and does not vary across municipalities within a state. The only deterrence variable that I consider is the amount of expenditures on police services that the municipality undertakes. In this paper no attempt will be made to estimate supply curves for specific types of crimes. Since police resources are hired by the municipality to reduce overall crime, my emphasis will be to estimate the overall effectiveness of police services.

The paper is organized as follows: Part II develops a model that attempts to explain how an individual municipality chooses its optimal level of safety. Part three sets forth an empirical framework for the model and presents the results of those tests. Part IV analyzes some of the implications of the model by looking at the effect of variations in certain types of exogenous variables.

II. The MOdel.

I shall begin the model by formulating an expression for the production of safety. The level of safety in a community depends, in part, on the degree of deterrence. The variable that shall be used to measure deterrence is the probability of conviction. But the probability of conviction itself, is "produced" by the community through the hiring of police services. Thus, there are two relationships that must be taken into account. The first is a behavioral function that relates safety in the community to the probability of conviction. The second is a production function that relates the probability of conviction to police expenditures.

The theoretical foundation for the behavioral function is based on a study by Ehrlich that was alluded to in the previous section. Ehrlich shows that some of the variables that have an effect on the crime rate are: the level of income, the degree of poverty, the wealth of the potential victim, etc... These factors are related in some manner to the relative costs and benefits of the crime, as seen by the offender. If an individual is unemployed, for example, the opportunity cost and the expected loss from partaking in a crime is not as great as for someone who is employed. Therefore, less of a disincentive exists for committing an offense. Similarly, if there are a large number of very wealthy families in the community, the expected payoff from crimes such as robbery and theft would rise. That, in turn, provides offenders with a greater incentive to commit such crimes in those richer communities. The above variables are all beyond the control of the municipality to vary in the short run. The only endogenous variable is the probability of conviction. As previously indicated, I assume that the severity of punishment does not vary systematically across municipalities within the state.

Let us consider the following equation:

1.1) $S_i=F(R_i,X_{2i},\ldots X_{ni},u_i)$ where:

S_i - index of safety level,

R_i - rate of conviction.

$X_{2i},\ldots X_{ni}$ - n-1 exogenous variables.

The subscript i refers to the i^{th} community.

The variable u_i is introduced to denote other factors that may affect the safety rate but can not be measured. One example may be the state of inter-group relations within the city. Another example may be the severity or leniecy of the local county and municipal court judges in handing down punishments. In order for the latter to have a deterrence effect on safety, it must be assumed that individual offenders are familiar with the sentencing habits of judges before they commit offenses.

I shall define S and (1-C), where C is the annual crime rate per capita. I measure S, rather than C, because a major concern of the model is to derive a demand curve for safety. Rather than having to work with a demand curve for less crime, (-C), I instead define safety as (1-C). Since C is unlikely to be greater than one, (in the sample used C varied from .005 to .118), the range of S is from zero to one, and can be interpreted as the probability of not being victimized over the time period.[1]

I shall assume that the previous equation is homogenous of the form:

1.1) $$S_i = R_i^{\gamma_1} X_{2i}^{\gamma_2} \cdots X_{ni}^{\gamma_n} u_i$$

The conviction rate, R, is defined as the number of offenders convicted divided by the crime index. In order for an offender to be convicted, he must first be apprehended. The probability of conviction can therefore be written as the rate of apprehension, (offenders apprehended / crime index), multiplied by the rate of conviction given apprehension (offenders convicted / offenders apprehended). Because they depend on different variables, it is important to distinguish between these two probabilities. The most obvious variable affecting the rate of apprehension is the level of police expenditures. Another factor might be the population density of the municipality. Once apprehended, the probability of conviction in court depends greatly on the resources that are available to the accused. The attitudes of prosecuter and judge may also have an impact on the probability of conviction.

The equation for the production of R can be written, in homogeneous form, as :

1.2) $$R_i = P_i^{\delta_1} (N-O)_i^{\delta_2} N_i^{-(\delta_1+\delta_2)} X_{n+1}^{\delta_{n+1}} \cdots X_{mi} V_i$$ where:

R - $\frac{\text{convicted offenders}}{\text{crime index}}$

P - police expenditures

N - population

[1] An alternative specification of the "Safety" variable is suggested in Appendix A.

O - crime index (total number of offenses reproted)

The right hand side of equation 1.2 includes all of the explanatory variables that determine both the apprehension rate and the conviction rate, given apprehension. These two sets of variables are combined into one equation because data on apprehensions of offenders is not available.[2] The error term, v_i, takes into account the impact of nonmeasured variables which are assumed to be randomly distributed. An example of such a variable may be the attitudes of local judges toward defendants.

Note that in equation 1.2 R is assumed to be homogeneous of degree zero with respect to police expenditures, offenses, and population. The reason for including N-O as an explanetory variable is that, intuitively one can argue, that as communities vary from low crime to high crime areas, it becomes increasingly difficult for a given number of police to maintain a constant R[3].

Although the probability of conviction may decrease as C increases, it is very likely that the absolute number of convictions rise. Landes and Posner attribute this to the fact that waiting times between offenses decline, and therefore the number of offenders apprehended

[2]Even if arrest data were available for municipalities in the sample, it could not be used as a reliable measure of apprehensions because:

i) Both offenders and non-offenders are arrested
ii) Police departments vary significantly in the number of arrests that are made. This may be due, in part, to the variety of pressures that are applied to the police. (either public pressure for more arrests or departmental pressure on policemen in the form of arrest quotas or witholding of promotions.)

increase. They compare it to the activity of fishing on a lake. As the number of fish in the lake increase, the output from a given amount of fishing resources will rise.[4]

Equation 1.2 can be rewritten as:

1.2')) $R_i = P_i^{\delta_1} S_i^{\delta_2} X_{n+1_i}^{\delta_{n+1}} \ldots X_{mi}^{\delta_m} V_i$ where P_i are now police expenditures per capita.

Combining 1.1 and 1.2 gives:

1.3) $S_i = P_i^{\alpha} X_{2i}^{\alpha_2} \ldots X_{ni}^{\alpha_n} X_{n+1_i}^{\alpha_{n+1}} \ldots X_{mi}^{\alpha_m} V_i$

where:

$$\alpha = \gamma_1 \delta_1 / (1 - \gamma_1 \delta_2)$$

$$\alpha_i = \gamma_i / (1 - \gamma_1 \delta_2) \qquad i = 2, \ldots n$$

$$\alpha_i = \gamma_i \delta_i / (1 - \gamma_1 \delta_2) \qquad i = n+1, \ldots m$$

In viewing a cross-section of municipalities, it is obvious that substantial variation exists in safety rates. Much of this can be explained by differences in the exogenous variables $X_2 \ldots X_m$. However, there is a good deal of variation in the amount of police expenditures

[3] By using N-O rather than O as the explanetory variable, I am altering the usual assumption of a constant elasticity of R with respect to the offense rate. By differentiating equation 1.2 with respect to C, and then multiplying both sides by C/R, one gets:

$$\mathcal{E}_{R,C} = \frac{C}{R} \frac{\partial R}{\partial C} = -\delta_2 \frac{C}{1-C}$$

per-capita. What are the reasons for the various levels of police expenditures? How can one explain the fact that in some communities, with relatively low crime rates, there is a great deal of policing, while in other places, where crime is a more serious problem, less is spent on police activities?

The answers to the above questions lie with the interaction between the supply function and the community demand curve for safety. To derive this demand curve I shall first maximize the demand curve of a single individual, (a benevolent dictator), who is empowered to make decisions for the community regarding the amount of police services it will employ. Later on I shall deal more explicitely with the problem of collective decisionmaking in a democratically elected government.

Suppose that society tries to maximize the following expected utulity function:

1.4) $V = SU_O + (1-S)U_1$

where: $U_O = U(Y_O-P)$ $\qquad$ $U_1 = U(Y_0 - P - L)$

Y_O - present value of expected lifetime earnings.

L - present value of loss resulting if individual is victimized.

Differentiating with respect to C gives:

$$\partial\xi/\partial c = -\delta_2/(1-c)^2$$

This result indicates that, holding P constant, as C continues to rise, the percentage drop in R becomes greater due to the limited resources of the police department.

[4] William M.Landes and Richard A. Posner, "The Private Enforcement of law". Journal of Legal Studies, 4, (January 1975), 1-46

P - per capita expenditure on police.

S=(1-C) - probability of not being victimized.

Differentiating with respect to S (to determine optimal S), and setting the derivative equal to zero:

1.5) $\frac{\partial V}{\partial S} = U_0 - U_1 - (SU_0' + (1-S)\ U_1')\frac{\partial P}{\partial S} = 0$

$(U_0 - U_1)$ is the extra utility achieved by a reduction in the probability of being victimized. (which is the same as an increase in S.)

$\bar{U}' = SU_0' + (1-S)U_1'$ is the expected marginal utility of an extra dollar of income.

<u>define</u>:

MB_s = as the ratio of the marginal utility of safety divided by the expected marginal utility of a dollar in alternative uses.

MC_s = as the marginal cost of safety.

The equilibrium condition (1.5) can be rewritten as:

1.5) $(U_0 - U_1)/\bar{U}' = \partial P/\partial S$ or $MBs = MCs$

To see how the slope of the MBs curve (demand curve) changes with respect to S, I take its second derivative:

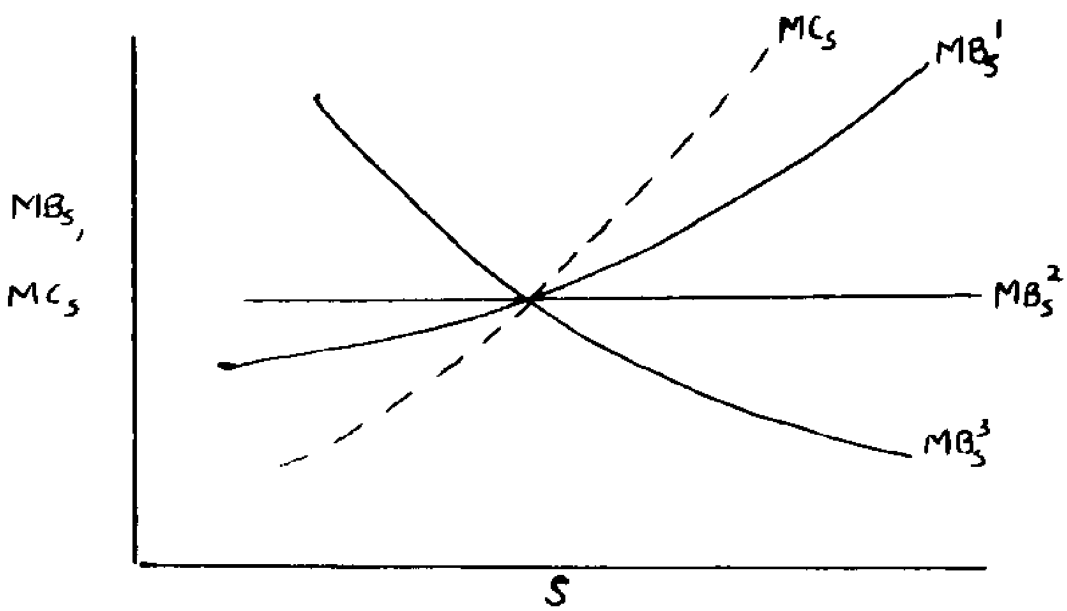
1.6) $\left(\bar{U}'(U_1' - U_0')\frac{\partial P}{\partial S} - (U_0 - U_1)\ [(U_0' - U_1') - \frac{\partial P}{\partial S}(SU_0'' + (1-S)\ U_1'')]\right) / \bar{U}'^2$

If the marginal utility of income is constant, then the slope of the demand curve for safety is horizontal. (provided that the loss per crime, L, is not a function of S) Otherwise the slope of the demand curve is ambigous. In order for there to be an equilibrium, the second order condition, equation 1.7, must be satisfied.

1.7) $\partial MB_S/\partial S < \partial MC_S/\partial S$

Equation 1.7 implies that the slope of the demand curve for safety must be less than the slope of the marginal cost surve. Figure 1 shows three possible situations that satisfy this condition.

figure 1.



Consider now what happens as one of the exogenous variables in the safety supply function, such as the rate of unemployment, varies. Depending on the nature of the function, such a change may cause a shift in the MCs curve. What has happened, is that due to the variation in the unemployment rate, it has now become more(or less) costly to provide for S. This change in the productivity of police occurs at all levels of S, and thus causes a shift in the MCs curve. (figure 2) The above would not be the case if the safety supply curve had a linear relationship with respect to P. In that case the productivity of the police would not change and there would be no shift in MCs.

The community, in determining the equilibrium level of S, equates MBs with the price (marginal cost). Suppose that some

Figure 2

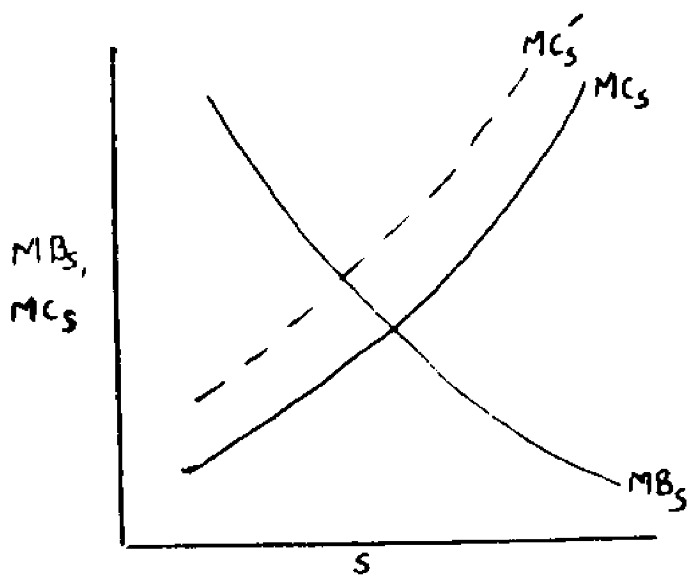
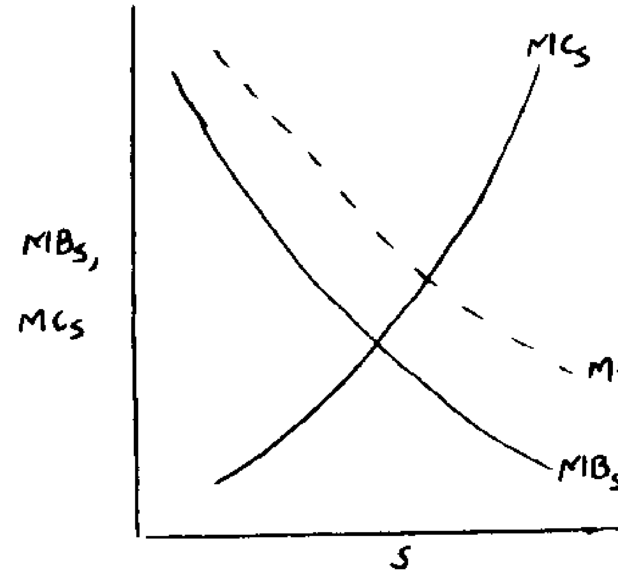


Figure 3



variation existed across communities in the amount of loss per crime (L). Those municipalities that suffer greater losses would most likely, experience a higher MB from safety.[5] (see Figure 3) I shall assume that a victim's losses are a function of certain exogenous variables (such as property values, income, etc,...) The demand curve can therefore be written as:

1.8) $S^d = \phi \; (\pi, Y_1, \ldots Y_k)$

where π is the marginal cost of safety (its price) and $Y_1 \ldots Y_k$ are k-1 exogenous variables.

[5] To see this simply differentiate MBs with respect to L:

$$\partial MB_s/\partial L = [(s u_0' + (1-s) u_1') u_1' + (u_0 - u_1)(1-s) u_1''] / \bar{u}'^2$$

Assuming positive marginal utility of income, an increase in L (which lowers income in cases of victimization) raises the utility achieved by an increase in S. The numerator of MSs will therefore rise. The denominator of MBs also rises if we assume diminishing m.u. of income since expected income falls as L rises. The net change in 1.5 is uncertain, although one could expect the growth of the numerator to to exceed that of the denominator. (since 1-S is small)

I now have essentially a two equation model. Equation 1.3 represents the production of safety function. The exogenous variables, $X_2 \ldots X_m$, are similar in that they each have an impact on S even if P is held constant. By taking the derivative of equation 1.3 with respect to P, one obtains the inverse of the marginal cost of safety(π). Depending on the technology of safety production, π may or may not be a function of the variables $X_2 \ldots X_m$. The other equation of the model is the demand curve of safety, equation 1.8. The variables $Y_1 \ldots Y_k$ cause a shift in demand even when π is held constant. Thus, the interaction of supply and demand determine the equilibrium levels of S and P, the only endogenous variables in the system.[6]

Consider now what happens as one of the 'X' variables, those in the supply of safety equation, varies. At first this generates a change in S, which the municipality could correct by altering P. If the X variable had no effect on π , the community would not allow for any net change in the overall safety rate. If , however, π were affected, the overall level of S would have to change depending on the demand curve. Similarly, as one of the 'Y' variables vary, the initial effect is for a change in the demand for S. That, in turn, forces an adjustment in the level of police expenditures to insure that the system stays in equilibrium. As is always the case, the exogenous variables alone are responsible for the resulting levels of S. and P.

Before it is possible to test the model empirically, there are

[6] R too is an endogenous variable. However, by combining equations 1.1 and 1.2, the safety supply curve can be written directly as a function of P.

some problems, which although they don't affect the basic concepts of demand and supply for safety, must be dealt with. One such difficulty stems from the fact that the local communuty is not the only source of police protection. There are, in actuality, three levels of police functioning throughout the state. In addition to the municipal forces, there are also state and county police units. These units render services to all communities within their respective jurisdictions. The nature of the distribution of these police services is not clear, but the manner in which they are allocated will have an important impact on the level of safety that is finally chosen by the municipalities.

There are numerous possible modes of distribution of public police protection, depending on the goal that the authorities seek to fulfill through this expenditure. Since very little is known about the distribution of government services by location, it is a matter of speculation as to what effect this area wide protection has on any particular community. I do hypothesize, however, that it is possible for the state and county to vary the intnesity of services rendered to different communities.

Suppose that atate and county police units were allocated on a purely per-capita basis, without regard to the crime index. This assumption implies a grant of police services to community A that is proportional to its population. A manner of distribution such as this would not appreciably affect the total quantity of police resources hired throughout the state, since the local police grant is not at all related to the level of safety.[7] The only impact that might be felt is that of an income effect, which may induce community A to hire more (or less) protection services, since its income is affected by the grant of police from the state and county. (If the state and counties are able to spend only by taxing the inhabitants of the municipalities, then even the income effects would balance.)

The above scenario would seem unlikely for several reasons. Firstly, the nature of the service is that police tend to gravitate towards crime. Clearly, it is unlikely for the authorities to permit some precincts to be overburdened, while officers in other communities have little or nothing to do. Furthermore, there is no economic rationale that would justify the allocation of scarce resources in the above manner.

A second possibility for the distribution of public protection would be to follow the assumption that the authorities seek to minimize total crime throughout the region. Doing so would entail allocation of resources such that the marginal product (in reduction of crime) of a dollar expended in one community would be the same as in all other communities. As previously mentioned the marginal product depends on the level of certain exogenous variables, such as unemployment and median income, as well as on the amount of local police services that each municipality employs.

[7]This assumes that the public protection never exceeds the optimal locally determined level of safety, (a likely proposition in view of the relatively minor role of the state and county in police work). As a result each community will supplement the state and county police until that point where the marginal benefit of a unit of protection no longer exceeds its cost. This, however, would have been the limit of police services hired even without any public participation.

The effect of the above method of distribution would be to seriously undermine the incentives of municipal governments in providing for their own safety. The state and county, in effect, penalizes the localities for which the marginal product of police services is low because the number of police already employed by the city is high. On the other hand, those places that maintain very little local protection, would be substantially supplemented by the state and county. Under this scheme there would be a tax of nearly one hundred percent imposed for policing any more than what the public authorities have already provided, since the only way to equalize the marginal product of police dollars across municipalities is by removing services from areas of low marginal product.

A third, and most plausible, possibility for the allocation of police resources, would stem from the state and county's desire to provide positive incentives for individual municipalities to control crime. This plan would entail the distribution of public protection to communities proportional to the municipal expenditure. Thus, for every dollar that a community spends on policing, it actually receives $(1+R')$ dollars of protection, with the state and county providing the additional fraction of a dollar (R').

If this scheme were in effect, the safety function (supply curve) would become:

1.3') $$S = (\hat{P}(1+R'))^{\alpha}X_2^{\alpha_2} \cdots X_m^{\alpha_m}.$$ where:

$\hat{P}$ - police resources provided by the city,

R' - some constant indicating the percentage of $\hat{P}$

that is allocated to the locality. (The subscript i has been deleted.)

Equation 1.3′ is the same function as 1.3 since $P=\hat{P}(1+R')$. $\hat{\pi}$ can now be defined as $\frac{\partial \hat{P}}{\partial S}$, or the marginal private cost of an additional unit of safety. It follows that:

$$1.9) \qquad \hat{\pi} = \frac{\partial \hat{P}}{\partial P}\frac{\partial P}{\partial S} = \frac{1}{1+R'}\frac{\partial P}{\partial S} = \frac{\pi}{1+R'}$$

The new demand curve for safety can now be written as:[8]

$$1.8') \qquad S^d = \phi(\hat{\pi}, Y_1, \ldots Y_k)$$

For purposes of estimation, I shall assume that the demand curve is of homogenous form.

$$1.8) \qquad S^d = \hat{\pi}^{\beta} Y_1^{\beta_1} \ldots Y_k^{\beta_k} V$$

One last issue that must be dealt with before completing the model is the question of how collective decisions are made in a democratically elected government. Thus far I have assumed that the utility function being maximized belongs to a single individual who is empowered to decide on the level of police expenditures spent by the city. In reality, this decision is made by municipal leaders who are elected by majority vote. How do these leaders arrive at their decisions?

In order to answer this question several assumptions will be made. Firstly, I assume that there is no discrimination in the

[8]An alternative possibility for incorperating state and county expenditures as part of the municipal police protection, which leads to somewhat different theoretical and empirical results, is presented in an appendix.

provision of the protection service among the members of the community. Secondly, I assume that all voters are knowledgeable regarding the expected costs and benefits of an additional unit of police protection. Since, in every democratically elected government, competition exists between political candidates, I can assume that the majority position will ultimately determine the course of action.

As has been pointed out a number of times in the past (Bowen 1943 and Barlow 1971), this majority position will tend to approximate the views of the voter with the median demand curve.[9] This holds, since any citizen would prefer to increase spending on safety whenever the marginal benefit of an additional unit of protection exceeds its cost. If I assume the marginal benefit curve to be a positive and monotonic function of income, then at any level of expenditure below the optimum of the median income voter, a clear majority would be in favor of more safety. This is so, since whenever the voter with median income finds the marginal benefit of an extra dollar's expenditure to be worthwhile, surely everyone with income above his will agree. On the other hand, if the voter with median income finds that too much is being spent on safety, all those with lesser demand curves will agree. Hence, whatever the median voter determines, he will always have a majority on his side. Only when he is indifferent (i.e. in his optimal position) will there be a standoff in the voting. That position will eventually remain in equilibrium.

[9]Neither Bowen nor Barlow discussed specifically the decision process in relation to police expenditures.

The above statements would naturally have to be modified if I was to include personal tastes and other factors in the demand curve for safety. For simplicity sake, I shall assume that the holder of the median value of these other variables is the median income voter.

In view of the above, I can now maximize the utility function of the median income person in order to get at the community demand curve for safety. The steps are identical to what has already been done from equation 1.4 through equation 1.9. The only change is that Y_o is now defined as the median income in the community.

There is, however, one additional problem. Thus far, I have implicitly assumed that the tax burden on each voter is the same. This, of course, is not the case. In the cities sampled most of the revenues were collected through the property tax. Since property value is generally positively correlated with income, it can be assumed that higher income citizens pay a greater absolute amount. In addition, for most communities there are other sources of revenue aside from the residential property tax. These include industrial taxes, taxes on commercial property, state aid, etc... To simplify matters, I shall assume that the voter with the medial income owns a house in the community of median value. [10]By multiplying property value by the adjusted

[10]This assumption is necessary in order to continue using the voter with median income as the critical decision maker. The demand for police protection can be viewed as a function of <u>net</u> benefit that is derived from it. If the individual with the median marginal benefit from police services, is also the one with median marginal cost, and if the slope of marginal benefit and marginal cost curves with respect to Y are both positive and linear, then the median net benefactor at any level of expenditures would be the median income voter. The graph shows the marginal benefit and marginal cost of a given level of P as (over)

municipal tax rate, I can obtain the tax burden for the median income citizen. I then divide this figure by the per-capita expenditure of the minicipal government, in order to get the share that the median income voter pays for every municipal dollar expended per-capita. This ratio will be greater than one since the median income homeowner generally represents a household containing several persons, while the expenditure figure is per-capita. I thus divide by the average number of persons per household.

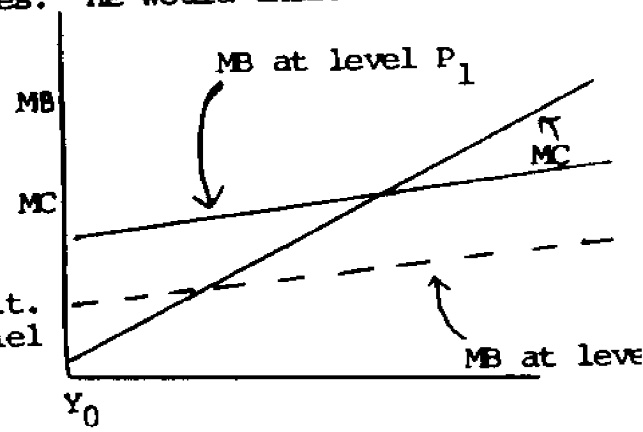
Taking the above considerations into account, I can rewrite 1.4 (the utility function being maximized):

1.4') $$V = SU(Y_0 - KP) + (1-S)\,U(Y_0 - L - KP)$$

where: Y_0 – median income in the community

$$K - \frac{\text{property tax paid by the median homeowner}}{\text{municipal expd. per-capita * number of persons per household}}$$

a function of income. Assume that Y_0 is the median income. At expenditure level P_1 the median income voter faces a positive marginal benefit from additional police expenditures. He would therefore increase expenditures until Pe, at which point his benefit is zero. In the case illustrated, where the slope of marginal cost with respect to Y is greater than the slope of marginal benefit, all people with income below Y_0 would have supported more P, while all people with income above Y_0 would have opposed it. (I am assuming that the curves are parallel at different levels of P.)



Differentiating with respect to S, and setting the derivative equal to zero, gives us:

1.5″) $$\frac{u_0 - u_1}{\bar{u}'} = K \frac{\partial P}{\partial S}$$

Equation 1.5″ is the same as the original first order condition, except that π is substituted by $K\pi$. The individual who maximizes his utility function does not only compute the marginal cost of a unit reduction in crime. He also considers how much he must contribute for every per-capita dollar spent by the city. Thus $K\pi$ represents the private marginal cost of expenditures on S, as seen by the median income voter.

If equation 1.5″ is modified so that it takes into account the marginal cost of the municipality alone, then the new demand curve for safety is:

1.10) $$S^d = (K\hat{\pi})^{\beta} Y_1^{\beta_1} \cdots Y_k^{\beta_k} V \, .$$

III Empirical Implementation of the Model.

The data base for this study consists of 181 municipalities in New Jersey. These include virtually all of the cities with populations between 5,000 and 50,000 persons. Nearly all of the data was taken from either state of federal sources. One reason that I chose all of the municipalities from a single state was to insure that the penal code is uniform over the entire sample. A second reason is that the definitions of different types of crimes varies across states. New Jersey was selected because it is one of the only states that annually publishes detailed crime reports covering all of its municipalities. (Federal data is distributed by the FBI, but it lists information dealing only with larger cities.) In addition, the state distributes a yearly comprehensive summary of all local revenue collections and expenditures.

By eliminating municipalities with populations above 50,000, cities such as Newark, Jersey City, and Trenton were deleted from the sample. There are a number of reasons for restricting the observations in this manner:

i) Very large cities are likely to require their police departments to perform additional functions, aside from direct crime control. These may include traffic direction and parking control, public relations programs, community education, etc... In such instances the amount spent on police services would overestimate the amount spent on crime prevention.

ii) Many of the assumptions that were made regarding the decision process for public police services may not be applicable in large urban areas. In such cities there are likely to be many different groups living in different neighborhoods. The possibility of discrimination in the provision of public police services arises. How then does the city allocate police resources among the different neighborhoods? Does the government seek to equalize crime throughout the city or does the government attempt to equalize the marginal product of police services? (Or might the authorities simply allocate an equal amount of resources to different neighborhoods?) Whatever the decision is, the usage of the median income citizen as the voter whose demand determines expenditures is inappropriate, since benefits from police vary, depending on which neighborhood the individual lives in. Instead, the decision on expenditures depends on whether a plan is able to gain a majority coalition by insuring that the marginal benefit of protection exceeds its marginal cost for a majority of voters.

iii) Cities with large business and commercial centers (such as those that exist in most large urban areas) may attract different types of crime than residential communities. That, in turn, might affect the productivity of police expenditures. In addition, homeowners and taxpayers may not consider the damage resulting from a crime against a business establishment as seriously as against a private individual. Thus, the demand for safety function may differ in large cities.

Table one shows a frequency distribution of the sample, broken down into different size cities. Column two shows the mean safety index for each group. Table two gives a list of the variables and a brief description. To give the reader an idea of the socio-economic background of the communities in the sample, the mean value for each variable is shown in the last column of table two.

Table One

population	number of observation	mean safety index
5,000 - 10,000	83	.9883
10,000 - 20,000	62	.9801
20,000 - 30,000	15	.9761
30,000 - 40,000	13	.9778
40,000 - 50,000	8	.9581

Table Two

variable	description	mean value
P	total police expd. per-capita	$ 27.03
R	probability of conviction $\left(\frac{\text{convictions}}{\text{crimes}} \right)$	.6261
S	safety index (1-crime index/population)	.9797
CIDX	county crime index per-capita	.0255
CMDINC	median income in county	$11,902
CNW	percent nonwhites in county	.0915

Table Two (continued)

DEN	municipal density per squate mile	$3138.04
FAM	percent of families with income over $15,000	.0468
HH	average number of persons per household	3.209
MDHOME	median home value in city	$25,373
MDINC	median income in city	$12,604
NOWRK	nonworker/worker ratio in city	1.352
NW	percent nonwhites in city	.0523
OV65	percent of population above age 65	.1005
UNEM	percent of unemployed persons in labor force	.0349

I shall, at first, estimate the safety supply curve, discussed in equation 1.1. A similar regression was estimated by Ehrlich, using cross-state data. He used the crime index per-capita as the dependant variable, rather than the safety rate that shall be used in this study. As measures of deterrence, Ehrlich considered the probability of incarceration and the average length of sentence. The results that Ehrlich obtained were consistent with the hypothesis that offenders act rationally. Both of the deterrence variables yielded significant negative elasticities on all the crime categories. In addition to measures of deterrence, the regressions contained variables on the right hand side measuring: i) the percent of Nonwhites in the state, ii) the median income of families, iii) the percentage of families below one half the median income. The latter three variables had positive and often significant effects on the crime categores.[1] The rationale behind using these as explanetory variables is that they each affect (enhance) the net benefit of a crime, as seen by the offender.[2]

As previously indicated, I do not consider each crime category separately. One of my primary purposes is to estimate a demand curve for safety in general, and for police services. The community, in maintaining its level of safety, employs a given amount of police services that are hired to combat all forms of crime. These police units are not hired for protection against any one type crime in particular.[3] (In very large cities, such as New York City, there may be special units dealing with specific type crimes, but even in such places the majority of the force is assigned to overall crime prevention.) The measure of safety that I use is S=1-C (1-crime index per-capita). S can be viewed as a measure of the probability of non-victimization over the year.[4]

[1]Ehrlich found that crimes against property had significant elasticities more often than crimes against the person. This may be explained by the fact that crimes against the person are frequently crimes of passion, and perhaps less subject to economic considerations. They did, however, display considerable deterrence elasticities.

[2]Other exogenous variables that were found to be inconclusive were unemployment, labor force participation, and age composition.

[3]This does not imply that departments do not internally allocate varying amounts of resources for the prevention of the various offenses. For a discussion on how society determines the degree of enforement for individual type crimes, see the appendix that deals with the weighting of the crime index.

[4]A problem which exists when considering the safety rate as 1-C is that the seriousness of each crime that is committed is not taken into account.

(over)

The first equation that is estimated is the supply of safety equation. As previously noted, there is no explanetory variable measuring the length of time served by the offender, since all of the municipalities come from a single state. I am implicitly assuming that the penal code is applied uniformly throughout the state. The method of estimation was TSLS.

$$2.1)\quad \ln S = \gamma_0 + \gamma_1 \ln R + \gamma_2 \ln MDINC + \gamma_3 \ln NW + \gamma_4 \ln CMDINC + \gamma_5 \ln CNW + \gamma_6 \ln NOWRK + \gamma_7 \ln UNEM + \gamma_8 \ln FAM + \ln U.$$

The endogenous variable, R, is the probability of conviction, and is defined as the total number of convictions divided by the crime index.[5] The rationale for choosing the other explanetory variables has been alluded to already, and shall only be briefly discussed here.

As the median income obtained in the legal marketplace increases, the incentives for individuals to commit crimes should decline. This is because both the opportunity cost of the crime, and the expected cost of punishment (i.e. the average length of time in jail * the

[4] (continued)
Unless I assume that the relative number of each type crime is about the same for all the municipalities, a weighting system is necessary. (i.e. A murder or rape would have to be given a greater weight than a larceny.) For a detailed discussion of alternative safety indicies that take this factor into account, see the appendix.

[5] The precise number of convictions for each municipality is not known since some convictions take place in the county courts rather than the municipal courts. As estimating procedure is used to correct for this. A more detailed description of this variable is found in the appendix.

earnings forgone during that time) have increased. Thus, one would expect 'MDINC' to have a positive elasticity on the safety index.

The variable 'NW' represents the percentage of persons in the municipality who are nonwhite. There are a number of reasons for believing that this variable should influence the safety rate. Firstly, if nonwhites do face racial discrimination in the legal marketplace, then they are more likely to be attracted to criminal careers, because discrimination is less prevalent there.[6] In addition, Swimmer (1974) points out that there is evidence of police discrimination against black victims. (i.e. Police on patrol give less help to blacks than to whites.) Since most crime is intraracial, if the above were true, the probability of apprehension of black offenders would be less than for white offenders, for the same type crime. Thus, less of a disincentive exists for nonwhites. Furthermore, the variable NW can be thought of as a summary variable that correlates highly with many economic and social factors, such as poverty, income inequality, family instability, attitudes towards law enforcement, etc... All of the above factors tend to either increase the net benefit of offenses, or reduce the loss resulting from punishment, thereby causing an increase in the crime rate.

Ehrlich also used the percentage of nonwhiles as an explanetory variable and obtained significant results. In my model, however,

[6] This is so, despite the fact that federal and state antidiscrimination laws apply in the legal marketplace only. The reason that there is less discrimination is that offenders usually tend to be self-employed.

there is an additional complication. Since all of the data is taken from municipalities that are situated quite close to one another geographically, it is relatively easy for offenders to travel across municipalities and commit offenses in cities other than where they live. Thus, a large number of offenders in community A, might cause more crime not only in A, but also in the sourrounding areas. (Ehrlich, however, avoids this problem by using state data, for which transportation costs across states are quite costly.)

To capture the impact of a municipality being in a high crime neighborhood, I have included some variables that are designed to provide data on the county in which the municipality is located. The variables 'CMDINC' and 'CNW' measure the county's median income and the county's proportion of nonwhites, respectively. (Even with these variables included, there may be some border communities that are affected more by a neighboring county than by the county in which it is located.)

The variable 'NOWRK' refers to the nonworker-worker ratio within a municiality. A nonworker is defined as an individual, above the age of fourteen, who is not in the labor force. Persons within this category come primarily from a number of groups.

i) young persons still attending school. Convicted offenders from this group are usually not treated as severly by society as are older offenders. Furthermore, it is often the case that young persons do not posses accurate information with regard to the possible consequences (future costs) of a criminal conviction. Thus less of a disincentive exists for these people to refrain from illegal activity.

ii) persons for whom the prospects of employment are so dim that they have given up even searching for a job. Such permanently unemployed persons are the most likely to turn to illegal occupations, (for which there are no entry barriers) since the net benefits stemming from crime are high.

iii) persons who are primarily engaged in nonmarket activities such as housework, caring for children, etc... For people in this group, the decision to remain at home is a form of specialization of labor within the family unit. Usually one spouse is engaged primarily in market activities, and the other spouse in nonmarket activities. In such cases there is no presumption that the returns from home employment are less than from outside occupations. (If they were the individual in question would opt for market employment.) For this group of nonworkers, therefore, the opportunity cost of, and the expected loss associated with an offense, are not assumed to be less than for other members in the community.

iv) retired persons. Nearly all members in this group are elderly or disabled, and consequently they would be very hard pressed to enter into an illegal occupation. (i.e. the probability of apprehension would be so high for them that it would discourage most offenses) On the other hand, communities with many elderly people may attract offenders, since the elderly can offer less resistance and are easier victims than younger persons.

The net effect of the nonworker-worker ratio on safety is hypothesized to be negative since the more nonworkers that there are, the more young, permanently unemployed, and retired persons there are likely to be.

The variable 'UNEM' takes into account people who are still members of the labor force, but who are temporarily unemployed. Here again the elasticity on safety should be negative because the opportunity cost of an offense is low. In addition, the expected loss in earnings from incarceration is low, since job prospects for the unemployed do not carry high wages. Thus, the elasticity of the UNEM variable on safety should be negative.

The variable 'FAM' refers to the percentage of families in the community whose incomes are above $15,000. The rationale here is that communities with many wealthy people provide more opportunities to offenders. This is because offenders only commit crimes if, in their view, the expected benefit exceeds the expected cost. Since the expected benefit is, to a large extent, a function of the victim's income and wealth, one expects that this variable should have a negative elasticity on safety. Note that the median income is held constant in the equation.

$$
\begin{aligned}
2.1)\quad \ln S = {} & \underset{(1.530)}{-.3151} + \underset{(2.247)}{.0218} \ln R + \underset{(3.404)}{.0349} \ln MDINC \\
& - \underset{(4.582)}{.0041} \ln NW + \underset{(0.280)}{.0053} \ln CMDINC + \underset{(0.353)}{.0007} \ln CNW \\
& - \underset{(2.500)}{.0236} \ln NOWRK - \underset{(1.469)}{.0046} \ln UNEM - \underset{(0.333)}{.0009} \ln FAM.
\end{aligned}
$$

The results in equation 2.1 match our expectations quite well.

It shows a positive and significant elasticity of R on S. The reason that the coefficients in the equation are generally quite small numbers is because the safety index does not vary greatly over the sample. Therefore, even if the elasticity of R on C were close to one, (as it is in some of Ehrlich's regressions) the impact on S=(1-C) would be much less in magnitude. (The value of S is usually very close to one.)

Turning now to the exogenous variables, the two most significant ones are NW and MDINC. As income rises the impact on S is strongly positive. On the other hand, as the percentage of nonwhites in the municipality rises, the effect on S is significantly negative. Both of these results are in line with the expectations of the model. In addition, both the nonworker-worker ratio and the unemployment rate, displayed significant negative elasticities, as had been predicted. The variable FAM also showed a negative elasticity, but with a very low 't' value. Perhaps this is due to the strong correlation between the median income variable and the number of families with income over $15,000.

The two county variables both proved inconclusive. As the median income in the county rose, the effect on safety was positive but insignificant. As the percentage of nonwhites in the county rose, the impact on safety was also positive, (which is contrary to our expectations) but here again the 't' value was very low.[7] The reason for

[7]When the regression in 2.1a was fitted without the NW variable, the elasticity of CNW was -.0026 with a 't' ratio of 1.604.

the low 't' values can be attributed to the high correlation between the corresponding county and municipal variables.

The estimation of equation 2.1a was carried out using the municipality as the basic unit of observation in the model. The theory states that the overall municipal safety rate is determined by such factors as the rate of conviction in the city, the median income in the city, the percentage of non-workers in the city, etc... The assumption is that the safety rate does not vary within the city itself. This means that the probability of non-victimization is identical for all members of the community. The underlying equation in the model, from the vantage point of each member of the community is:

$$2.1)\qquad \ln S_{ij} = \gamma_0 + \gamma_1 \ln R_i + \gamma_2 \ln X_{2_i} + \ldots + \gamma_m \ln X_{m_i} + U_i$$

where: the subscript i refers to the i^{th} municipality

the subscript j refers to the j^{th} individual.

Since the value of S_{ij} is the same for all members in each community,[8] the variance of the error term within the i^{th} community is zero. Thus when I aggregate, by considering the municipality as the unit of observation, it is not necessary to weight each observation.

A somewhat different way of looking at the model would be to

[8]The fact that at the end of the time period some members will have been victimized and others not, does not change the probability of victimization in the eyes of each citizen. It is not necessary to view S as a binary variable, since I am concerned with a probability in this case.

drop the assumption that the safety rate doesn't vary within each municipality. There may be some factors, such as an individual's own income, that may cause him to have a greater or lesser probability of non-victimization than other members of his own community. (This is clearly the case in very large cities that have many different types of neighborhoods.) In that case the underlying equation in the model would be:

$$2.1\ ) \qquad \ln S_{ij} = \gamma_0 + \gamma_1 \ln R_{ij} + \gamma_2 \ln X_{2_{ij}} + \ldots \gamma_m \ln X_{m_{ij}} + U_{ij}$$

By using municipal data, I am now taking the average value of each variable. (In the case of median income, I am using median income as an approximation of the mean income.)

$$2.1\ ) \qquad \ln \bar{S}_i = \gamma_0 + \gamma_1 \ln \bar{R}_i + \gamma_2 \ln \bar{X}_{2_1} + \ldots \gamma_m \ln \bar{X}_{m_i} + \bar{U}_i$$

In order to correct for heteroscedasticity, it is necessary to weigh the observations by the square root of the municipal populations.[9] Equation 2.1b gives the results of the weighted regressions, using the same variables as in 2.1a.

$$2.1b) \qquad \ln S = \underset{(3.326)}{-.2640} + \underset{(3.866)}{.0291 \ln R} + \underset{(4.870)}{.0540 \ln MDINC}$$

$$\underset{(6.063)}{-.0066 \ln NW} + \underset{(0.446)}{.0088 \ln CMDINC} + \underset{(0.715)}{.0018 \ln CNW}$$

$$\underset{(3.742)}{-.0395 \ln NOWRK} - \underset{(0.331)}{.0014 \ln UNEM} + \underset{(1.181)}{.0038 \ln FAM.}$$

[9] It should be pointed out that the error terms for the individual can, strictly speaking, not be normally distributed, because S is restricted to a 0 - 1 range. However, the normal distribution may be a good approximation of the distribution on S, since S is a continous variable rather than a binary variable.

The coefficients of the weighted regression give results that are quite similar in sign and magnitude to equation 2.1a. Note that the t ratios on the R variable, and on most of the exogenous variables are even more significant now, than in equation 2.1a. The only variable whose elasticity changes in sign as a result of weighting is FAM. This positive coefficient, which is contrary to the expectations of the model, may be due to the strong relationship between the number of families with income above $15,000, and many other envionmental variables such as median income, unemployment, proportion of nonwhites, etc... In other words, even if high income people do attract offenders from the outside, they happen to live in communities with so few potential offenders, that the net impact on safety is not clear. Note that in both the unweighted and the weighted regressions, ln MDINC displays a very strong and significant positive coefficient on safety, while ln FAM (which also measures an aspect of income distribution) does not.

The next equation to be estimated is the R function. (conviction rate) One premise of the model is that the community determines the appropriate level of police expenditures in an attempt to apprehend and convict offenders, in order to deter criminal activity. Yet, even a cursory look at the sample indicates that there are some municipalities that spend very little per-capita on police expenditures and enjoy a high degree of safety, while others, with much greater policing expenditures, suffer from a great deal of crime. The reason for such differences in police effectiveness is that there are environmental variables that affect the ability of the police to deter crime.

One can therefore write the equation for the 'production of R' as follows:

$$2.2)\qquad \ln R = \delta_0 + \delta_1 \ln P + \delta_2 \ln S + \delta_3 \ln DEN + \delta_4 \ln MDINC + \delta_5 \ln UNEM + \delta_6 \ln CIDX + U.$$

The two endogenous variables on the right side of equation 2.2 should show positive elasticities. As P (police expenditures per-capita) increases, then cetarius paribus, one would expect an increase in R. Holding P constant, an increase in S implies that fewer crimes per-capita occur in the municipality. This means fewer crimes per unit of police services, which would lead one to anticipate an increase in the rate of apprehension and conviction.[10]

The variable "DEN" refers to the density of the city. The impact that it has on R is a question that involves solely the technology of crime control. It would appear that the denser an area is, the more avenues of escape an offender might have.

Whether an offender will be convicted once he is charged, depends on a number of factors. Some controversy has existed over whether our legal system discriminates against the poor. Possible reasons as to why middle income or wealthy offenders might be convicted less often than offenders from lower socio-economic status, include:

[10]In a very similar regression, Ehrlich found that C has a strong negative elasticity on R, which approaches -1. C, of course, is (1-S).

i) Higher income persons are better able to afford effective legal counsel.

ii) Higher income persons receive empathy from middle income persons judging them.

iii) Higher income persons generally commit less crimes. Thus, in cases of doubt, a judge or jury are more likely to conclude that the social status of the offender would not have allowed him to commit the offense.

An additional factor that might affect the probability of conviction is the level of criminal activity that takes place outside the municipality. If the city is a 'crime importer' it may be somewhat difficult for offenders to be apprehended by local police, since many offenders live outside the city. Furthermore, if there are many crimes in the sourrounding area the county police may be too overburdened to assist appreciably any of the municipalities. In addition, the more offenses that are committed in the county, the greater the load for the county judicial system. All of these considerations would tend to lead to a lowering of the probability of conviction in any of the cities in the county. Thus, "CIDX", the county crime index per-capita, should have a negative impact on R.

If the arguments regarding the impact of the median income variable are valid, then the same logic should lead to the opposite elasticity for ln UNEM. This implies that as the percentage of persons in the labor force who are unemployed increases, the effect on the probability of conviction should be positive.

The results of equation 2.2 are:

2.2a)

$$\ln R = \underset{(2.961)}{11.28} + \underset{(1.050)}{.4140} \ln P + \underset{(1.203)}{11.137} \ln S$$

$$- \underset{(3.285)}{.2046} \ln DEN - \underset{(3.162)}{1.272} \ln MDINC + \underset{(0.297)}{.0424} \ln UNEM$$

$$+ \underset{(0.407)}{.0541} \ln CIDX$$

When the observations were weighted by the square root of population size, the results were:

2.2b)

$$\ln R = \underset{(3.395)}{11.59} + \underset{(1.017)}{.3631} \ln P + \underset{(1.725)}{10.695} \ln S$$

$$- \underset{(4.027)}{.2336} \ln DEN - \underset{(3.431)}{1.174} \ln MDINC - \underset{(0.193)}{.0278} \ln UNEM$$

$$- \underset{(0.151)}{.0189} \ln CIDX$$

It should be noted that P is an imperfect measure of the quantity of police services that are devoted to crime prevention. Firstly, P takes into account all police activities, including traffic control, parking violations, etc... Furthermore, P refers to the monetary outlays of each community for police services. I am implicitly assuming that each city in the sample receives the same services for every dollar expended. This assumption is quite plausible when dealing with small cities that can, in effect, compete for the lowest price and most efficient protection. Large cities such as Newark or Jersey City are subject to collective bargaining, which could result in substantially increased pay scales. (Since all of the observations are from the same geographic region, it is not necessary to consider cost of living differences.)

The results of 2.2a and 2.2b are very similar and are generally in line with our expectations. The P variable displays a positive elasticity on R, with a t value that is slightly greater than one. The same holds for the safety index. The density variable has a strong negative impact on R. Both the negative direction and the strength of the coefficient of ln MDINC are in line with our expectations. The results on the UNEM and CIDX variables are inconclusive in both cases. Here again, this may be due to the relationship between these two variables and some of the others on the right hand side of the equation.

Assuming the validity of the estimates from equations 2.1 and 2.2, I can now combine those results and obtain an equation for safety as a function of police expenditures. From 1.1 and 1.2, I can rewrite 1.3 in log form.

2.3) $$\ln S = \alpha_0 + \alpha \ln P + \alpha_2 \ln X_2 \ldots + \alpha_n \ln X_n + \alpha_{n+1} \ln X_{n+1} \ldots + \alpha_m \ln X_m .$$

where:

$$\alpha = \frac{\gamma_1 \delta_1}{1 - \gamma_1 \delta_2}$$

$$\alpha_i = \frac{\gamma_i}{1 - \gamma_1 \delta_2} \qquad i = 2 \ldots n$$

$$\alpha_i = \frac{\gamma_1 \delta_i}{1 - \gamma_1 \delta_2} \qquad i = n+1 \ldots m$$

In reality, the community views P as its only input for increasing safety. Equation 2.3 is therefore the true safety production function. Equation 2.1 can be thought of as a behavioral function indicating the deterrence effect of R, while equation 2.2 is the

Table 3.

Estimated Elasticities of Safety Production Function.

Variable	Unweighted	Weighted
P	.0119	.0154
MDINC	.0095	.0287
NW	-.0054	-.0096
UNEM	-.0049	-.0032
NOWRK	-.0312	-.0573
DEN	-.0059	-.0099
FAM	-.0012	.0055

production function for R. The estimates for equation 2.3, obtained by utilizing the results of 2.2 and 2.2, are shown in table 3.[11]

The last equation to be estimated is the demand curve for safety. Equation 1.8 stated that the demand for S is a function of the marginal cost of S and various exogenous variables. In order to get at the marginal cost of S, I first rewrite equation 1.3 so that P is now a function of S.

2.4) $$P = S^{1/\alpha} X_2^{-\alpha_2/\alpha} \cdots X_m^{-\alpha_m/\alpha}.$$

[11]The elasticities of the county variables, which proved insignificant in 2.1 and 2.2, were not included in table 3.

Equation 2.4 is, in actuality, the derived demand curve for P. The exogenous variables, $X_2 \ldots X_m$ are from the safety production function given in equation 2.3. What this means is that the quantity of P that is purchased depends on the equilibrium level of S that is consumed, as well as on the exogenous variables that help to determine the productivity of P. ($X_2 \ldots X_m$ have an impact on the productivity of P due to the Cobb-Douglas nature of the functions postulated in equations 2.1 and 2.2.) The only question that remains is how the equilibrium quantity of S is decided upon. The answer lies with the demand curve.

Differentiating 2.4 with respect to S, gives:

2.5) $\frac{\partial P}{\partial S} = \pi = \alpha^{-1} P/S$

$\frac{\partial P}{\partial S}$ is the marginal police expenditure required to insure one more unit of safety. (i.e. the marginal cost of S) When estimating the demand curve for S, I can simply use P/S as a measure of MCs, since α^{-1} is a constant and the equation that I am estimating is in log linear form.

It was pointed out in the previous chapter that the community is concerned with the private marginal cost of safety, rather than the social MCs. The private MCs takes into account the additional state and county police units that are gained for every dollar of increase in P.

($\hat{P} = P/(1+R')$) Rewriting 2.4 gives:

2.4') $\hat{P}(1+R') = S^{1/\alpha} X_2^{-\alpha_1/\alpha} \ldots X_m^{-\alpha_m/\alpha}$. Thus:

2.6) $\frac{\partial \hat{P}}{\partial S} = \hat{\pi} = \alpha^{-1}\hat{P}/S.$

When estimating the demand curve for safety, I now use the municipal expenditures on police per-capita, divided by the safety index, as the measure of $\hat{\pi}$.

An additional point that was made in the previous chapter was that the tax burden on the median income voter must be considered. I therefore use $K(\hat{P}/S)$ as the measure of the private marginal cost of safety as seen by the median income citizen. K is the amount that the median income voter must pay for every municipal dollar expended. (See Pp. 25-31 for a more detailed discussion.)

The exogenous variables that enter into the demand function are there because they affect the loss per offense. Municipalities that suffer very heavy losses per crime, either financially or otherwise, will purchase more safety than cities with smaller average losses, even if the MCs were the same for the two localities. The demand equation can be written as follows:

2.7) $$\ln S = \beta_0 + \beta \ln k\hat{\pi} + \beta_2 \ln MDHOME + \beta_3 \ln MDINC + \beta_4 \ln OV65 + \beta_5 \ln HH + U.$$

The sign of the coefficient of the ln $k\hat{\pi}$ variable is not intuitively obvious. In general one asumes that demand curves have negative price elasticities. In the case of crime elimination however, as long as the average loss from a crime doesn't change, the net benefit would be constant, regardless of how much safety has been 'consumed' already. This is especially true if I assume that individuals maximize expected income when they decide on how much safety to purchase. Of course, it is quite likely that as S declines the marginal loss from an offense increases, particularly when one considers such factors as increased fear and anxiety and additional expenditures on private protection. (A rational offender would always try to keep the damage that he causes at a minimum for any given level of net benefit from his offense. The greater the total number of crimes in an area, the greater the competition among offenders is. This may force offenders to opt for more damaging offenses in high crime areas.)

The variable MDHOME refers to the median home value in the community. The more valuable the property that an individual owns, the greater the loss he is likely to suffer from such crimes as burglary, robbery and auto theft. One would expect, therefore that MDHOME should have a positive elasticity on the demand for safety. The same logic holds true for the variable MDINC, with the additional consideration that high income persons also suffer greater losses from crime against the person such as murder and assult. (due to losses in earnings) The fact that these two variables are so closely related may generate a problem of multicolinearity on the regression.

The loss per crime that elderly persons suffer may be higher than for middle age persons, since an elderly person may be more seriously injured if he is victimized. Furthermore, the fear and anxiety that comes from the knowledge that escaping from or resisting an offender is virtually impossible may substantially increase the loss due to crime. Therefore, one would expect OV65 to show a positive elasticity with respect to S.

The variable HH refers to the average number of persons per household. It can be taken as an indicator of the relative size and proportion of families in the municipality. This variable can also be expected to have a positive demand elasticity on S, since, as HH increases, it implies that there are a large number of dependents (particularly children), most of whom are quite vulnerable to crime.

The unweighted regression results from the demand curve for safety are given in 2.7a.

2.7a)

$$\ln S = \underset{(3.482)}{-.2579} - \underset{(2.627)}{.0259} \ln k + \underset{(0.662)}{.0137} \ln HH$$

$$+ \underset{(3.686)}{.0420} \ln MDINC + \underset{(0.997)}{.0077} \ln MDHOME$$

$$+ \underset{(0.511)}{.0025} \ln OV65.$$

In line with our expectations, the marginal cost variable h... a strong negative elasticity on demand. All of the coefficients obtained for the exogenous variables are also consistent with the expectations of the model. The t values for the ln HH and ln OV65 variables, while positive, are not very conclusive. For MDINC the positive elasticity is significant at greater than a 99 percent level of confidence. The results also indicate that as median home values increase, so does the demand for safety. In this case the t ratio approaches one. It is interesting to note that when ln MDINC is removed as an explanatory variable, all of the other exogenous variables (particularly ln HH and ln MDHOME) gain in significance.

$$2.7a') \quad \ln S = \underset{(1.473)}{0.797} - \underset{(1.521)}{.0136} \ln k + \underset{(3.344)}{.0555} \ln HH$$

$$+ \underset{(2.663)}{.0183} \ln MDHOME + \underset{(1.039)}{.0049} \ln OV65.$$

The implication of the above results is that, in 2.7a, much of the impact of ln HH and ln MDHOME is already considered by the ln MDINC variable.

The demand curve results using a weighted regression are given in 2.7b.

$$2.7b) \quad \ln S = -\underset{(4.876)}{.4416} - \underset{(0.792)}{.0075} \ln k + \underset{(1.452)}{.0327} \ln HH$$

$$+ \underset{(3.963)}{.5039} \ln MDINC - \underset{(0.459)}{.0043} \ln MDHOME$$

$$- \underset{(0.400)}{.0023} \ln OV65.$$

In 2.7b the elasticity of the marginal cost on safety, while still negative, is of much smaller magnitude and significance than previously. The positive sign and the t ratio of the coefficient of ln MDINC is about what it was for the unweighted regression. For ln HH the coefficient was again positive with a t ratio more significant than in 2.7a. The variables ln OV65 and ln MDHOME, however, now show negative coefficients, (which is contrary to the expectations of the model) with inconclusive t ratios.

The issue of whether the demand curve should be weighted at all is questionable. In line with the discussion presented in the previous chapter, it would seem that, theoretically at least, the median income citizen is the one who determines the demand for safety. Even if this weren't quite the case, the decision on how much safety to purchase would still be the result of some concensus within the community. Thus, in every municipality, the amount of safety demanded is the same for all members of the community. If this were true the variance of the error term in the demand curve for persons living in the i th community would be zero, and consequently the problem of heteroskedasticity would not arise. It would therefore be unnecessary to weight the demand curve.

IV. Implications of the Model.

In the previous section I developed a simultaneous model designed to determine the optimal level of safety. My underlying assumption was that communities are able to choose how much safety they will have by varying the quantity of police resources that they hire. In this section I shall examine the impact of differences in the exogenous variables, and what effect they have on the equilibrium levels of S and P.

i) Let us first consider that happens as one of the exogenous variables in equation 1.3 (the safety production function) varies. By differentiating with respect to $\hat{P}$, 1 get:

$$3.1)\qquad \hat{\pi} = \alpha^{-1} S^{\frac{1-\alpha}{\alpha}} X_2^{\frac{-\alpha_2}{\alpha}} \ldots X_m^{\frac{-\alpha_m}{\alpha}} (1+R')^{-1}$$

Equation 3.1 shows how the marginal cost of safety depends jointly on the level of S that is chosen, and on the exogenous variables in the production function of S. Figure 4 depicts the marginal cost curve (BB) as a function of S. Note that this curve is positively sloped with a constant elasticity of $(1-\alpha)/\alpha$. A variation in one of the 'X' variables, (such as X_2) causes a shift in the marginal cost at all levels of S. That, in turn, has an empact on the equilibrium level of safety.

From equation 1.10, I can write:

$$3.2)\qquad \frac{dS}{dX_2} = \frac{dS}{d\hat{\pi}} \frac{d\hat{\pi}}{dX_2} = \beta \frac{S}{\hat{\pi}} \frac{d\hat{\pi}}{dX_2}$$

Differentiating 3.1 with respect to X_2 gives:

3.3) $$\frac{d\hat{\pi}}{dX_2} = \frac{(1-\alpha)}{\alpha}\,\frac{\hat{\pi}}{S}\,\frac{dS}{dX_2} - \frac{\hat{\pi}\,\alpha_2}{X_2\,\alpha}$$

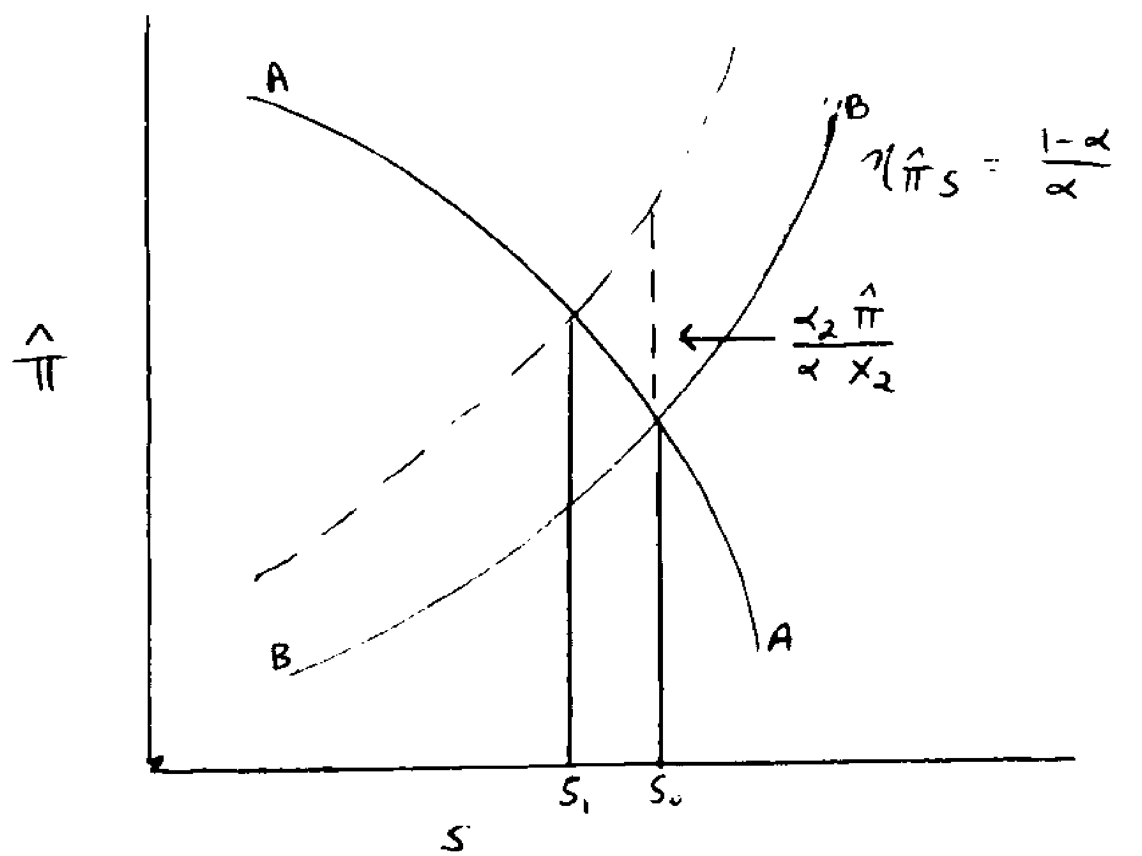
Combining 3.2 and 3.3, I get:

3.4) $$\frac{dS}{dX_2} = \beta\,\frac{(1-\alpha)}{\alpha}\,\frac{dS}{dX_2} - \beta\,\frac{S\,\alpha_2}{\alpha\,X_2}$$

It follows that:

3.4) $$\frac{dS}{dX_2} = \frac{\beta S \alpha_2}{X_2\,(\alpha - \beta + \beta\alpha)}$$ or $$\eta_{SX2} = \frac{-\alpha_2\,\beta}{(\alpha - \beta + \beta\alpha)}.$$

Figure 4.



The elasticity of S with respect to X_2, given in 3.5, represents the net effect of a change in one of the exogenous variables on the equilibrium level of safety. The change in the old equilibrium stems from a movement along the uncompensated demand curve for safety, resulting from an increase or decrease in $\hat{\pi}$. The second term on the right hand side of equation 3.3 is the change in $\hat{\pi}$ that would occur if S were held constant. (i.e. a shift in the marginal cost) In equilibrium, however, the community will not maintain the same level of S as before. Any change in the marginal cost causes an opposite change in the safety level because of the negative elasticity of the demand curve.

In the example shown (figure 4) the variation in X_2 resulted in a higher marginal cost at all levels of S. In response to this increase, the community moved up along its demand curve. The net result was a reduction in the amount of safety it 'consumes' from S_o to S_1. Note that the sign of η_{SX_2} is the same as the sign of α_2, provided that $\frac{\alpha}{1-\alpha} > \beta$, which is the case according to our assumption that $\beta < 0$ and $(0 \leq \alpha \leq 1)$. This means that is a change in X_2 has a negative impact on the safety production function, the new equilibrium level of safety will decline.

ii) Consider now the impact of a variation of an exogenous variable in the demand curve for safety.

Differentiating equation 1.10 gives:

$$3.6) \quad \frac{dS}{dY_1} = \beta \frac{S}{\hat{\pi}} \frac{d\hat{\pi}}{dY_1} + \beta_1 \frac{S}{Y_1}$$

Next, take the derivative of $\hat{\pi}$ (equation 3.1) with respect to Y_i and substitute the result in 3.6. Thus:

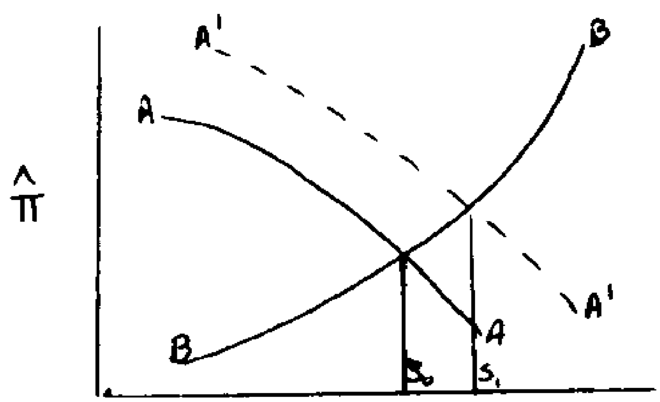
3.7) $$\frac{dS}{dY_i} = \frac{S}{Y_1} \frac{\alpha \beta_1}{(\alpha - \beta + \alpha\beta)} \quad \text{or} \quad \eta_{sy_1} = \frac{\alpha \beta_1}{(\alpha - \beta + \alpha \beta)}$$

From 3.7 it is clear that the elasticity of S with respect to Y_i varies directly with the sign of β_i. What this says is that if one of the exogenous variables in the demand function, which has a positive elasticity, varies, the net result will be more safety. In the previous chapter it was shown that one such variable is MDHOME. Holding all other factors constant, families with expensive properties have more to lose from crimes such as burglary and larceny. They, therefore, increase their demand for police protection and the net result is more S.

The above process can be seen in figure 5. As in figure 4, AA represents the demand curve for safety, while BB is its marginal cost. The curve A^1A^1 shows the shift in demand due to a variation in one of the 'Y' variables. Whether the new equilibrium level of safety (S_1) will be greater or less than S_o, depends on the sign of β_1.

iii) Suppose that there exists an exogenous variable that affects both the demand curve and the production function of S.

figure 5.



An example of such a variable is the median income in a community. As it increases the benefit-cost differential to potential offenders between legal and illegal activities declines. In addition, the opportunity cost of imprisonment rises. Thus, one expects fewer crimes. On the other hand, as was just indicated, the demand curve for safety shifts outwards since higher income people have more to lose in the event of a crime. The net result on the level of safety is obvious. Both from the demand side and from the supple side, the number of crimes should decline as median income increases.
To see all this more clearly, let us insert a new (set of) variables, Z, in equations 1.3′ and 1.10:

$$1.3^*) \qquad S = (\hat{P}(1+R')^{\alpha})\, X_2^{\alpha_2} \cdots X_{m-z}^{\alpha_{m-z}} Z^{\alpha_z}$$

$$1.10^*) \qquad S = (K\hat{\pi})^{\beta}\, Y_1^{\beta_1} \cdots Y_{k-z}^{\beta_{k-z}} Z^{\beta_z}$$

Differentiating equation 1.3* with respect to $\hat{P}$, and then obtaining an equation for the marginal cost of safety similar to that of 3.1, leads us to:

$$3.1^*) \qquad \hat{\pi} = \frac{d\hat{P}}{dS} = \alpha^{-1} S^{\frac{1-\alpha}{\alpha}}\, X_2^{-\frac{\alpha_2}{\alpha}} \cdots Z^{-\frac{\alpha_z}{\alpha}} (1+R')^{-1}$$

The way in which one finds the net impact of Z on S, is similar to much of what has already been done. The only difference now is that Z is a variable in both the safety production function and the safety demand curve.

Thus:

$$3.3^*) \quad \frac{d\hat{\Pi}}{dZ} = \frac{(1-\alpha)}{\alpha}\frac{\hat{\Pi}}{S}\frac{dS}{dZ} - \frac{\alpha_z}{\alpha}\frac{\hat{\Pi}}{Z}$$

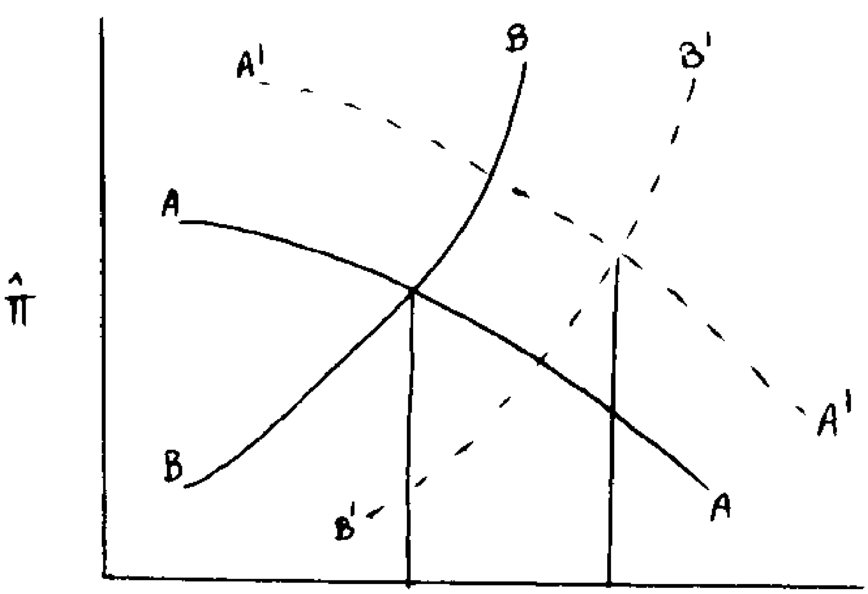
$$3.6^*) \quad \frac{dS}{dZ} = \beta \frac{S}{\hat{\Pi}} \frac{d\hat{\Pi}}{dZ} + \beta_z \frac{S}{Z}$$

Combining the two previous equations gives:

$$3.8) \quad \frac{dS}{dZ} = \frac{S}{Z}\frac{\beta_z\alpha - \beta\alpha_z}{\alpha - \beta + \beta\alpha} \quad \text{or} \quad \eta_{sz} = \frac{\beta_z\alpha - \beta\alpha_z}{\alpha - \beta + \beta\alpha}$$

As is clear, the sign of η_{sz} depends on the two terms in the numerator of 3.8. $\beta_z\alpha$ is the result of the shift in demand, (which in the case of median income is positive), while $\beta\alpha_z$ stems from the shift in marginal cost. This process is seen in figure 6.

figure 6.



Equations 3.5, 3.7, and 3.8 give us the reduced form elasticities of the exogenous variables on S, in terms of the coefficients

estimated in the previous chapter. These elasticities are presented in table four. In the last column of table four, I show the elasticities that were obtained when fitting S as a function of the exogenous variables only (using OLS). Note that in most cases the elasticities based on our model are quite close to the OLS estimates. The problem of multicolinearity would seemingly be a very serious one in this latter regression.

Table 4.

Estimated Reduced Form Elasticities of Exogenous Variables.

Variable	Unweighted	Weighted	OLS[1]
NW	-.0037	-.0065	-.0042*
MDINC	.0199	.0359	.0321*
UNEM	-.0034	-.0022	-.0073*
NOWRK	-.0216	-.0387	-.0408*
DEN	-.0041	-.0067	.0034*
FAM	-.0008	.0073	-.0007
HH	.0043	.0108	.0881*
MDHOME	.0024	- 0014	-.0030
OV65	.0008	-.0007	.0076

Turning now to the determination of the equilibrium quantity of police expenditures, I first transform equation 1.3 in order to get at the derived demand function for police expenditures.

3.9) $$\hat{P} = S^{1/\alpha} X_2^{-\alpha_2/\alpha} \cdots X_m^{-\alpha_m/\alpha} (1+R)^{-1}$$

[1] An asterick indicates that the 't' ratio for that variable in the OLS regression was greater than 2.0 The OLS regression was weighted by the square root of population.

i) In order to see the impact on P, as one of the 'X' variables changes, I simply differentiate $\hat{P}$ with respect to X_2.

$$3.10) \quad \frac{d\hat{P}}{dX_2} = \frac{\partial \hat{P} dS}{\partial S dX_2} + \frac{dP}{dX_2}\Big|_S = -\frac{\alpha_2}{\alpha}\frac{P}{X_2}\left(1 + \frac{\beta}{\alpha - \beta + \beta\alpha}\right)$$

or

$$\eta_{PX_2} = -\frac{\alpha_2}{\alpha}\left(1 + \frac{\beta}{\alpha - \beta + \beta\alpha}\right)$$

The second term on the right hand side of 3.10 shows the amount of $\hat{P}$ necessary to maintain a constant level of S, while the first term is the output effect on $\hat{P}$ due to the change in S. The resulting (reduced form) elasticity of X_2 with respect to $\hat{P}$ will be of the opposite sign of α_2, provided that $\beta > -1$. (which is very likely since the coefficients on ln S are generally very small numbers in absolute value). This means that if α_2 were to have a negative impact on the safety production function, the equilibrium police expenditure would rise even though S would fall.

To see how a variation in Y_i affects police expenditures, simple differentiate equation 3.9 with respect to Y_i, and substitute the results from 3.7.

$$3.11) \quad \frac{d\hat{P}}{dY_i} = \frac{\hat{P}\beta_2}{Y_i(\alpha - \beta + \beta\alpha)} \qquad \text{or} \quad \eta_{\hat{P}Y_i} = \frac{\beta_2}{\alpha - \beta + \beta\alpha}$$

Equation 3.11 tells us that the percentage change in $\hat{P}$ due to a variation in Y_i, will be exactly $\frac{1}{\alpha}$ times η_{SY_i}.

Table 5 .

Estimated Reduced Form Elasticities for Police Expenditures.

Variable	Unweighted	Weighted	OLS
NW	.1403	.2023	.0698*
MDINC	.8731	1.337	-.6794
UNEM	.1273	.0674	-.0687
NOWRK	.8107	1.208	.0259
FAM	.0312	-.1159	-.0019
HH	.3653	1.434	.5236
MDHOME	.2053	-.1886	.5103*
OV65	.0667	-.1009	.3543*
DEN	.1533	.2086	.0259

Since the variable Y_i has no direct effect on the safety production function, the only cause for an adjustment in $\hat{P}$ is the change in S. Equation 3.9, however, already indicated to us that for every one percent change in S, $\hat{P}$ varies by α^{-1} percent.

iii) The impact on police expenditures of a variation in a Z variable, can be seen by first rewriting 3.9 to include Z.

$$3.9^{*}) \qquad \hat{P} = S^{\frac{1}{\alpha}} X_2^{\frac{-\alpha_2}{\alpha}} \cdots Z^{\frac{-\alpha_z}{\alpha}} .$$

Differentiating with respect to Z and substituting the results from 3.9 gives:

$$3.12)\quad \frac{d\hat{P}}{dZ} = \frac{\hat{P}}{\alpha Z}\frac{(\beta_z\alpha - \beta\alpha_z) -}{(\alpha - \beta + \beta\alpha)} \frac{\alpha_z \hat{P}}{\alpha Z} \quad \text{or } \eta_{\hat{P}z} = \frac{(\beta_z\alpha - \beta\alpha_z}{\alpha(\alpha - \beta + \beta\alpha}$$

The reduced form elasticities for $\hat{P}$ are given in table five, along with the OLS estimates. Note that MDINC displays a negative OLS estimate although our model predicts a positive elasticity. When median income increases there are, in reality, two opposing forces operating. On the one hand fewer offenses are supplied, thereby lowering the demand for police services. On the other hand, as losses per crime rise, the demand for police (safety) also increases. Our model predicts that the latter will dominate and MDINC will generate an increase in overall safety. The OLS estimate shows the opposite result. Note, however, that in the OLS equation MDHOME has a much greater positive impact on $\hat{P}$ than what our model predicts. (The 't' ratio for MDHOME is 3.994.) What might be happening then, is that the OLS elasticity of MDHOME reflects the increased demand for $\hat{P}$ due to increased income and wealth. As noted previously the serious problem of multicolinearity makes the estimated coefficients of this latter regression (the OLS) very suspect.

V. Summary and Conclusions.

This study attempts to deal with two independent issues, each of which relates to the process by which the equilibrium level of safety is chosen by society. First of all, I look at the decision process from the point of view of the suppliers of crime. As with most decisions made by rational individuals, the amount of illegal act-tivity that is undertaken by an offender is part of an optimal allo-cation of resources. Before deciding on his course of action, the offender maximizes his utility function by taking into account the possible benefits and losses of his act. In the case of crime, these benefits and losses depend on the extent of the potential gain from the offense, the probability of being punished, and the severity of punishment. Naturally it is impossible to know every person's utility function. It is also impossible to know how each individual asseses the net benefit and loss that he will derive from his actions. What the above theory does suggest, however, is that there exists some function that relates the number of offenses commited by a person to some variables that affect the expected utility derived from the offense.

In addition to developing a function for the supple of offenses, I also look into the question of how society helps to determine the level of safety. By deciding upon the degree of enforcement of the criminal law, society can directly control the incentives that off-enders experience. There is little question that with enough expen-ditures it would be possible to apprehend and punish nearly every offender. The reason this is not done is because such enforcement would be very costly. Society must therefore determine just how much safety it will purchase. The decision rule will generally be to stop enforcing only when the marginal harm from an additional crime no longer exceeds the cost of preventing that crime. I have assumed that this determination, which is made collectively, is subject to the principle of majority rule, as are other decisions made by democratically elected governments.

Chapter two develops a theoretical model of this interaction between offender and society. The basic relationships proposed are those of a production function for safety and a demand function for safety. The production of safety is generated, in the short run, through the purchasing of police services.[1] The manner by which the police contribute to safety is by increasing the rate of conviction of offenders. There are, of course, many environmental variables that affect this process. As a result, for some communities the provision of safety may be much more costly than for others. This marginal cost variable enters into the municipal demand function for safety. The exogenous variables that also have an impact on the demand curve, are all related, in some manner, to the loss per crime suffered in the community.

1 In the long run expenditures on various social programs may be more effective in preventing crimes than money spent on police. Such services, however, must be undertaken by either the state or federal governments, because a local government that provides this type of program would not be able to reap most of its benefits.

Chapter three provides an empirical implementation of the equations formulated in the previous chapter. All of the major empirical results were consistent with the assumptions of the model. The rate of conviction was shown to have a significant positive elasticity on the safety rate. Those environmental variables, which can be interperted as indicating an above average net benefit from crime, produced negative elasticities, while those variables that are believed to reduce the incentives of offenders, displayed positive effects on S. Despite the shortcomings of the measure used to estimate police services, the elasticity of P on R was positive. On the demand side it was shown that an increase in marginal cost produced a negative impact on the quantity of safety that was demanded. Increases in exogenous variables, such as income and wealth, which are positively related to the losses per crime that victims suffer, both displayed positive elasticities on the demand for safety.

Chapter four presents a discussion of the net effects of the environmental variables on safety and police expenditures. The usefulness of those results is that they underscore the manner in which the exogenous variables have an impact on S and P. Consider, for example, a variable such as the rate of unemployment. An investigator who simply fits an OLS regression, with S on the left hand side and the exogeneous variables on the right hand side, would most probably find that unemployment has a negative impact on safety. What is not revealed by the OLS regression, however, is that this negative elasticity is the result of several forces interacting with one another. Intitially, as unemployment rose, with police being held constant, the number of crimes also rose. Since there were more offenses that were taking place, the marginal cost of safety declined. That, in turn, led the community to increase its demand for safety by purchasing more police services. Thus, the net impact of unemployment on S, was moderated, in part, by the increase in police expenditures. Clearly such a result, which can only be gotten by estimating s simultaneous model such as ours, is of great value to a social planner who seeks to estimate the gains from, say, a job training program.

It should be stressed that the findings of this study were, at times, hampered by limitations in the data that was available. For example, the true impact that offenders living outside the municipality have on the safety rate, could not be examined because there is no published data that lists the residences of convicted offenders. Similarly, there is no information available indicating what crimes offenders are convicted for in the courts, and what the length of sentences are. In relation to this point, one area of possible future research is whether or not there is any variation at all in the severity of punishment across municipalities, and, if so, what effect does this have on deterrence.

APPENDIX A.

A Logit Specification of the Safety Variable.

An alternative specification of the safety variable that was used in the text is the logit of S, which is defined as S/(1-S). The logit is a monotonic transformation of the safety index, and can be viewed simply as the odds in favor of not being victimized. An advantage of the logit specification is that the dependent variable is not restricted to values between zero and one.[1] When equation 2.1 was fitter using ln S/(1-S), rather than ln S, as the left hand variable, the results were:

$$\text{A.1)} \quad \ln S/(1-S) = \underset{(0.785)}{-4.818} + \underset{(1.759)}{.5084} \ln R - \underset{(5.314)}{.1416} \ln NW$$

$$+ \underset{(3.329)}{1.015} \ln MDINC + \underset{(0.151)}{.0845} \ln CMDINC + \underset{(0.538)}{.0339} \ln CNW$$

$$- \underset{(1.079)}{.3028} \ln NOWRK - \underset{(2.260)}{.2119} \ln UNEM - \underset{(0.968)}{.0786} \ln FAM.$$

For the weighted regression, the results were:

[1]The logit specification has often been used in cases when the dependent variable can only take on values of zero or one (i.e. a binary variable). In those cases the observations should be weighted by the square root of $n_i S_i(1-S_i)$, where n_i is the population of the ith city. The above term is proportional with the approximate standard deviation of the error term. In our model, however, the dependent variable is not assumed to be binary. S represents the probability of non-victimization, and is continous over the range of zero to one. The only reason for weighting the observations would be if heteroskedasticity existed, as was discussed in the text. The weight that was used in A.2 was the square root of population size.

$$\text{A.2)}\quad \ln S/(1-S) = \underset{(1.642)}{-7.719} + \underset{(2.538)}{.4489} \ln R - \underset{(7.440)}{.1915} \ln NW$$

$$+ \underset{)4.699)}{1.233} \ln MDINC + \underset{(0.319)}{.1490} \ln CMDINC + \underset{(1.239)}{.0738} \ln CNW$$

$$- \underset{(1.277)}{.3186} \ln NOWRK - \underset{(1.165)}{.1207} \ln UNEM - \underset{(0.105)}{.0080} \ln FAM.$$

The coefficient of ln R can be interperted as the elasticity of the conviction rate on the odds of not being victimized.[2] It is also equal to minus the elasticity of R on the odds of being victimized. Note that the above results are similar to the results for the corresponding regressions in the text.[3]

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[2]This is because the interchanging of S and 1-S leaves the regression unchanged, except for the signs of the coefficients.

[3]The reason that I do not show the demand for safety being estimated using a logit specification is that this would require a new and complicated term as an estimate of marginal cost. The term $k(\hat{P}/S)$ would be inappropriate, since the application 2.2 to A.1 would not lead to a marginal cost variable that is proportional to $k(\hat{P}/S)$.

APPENDIX B.

The Measure of R.

The variable R, defined as the rate of conviction, should technically take into account all of the convictions resulting from offenses committed in a municipality, divided by the total number of offenses in that municipality. Due to data limitations, there were several problems encountered when trying to arrive at this figure.

i) The criminal justice system in New Jersey (the state from which all the data was taken) includes 21 county courts for each of the counties, and 523 municipal courts. The municipal courts have jurisdiction over less serious cases such as assault, battery, larceny, and many other cases, for which the persons charged waive indictment and trial by jury. More serious cases, such as murder and rape, are taken by the higher courts.[1] Despite its limited jurisdiction the municipal court system handles over 80% of all criminal matters that are brought before the judiciary in New Jersey.

The problem was that data was only available on the total number of criminal convictions in the county courts, and the number of criminal convictions in the municipal courts. For the county judiciary, however, no breakdown was given to indicate the number of convictions stemming from offenses in any given municipality. Thus,

[1]With the exception of a few cases, the higher level state courts handle criminal matters only on appeal.

it was necessary to somehow allocate the county convictions to each of the cities within its geographic jurisdiction. The way this was done was to assume that the number of convictions from a given city in a county court, was proportional to the number of convictions handed down in that municipality's own court. The rationale behind this is that in cities where many offenders are apprehended and there are a large number of municipal court convictions, there will be a corresponding large number of county court cases. The way in which R_i was estimated can be written as follows:

B.1) $$R_i = \frac{\text{convictions}_i}{\text{crime index}_i} \left(1 + \frac{\text{county convictions}}{\sum_i \text{convictions}_i} \right),$$

where i represents the ith municipality.

ii) A second problem encountered with the data was that the municipal court figures indicated convictions on all types of offenses, even minor ones that aren't taken into account in the safety index. Such offenses include non-atrocious assault and larceny under $50, both of which are not among the seven index crimes that comprise the FBI crime index. It seems reasonable, however, to assume that the total number of convictions is a good proxy (i.e. the two figures are closely related) for the number of convictions that are handed down for index crimes. Thsi is particularly important in light of the fact that R is really only an indirect measure of how offenders asses their own personal probability of conviction. (i.e. how much deterrence there is) Generally, offenders do not posses detailed information as to what crimes were solved in a particular city and who was punished. Rather, they form an impression based on the overall effectivness of the police and the overall activity of the courts.

It is interesting that despite the shortcomings in the measurement of the conviction rate, the significance of R as an explanetory variable proved highly significant in every case. All of the other variables were also obtained from state or federal sources. (Census data was used for most of the environmental variables) The previous appendix describes a variation in the measurement of the safety index. Appendix D suggests an alternative approach for the figuring of the P variable.

APPENDIX C.

Considering the Severity of Offenses in the Safety Index.

The subject of this discussion is to present two different approaches to a measure of safety that take into account the seriousness of crimes that are committed. Thus far, when considering the safety index, I never concerned myself with the fact that some crimes cause more damage than others. The safety index has been defined as 1-C, where C is the sum of all index crimes divided by the municipal population. This popular definition of the crime index, which is used by the FBI, also does not concern itself with trying to compare the seriousness of one type of crime in relation to others.

The problem, however, is that when society determines how much resources it will spend in order to reduce the number of offenses, it does take into account the amount of damage that is caused by each type of crime. Unless one assumes that the relative number of all the types of crimes is about the same over the sample, it is necessary to develop a weighting scheme that ranks each offense in accordance with the social harm that it causes. (Another way of avoiding this problem, is to assume that variations in the mix of crimes do exist, but these variations are randomly distributed and can't be predicted by government leaders.)

In 1964 a comprehensive survey was completed by Sellin and Wolfgang, in which they attempted to index delinquency by weighting the seriousness of offenses.[1] The way the study was undertaken was to present

[1]Sellin, Thorsten and Wolfgang, Marvin E., The Measurement of Delinquency, New York: John Wiley & Sons, 1964.

lengthy questionnaires to a large number of carefully selected people. These people were asked to indicate how they felt about the relative seriousness of 141 different criminal events. The events ranged from the very severe, (for example, Number one, "An offender stabs a person to death.") to the very benign. (for example, Number 133, "The offender trespasses in a railroad yard ." Often the exact same events were repeated, with the only difference being in the amount of loss that the victim suffers. (For example, offense description number 44 was, "The offender breaks into a department store and steals merchandise worth $1,000.", while number 45 was, "The offender breaks into a department store and steals merchandise worth $5.")[2] Three groups of people were chosen to rank the severity of the offensive events. They included a total of 38 juvenile court judges, 286 police officers, and 245 university students.

The resulting index of the severity of criminal events consisted of six different categories of harm, caused by the offender. Each one of the categories was then further divided according to the degree of damage that the victim suffered. The six categories were:

1) Did the victim receive any bodily injuries? (i.e. Was he hospitalized or not, was he killed, etc...)

2) Was the victim subject to a forcible sexual act?

3) Was the victim subjected to physical or verbal intimidation or intimidation by a dangerous weapon?

[2] ibid. page 383.

4) Were there any premises that were forcibly entered?

5) Were there any motor vehicles stolen?

6) What was the extent of property loss resulting from theft, damage or destruction of property?

Based on these classifications, individual crimes could now be ranked according to the number of categories they fell under, and according to the extent of damage that they caused. In some cases crimes involved only one event. For example, a simple larceny, in which the victim was neither injured nor intimidated, would fall under only one category. The score for such a crime would depend on the value of what was stolen. If the amount was less than $10, the score would be only one, the lowest possible score. If, for example, the amount would have been from $251-2000, the score would have been three points.

There are many crimes that are quite complex and involve a series of events, each of which causes harm to the victim. For example, an offender who attacks his victim and causes personal injury, in addition to stealing $3,000 worth of property, would require his action to be classified under two categories of events, rather than one. One aspect of this crime involves the personal injury to the victim. If the victim has to be hospitalized, the number of points scored would be seven. (Had the victim been killed, the score would have been 26 - the highest possible score.) In addition to the injury, another four points must be added to this crime since $3,000 was taken from the victim.

The safety index that I shall use, which accounts for the severity of offenses, is based on the results of this study by Sellin and Wolfgang. The relative weights of the seven index crimes are given in Table Cl. These weights were obtained by assessing the average damage of each of the seven index crimes and then applying the results that Sellin and Wolfgang obtained. For example, in the case of assault, about 35% of the victims require hospitalization, about 53% are treated and discharged and about 12% suffer only minor injuries. The points applied to the above three outcomes are 7, 4, and 1, respectively. To find the average point score in this case, I simply took the weighted average of the possible outcomes.[3] (i.e. 1*. 12 + 4*.53 + 7* .35 = 4.7)

[3]The information regarding the damage caused by the various crimes was taken from FBI data. See, The Challange of Crime in a Free Society, Washington: U.S. Government Printing Office, 1967. (page 19)

It should be noted that in the same study, the federal government attempted to also asses the economic impact of crimes. The average cost of a murder, for example, was estimated at $76,000, while for a robbery the loss was set at $274. The problem with these numbers is that they do not consider the true social cost. In the case of murder, the above figure was arrived at by measuring the earnings capacity of the average victim, discounted at five percent. The costs of fear, pain and discomfort suffered by the victim and his family were not considered. Nor does this figure take into account the expenses incurred by society to apprehend, convict and punish the offender. The same problems hold true for the estimate of the economic impact of robbery. Clearly the above figures underestimate the true loss. (The figure used for robbery probably should be considered a transfer rather than a social cost, since it only takes into account the value of the property robbed.) Another difficulty with using these government figures, is that for some crimes, such as assault and rape, no estimate of the damage is given.

Table Cl.

Offense	Weight	Weight (normalized)
Murder	26	8.58
Rape	10	3.30
Assault	4.7	1.55
Robbery	6.2	2.05
Burglary	3	.99
Larceny	2	.66
Auto theft	3	.99

The weighted crime index for the i^{th} municipality can now be written as follows:

C.1) $$C_i^* = \sum_j W_j O_{ij}$$

where i refers to the ith municipality,

j refers to the jth type offense, (j = 1,...7)

O_{ij} refers to the number of the jth type offenses that occurred in the ith municipality,

W_j refers to the weight applied to the jth type offense. (See Table Cl)

The third column of table Cl shows the weights that were actually used when estimating the regressions. What was done was to normalize the W_j's so that the average of the weighted crime index should equal the average of the old crime index. This was accomplished by multiplying each W_j by the sum of all offenses in the state (unweighted), and then divide the result by $\sum_j (W_j \sum_i O_{ij})$.

The results of the unweighted regression for the safety supply curve is given in C.2 The only difference in the estimation between this equation and the equation 2.1a, is that in C.2, S has been substituted by S^*. (the corrected safety index)

$$\text{C.2)} \quad \ln S^* = \underset{(1.378)}{-.2808} + \underset{(2.276)}{.02185} \ln R - \underset{(4.761)}{.0042} \ln NW$$

$$+ \underset{(3.552)}{.0360} \ln MDINC + \underset{(0.058)}{.0011} \ln CMDINC + \underset{(0.110)}{.0002} \ln CNW$$

$$- \underset{(2.634)}{.0246} \ln NOWRK - \underset{(1.396)}{.0043} \ln UNEM - \underset{(0.394)}{.0011} \ln FAM.$$

Note that the results of equation C.2 are very similar to the corresponding results in the text for the 'uncorrected' safety index. The production function for R and the safety demand curve are given in equations C.3 and C.4 respectively. In both cases the safety index used was $S^* = 1\text{-}C^*$.[4]

$$\text{C.3)} \quad \ln R = \underset{(2.843)}{10.69} + \underset{(0.895)}{.3471} \ln P + \underset{(1.011)}{9.656} \ln S^*$$

[4]In none of the regressions brought down in this appendix were the observations weighted by the square root of population size. However, as with the estimates that are presented here, the elasticities for the corrected safety index are extremely close to those presented in the text when the equations were weighted.

C.3) Continued

$$- 1.200 \ln MDINC - .1961 \ln DEN + .0268 \ln UNEM$$
$$(3.030) \quad (3.183) \quad (0.188)$$

$$+ .0558 \ln CIDX.$$
$$(0.416)$$

C.4) $$\ln S = - .2429 - .0312 \ln K\hat{\pi} + .0101 \ln HH$$
$$(3.216) \quad (3.124) \quad (1.403)$$

$$+ .0032 \ln OV65. + .0438 \ln MDINC + .0118 \ln MDHOME$$
$$(.6336) \quad (3.772) \quad (1.403)$$

Here again the results are remarkably similar to those of the text. This similarity may be taken as evidence that either there is no variation in the offense mix across municipalities, or that the variation is random.

One advantage of the approach taken by Sellin and Wolfgang is that their results are based on the opinions of a sample chosen from the general public. Since it is the general public that decides upon the level of enforcement, it is their opinions that are most important. A problem with these results, however, is that the public was not asked to consider any other costs aside from the loss that the victim suffers. (i.e. The costs of apprehension, conviction and punishment were not taken into account.) Furthermore, it seems to be quite a formidable task for someone to asses the severity of numerous types of crimes, while not having experienced even a fraction of them. I therefore suggest an alternative way of measuring the seriousness of different offenses, based on an analysis of the activities of police departments with regard to apprehension rates. If one assumes that police departments are responsive to society's wants, then the way in which the police allocate their time and resources in deterring the various offenses should be a good indication of just how society ranks these offenses.

Consider a police department working within a given budget, B. The goal of the police is to minimize the damage caused by crimes, while still operating within its own budget constraint. The department should therefore minimize the following expression:

C.5) $$D_1 O_1 + D_i O_i + \ldots . - \lambda (c_1 + c_i + \ldots . - B)$$

where D_i - damage stemming from ith offense.

O_i - number of ith offenses,

a_i - arrest rate for ith offense, (i.e. $\frac{\text{Arrests}}{O_i}$ i)

c_i - cost of a_i.

Differentiating with respect to a_i, gives the equilibrium condition for expending police resources on any of the offenses.

C.5) $$D_i \frac{dO_i}{da_i} = \lambda \frac{dc_i}{da_i}$$

The left hand term of equation C.5 represents the marginal benefit of an increase in a_i. This equals the change in the number of ith type offenses due to the increase in a_i, ($\frac{dO_i}{da_i}$), multiplied by the damage caused by each such offense. $\frac{dO}{da}{}_{i}^{i}$ can be further broken down into:

$$c.6)\qquad \frac{dO_i}{da_i} = \frac{dO}{dR}{}_{i}^{i}\ \frac{dR}{da}{}_{i}^{i}$$

$\frac{dO_i}{dR_i}$ refers to the deterrence effect of an increase in the conviction rate of the ith type offense. Estimates of this deterrence effect were obtained by Ehrlich, when he looked into the impact of convictions on each of the seven crime categories.[5] The term $\frac{dR}{da}{}_{i}^{i}$ represents the change in the conviction rate resulting from an increase in the arrest rate. For simplicity, I shall assume that $\frac{dR_i}{da_i}$ is a constant and is equal to $\frac{R_i}{a_i}$.[6] The precentage of arrested persons who are convicted ($\frac{R}{a}{}_{i}^{i}$), is reported annually by the FBI, for each of the seven index crimes. Equation c.5 can thus be rewritten as:

$$c.7)\qquad D_i\,\varphi_i\ \frac{O}{a}{}_{i}^{i} = \lambda\,\frac{dc}{da}{}_{i}^{i}$$

where φ_i is the deterrence elasticity of R_i on O_i.

The term $\frac{dc}{da}{}_{i}^{i}$ represents the cost of increasing the arrest rate on the ith type offense. Unfortunately very little research has been

[5] See Ehrlich (1974), pages (100-101).

[6] What I am assuming here is that the functional relationship between R_i and a_i is $R_i = k\,a_i$. This means that for every arrest there is a constant probability of conviction.
Thus $\frac{dR}{da}{}_{i}^{i} = k = \frac{R}{a}{}_{i}^{i}$.

undertaken that has sought to analyze the police costs for the apprehension of specific offenders. Such an analysis would be particularly difficult because much of police work is spent on activities such as patrolling, which affects the arrest rates of all types of offenses simultaneously. Intuitively one might argue that it is less costly for the police to apprehend offenders who commit minor cimes than those who commit major crimes. This is because minor offenders stand less to lose if they are apprehended. On the other hand one could argue, that in cases of major crimes the victim(s) is likely to suffer a very large loss. Consequently he (and others) is much more eager to help the authorities apprehend the offender. That, in turn would serve to lower police costs. To avoid speculation I shall simply assume that the cost of increasing the arrest rate, for any offense category, is proportional only to the number of crimes that takes place. Thus $\frac{dc_i}{da_i} = Pa \times O_i$. Equation C.7 can now be rewritten as:

C.8) $D_i = \lambda \, Pa \, a_i \, / \, \psi_i$. This implies that:

C.9) $\frac{D_i}{D_{i+1}} = \frac{a_i}{a_{i+1}} \cdot \frac{/\psi_i}{/\psi_{i+1}}$. $i = 1, \ldots 6.$

Applying the ψ_i's that Ehrlich obtained (i.e. the deterrence elasticities), I now arrive at a system of relative weights for the damages caused by the various offenses. Theoretically, these damages take into account all of the costs that society considers. The relative weights are then normalized so that the average municipal weighted crime index is about equal to the average municipal un-

Table C2.

OFFENSE	WEIGHT
Murder	2.54
Rape	1.92
Assault	2.14
Robbery	0.91
Burglary	0.74
Larceny	0.98
Auto theft	1.25

weighted crime index. The weights that were obtained are shown in Table C2.

Equations C.10, C.11 and C.12 show the regression results for the supply of safety equation, the production of R equation, and the demand of safety equation, respectively. In all cases the dependant variable, S, was arrived at by first weighting the offenses of each municipality by the weights given in Table C2.

$$\text{C.10)}\quad \ln S = \underset{(1.373)}{-.2664} + \underset{(2.132)}{.0195} \ln R - \underset{(4.782)}{.0040} \ln NW$$

$$+ \underset{(3.643)}{.0351} \ln MDINC - \underset{(0.018)}{.0003} \ln CMDINC + \underset{(0.196)}{.0004} \ln CNW$$

C.10) Continued

$$- .0229 \ln NOWRK \underset{(2.580)}{} - .0050 \ln UNEM \underset{(1.689)}{} - .0012 \ln FAM.\underset{(0.472)}{}$$

C.11)

$$\ln R = \underset{(2.691)}{10.58} + \underset{(0.793)}{.3097} \ln P + \underset{(0.855)}{8.538} \ln S$$

$$- \underset{(2.846)}{1.171} \ln MDINC - \underset{(3.143)}{.1931} \ln DEN + \underset{(0.165)}{.0240} \ln UNEM$$

$$+ \underset{(0.368)}{.0497} \ln CIDX.$$

C.12)

$$\ln S = - \underset{(3.345)}{.2557} - \underset{(2.932)}{.0297} \ln k\hat{\pi} + \underset{(0.490)}{.0104} \ln HH$$

$$+ \underset{(3.737)}{.0439} \ln MDINC + \underset{(1.335)}{.0106} \ln MDHOME$$

$$+ \underset{(0.571)}{.0029} \ln OV65.$$

Despite the questionable assumptions that were used to arrive at the weighting scheme, the results of the above regressions are highly consistent with those in the text. This again may be taken as an indication that the variation in the offense mix across municipalities is not a significant factor when measuring safety.

APPENDIX D.

An Alternative Measure for P.

In chapter two the problem of inter-governmental transfers of police services was discussed. The question considered was how state and county police units are allocated among the individual municipalities. Several possible methods of distribution were mentioned. The one that was adopted, and later used in the empirical section, was that areawide inter-governmental police units are distributed to municipalities in proportion to local expenditures on police services. ($P = \hat{P}(1+R')$) By distributing public protection in this manner, the authorities are, in effect, lowering the marginal cost of safety, from the point of view of the municipal government. The result is that more safety will be consumed.

One problem with the above approach is that it will result in a small allocation to poor cities, that can not afford high per-capita expenditures. To rich cities, on the other hand, the allocation will also be proportional to their police expenditures, which may be quite high. From a point of view of equity, such a distribution might not be acceptable. An alternative plan would be for the state and county authorities to allocate police resources on a per-crime basis. Doing so would insure that communities with the greatest amount of crime receive the most public protection. If such a scheme were adopted, each municipality would act as if the safety production function it faces is:

$$\text{D.1} \qquad S = (\hat{P} + R^{*} C)^{\alpha} X_2^{\alpha_2} \ldots X_m^{\alpha_m}.$$

D.1) Continued

where R^* are the police resources per crime provided to the ith municipality.

The change in the expression used to measure police expenditures will have a direct effect on the estimation of the production function for R (the conviction rate). Equations D.2a and D.2b present the results of the unweighted and weighted regressions of R respectively, which correspond to equations 2.2a and 2.2b in the text. The only difference is that now P is $\hat{P}+R^* C$ rather than $\hat{P}(1+R)$.[1]

D.2a)
$$\ln R = \underset{(4.144)}{14.81} + \underset{(2.015)}{.9072} \ln P + \underset{(2.418)}{27.34} \ln S$$
$$- \underset{(4.432)}{1.715} \ln MDINC - \underset{(3.592)}{.2329} \ln DEN + \underset{(0.701)}{.1005} \ln UNEM$$
$$- \underset{(0.017)}{.0023} \ln CIDX.$$

D.2b)
$$\ln R = \underset{(3.947)}{13.09} + \underset{(1.668)}{.6774} \ln P + \underset{(2.384)}{18.59} \ln S$$
$$- \underset{(4.105)}{1.380} \ln MDINC - \underset{(4.319)}{.2566} \ln DEN$$
$$- \underset{(0.052)}{.0075} \ln UNEM - \underset{(0.422)}{.0531} \ln CIDX.$$

[1] R^* is gotten by simply dividing the total amount of state police expenditures by the total number of crimes in the state, and doing the same for each county. The sum of these two amounts is the per-crime contribution that is available to each locality.

Note that the elasticity of P on the conviction rate is more significantly positive when state and county police expenditures are assumed to be allocated on a per-crime basis. A problem with this assumption, however, is that it discourages communities from purchasing safety, because it increases the marginal cost of safety. By rewriting equation D.1 and differentiating with respect to S, one obtains the term for the marginal cost of safety.

$$\text{D.3)} \qquad P = S^{1/\alpha} X_2^{-\alpha_2/\alpha} \ldots X_m^{-\alpha_m/\alpha} - R^* S^{-1}$$

$$\text{D.4)} \qquad \hat{\pi} = \frac{dP}{dS} = \alpha^{-1} S^{\frac{1}{\alpha} - 1} X_2^{-\frac{\alpha_2}{\alpha}} \ldots X_m^{-\frac{\alpha_m}{\alpha}} + \frac{R^*}{S^2}$$

From equation 1.3 it is clear that $\frac{dP}{dS} = \pi = \alpha^{-1} S^{\frac{1}{\alpha} - 1} X_2^{-\frac{\alpha_2}{\alpha}} \ldots$

It follows that $\hat{\pi} = \pi + \frac{R}{S^2} > \pi$.

The fact that each municipality now experiences a marginal cost that is greater than π (the social marginal cost), is a result of the link between the state and county's allocation of police resources and the number of municipal crimes. Under this scheme for every crime that is eliminated, the community must not only pay for the cost of elimination, but it must also suffer the consequence of receiving less aid from the state and county. The net result is that the incentive for reducing the number of crimes would be substantially reduced if the above policy were in effect.

APPENDIX E.

The Effect of Under-Reporting of Crime.

The data on crime used in the text included only those crimes that were reported to the police. It has often been pointed out, however, that there are a large number of offenses that go unreported. The subject of this discussion is to examine what effect, if any, such under-reporting has on the estimated elasticities of the safety production function and the safety demand curve.

There have been several surveys that have attempted to measure the extent of crime that goes unreported. Most of the studys consisted of interviews with members of households regarding the number of times that they, or members of their family, were victimized over the previous year. One such survey, carried out by the National Opinion Research Center, interviewed 10,000 households and found that the incidence of crime was often several times higher than reported.[1] When those victims who had not notified the police were asked why they had not done so, the reason most frequently given was that they believed that the police would not be effective in apprehending and punishing the offender. This reason was given by 63 percent of those not reporting burglaries, by 62 percent of those not reporting larcenies, and by 50 percent of those not reporting

[1] See President's Commission of Law Enforcement and Administration of Justice, The Challange of Crime in a Free Society, Washington, U.S. Government Printing Office, 1967, Pp 20-22.

assaults.[2]

The results of the NORC survey indicate that as individuals become more confident that the police can solve crimes and recover losses, they will be induced to report crimes more often. Thus, as communities increase their efficiency in apprehending and convicting offenders, a greater percentage of crimes will be recorded by the police. This can be represented as follows:

E.1) $S/S^* = AR^{\theta}$ where:

S^* - actual safety rate $\left(1 - \frac{\text{actual number of offenses}}{\text{population}}\right)$

S - reported safety rate $\left(1 - \frac{\text{reported offenses}}{\text{population}}\right)$.

The S. term is the safety rate that has been used in the empirical analysis in the text. Since the actual number of crimes must be at least equal to the number of reported crimes, S/S^* can never be less than one. (I am discounting the possibility of an individual reporting a crime that never took place.) In general, $S/S^* > 1$. R is the same conviction rate that is defined in the text (i.e. convictions/ reported offenses). I hypothesize, based on the NORC study, that as R increases, the actual safety rate moves closer to the reported

[2] The other reasons given for not reporting offenses were, (in order of importance), i) the offense was a private matter or the victim did not want to harm the offender, ii) the victim was too confused and did not know how to report, iii) the victim did not want to take the time out to report, iv) the victim feared reprisal.

safety rate. Thus, $\theta < 0$. Rewriting E.1 and then differentiating with respect to R, gives:

E.1) $$S = AR^{\theta} S^{*}.$$

E.2) $$\frac{dS}{dR} = AR^{\theta}\frac{dS^{*}}{dR} + S^{*}\theta\frac{AR^{\theta}}{R} = (S/S^{*})\frac{dS^{*}}{dR} + S^{*}\frac{\partial(S/S^{*})}{\partial R}$$

An increase in R is now shown to have 2 effects on S, the safety rate. On the one hand the actual number of crimes declines due to deterrence, thereby causing the level of reported safety to rise. This is shown by the first term on the right side of Equation E.2. On the other hand the percentage of reported crimes also rises, thereby decreasing the apparent safety level (second term on right side of E.2). The above equation can be solved by substituting from eq 1.1 in the text. Thus:

E.3) $$\alpha\frac{S}{R} = AR^{\theta}\left(\frac{dS^{*}}{dR} + \theta\frac{S^{*}}{R}\right)$$

Multiplying both sides by R/S^{*} gives:

E.4) $$\alpha\, S/S^{*} = AR^{\theta}\left(\mathcal{E}_{S^{*},R} + \theta\right) \quad \text{or} \quad \alpha = \mathcal{E}_{S^{*},R} + \theta.$$

It is seen that α underestimates the elasticity of R on the actual safety supply curve, (since $\theta < 0$). The elasticities of the other variables in the supply curve, (X_2 for example), are not affected since, according to the assumptions in Equation E.1, S/S^{*} is proportional only to R .

E.5) $$\frac{dS^*}{dX_2} = \frac{dS^*}{dS} \frac{dS}{dX_2} = AR^{-\theta} \alpha_2 \frac{S}{X_2}$$

Multiplying by X_2/S^* gives:

E.6) $$\epsilon_{S^*,X_2} = \alpha_2$$

Consider now the impact of under-reporting on the safety demand curve. E.7 is the safety production function, with the actual safety rate rather than the reported safety rate as the dependent variable.

E.7) $$S^* = P^{\alpha^*} X_2^{\alpha_2^*} \ldots X_m^{\alpha_m^*} . \quad \text{where: } \alpha^* = \epsilon_{S^*,R} \delta_1 / (1 - \epsilon_{S^*R} \delta_2)$$

$$\alpha_i^* = \epsilon_{S^*X_i} / (1 - \epsilon_{S^*R} \delta_2) \qquad i = 1 \ldots n$$

$$\alpha_i^* = \epsilon_{S^*X_i} \delta_i / (1 - \epsilon_{S^*R} \delta_2) \qquad i = n, \ldots m.$$

By differentiating E.7, one obtains a term for the marginal cost of a change in S^*.

E.8) $$\pi^* = \frac{P}{S^*} \frac{1}{\alpha^*}$$

The demand for S^* can now be written as follows:

E.9) $$S^* = (k\hat{\pi}^*)^{\beta^*} Y_1^{\beta_1^*} \ldots Y_k^{\beta_k^*} . \qquad \text{Thus:}$$

E.10) $$\frac{dS^*}{d\hat{\pi}^*} = \frac{dS^*}{dS} \frac{dS}{d\hat{\pi}} \frac{d\hat{\pi}}{d\hat{\pi}^*} . \qquad \text{but} \quad \frac{\hat{\pi}}{\hat{\pi}^*} = \frac{\alpha^* S^*}{\alpha\ S} = \frac{\alpha^*}{\alpha\ AR} .$$

Therefore:

E.11) $$\frac{dS^*}{d\hat{\pi}^*} = \frac{\beta S}{AR^{\theta}\ \hat{\pi}} \frac{\alpha^*}{\alpha\ AR^{\theta}} . \quad \text{or} \quad \beta^* = \eta_{S^*\pi^*} = \beta .$$

It is thus shown that in the above case the estimated elasticity of the demand curve remains the same, whether the actual or the reported safety level is used as the dependent variable.

It should be noted that it is only desirable to use S^*, rather than S, if the decision markers in the community are aware of S^*. Intuitively one might argue that this is indeed the case, since residents of a community do not generally look at the crime statistics in order to determine how safe they feel. Instead, they usually make judgments based on their own victimization experiences, or on those of their friends. For large municipalities, however, such ad hoc judgments may be deemed inadequate. In those cases it would be more appropriate to use S rather than S^*, since the municipal decisions are based on the reported safety rate.

APPENDIX F.

The impact of Income on the Marginal Benefit of Safety.

In this appendix I analyze the possible effect of an increase in income (Yo) on the marginal benefit of safety, while assuming that L is held constant. I have already pointed out in the text that the major impact of an increase in Yo will be to increase the loss per-crime. That, in turn, causes a shift in the marginal benefit curve, as has been noted in Chapter Two. (See footnote 5.) The question that I am addressing now is whether there is any shift in MBs due to Yo, that is independent of the change that occurs in L. The formula for the marginal benefit of safety is given in the text as:

$$\text{F.1)} \qquad MBs = \frac{U_0 - U_1}{\bar{U}'}$$

Differentiating with respect to Yo gives:

$$\text{F.2)} \qquad \frac{dMBs}{dYo} = \frac{\bar{U}'(U_0' - U_1') - (U_0 - U_1)\bar{U}''}{U^2}$$

$$\text{where} \qquad \bar{U}'' = SU_0'' + (1-S)U_1''$$

The sign of F.2 is indeterminate. It can be shown, however, that if the marginal benefit of safety is negatively sloped with respect to an increase in S, then MBs increases as Yo does.

The change in MBs with respect to S is given in the text in formula 1.6.

1.6) $$\frac{dMBs}{dS} = \frac{\bar{U}(U_1' - U_0')\,\partial P/\partial S \;-\; (U_0 - U_1)\;(U_0' - U_1' - (\partial P/\partial S)\bar{U}'')\bar{U}'}{U^2}$$

By substituting $U_0 - U_1 = \frac{\partial P}{\partial S}\bar{U}'$, 1.6 becomes:

F.3) $$\frac{dMBs}{dS} = \frac{\partial P}{U^2 \partial S}\left(2(U_1' - U_0') + \frac{\partial P}{\partial S}\bar{U}'' \right)$$

If the marginal benefit of safety has a negative slope with respect to S, then:

$$(U_1' - U_0') + \frac{\partial P}{2\,\partial S}\bar{U}'' < 0,$$

which implies that:

$$(U_0' - U_1') - \frac{U_0 - U_1}{2\bar{U}'}\bar{U}'' > 0.$$

Assuming diminishing marginal utility of income,

F.4) $$U_0' - U_1' - \frac{U_0 - U_1}{\bar{U}'}\bar{U}'' > U_0' - U_1' - \frac{U_0 - U_1}{2\bar{U}'}\bar{U}'' > 0.$$

The first term of the inequality of F.4 is equal to $\frac{dMBs}{dYo}\bar{U}'$. (See F.2) This, however, is shown to be positive if one assumes that $\frac{dMBs}{dYo}$ is negative.

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