THE COST OF CRIME TO VICTIMS:

AN EMPIRICAL ANALYSIS

by

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February, 1978 No. 78-04

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The last decade or so has witnessed a burgeoning attention to the economics of law and legal institutions. Considerable work has been done in such areas as the optimal amount of law enforcement, response of criminals to various kinds of enforcement and penalties, and the compensation of victims.[1] Nevertheless, little if any attention has been given to a rigorous empirical study of the costs that crime imposes on its victims and potential victims. The aim of the present investigation is to make progress in filling this important gap.

Until now, the most popular method for computing crime has been that followed by the President's Commission on Law Enforcement.[2] This is a direct estimate approach which includes such things as the estimated market value of goods and property stolen or destroyed, loss of earnings due to personal injury or death, a rough estimate of expenditures to avoid crime by individuals and public agencies, etc. This method is replete with

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*I am heavily indebted to William M. Landes for a great deal of assistance. I would also like to thank Sam Pelzman and George Stigler for many helpful suggestions. None of these individuals is responsible for remaining errors.

[1] See G.S. Becker, "Crime and Punishment: An Economic Approach," Journal of Political Economy 76 (March-April 1968), 169-217; G.J. Stigler, "The Optimum Enforcement of Laws," Journal of Political Economy 78 (May-June 1970), 526-36; I. Ehrlich, "The Deterrent Effect of Capital Punishment: A Question of Life and Death," American Economic Review 65 (June 1975); 297-417.

[2] U.S., President's Commission on Law Enforcement and Administration of Justice, Crime and Its Impact--An Assessment, Task Force Reports (Washington, D.C.: Government Printing Office, 1967), p. 44.

several important defects not characteristic of our approach. First, there are serious problems in determining empirically what constitutes protection against crime, and hence there may be significant omissions (e.g., fear-of-crime related taxi rides home).[1] Second, loss of earnings due to various crimes against persons may not capture the full (subjective) costs to victims. In order to submit willingly to such crimes, individuals might well have to be compensated for more than their lost money earnings. Finally, in the presence of risk aversion, the direct estimate technique may seriously understate crime costs because, in this context, these costs will exceed the expected value of losses.

In contrast, the approach undertaken in the present study, which focuses on changes in property values associated with changes in crime, has the virtue of being able to capture (at least in principle) the costs of self-protection, the true value of lost life and limb, and the risk element of crime costs.[2]

The study is arranged as follows. The theoretical framework is presented in Section 1. A detailed empirical analysis of seventeen census tracts in the University of Chicago area (Hyde Park-Kenwood) is discussed in Section 2, and an extension of the analysis to the whole city of Chicago is undertaken in Section 3. Finally, Section 4 summarizes our results and presents some rough estimates of the dollar cost of crime to victims and potential victims.

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[1] Becker, "Crime and Punishment."

[2] This is the case so long as the types of crime under investigation are locationally specific; to the extent that they are not, our procedure yields only approximate crime costs even in principle.

I. Theoretical Framework

1. General Conception of the Model

Let us assume a closed system made up on n communities or blocks. Assume further that the system is characterized by a competitive housing industry, and in each community of that system a (not necessarily different) firm or group of firms produces the housing services (Z_i). They use land (L_i--fixed in supply for each community), capital (K_i--perfectly elastic in supply), and "self"-protection (SP_i, also perfectly elastic in supply). The firm's production function is affected by the level of crime in the community (C_i). It can produce less Z_i for given K_i and L_i, the higher is the actual level of crime (for a complete list of variable names, see appendix). The produced housing services in community i are, by assumption, perfect substitutes for those in j (for all $i \neq j$). This ensures that the price of Z must be uniform thoughout the n communities.

Since the prices of Z, SP and K are the same in all communities, our theory implies that land prices will have to adjust to (i.e., fully compensate) the different production costs that otherwise would result from various crime levels, if production in all communities is to yield equal returns. Suppose, for example, returns in community i were to exceed those in j, then demands for the inelastic factor L_i would increase until its price had risen sufficiently to wipe out these extra profits. In long-run equilibrium, all will earn the same returns and, consequently, there will be no crime advantages for the firm.

The determinants of the endowed or zero self-protection level of crime ($\hat{C}$) are exogenous to the model.[1] The actual level of crime (C), however, is affected by the amount of self-protection, and hence is viewed as an endogenous variable.

The firm's choice variables with respect to which it maximizes profits in a given community are K and SP. L is a fixed factor and, as we have indicated, $\hat{C}$ is exogenous.

2. Presentation of the Model

Let us write the firm's production function in the following way (suppressing subscripts to simplify the notation):

$$Z = g \cdot f(K,L) \tag{1}$$

where

$$g = g(C(SP;\hat{C})) \tag{1a}$$

The function is assumed to have a number of restrictions: a) linear homogeneity in K and L; b) $dg/dC < 0$; c) $\partial C/\partial SP < 0$; d) $\partial^2 C/\partial SP \partial \hat{C} < 0$; and e) $dC/d\hat{C} > 0$. Restriction (d) means that an increase in exogenous crime raises the marginal product of self-protection. The last restriction (e) requires that <u>even after</u> optimal readjustment of self-protection, the actual crime level will be higher the greater is $\hat{C}$. Although this doubtless has considerable intuitive appeal,

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[1] In the absence of self-protection there is, nevertheless, a finite amount of crime for two reasons. First, some collective protection may be provided by the public authorities through the tax system (the mechanism by which this protection is provided and how it responds to changes in the crime rate are clearly beyond the scope of this paper). Second, the marginal resource cost of committing crime is, of course, positive (and probably rising) even in the absence of all protection.

it would be well to specify precisely the basis upon which this statement rests. That an increase in $\hat{C}$, because it raises $-\partial C/\partial SP$ and (holding K constant) the quantity of SP employed, would reduce the actual level of crime below its previous level is inconsistent with out general assumption that crime is an economic "bad." If the previous effect were true, then $\hat{C}$ would be an economic good since firms had the option of increasing SP before $\hat{C}$ rose, but did not. In effect, the increased $\hat{C}$ would have lowered the price of reducing actual crime.

The firm, then, behaves as if it maximizes the following profit function with respect to K and SP:

$$\pi = P_z[f(K,\hat{L}) \cdot g(C(SP;\hat{C}))] - P_\ell L - P_k K - P_{sp} SP \tag{2}$$

where π = profits, P_Z = price of a unit of Z, P_ℓ = price of a unit of land, P = price of a unit of capital, P_{SP} = price of a unit of self-protection. P_Z, the numeraire, is fixed. The first order conditions are

$$\frac{\partial \pi}{\partial K} = P_z \cdot f_k \cdot g - P_k = 0 \tag{3}$$

$$\frac{\partial \pi}{\partial SP} = P_z \cdot f \cdot \frac{\partial g}{\partial C} \cdot \frac{\partial C}{\partial SP} - P_{sp} = 0. \tag{4}$$

The decision variables--K and SP--are at equilibrium levels when the price of each input is equal to the value of its respective marginal products in terms of Z.

The firm is in long-run zero profit equilibrium when the value of the total product is exactly exhausted by the land, capital and self-protection payments, i.e., when

$$ZP_z = LP_\ell + KP_k + SP\ P_{sp} \tag{5}$$

On the basis of this simple framework, we shall first investigate the response of factor inputs (capital and self-protection) to a rise in the endowed crime rate, and then we shall proceed to determine the impact of such a rise on the price of land.[1]

(1) Returning to the first order condition (equation 3), it is clear that so long as an increase in $\hat{C}$ results in a lowering of g in equilibrium, the amount of capital, K, must fall. The equilibrium value of g will, in fact, fall if an increase in $\hat{C}$ results, as we have claimed, in higher actual crime (C), even after the optimal readjustment of self-protection (equation 4). Since there is diminishing returns to K, the only way that the value of the marginal product of $K(P_z \cdot f_k \cdot g)$ can remain equal to its fixed price is for the quantity of K employed to drop. Hence, under these assumptions, the sign of $dK/d\hat{C}$ must be negative.

(2) Holding K constant (as it would be in a short-run analysis), there is no doubt that an increase in $\hat{C}$ would (via $-\partial^2 C/\partial SP \partial \hat{C} > 0$) lead to an increase in the quantity of SP employed. However, the sign of the <u>total</u> derivative $(dSP/d\hat{C})$ which permits optimal adjustment of K is unclear. Since K falls, then so will f (equation 4) and hence it is possible that this fall will more than offset the rise in $(\partial g/\partial C \cdot \partial C/\partial SP)$. That is, while a rise in $\hat{C}$ raises the marginal "physical" product of SP, the marginal <u>value</u> product $(P_z \cdot f \cdot \partial g/\partial \hat{C} \cdot$

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[1] A more detailed mathematical analysis is to be found in Mario J. Rizzo, "Rents, Property Values and the Cost of Crime to Victims," University of Chicago, Department of Economics, Ph.D. Dissertation (August 1977), Appendix II.

$\partial C/\partial SP$) might decline. Firms might let K so deteriorate that the value of what is being protected might fall substantially, enough to offset an increase in the "physical" efficiency of SP. Hence, in the long run, the sign of dSP/dC can be either positive or negative, and no a priori restrictions can be placed upon it.

(3) Now that we have discussed the impact of a change in $\hat{C}$ on K and SP, let us determine the impact of the former on the price of land. Equation (5) can be written as

$$P_\ell = \frac{P_z}{L} Z - \frac{P_k}{L} K - \frac{P_{sp}}{L} SP \tag{6}$$

Taking the total differential of P_ℓ (assuming P_z, P_k, P_{sp} constant) and making appropriate substitutions yields

$$dP_\ell = \frac{P_z}{L} f \frac{\partial g}{\partial C} \frac{\partial C}{\partial \hat{C}} d\hat{C} \tag{7}$$

Transforming the lefthand side into elasticity form gives us

$$\frac{dP_\ell}{d\hat{C}} \frac{\hat{C}}{P_\ell} = \underset{(+)}{\frac{P_z}{L}} \underset{(+)}{f} \underset{(-)}{\frac{\partial g}{\partial C}} \underset{(+)}{\frac{\partial C}{\partial \hat{C}}} \underset{(+)}{\frac{\hat{C}}{P_\ell}} < 0 \tag{8}$$

Hence, it is evident that, regardless of the sign on $dSP/d\hat{C}$, the effect of a rise in $\hat{C}$ on P_ℓ is necessarily negative.

The unobservable total elasticity $dP_\ell/d\hat{C} \cdot \hat{C}/P_\ell$, because it allows for optimal adjustment of SP, may be interpreted as having the same sign as the observable $dP_\ell/d\hat{C} \cdot \hat{C}/P_\ell$. To see this more clearly, let us rewrite equation (8) in terms of the observable elasticity. Making substitutions yields:

$$\frac{dP_\ell}{dC}\,\frac{C}{P_\ell} = \underset{(-)}{\frac{-\varepsilon_{g\hat{c}}}{s_\ell}}\;\underset{(+)}{\frac{1}{\varepsilon_{c\hat{c}}}} < 0 \qquad (9)$$

where $-\varepsilon_{g\hat{c}}$ = the elasticity of g with respect to $\hat{C}$, s_ℓ = the share of expenditures on housing services ($P_z \cdot Z$), and $\varepsilon_{c\hat{c}}$ = the elasticity of C with respect to $\hat{C}$. From (9) it follows that not only is the observable elasticity necessarily negative, but also that the greater the percentage decline in g and the smaller the share of land, the greater is the percentage reduction in P_ℓ.

3. Application of the Model

At the margin, the consumer is indifferent as between self-protection and endurance of an additional unit of crime.[1] Hence (assuming that a small change in $\hat{C}$ is associated with a small change in SP), the price of land-endowed crime elasticity ($dP_\ell/d\hat{C} \cdot \hat{C}/P_\ell$) is not affected by changes in self-protection (equation 8). It does not matter whether the effect of additional $\hat{C}$ is by way of greater actual victimization or through the costs of additional self-protection. Nevertheless, the price of land-actual crime elasticity is affected by changes in self-protection. The greater the increase in SP induced by a rise in endowed crime the smaller (*ceteris paribus*) will be $\varepsilon_{c\hat{c}}$. From an examination of (9), it ought to be clear that a smaller $\varepsilon_{c\hat{c}}$ will be associated with a larger elasticity of P_ℓ with respect to observable crime.

In general, there is no presumption about the relative magnitudes of these elasticities. However, we can say that the cost of crime will not be

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[1] In equilibrium, this marginal cost of self-protection is equal to the cost of the increment in crime that is being avoided through SP.

misstated by the observable elasticity in any event. If, for example, a one percent rise in $\hat{C}$ is associated with a less than one percent rise in C, then the observed elasticity will be greater than the theoretical. Nevertheless, this does not mean that we have over-estimated the true cost of crime. Remember that the smaller percentage rise in C is the consequence of the increased productivity of the existing quantity of SP and, say, an increase in the amount of SP employed.[1] Hence, this (smaller) percentage rise in C carries with it both the marginal effects of actual crime <u>and</u> the marginal costs of self-protection.[2] Since self-protection ought to be considered a genuine crime cost, no overstatement is involved.

In our empirical estimates, therefore, it would be unnecessary to include some measure of SP as an independent variable explaining property values.[3] This is captured in the percentage change of C. The effect is to combine the marginal cost of actual crime with the marginal cost of crime avoidance (self-protection) in the coefficient of ℓn C, the sum of which constitute the cost of crime.[4]

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[1]Of course, SP need not rise if K fell sufficiently. See argument in Section 2, above.

[2]Or the marginal effects of crime-induced capital deterioration.

[3]More precisely, it is unnecessary to include a measure of the self-protection which is not embodied in the housing structure (e.g., crime-induced taxi rides home). However, the omission of embodied self-protection (e.g., locks on the door) as an independent variable will tend to create a downward bias in our estimates of the cost of crime. This is because embodied self-protection will raise the value of the structure (while, of course, lowering the value of the site). To the extent, therefore, that our property value measures do not capture pure site value, it will appear as if crime has reduced site property values by less than it actually has.

[4]We do not include a measure of collective protection as an indepen-

Our theoretical framework, like many in the area of urban economics, employs the Ricardian assumption of an inelastic supply of land. To the extent, however, that land is not perfectly inelastic in supply, the effect of crime on the price of land understates the true cost of crime. If capital were somewhat less than perfectly elastic in supply, then, to some degree, the price of capital would be a residuum and would capture some of these crime costs. However, in the long run, this is unlikely to be the case. Therefore, insofar as crime costs can be measured by some implicit market they are likely to be captured by land and not capital prices.

II. Hyde Park-Kenwood

1. The Data: Nature and Sources

The first part of our empirical study consists of a block-by-block analysis of Chicago's Hyde Park and part-of-Kenwood communities (essentially, the University of Chicago area).[1] These communities were chosen because the South East Chicago Commission had tabulated for them a detailed record of crime on a block basis.

Three types of data are used as dependent variables. First, we collected 1970 contract rents of renter-occupied housing (from the Census of Housing)

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dent variable because, on the assumption that tax rates in a given political subdivision (e.g., Chicago) are the same everywhere, differences in collective protection are basically differences in the exogenous crime environment.

[1]This includes thirteen Hyde Park census tracts (excluding tract 4113, which is characterized by high transient population--see Section 4, below), and the four available Kenwood tracts.

for 111 blocks in this area.[1] Second, we used 324 prices (85 blocks) of single-family homes transacted over the five-year period 1968-72.[2] Third, we then returned to the Census of Housing and used owner-estimated 1969 values of owner-occupied housing for the total of 68 blocks for which data were available. A comparison of the results of the latter two sets of regressions would probably be suggestive of the reliability of owner-estimated values versus true (transaction) prices.

In the first section, we examined the impact of crime on the theoretical variable P_{ℓ} which is the rental price per unit of site (land). The contract rent data collected for renter-occupied housing and used in this section approximately correspond to $P_{\ell} \cdot L + P_k \cdot K$.[3] When the size of the apartment and the quantity of capital embodied in it are held constant, we can determine the effect of an environmental variable (such as crime) on site rents per homogeneous unit. The property value data consist of the value of the structure and the land. This approximately corresponds to the net discounted value of the future $P_{\ell} \cdot L + P_k \cdot K$. If we hold the lot size and quantity of embodied capital constant, we are able to determine the effect of crime on site property values per homogeneous unit.

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[1]There were about 150 blocks in the census tracts studied, but only for 111 of them were rental data published in the 1970 Census of Housing.

[2]These were collected by Professor Brian J.L. Berry, Formerly of the Department of Geography, University of Chicago (now of Harvard University).

[3]If "self-protection" is also being rented to the consumer in a joint product (e.g., locks, gates on windows, etc.), then $P_{sp} \cdot SP$ is also measured.

Extensive reported crime data were compiled from information collected by the South East Chicago Commission on all the FBI index crimes.[1] Two types of crime rates were computed. First, a rate of crime-on-the-block was assigned to each of the census blocks (own-block crime rate). Second, a rate for the average of all of the contiguous blocks (excluding the own-block) was assigned to every census block. All of these "rates" were the absolute number of crimes per 1,000 population, averaged over the three-year period 1969-71. The categories of crime used were total index crimes, crimes against persons, and crimes against property.[2]

2. Functional Form

The dependent variables and most of the independent variables, including crime, were entered into the estimating equations in logarithmic form. The log transformation of the rent or property variable is useful because it enhances at least an informal comparison of the effect crime has on rents versus property values since the units compared are now the same. The log transformation of the crime variables is particularly important. On the assumption of equal percentage rates of under-reporting in the crime statistics for the various blocks (rather than equal absolute amounts of under-reporting--a plausible a priori assumption), the log transformation was deemed beneficial.[3] This is

[1] Index crimes are murder, non-negligent manslaughter, forcible rape, robbery, serious assault, burglary, theft, and auto-theft.

[2] Results for two specific crimes--burglary and robbery--are included in Mario J. Rizzo, "Rents, Property Values and the Cost of Crime to Victims," op. cit.

[3] See I. Ehrlich, "Participation in Illegitimate Activities," Journal of Political Economy 81 (May-June 1973), 561.

because with equal percentage under-reporting the absolute differences among crime totals on the various blocks are understated by the measured statistics as compared to the absolute differences among the true crime totals. By concerning ourselves only with percentage differences, we obviate this difficulty.

3. Aspects of the Crime Data

Prior to examining our estimating equations, let us investigate briefly the stability of crime over the three-year period for which we have data. If crime levels jumped around unpredictably from year to year, we would not expect much effect, if any, of crime on rents or property values because the market would then be unable to anticipate such changes in price differentials.

To examine this issue we correlated the absolute number of index crimes for 1969-71 for all 119 blocks in our sample. Although three years is a short period of time, the results are suggestive. They indicate a high positive correlation between yearly totals of crime. In addition, there was an even somewhat higher correlation between the absolute number of contiguous block crimes over the same period. All of these results suggest that the permanent component is substantial in any given year's total as there exists a linear function which enables us to predict much of next year's crime on the basis of this year's.[1]

The last aspect of the crime data which we shall investigate before turning to the regressions is the degree to which contiguous and own-block

[1]The correlation between the logs of yearly crime totals are .78 for 1969 and 1970, .72 for 1969 and 1970, and .75 for 1970 and 1971. The corresponding coefficients of correlation for contiguous block crime are .89, .86, and .85, respectively.

crime are correlated. Given knowledge of the contiguous block's crime, can we predict the own-block crime rate (and vice versa)? Surprisingly, the correlation results indicate that we cannot predict very much of the one from knowledge of the other other. The correlation between own-block and contiguous blocks total crime is only .32, with burglary having the highest correlation (.42).

These results are consistent with the view that criminals, whether because the productivity of their resources differs substantially from block to block or because costs differ, are highly mobile with respect to their activities. Nevertheless, this conclusion ought to be interpreted with great caution because of the measurement difficulties involved.[1]

4. Transient Population

In order to estimate the impact of crime on (site) rents or (site) property values, we must hold constant, in effect, the quantity of K embodied in the property[2] and all the other factors which affect site value. In the theoretical section, we assumed these factors away by postulating that the blocks or communities were the same except for differing levels of crime.

However, before we can estimate this impact of the crime rate on rents and property values, we must ensure the accuracy of that rate by using a reliable

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[1]Another reason for the low own- and contiguous-block crime correlation lies in the transient population issue discussed in Section 4. Examination of the data reveals that blocks with high transient population (and hence an overstated crime rate) are generally surrounded by non-transient blocks. To the extent that this is the case, higher than average own-block rates will often be associated with lower than average contiguous block rates.

[2]We assume capital to be homogeneous (apologies to Joan Robinson and Ludwig Lachmann), and hence a house or apartment of better quality is merely one with a greater quantity of capital units embodied in it.

measure of population. Unfortunately, for some blocks no such reliable measure is available. These are blocks which are characterized by a heavy transient population such as those with shopping areas.[1] The presence of considerable transient population generates an inaccurate measure of per capita crimes. To indicate simply the nature of this problem, consider the following. The measured population for an area does not include the so-called transient population, and since some of these latter people are victims of crime, the crime rate to the true residents is thereby overstated. If the observed crime rate for each area were proportionately overstated by the same amount, then, obviously, the true percentage difference in these rates would be undistorted. This, however, is not the case. Almost all of the transient population is contained in areas where both measured population is low and measured crime rates are high. Hence, in these high measured crime areas the percentage understatement of the population subject to crime will be largest, and thus the percentage overstatement of measured crime rates will be greatest. The high crime rates, then, are distorted upwards by a greater percentage than the low crime rates.

We have attempted to deal with this problem by introducing a transient population dummy variable (TPD) into our regression equations. A block is assigned a value of one, if it has substantial transient population, and zero

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[1] Blocks were considered to have a heavy transient population if they met any one of the following criteria: the block had a substantial number of daily shoppers; was contiguous to an Illinois Central commuter train station; had a relatively large park; had hotels or motels (transients in hotels or motels are not counted as population on that block by the Census Bureau); contained a school or hospital; or had a relatively large parking lot. The Census Bureau population figures contain only the permanent population of the block.

if it does not. The TPD serves to hold transient population constant and thus to ensure that (percentage) changes in the measured crime rate more closely approximate changes in the true crime rate. This reduces the distorting effect of the incorrectly measured high crime blocks.[1]

5. Rent Equations

There were 111 census blocks in the University of Chicago neighborhood for which contract rent data were available. These observations were regressed on measures of the quantity of capital embodied in the renter-occupied housing as well as environmental variables besides crime. The following non-crime variables were entered into the estimating equations:

LANRR	=	log of average number of renter rooms
LNEW60	=	log of proportion of housing built after 1960
LINC	=	log of median family income
DISUC	=	distance from University of Chicago campus
WHPRO	=	the proportion of whites
EHPD	=	East Hyde Park dummy; East = 1
PD	=	park dummy; contiguous to a park = 1
TPD	=	transient population dummy; transient = 1

The average number of rooms (LANRR), the proportion of housing constructed after 1960 (LNEW60), and median family income (LINC) fit into the capital category. Income is interpreted as a proxy for the quality elements which we have not captured in our other variables. It is especially important to take into account adequately the quality aspect because one might make a plausible case that high crime blocks (also low-income areas) are low housing

[1]The problem is not entirely eliminated, however. Because of this it was thought best to omit the census tract (4113) which contains the University of Chicago campus. This tract has a small permanent population but a high transient population.

quality blocks and hence what appears to be the effect of crime on rents (and property values) is, in large part, the effect of low quality. However, because the Census of Housing does not report income on a block-by-block basis, we were forced to assign to each block in a census tract the income statistic for that tract as a whole. (There are 17 tracts in our 111 census blocks.) So the usefulness of income as a quality proxy in this body of the data is limited. A priori, we do not expect a very large or significant effect of this variable. LNEW60 is another variable for which we do not have a block breakdown. Again, we assign a value to each block on the basis of the tract in which it is located.

Distance from the University of Chicago campus (DISUC), the proportion of whites (WHPRO), the East Hyde Park dummy (EHPD), and the contiguity to a park dummy (PD) can all be viewed as environmental factors which affect the quantity of housing services (Z) which can be produced with given land and capital. In other words, these variables affect the amount of housing services which are embodied in a certain physically specified quantity of housing. Hence, they will affect the price of an observed unit of housing. As a consequence, these factors must be held in constant to isolate the effect of crime.

Examining briefly (Table 1) the non-crime variables in our estimating equations, we find a number of interesting results. However, as the purpose of this study was not to compile a "complete" list of the determinants of rents and their significance, we have been more concerned with "zeroing in" on the crime variables than on the other independent variables. Our discussion, then, of the other variables will be rather limited.

TABLE 1

HYDE PARK RENT REGRESSIONS WITH INCOME

Independent Variables	Dependent Variable: LRENT (n = 111)		
C	3.91 (5.56)	3.89 (5.48)	3.81 (5.38)
LANRR	0.37 (6.70)	0.35 (6.41)	0.38 (6.93)
LNEW60	0.02 (1.51)	0.01 (0.89)	0.03 (1.70)
DISUC	0.15 (2.69)	0.06 (1.16)	0.18 (3.15)
WHPRO	0.28 (6.19)	0.25 (5.46)	0.29 (6.39)
EHPD	0.08 (1.64)	0.11 (2.12)	0.08 (1.49)
PD	0.003 (0.12)	0.01 (0.35)	0.002 (0.07)
TPD	-0.001 (0.04)	-0.024 (0.77)	-0.005 (0.17)
LINC	0.11 (1.34)	0.07 (0.90)	0.11 (1.49)
LTO3	-0.098 (3.97)	--	--
LMCTO3	-0.077 (3.28)	--	--
LVPER3	--	-0.057 (3.57)	--
LMCVPER	--	-0.062 (3.75)	--
LVPRO3	--	--	-0.103 (4.09)
LMCPRO	--	--	-0.075 (2.86)
	R^2 = .673	R^2 = .669	R^2 = .668
	SE = .130	SE = .131	SE = .131

t values in parentheses.

LANRR behaves as we would expect with a strong positive effect on rents. The sign of LNEW60 is also positive as expected but is smaller and less significant statistically. Doubtless, this is due, in large part, to the measurement difficulty noted above. The sign of DISUC, however, is puzzling. Hyde Park is essentially a university community and, as such, one might expect proximity (ceteris paribus) to the camput to raise rents and, hence, that the sign of DISUC would be negative. A plausible explanation for the significant positive coefficient is that DISUC is confounding the pure distance effect with an environmental amenities effect. Within the class of renter-occupied units, it is often true that housing units farther from the university are closer to shopping areas and transportation.

WHPRO has a highly significant positive coefficient. This should be interpreted with caution and not as a pure race variable. Since it is well documented that, on average, whites inhabit higher quality housing than do non-whites,[1] WHPRO is probably a better measure of average quality on a block than is LINC (or LNEW60). This is because for racial composition, unlike income or building age, we have a block-by-block breakdown. Hence WHPRO ought to be interpreted as, in part, a housing quality measure.

EHPD has an expected significant positive coefficient reflecting, presumably, the greater amenities available in East Hyde Park such as increased proximity on average to transportation and to Lake Michigan, more convenient shopping and, possibly, the higher quality of housing.

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[1]On this see M.R. Straszheim, An Econometric Analysis of the Urban Housing Market (New York: Columbia University Press for the National Bureau of Economic Research, 1975), p. 56.

Finally, the contiguity to a park dummy (PD) does not have the expected statistically significant positive sign. It was thought that holding crime constant, proximity to a park would be an amenity.

6. Crime Elasticity Estimates in Rent Regressions

Estimates were obtained for three major crime variables: total index crimes; crimes against persons; and crimes against property. It is important to note that the crime measures are unweighted and hence, obviously, a one percent increase in the total may not be accompanied by a one percent increase in the component crimes.

The three crime variables were run in separate regressions, each containing the own-block measure and the contiguous blocks measure of that crime category. Results are presented in Table 1. Since income is also a proxy for many other things besides housing quality, these equations were re-estimated without income (LINC) as an independent variable. These results are not presented because they are virtually identical to those of Table 1. In particular, it is clear that the inclusion of income does not change the crime coefficients. We can conclude that, subject to the limitations of median tract income as a proxy for housing quality, the crime coefficient is not picking up the effect of low quality on rents.

Table 2 reports the total or summed effect of crime on the block and crime on the contiguous blocks as well as the relevant t values. The sum of the coefficients should be interpreted as the (percentage) effect of a one percent increase in both own-block and contiguous blocks crims as we "move" from one sub-area to another in this community (i.e., the differential rent effect). As

7. Property Values: Transaction Prices

In order to determine the impact of our crime measures on property values, a data set of 324 transactions of single-family houses was used. These transactions took place between 1968 and 1972 in 17 Hyde Park-Kenwood census tracts (in the same area covered by our rent data). Each sale was treated as a separate observation and so the estimating equations had 324 observations. The disaggregation explains the low R^2 that characterizes these results in contrast to the considerably higher R^2 in the rent equations.

As a measure of lot size was not available for these house sales, a proxy was developed in an effort to hold lot size constant. Two variables function as this proxy: the ratio of single-family houses to the total number of housing units on the block (LSINPRO), and the absolute number of single-unit houses on the block (LUNITS1). They were both entered in logarithmic form. Holding the proportion of single-family houses constant, an increase in the absolute number reduces the (average) lot size available to each. The expected sign of LUNITS1 is thus negative. Now, holding the absolute number of single-family houses constant, raising their proportion increases the (average) lot size. Hence the expected sign of LSINPRO is positive. Together they yield a lot size proxy.[1]

[1] It might be suggested that an increase in the proportion of single-family houses (or a decrease in the proportion of renter-occupied housing) has no effect, *ceteris paribus*, on average lot size, but rather captures the height of apartment buildings. This interpretation, of course, leaves the signs of the LSINPRO and LUNITS1 coefficients unexplained. Why, for example,

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Since the observations for the dependent variable are not contemporaneous, a year dummy (YD) was introduced to account for a pure "inflation" effect. If the sale was made in either 1968 or 1969 a zero was assigned; sales between 1970 and 1972 (inclusive) were assigned a one.[1]

The first two variables in Table 3 (LANRO and LNEW60) are of the expected sign although smaller and weaker statistically than their counterparts in Table 1. This is to be expected, however, since for neither of these two variables was data available on the characteristics of the particular house sold. In the former case, therefore, the average characteristic for the entire block was used and in the latter case the tract average had to serve as a best available proxy.

In these regressions, distance from the University of Chicago campus (DISUC) shows up with the expected negative sign and is statistically significant. The sign of LINC, on the other hand, is statistically insignificant. The proportion of whites (WHPRO) which was a very significant variable in the rent regressions is totally insignificant here (although of the same positive sign). This is perhaps due to the considerably lower variation in this variable among houses sold than among renter-occupied units. The negative sign on the East Hyde Park dummy (EHPD) is inconsistent with our expectations and with rent results.

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should we expect that holding the height of apartment buildings constant (LSINPRO on this interpretation), an increase in the number of single-family houses will lower the price of the latter? It should be noted that the argument in the text implicitly assumes that the size of the block is held constant. A map analysis of this area indicates that the blocks do not differ very substantially in size, so the assumption seems generally warranted.

[1]A further breakdown of the sales dates was not available in this data.

TABLE 3

HYDE PARK SALES PRICE REGRESSIONS

Independent Variables	Dependent Variable: LSVAL (n = 324)		
C	11.42	10.65	11.49
LANRO	0.130 (1.03)	0.191 (1.55)	0.108 (0.86)
LNEW60	0.049 (1.36)	0.049 (1.36)	0.054 (1.52)
DISUC	-0.089 (1.81)	-0.20 (1.86)	-0.026 (1.22)
LINC	-0.057 (0.40)	-0.118 (0.81)	-0.034 (0.24)
WHPRO	0.006 (0.057)	0.014 (0.13)	0.013 (0.13)
EHPD	-0.11 (1.02)	-0.10 (0.92)	-0.13 (1.18)
PD	0.23 (3.78)	0.22 (3.57)	0.22 (3.73)
YD	0.18 (3.76)	0.18 (3.71)	0.18 (3.88)
TPD	0.26 (4.02)	0.19 (3.44)	0.27 (4.28)
LSINPRO	0.093 (2.69)	0.075 (2.17)	0.092 (2.72)
LUNITS1	-0.059 (1.63)	-0.054 (1.48)	-0.054 (1.52)
LTO3	-0.167 (2.71)	--	--
LMCTO3	-0.061 (1.37)	--	--
LVPER3	--	-0.079 (2.27)	--
LMCVPER		-0.016 (0.61)	

Table 3--continued.

Independent Variables	Dependent Variable: LSVAL (n = 324)		
LVPRO3	--	--	-0.183 (3.19)
LMCVPRO	--	--	-0.075 (1.40)
	R^2 = .23	R^2 = .22	R^2 = .23
	SE = .380	SE = .382	SE = .378

The last five non-crime variables--PD, YD, TPD, LSINPRO, LUNITS1--are all statistically significant and consistent with our expectations as outlined previously.

Turning now to the crime coefficients, the results in Table 3 as contrasted to Table 1 suggest that the (elasticity) effect on property values is somewhat greater than that on rents. Furthermore, in this case (as in the rent regressions) the coefficients of the own and contiguous crimes are not significantly different. In Table 4 are presented the sum of the own-block and contiguous block crime effects with the appropriate t values for the major crime categories. Each is highly significant.

8. Owner-Estimated Property Values

This is really a prelude to the next section. In the Chicago-wide data discussed in that section, we used owner-estimated values as the dependent variable. In order to get some suggestion of the direction of bias produced by

TABLE 4

SUM OF OWN AND CONTIGUOUS EFFECTS

Dependent Variable: LSVAL (n = 324)		
Crime	Elasticity	t-statistic
Total Index Crimes	-0.228	-2.85
Crimes Against Persons	-0.095	-2.03
Crimes Against Property	-0.258	-3.14

using estimates instead of true market values, we ran essentially the same regressions as in Table 3 with Census of Housing owner-estimated property values instead of the sales prices. Unfortunately, estimates were available for only 68 blocks and hence the samples do not fully overlap (only 54 blocks had both sales price data and estimated values in comparison with 85 blocks having the former). The main difference between these two sets of data is that the estimates refer to all owner-occupied housing and not just single-family houses.

The crime coefficients of the main categories and their appropriate t values dropped sharply. The elasticities are about half the size of those in the sales price equations (Table 4).[1] Clearly, the results suggest that if there is any systematic bias introduced by using owner-estimates as the dependent variable, it is in the downward (in absolute value) direction. Yet the t statistics are rather small (even for one-tailed tests) and so the evidence presented here is rather limited.

[1]The elasticities of the sum of the own-block and contiguous effects are -.120 (t = -1.11), -.053 (t = -.88), and -.096 (t = -.88) for total index crimes, crimes against persons, and crimes against property, respectively.

As we shall explain in greater detail in Section III, we have reason to believe that the imperfections of owner-estimates decrease as the level of aggregation increases. Therefore, it is less likely that we are biasing our results (in any direction) as we enlarge our unit of observation.

III. City of Chicago

1. The Data Base

The two basic sources of data for this section are the 1970 Census of Housing and the Chicago Police Department Crime Summary Sheet. The units of observation are the community areas into which Chicago has been divided by the Department of Development and Planning. Each of these communities is an aggregation of census tracts. Tracts, of course, are the largest intra-city unit for which the Census Bureau reports data. However, the Department of Development and Planning has summarized much of this data on a community basis (in the Chicago Statistical Abstract) and we have made use of it in the present study.

Unfortunately, crime data are generally not available on any official basis for the community area. The Police Department records reported crime data for 21 police districts in the city.[1] From this, crime rates were constructed by dividing the number of crimes of various types by the 1970 population in each of the 21 districts and, then, multiplying these ratios by 100,000

[1]Crimes are also reported on a beat basis but the unit of observation is not geographically constant. A "beat" may change up to four times per year depending on the changes in police power deemed necessary in an area. A "beat" is actually a unit of police input, so if the crime rate rises in a given "beat" it may then become, say, two "beats." Hence the "beat" is generally an unreliable unit of observation for our purposes.

in order to yield the absolute number of each crime per 100,000 population. The number of crimes per 100,000 residents was estimated for each of the communities: 1) by assigning the police district value when more than 90 percent of the tracts in the community were in a single district; and 2) if fewer than 90 percent of its census tracts were in a given police district, the assigned crime figure was a weighted linear combination of those prevailing in the several crime districts (where the weights were determined by the proportion of census tracts in each district). The actual crime rate used in the regressions, however, was a three-year average (1969-71) of the rates so computed.[1]

2. Stability of Crime

The correlation between successive absolute levels of crime is higher for the more aggregated districts studied in the Chicago-wide data than for block-by-block crime observations (whether own or contiguous).[2] This suggests, as is plausible to expect, that the permanent crime component is greater the higher the level of aggregation. Furthermore (as we also might have anticipated), the usefulness of any given year's crime as a predictor of future crime falls as we extend the time horizon. Nevertheless, even after five years, the

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[1]We have used three-year averages because we are interested in permanent, not transitory, crime rates. The Loop and the Near North Side were omitted from this study because of heavy daily transient populations. For the Near South Side (as well as the Loop) there were no available property value data from the Census of Housing, so it was omitted. Hyde Park and Kenwood were omitted because their outlying position in a scatter of property values on crime indicated the presence of special factors. These communities were studied separately in Section II.

[2]The typical pattern of results can be seen in the correlation of the log of the number of total index and non-index crimes for 1969 with that of the five subsequent years. The results for 1970-74 inclusive are .98, .90, .86, .73, and .62, respectively. For greater detail, see Mario J. Rizzo, "Rents, Property Values and the Cost of Crime to Victims," op. cit., pp. 41-42.

correlation is still significant (e.g., total crime in 1969 and total crime in 1974 have a .62 correlation).

3. Ordinary Least Squares Results

The empirical form of the model is essentially the same as it was in Section II. The natural log of rents or (owner-estimated) property values was regressed against surrogates for the quantity of capital embodied in the housing as well as other environmental variables besides crime. The crime variables were, as before, entered in logarithmic form.[1]

a. Without Income

(i) Rents. Examination of equation (1) in Table 5 reveals an elasticity of our overall crime measure (LTOT3) with respect to rents of -0.24 (significant at the .01 level). It should be noted that LTOT3 is an unweighted measure which consists of the total of both non-index and index crimes. As such, it is more aggregated than the total measure used in Section II (LTO3) which included only index crimes. The equivalent index crime variable in this section is LINDE3.

There is a striking similarity of the Section II results in Table 2 with those in Table 6. The Hyde Park rent estimates (without income) are virtually identical to the Chicago rent estimates (without income) in the major

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[1] It should also be noted that the lot size proxies used in the previous chapter were dropped from the property value equations in this chapter because their coefficients were insignificant and their impact on any of the other independent variables was virtually zero.

TABLE 5

CHICAGO OLS RESULTS

Independent Variables	Dependent Variables			
	LRENT (1)	LVAL (2)	LRENT (3)	LVAL (4)
C	6.51	11.06	1.02	1.31
LMNR	0.59 (2.34)	0.55 (2.45)	0.20 (0.78)	0.15 (0.66)
LNEW60	0.12 (4.42)	0.11 (4.47)	0.09 (3.48)	0.08 (3.48)
WHPRO	-0.39 (5.36)	-0.13 (2.06)	-0.51 (6.73)	-0.25 (3.91)
DISCBD	-0.008 (0.91)	0.007 (0.88)	-0.01 (1.26)	0.004 (0.66)
NSD	0.22 (5.21)	0.28 (7.31)	0.20 (4.86)	0.25 (7.24)
LD	0.08 (1.28)	0.07 (1.24)	0.04 (0.78)	0.03 (0.66)
PUB	-0.87 (4.82)	-0.22 (1.35)	-0.49 (2.44)	0.18 (1.03)
LINC	--	--	0.57 (3.42)	0.60 (4.14)
LTOT3	-0.24 (3.35)	-0.20 (3.20)	-0.15 (2.09)	-0.11 (1.70)
R^2	0.67	0.77	0.73	0.82
n	71	71	71	71

NOTE: The numbers in parentheses are the absolute values of the t statistics.

crime categories. This is especially interesting in view of the fact that the compared Hyde Park estimates are the sums of the own and contiguous effects. This may be suggestive of the capturing of both these effects by the own-crime rate on the more aggregated community basis. These results are consistent with the plausible a priori presupposition that the more aggregated the unit of observation the less contiguous crime ought to matter.

TABLE 6

EFFECT OF SPECIFIC CRIME CATEGORIES
(OLS)

	Dependent Variables			
Independent Variables	LRENT (without income) (1)	LVAL (without income) (2)	LRENT (with income) (3)	LVAL (with income) (4)
LINDE3	-0.15 (2.84)	-0.14 (3.07)	-0.07 (1.41)	-0.06 (1.49)
LPROP3	-0.15 (2.82)	-0.14 (2.94)	-0.03 (1.45)	-0.06 (1.42)
LPER3	-0.08 (2.71)	-0.09 (3.68)	-0.03 (1.27)	-0.05 (2.15)

Note: The numbers in parentheses are the absolute values of the t statistics. Each crime variable was entered in a separate regression with independent variables as in Table 5.

Turning now to the non-crime variables, there are a number of interesting results.

The public housing variable (PUB)--the proportion of public housing--has the expected impact in reducing rents both because of the subsidy effect on rents and the possible disamenity effect on the neighborhood.

The effect of an increase in the proportion of whites (WHPRO) is to lower rather than raise rents. This is directly opposite the effect found in the Hyde Park Study. There is greater reason to believe that here we have isolated a genuine race effect. This is because we were better able to capture the quality of the housing in Chicago regressions as LNEW60 (and later LINC) is measured for the same unit of observation as the dependent variable. This, the reader will recall, we were unable to do in the Hyde Park study. The negative coefficient of WHPRO is consistent with the results found in many other studies.[1] This is normally interpreted as a discrimination effect: landlords will only rent to blacks at a premium.

The positive coefficient of the North-South dummy variable (NSD) indicates that we have still not captured all of the factors which make rents on the North Side of Chicago higher than on the South. Proximity to entertainment, shopping, areas, etc., may play some role.

Two puzzling results are the relatively weak (low t values) coefficients for the proximity to the lake dummy (LD) and the distance from State and Madison (DISCBD). Furthermore, the coefficient of the latter variable--even if statistically significant--is small. The low t values for LD and DISCBD in Table 5

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[1] See, for example, T. King and P. Mieszkowski, "Racial Discrimination, Segregation, and the Price of Housing," Journal of Political Economy 81 (May-June 1973), 590-606, and J. Kain and J. Quigley, Housing Markets and Racial Discrimination: A Microeconomic Analysis (New York: Columbia University Press for the National Bureau of Economic Research, 1975), Chapter 8.

is doubtless at least in part due to the 0.55 simple correlation coefficient which exists between LMNR and LD, as well as between LMNR and DISCBD.

Finally, LNEW60 is a quality proxy which behaves in the expected fashion: the greater proportion of new structures in an area the higher are rents (and property values). An additional aspect of this is that the existence of new structures may also raise the rents in old ones by conferring an external benefit.

(ii) Property Values. The property value data are for owner-occupied houses or buildings, the market value of which is estimated by the owner. Since only owner-occupied houses are covered, there is a much smaller degree of overlap with the units considered in the rent data than might otherwise be the case. Furthermore, it is important for any estimate of the dollar cost of crime based on our results to know to what extent owner-estimates deviate from true market values. The only study on this matter of which we are aware lends support to the belief that averages of owner-estimated values are not far off the mark. Kish and Lansing have found that for 568 homes the mean of the respondents' (homeowners) estimates is only $350 higher than the mean of $9,200 for the professional appraisers' estimates.[1] An implication of this study is that since errors on an individual basis are frequently quite large that increasing the level of aggregation will decrease the divergence of the average owner-estimate from the professional appraisers' estimate (the market value proxy). This view is broadly supported by an analysis of the estimated values and sales price data in the Hyde Park study. When these two

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[1] L. Kish and J. Lansing, "Response Errors in Estimating the Value of Homes," Journal of the American Statistical Association 49 (1954); 520-32.

sets of "prices" were correlated on a block-by-block basis, the correlation coefficient was 0.32. However, when they were aggregated on a tract basis, the correlation coefficient rose to 0.44.

Comparison of the results in Table 6 with those in Table 4 indicate that, overall, our Chicago (owner-estimated) property value results are somewhat lower than the sales price results for Hyde Park. It is also interesting to note, however, that the owner-estimated Hyde Park results for total index crime are quite close to Chicago-wide results for the same category (LINDE3).

A comparison of columns (1) and (3) with (2) and (4) in Tables 5 and 6 will show that the crime coefficients are virtually the same whether property values or rents are the dependent variable. However, the t values for all of the crime variables (except LTOT3) are somewhat higher in the former case.

b. With Income

Regressions (1) and (2) in Tables 5 and 6 were re-estimated with the natural log of median family income (LINC) included as an independent variable because the equation without income lacked any measure of the quality of the housing unit except LNEW60 and LMNR. Income, as it was felt in Section II, would act as a proxy variable for the quality elements we have not captured. However, the introduction of LINC as a regressor creates serious multicollinearity problems (this was not a problem in the last section); of special importance is the high negative (simple) correlation between our measures of crime and income (e.g., -0.80 between LTOT3 and LINC). The coefficients of the crime variables remain unbiased, of course, but their reliability decreases and it may become impossible to separate out the effect of crime from the effect of income.

Turning to Table 5, we find that (unlike the Hyde Park study), the coefficients of the income variable are highly significant and of the expected positive sign. It is quite interesting to note that in equation (3) the coefficient of LTOT3 is (despite the collinearity problem), still significant at the .05 level with the usual negative sign. Expectedly, the coefficient has fallen in magnitude from -0.24 to -0.15. A plausible explanation of this fall is that it represents, at least in part, the degree to which low quality had been confounded with high crime in its effect on rents. A glance at Table 5 will show that the effect on the property value equations arising out of the introduction of LINC very closely parallels its effect on the rent equations.

4. Two-Stage Least Squares Results

The TSLS regression technique was employed because of considerations of a two-way "causal" relationship existing between crime and property values (and, of course, rents). Returning for a moment to our theoretical framework, it is obvious from equation (4) that the greater the value of what is to be protected (i.e., the greater is $P_z \cdot f$), the greater will be the quantity of self-protection for any given $\hat{C}$ (endowed crime). Therefore, by extension, the observed crime rate is a negative function of the level of property values. This is because the value of the marginal product of self-protection is greater for any given $\hat{C}$ and also for a given marginal "physical" product of SP, the greater is the value of the property (for whatever reason).[1]

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[1] In equations we are saying: 1) $C = f(\hat{C}, SP)$; 2) $SP = h(p.V., \hat{C})$; 3) $C = g(\hat{C}, P.V.)$. A more complete general equilibrium model would view even the zero self-protection supply of crime as endogenous. In this case, it would be plausible to assume that high property values may serve as a proxy for high opportunity costs of crime (i.e., high-paying legitimate opportunities), and hence induce less crime for a given level of SP.

The procedure is to purge the crime variables of their dependence on property values (and rents) or, more exactly, of their correlation with the disturbance term in the equation. Specifically, we regressed the endogenous crime variables (LTOT3, LINDE3, etc.) on the predetermined variables in the system[1] in order to generate the purged variables $\widehat{\text{LTOT3}}$, $\widehat{\text{LINDE3}}$, etc., with which we then estimated the original equation. TSLS estimates were not undertaken in the Hyde Park-Kenwood study because values for most of the predetermined variables were not available on the requisite block-by-block basis.

Turning our attention to the rent equations (without income) in Tables 7 and 8, we see that the magnitude of the crime coefficients has changed considerably from the OLS results. Generally speaking, these coefficients have doubled in size, lending support to the position that the simultaneity problem was, indeed, significant. Furthermore, in every case (except equation 1, Table 7), there was a substantial rise in the ratio of the estimated coefficients to the asymptotically unbiased (i.e., consistent) estimated standard errors.

The effects described are even more pronounced in the property value (without income) equations. Here, the coefficients more than double and each is significant at the .01 level.

Next, we estimated the second-stage rent regression equations with income (LINC) as an independent variable. The reason for including income is the same as in the OLS case. However, the problem of collinearity is

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[1]The predetermined variables are LMNR, LNEW60, WHPRO, DISCBD, NSD, LD, PUB, LINC, YOUTH, EDUC, UN, DEN, INEQ, WELF, MF, PART (all defined in appendix). On exactly how these variables affect crime, see Ehrlich, "Participation in Illegitimate Activities."

TABLE 7

CHICAGO TSLS RESULTS

Independent Variables	Dependent Variables			
	LRENT (1)	LVAL (2)	LRENT (3)	LVAL (4)
C	8.29	13.52	1.45	7.40
LMNR	0.48 (1.80)	0.41 (1.60)	0.20 (0.78)	0.16 (0.68)
LNEW60	0.10 (3.43)	0.08 (2.99)	0.09 (3.38)	0.07 (3.11)
WHPRO	-0.50 (5.08)	-0.29 (3.06)	-0.52 (5.91)	-0.30 (3.85)
DISCBD	-0.01 (1.20)	0.002 (0.27)	-0.01 (1.27)	0.003 (0.42)
NSD	0.20 (4.40)	0.26 (5.78)	0.19 (4.76)	0.25 (6.74)
LD	0.11 (1.70)	0.12 (1.84)	0.05 (0.79)	0.06 (1.07)
PUB	-0.84 (4.45)	-0.18 (1.01)	-0.50 (2.40)	0.12 (0.67)
LINC	--	--	0.55 (2.78)	0.49 (2.79)
$\widehat{\text{LTOT3}}$	-0.41 (3.33)	-0.45 (3.78)	-0.17 (1.24)	-0.23 (1.86)

NOTE: The numbers in parentheses are the absolute values of the ratio of the estimated coefficient to the asymptotic standard error.

substantially worse. Here, for example, the simple correlation coefficient between LINC and $\widehat{\text{LTOT3}}$ (the fitted crime variable) is almost -0.90 as compared to -0.80 between LINC and LTOT3.

TABLE 8

EFFECT OF SPECIFIC CRIME CATEGORIES

Independent Variables	Dependent Variables			
	LRENT (without income) (1)	LVAL (without income) (2)	LRENT (with income) (3)	LVAL (with income) (4)
$\widehat{\text{LINDE3}}$	-0.29 (3.24)	-0.32 (3.86)	-0.11 (1.10)	-0.16 (1.86)
$\widehat{\text{LPROP3}}$	-0.31 (3.25)	-0.33 (3.74)	-0.13 (1.21)	-0.16 (1.78)
$\widehat{\text{LPER3}}$	-0.19 (3.12)	-0.24 (4.09)	-0.05 (0.66)	-0.16 (2.22)

As is evident from a comparison of the rent equations, the introduction of income very substantially reduces the magnitude of the crime coefficients. More importantly, however, the levels of significance fall considerably. Yet, especially for $\widehat{\text{LTOT3}}$, the results are still very highly suggestive and all in the expected direction.

The results of the property value equations are more "generous." Here again the coefficients drop substantially in magnitude but the significance levels are higher.

IV. The Cost of Crime to Victims

In the course of this section, we shall complete the analysis of the previous two by deriving from our regression coefficients some rough measures of the cost that crime imposes upon its victims and potential victims. This measure of cost will be an individualistic one, i.e., dependent upon the evaluations of individuals revealed through the housing market, rather than on "society's" evaluation of the harm done to particular people.

In order to calculate the cost of crime, we must first place an interpretation on the housing price-crime gradient which we have empirically estimated. If all the firms which produce housing services (Z) have identical production functions, then, provided that we have adequately controlled for all of the inputs into Z including the other environmental variables, the marginal impact of crime schedules should be the same for each of these firms. In this case, we may interpret the housing price-crime gradient as the marginal cost of crime schedule. Proceeding on this assumption, we have calculated crime costs by comparing the difference between the predicted value of property (or rents) at the mean crime rate and at a rate which is about one-half of the mean.[1] The difference between the two property values answers the following question: If the crime rate in the city of Chicago were to fall from a level of 7,331 crimes per 100,000 to 3,604 per 100,000, what would be the savings in crime costs; or to put it in an equivalent way, what is the incremental cost

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[1] Since we have estimated the equations in logarithmic form, the mean referred to here is the mean of the log of crime (not the log of the mean). This is simply the geometric mean of the crime rates in their natural form.

of a rise in crime from one half the (current) mean to the mean? This is the question we shall attempt to answer subject to the limitations of our methods of analysis. It is important to understand that we chose to ask this question rather than the more daring one: What is the cost of the total amount of existing crime? This is because of the large errors inherent in extrapolating a regression estimate beyond the range of any observations in the sample (3,604 crimes per 100,000 is the lowest crime level for any community in our sample).

In Table 9 we have presented four alternative measures of the partial cost of crime (index plus non-index) for Chicago--a different one for each method of estimation used. The TSLS results are perhaps the more reliable as they take account of the simultaneity issue discussed in the previous section. The range over the whole table is between \$147 million and \$509 million per year, with the more probable range being the narrower \$211 million to \$509 million.

In Table 10 these data are presented on five different bases including the per capita cost of crime and the average cost per crime. The former might reasonably be interpreted as the expected value of losses (directly or indirectly) through crime for the typical individual, and the latter as expected value of losses <u>given</u> victimization. Crime costs as a proportion of the rental or capital value of the unit (third and fourth categories) are also tabulated and represent some additional costs of living in a particular unit as a percentage of the direct outlays.

Turning now to Table 11, we present the results of a similar question for the Hyde Park-Kenwood community. The main differences here are that we

TABLE 9

PARTIAL YEARLY COST OF CRIME IN CHICAGO

Method	Rents (millions of dollars)	Property Values* (millions of dollars)	Total (millions of dollars)
OLS (without income)	174.67	77.97 (1,146.6)	252.64
OLS (with income)	105.61	41.45 (609.59)	147.06
TSLS (without income)	317.53	192.35 (2,828.79)	509.85
TSLS (with income)	120.63	90.65 (1,333.09)	211.28

*The first figure is a flow yearly estimate based on a conservative rate of interest: .068--the rate prevailing on two- to seven-year government securities in 1969. The figures in parentheses are the total capital value impact. All of the entries are the per housing unit cost multiplied by the number of units.

TABLE 10

CHICAGO CRIME COST SUMMARY STATISTICS

Basis	Method			
	OLS (without income)	OLS (with income)	TSLS (without income)	TSLS (with income)
Per Capita	$ 78	$ 46	$ 158	$ 66
Per Housing Unit	$ 238	$ 139	$ 480	$ 199
Cost per Renter Unit/ Mean Rent per Year	.198	.119	.360	.136
Cost per Owner Unit/ Mean Property Value*	.147	.078	.364	.171
Cost/Crimes**	$1,755	$1,022	$3,542	$1,468

*Both the numerator and denominator are in capital value terms.

**The partial crime costs of table 17 are divided by one-half the total number of crimes since it is the cost of the latter which is being measured.

have asked what is the incremental crime cost (index only) when we "go" from one-half the Hyde Park-Kenwood mean (rather than the Chicago mean) to that mean itself. The property value estimate is based on a generalization of the results for the 324 transaction prices over all the owner-occupied housing units in the area. Since the differences between the results with income as an independent variable and these are negligible, we present only one set of estimates.

TABLE 11

PARTIAL YEARLY CRIME COST FOR HYDE PARK-KENWOOD
(OLS without income)

Rents (millions of dollars)	Property Values* (millions of dollars)	Total (millions of dollars)
3.47	1.15 (17.04)	4.62

*See Table 9 for explanation.

Recall that non-index crime totals were not available for Hyde Park-Kenwood, so the results in Tables 9 and 11 are not directly comparable. To facilitate comparison, we have computed index crime costs for the city of Chicago and compared them on the five bases of Table 10 to the same costs in Hyde Park. Table 12 presents these results. It is clear that, in the sense of our intellectual experiment, crime costs are considerably higher in the Hyde Park-Kenwood community. This is partly because the crime <u>rate</u> is higher and so a one-half reduction in the average is a greater absolute amount per capita. This, however, does not fully exhaust the matter, as the (average) cost per crime is 48 percent higher in Hyde Park than for the entire city of Chicago. Therefore, not only is the expected value of losses for the typical individual in Hyde Park more than double that for the average Chicagoan, but the cost given only a single victimization is very substantially higher.

TABLE 12

COMPARISON OF CRIME* COSTS: HYDE PARK-KENWOOD AND CHICAGO
(OLS without income)

Basis	Hyde Park-Kenwood	Chicago
Per Capita	$ 102	$ 49
Per Housing Unit	$ 224	$ 148
Cost per Renter Unit/Mean Rent per Year	.131	.119
Cost per Owner Unit/Mean Property Value	.113	.097
Cost/Crimes	$3,949	$2,668

*Index crimes only.

Before we conclude, it would be well to summarize briefly what has been shown by our crime cost estimates. We have measured the cost of actual crime plus crime-related self-protection expenditures as revealed by differential residential property values and rents.[1] Since none of the observations in any

[1] It might be thought that since we are observing differential rents and values within Chicago that the (un-) attractiveness of the city as a whole versus, say, the suburbs is not measured in our empirical work. This is true

of our samples has anything approaching a zero crime rate, we only extrapolated our results to crime rates within the range of our samples. Hence, we derive a partial crime cost for several different methods of estimation.[1]

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but not relevant for our purposes. If we had attempted to measure the total cost of crime this would be a problem. However, we have concerned ourselves with changes (or differences) in crime as actually existing in our sample and hence the differential prices should pick up the full cost of various crime imcrements, *ceteris paribus*.

[1]The crime cost estimates derived in this study are not actually comparable to the direct estimates of the President's Commission on Law Enforcement (see Crime and Its Impact--An Assessment, p. 44). There are two major reasons for this. First, the latter estimates are of the total cost of crime. Merely to double our partial estimates for comparison would imply knowledge of the functional relationship between crime and property values at levels of crime which do not appear in our samples. Second, our estimates concern only the impact of crime on residential housing, ignoring crimes against businesses and in business areas. This means that our estimates, *ceteris paribus*, understate the full cost of crime. With these caveats in mind, an adaptation of the 1965 President's Commission on Law Enforcement estimates for the cost of index crime plus private protection amounts to $79 per capita and $2,375 per crime for Chicago. (This estimate was obtained by apportioning national crime costs to Chicago on the basis of its share of total index crimes.) A doubling of our estimates in Table 12 yields a per capita crime cost for Chicago of approximately $99 for 1970 ($85 in constant 1965 dollars). The relevant cost per crime is unchanged at $2,668 ($,294 in 1965 dollars). The reader is warned against facile use of these comparisons.

APPENDIX

Theory

C	= exogenous level of crime, i.e., the actual crime level in the absence of self-protection
C	= actual crime
SP	= self-protection
K	= capital
L	= land
π	= profits
P_z, P_{sp}, P_k, P_ℓ	= price of Z, SP, K and L
Z	= housing services
ε_{cc}	= elasticity of C with respect to $\dot{C}$
$-\varepsilon_{gc}$	= elasticity of g with respect to C
s_ℓ	= share of land in total expenditure on housing services

Empirical Estimates

C	= constant
LVAL	= log of owner-estimated property values
LSVAL	= log of transaction prices of single-family homes
LRENT	= log of contract rents
LMNR	= log of median number of rooms (owner- and renter-occupied)
LANRO	= log of average number of rooms in owner-occupied housing
LANRR	= log of average number of rooms in renter-occupied housing
LNEW60	= log of the proportion of housing built since 1960
WHPRO	= proportion of whites in population

DISCBD = distance from central business district in miles (State and Madison)

DISUC = distance from the University of Chicago campus

NSD = North-South Dummy: if community is north of Loop, assign 1; if not, assign 0

LD = Lake Dummy: if community borders Lake Michigan, assign 1; if not, assign 0

PD = Park Dummy: if block is contiguous to a park, assign 1; if not, assign 0

YD = Year Dummy: if house sale was made in either 1968 or 1969, assign 0; if in 1970, 1971 or 1972, assign 1

TPD = Transient Population Dummy: if block has high transient population, assign 1; if not, assign 0

PUB = proportion of total housing units which are public housing

LINC = log of median family income for 1969

LTOT3 = log of 1969-71 average of total index and non-index crimes per 100,000 population

LINDE3 = log of 1969-71 average of index crimes per 100,000 population (Chicago study)

LTO3 = log of 1969-71 total index crimes per 1,000 population (Hyde Park study)

LVPER3, LPER3 = log of 1969-71 crimes against persons per 1,000 and 100,000 population, respectively

LVPRO3, LPRO3 = log of 1969-71 crimes against property per 1,000 and 100,000 population, respectively

LMCTO3 = log of 1969-71 index crimes per 1,000 for contiguous blocks

LMCVPER = LVPER3 for contiguous blocks

LMCVPRO = LVPRO3 for contiguous blocks.

YOUTH*[1] = proportion of population between ages 15-24

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[1] An asterisk indicates a variable used only in the first stage of TSLS estimates.

EDUC* = median years of schooling

UN* = unemployment rate

DEN* = density; number of persons per square mile

INEQ* = proportion below one-half median income

WELF* = proportion receiving welfare

MF* = ratio of males to females

PART* = labor force participation rate