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CRIME IN URBAN AREAS:
NEW EVIDENCE AND RESULTS

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ABSTRACT

Crime supply functions are reestimated in this paper using data corrected for victim underreporting. It is found in both a mean-variance specification and a conventional crime supply function which includes measures of the offender's gains and losses involved in property crimes that certainty and severity of punishment still deter. When correction for underreporting is made, the effects on the rates of robbery, burglary, larceny and auto theft of increases in prison admission rates and prison sentence lengths remain negative. This seeming support for the "deterrence hypothesis" must be balanced against the strong evidence that improved legitimate opportunities have a negative effect on crime. Use of improved crime data and a more intuitive economic specification of the offense supply function leads to the conclusion that higher income is a better deterrent to some crimes than increased punishment.

1. INTRODUCTION

Major attempts in recent years to estimate crime supply curves have been seriously flawed by use of extremely poor crime data. Although some authors (Ehrlich, 1973; Sjoquist, 1973) acknowledge the limitations of utilizing the questionable Uniform Crime Reports data collected from cities and states by the FBI, none has attempted to correct for the bias in their results that arises from systematic underreporting of crimes.

Both victims and local law enforcement agencies underreport crimes. Victims do so because the benefits of reporting a personally disturbing incident often fall short of the costs of appearing at line-ups, testifying in court, going through long months of taxing anxiety, often to see the offender acquitted or their stolen goods unreturned. Law enforcement officials may underreport because local crime rates are indicators of the effectiveness of police services. Of course, law enforcement agencies can overreport crimes to create an illusion of lawlessness justifying increases in municipal appropriations for crime fighting. So, in either case the reported crime rate need not measure true crime.

This paper summarizes results of estimations of crime supply curves that appropriately take account of victim underreporting of crime. Although it is the task of future exercises to incorporate law enforcement under- and overreporting into the analysis, the current effort does model the effect of the reporting behavior of crime victims on police response to crime.

2. BACKGROUND

Theoretical ground work for most econometric models of crime was essentially laid in Gary Becker's (1968) conceptualization of crime as a process of rational choice. Maximizing the expected utility of income, the potential offender chooses an optimal allocation of effort expended in illegal activities which is found to depend upon the certainty and severity of punishment. Extensions of the model have been estimated by Ehrlich (1973), Sjoquist (1973), Carr-Hill and Stern (1973), Swimmer (1974), Mathur (1978), and others. The investigations are all primarily tests of the deterrence hypothesis. But a better generalization of the economic model should incorporate gains and losses of engaging in crime. While the deterrence variables--certainty and severity of punishment--affect gains and losses in a straightforward way, their effects on participation in crime are ambiguous in theory, as Block and Heinke (1975) have shown. Moreover, if the analysis purports to explain variations in urban crime, as that of Hoch (1975) and Kau and Rubin (1975) does, then characteristics of cities and their relative criminal opportunities should be the appropriate explanatory variables.

More serious is the potential simultaneity between arrests, conviction, imprisonment and crime. Blumstein et al. (1978) point out that there are major identification problems in many specifications of the crime supply function and that even when such models are correctly identified, ambiguities arise from the difficulty of distinguishing between incapacitation and deterrent effects of punishment.

The problems of previous works are compounded by the use of reported crime data. Newer studies such as that of Myers (forthcoming) utilize microdata sets and measure participation in crime by rearrest rates or recidivism. To the extent that most crimes are comitted by repeat offenders, this may be as good a measure of crime as any. But we are unable to define geographical locations of offenders because of the limitations of confidentiality, and these microdata sets may be of little use in describing interurban variations in crime. National victimization surveys, providing measures of criminal incidents, may prove to be a superior source of data for future crime supply estimations. This paper explores how these data might be used.

3. THE MODEL

Described in some detail elsewhere (Myers, 1976) is a complete model of an urban crime system. Since our concern here is only the offense supply, we merely sketch the model below. For convenience the model is limited to crimes of robbery, burglary, larceny, and auto theft.

There are three sectors of the urban crime system, characterizing the behavior of offenders, victims, and law enforcement agencies respectively.

Offender Sector

Offenders are assumed to face two income-earning activities, work and crime, both receiving uncertain returns. For returns independently, identically, and normally distributed, or for identical utility functions quadratic in income, it can be shown that the urban supply of crime will be a function of the expected rate of return to crime, $E(r_c)$, the expected rate of return to work, $E(r_w)$, the variances of returns to crime and work, $Var(r_c)$, $Var(r_w)$, and the covariance of returns to crime and work, $Cov(r_c, r_w)$. Hence

$$\text{Offense Supply} = f(E(r_c),\ E(r_w),\ Var(r_c),\ Var(r_w),\ Cov(r_c,\ r_w)) \quad (1)$$

Convenient expressions can be derived for each of these variables.

Let r_i be the stochastic rate of return to offense i, then

$$r_i = \begin{cases} G_i & \text{if not caught} \\ -L_i & \text{if caught and imprisoned} \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Let the probability of not being caught be $(1 - \alpha_i)$ and the probability of being caught and going to jail be γ_i. It is assumed that G_i and L_i are independently distributed and the events getting caught and going to jail are independent. Hence, the expected rate of return is given by:

$$E(r_i) = (1 - \alpha_i)\ E(G_i) - \gamma_i E(L_i) \quad (3)$$

Given that

$$E(r_i^2) = (1 - \alpha_i)\ \left[Var(G_i) + E(G_i)^2\right] + \gamma_i\left[Var(L_i) + E(L_i)^2\right] \quad (4)$$

and assuming--for computational convenience--that $V(G_i)$ and $V(L_i)$ are zero, then the variance of returns is given by:

$$\mathrm{Var}(r_i) = (1 - \alpha_i)\, E(G_i)^2 + \gamma_i E(L_i)^2 - E(r_i)^2 \; . \tag{5}$$

The probability of getting caught, α, is given by the ratio of arrests to offenses. The probability of going to jail, γ, is given by the ratio of prison admissions to offenses. Since prison admissions are known only for states, it is assumed that:

$$C_i^j = (P^j/P) \cdot C_i \tag{6}$$

where C_i^j is the number of court admissions to prison for the i^{th} offense from city j, C_i is the total state court admissions for offense i, P is state population and P^j is population of city j.

The expected gain is given by the average value of stolen goods. The expected pecuniary loss (ignoring psychic costs of imprisonment) is defined as:

$$E(L) = E(S)\ \left[E(y) - R - .2E(y)\right] \tag{7}$$

when S is sentence length, y foregone income, and R is rental payments. Equation (7) suggests that the expected loss if sent to prison is the expected foregone income while in jail less the room less board (approximately 20% of income is spent for food by the average individual) for the expected period of incarceration.

Similarly, it is possible to derive a convenient expression of returns to work. Let u be the conditional probability of being unemployed, c the probability of being in the civilian labor force, and ℓ per capita wage income. The expected return to work is:

$$E(r_w) = (1 - u)c \cdot \ell \ . \tag{8}$$

The variance of the return to work, computed assuming that c and u are probabilities for dichotomous random variables distributed independently, is

$$\mathrm{Var}(r_w) = (1 - E(r_w)) \cdot E(r_w) \ . \tag{9}$$

The covariance of returns between work and crime is given by:

$$\mathrm{Cov}(r_w, r_c) = \rho_{wc} \ \mathrm{Var}(r_c) \cdot \mathrm{Var}(r_w) \tag{10}$$

where ρ_{wc} is the correlation between returns to work and crime.

The correlation between returns is assumed to be a constant denoting the systematic relationship among activities due (but not exclusively) to institutional controls (i.e., police practices, court behavior, etc.). We approximate ρ_{cw} by correlating $E(r_c)$ and $E(r_w)$ for all cities in our sample.

Victim Sector

In order to derive a measure of the "true" crime rate, reported crime rates are divided by the probability that a victimization was reported. Victims are assumed to maximize the expected utility of reporting or not reporting an offense. The probability of reporting is found to depend upon a vector of personal characteristics, the value of the goods stolen, the probability that the goods are returned, and the probability that someone is caught.

Law Enforcement Sector

Total arrests for all crimes (here, robbery, larceny, burglary, and auto theft) are derived from a production function, dependent upon population density, total crimes reported, current expenditures and capital outlays on police and the criminal justice system, percentage of the population that is nonwhite and percentage change in the black population.

Arrests for a given crime are determined by an administrative decision. The policy of dividing total arrests among various crimes is assumed to depend upon the seriousness of the crime measured by the probability that victims report it and upon what fraction that crime is of total crimes.

4. ESTIMATION OF THE OFFENSE SUPPLY FUNCTION

In Table 1, the results of two-stage least squares estimates of coefficients are presented; the true offense rate is assumed to be a linear function of the means, variances, and covariances of returns which are corrected for reporting bias. (A complete description of data and methods is provided in the appendix.)

An increase in the variance in the rate of return to crime is expected to lower the crime rate; the effect of the expected rate of return is positive or possibly negative; the variance in the rate of return to work is expected to be positively related to the crime rate; while the effect of expected returns to work is similarly indeterminate.

The effects of changes in the covariance of returns depend upon whether work and crime returns are positively or negatively correlated and upon the fraction of time spent in crime. It can be shown that when the covariance of returns increases, the supply of crime will rise or fall for returns to crime and work positively correlated, as participation in crime is more than or less than one half of time available. For cov $(r_w, r_c) > 0$,

$$\frac{\partial t_c^*}{\partial cov} \gtrless 0 \text{ as } t_c^* \gtrless 1/2$$

For cov $(r_w, r_c) < 0$,

$$\frac{\partial t_c^*}{\partial cov} \lessgtr 0 \quad \text{as} \quad t_c^* \gtrless Y_2$$

Similarly it is possible to show that for the returns to work and crime negatively correlated, participation in crime will rise or fall for increased covariance of returns as participation in crime accounts for less than or for more than one half of income-earning time.

The correlations of returns to burglary and work, and larceny and work are positive (ρ = .287 and .321 respectively). Hence, if it is assumed that less than 50% of one's time is spent in burglary or larceny on the average, then increases in the covariance of returns should reduce participation in crime. Auto theft and work exhibit negatively correlated returns (ρ = -.146). Should time spent in auto theft on the average be less than one half of total income earning time, increases in covariance of returns to work and auto theft should

Table 1

2 SLS estimates of Coefficients in Linear Portfolio Model of Offense Supply
(t-statistics in parentheses)

		INDEPENDENT VARIABLES				
Dependent Variables (Offense rate)	Constant	$E(r_i)$	$V(r_i)$	$Var(r_w)$	$E(r_w)$	$Cov(r_i r_w)$
Robbery	0.002 (0.351)	1.327E-05 (2.693)	-1.128E-09 (-2.296)	1.070E-09 (0.264)	3.694E-06 (0.347)	5.331E-09 (1.466)
Burglary	0.031 (3.179)	1.183E-05 (0.589)	-4.742E-09 (0.167)	1.148E-11 (0.002)	1.058E-05 (0.544)	-1.081E-07 (-4.558)
Larceny	0.131 (3.503)	-2.978E-04 (-2.262)	-1.893E-06 (-1.427)	1.237E-08 (0.455)	2.039E-05 (0.513)	-4.205E-07 (-2.825)
Auto theft	-0.006 (-0.682)	2.287E-05 (3.632)	-6.381E-08 (-2.454)	-9.295E-09 (-1.497)	2.993E-05 (1.810)	7.279E-08 (1.314)

increase participation in crime. Robbery and work returns are only weakly correlated (ρ = .008), although positive correlation implies that time in robbery will rise or fall for increased covariance of returns according to whether time spent in robbery exceeds or is less than 50% of total income-earning time.

The results support the mean-variance specification of inter-urban variations in crime. Everywhere increased risk in crime reduces participation in crime, as expected in theory. Increased joint risk of engaging in work and crime follows our predictions. The ambiguous signs of the expected returns to work and crime are anticipated in theory; although, with the exception of larceny, increased expected returns to crime increase optimal participation in crime. The special case of larceny, however, fits neatly into the framework of the familiar case of inferior goods in consumer theory. The supply of larcenies may be backward bending, because of the dominance expected income effect resulting from changes in the expected rate of return to larceny.

In general, we expect to find the effect of increased risk in work to be positive or zero. In fact, in every equation, at a significance level of 5%, we reject the hypothesis that the estimated coefficient for risk in work is significantly different from zero.

It is easy to see, by way of straightforward differentiation of equations (3) to (5), that increases in the probability of getting caught need not reduce crime, given our estimates of the effects of the returns to crime. For example, the effect of an increase in the arrest rate on burglary is

$$\frac{\partial(\text{Burgl})}{\partial\alpha} = \beta\ \rho_{rw}\ \sigma_w \frac{\partial\sigma_r}{\partial\alpha}, \tag{11}$$

where β is the negative estimated effect of the covariance of returns on the burglary rate (the other effects are insignificant); ρ_{rw} is the correlation between returns to crime and work (found to be positive); σ_w is the square root of the variance of returns to work, obviously positive; and $\partial\sigma_r/\partial\alpha$ is the effect of the arrest rate on the square root of the variance of returns to income. This last effect will have the same sign as that of $\partial\text{Var}(r)/\partial\alpha$. From equations (3) and (5) this is found to be of the same sign as

$$\left[2(1 - \alpha)\ E(G) - E(G) - 2\gamma E(L)\right] \tag{12}$$

If the probability of getting caught is greater than or equal to one half, equation (12) will be negative and hence the right-hand side of (11) will be positive: increased certainty of punishment can lead to higher participation in crime. It is not realistic that the arrest rate for burglary be greater than one half. In fact, for our sample the average α is .093, ranging from a low of .028 to a high of .606. Nonetheless, by differentiation of equation (5), it is easy to see even for $\alpha < 0.5$ that it is possible for $\partial\ \text{var}(r)/\partial\alpha$ to be negative and hence for the effect of certainty of punishment on crime to be positive.

This point can be made more explicit by reestimating the crime supply function with measures of arrests, probability of imprisonment, prison sentence lengths, gains to crime, legitimate income, and another potential source of income, welfare benefits. Excluded from the equation are important determinants of returns to work, the unemployment rate and labor force participation rate, and variables entered by others as income inequality. These estimates are displayed in Table 2.

The gain variable suffers from the fact that no adjustments are made for reporting bias. The observations on G_i are reported values of goods stolen. In addition, although conventional wisdom would suggest that increasing illegal gain would lead to increased participation in crime, supply decisions must balance changing average returns against varying risk. Obviously as the gain increases the expected return to crime rises. But, the variance of returns, a measure of risk, also rises. Robbing the local "7-11" may net a low average return, but the dispersion around the mean may be small. Hence, rising gain should unambiguously result in higher participation in crime only if risk were held constant. The measures of the severity and certainty of punishment are inversely related to crime except in the case of burglary. Here, as in our simple example above, increased probability of arrest leads to higher burglary rates. Even after correcting for underreporting, our results are similar to Mathur's, Ehrlich's, and others wherein it is found that the certainty of punishment (imprisonment) is a greater deterent to crime than the severity of punishment. This result holds for robbery and larceny (others have found a positive coefficient for the effect of punishment on larceny). The differential effect of certainty of punishment over severity is small for burglary and auto theft.

Importantly, our estimates of the effects of income are larger than those reported by other authors. Omitted is a measure of the proportion of the population that is black. But if "percent black" is intended to capture differences in legitimate opportunities, then income itself should be included in the equation, and not race.

Table 2

2 SLS Estimates of Coefficients in Log-Linear Model of Offense Supply.
(t-statistics in parentheses)

Independent Variables	Dependent Variables			
	Robbery	Burglary	Larceny	Auto Theft
Constant	-4.027 (-1.223)	4.889 (1.519)	8.349 (3.896)	-3.239 (-0.659)
Gain	-0.164 (-0.087)	-0.012 (-0.087)	-0.325 (-2.869)	-0.152 (-0.652)
Prob. of arrest	-0.383 (-1.742)	0.500 (1.757)	-0.397 (-2.433)	-0.949 (-4.108)
Prob. of imprisonment	-0.878 (-12.735)	-0.487 (-5.395)	-0.471 (-7.868)	-0.012 (-0.185)
Severity of punishment	-0.572) (-4.092)	-0.422 (-3.167)	-0.247 (-2.311)	-0.018 (-0.970)
Income	-0.147 (-0.375)	-0.658 (-1.789)	-0.990 (-3.105)	-0.791 (-1.643)
Welfare benefits	-0.453 (-2.011)	-0.435 (-1.669)	-0.707 (-3.574)	0.675 (2.494)

Note: Offense rate is corrected for reporting bias using 2 SLS estimates of report probabilities

5. SUMMARY AND CONCLUSIONS

In this paper new estimates of the supply of urban property crimes are obtained by using crime data corrected for victim underreporting and by specification of a mean-variance model of offense supply. It is found that the returns to crime and work significantly affect the rates of urban crime. Specifically, crime rates are lower in areas with higher incomes and higher "costs" of crime. The certainty and severity of imprisonment are inversely related to crime rates even using data corrected for underreporting. However, the certainty of apprehension can lead to either increases or decreases in crime rates.

While further support is given in this paper to what has come to be called the "deterrence hypothesis", an important qualification emerges. The magnitude of the effect of legitimate opportunities on crime may be larger than previously estimated using uncorrected crime data. Moreover, a more intuitive specification of the crime supply function, using increments of the distributions of returns to work and crime, yields results suggesting that the joint risk of engaging in work and crime is a major determinant of crime rates. Here, we are regarding the covariance of returns to work and crime as a measure of the joint risk. Clearly, low income, high turnover, secondary labor market jobs can provide easy access to criminal work. Burglary and larceny are frequently inside, on-the-job crimes. The returns to burglary and larceny are positively correlated with work returns. If the joint risk of engaging in work and crime is higher in the primary labor market jobs, then moving workers out of the secondary labor market into better jobs will reduce these types of thefts. Labor market strategies for reducing crime among ex-offenders could be more effective if these examples of interactions between legitimate and illegitimate opportunities were more explicitly recognized.

APPENDIX

SOURCES OF DATA

1. Victimization report probabilities are obtained for 28 cities from:

    a. U.S. Department of Justice. Crimes and Victims - A Report on The Dayton-San Jose Pilot Survey of Victimization. Washington, D.C.: LEAA, 1974.

    b. ____________________. Crime in Eight American Cities. Washington, D.C.: National Criminal Justice Information and Statistics Service, 1974.

    c. ____________________. Crime in the Nation's Five Largest Cities, Washington, D.C.: ;National Criminal Justice Information and Statistics Service, 1974.

    d. ____________________. Criminal Victimization Surveys in 13 American Cities, Washington, D.C.: National Criminal Justice Information and Statistics Service, 1975.

2. Reported offense rates are obtained from 154 cities from:

    U.S. Department of Justice. Uniform Crime Reports for the United States, 1970. Washington, D.C.: Federal Bureau of Investigation, 1971.

3. Arrests, return of stolen goods, value of stolen goods are available from:

    Uniform Crime Reporting Section, FBI, U.S. Department of Justice. Unpublished data collected by permission of the UCR Section from 1970 "Return A" and "Supplement to Return A" for cities submitting these forms. For full review of annual and monthly forms filed by participating cities with the UCR see: U.S. Department of Justice, UCR Handbook, Washington, D.C.: Government Printing Office, 1974.

4. Prison sentence lengths and court admissions to prison data are obtained from:

    U.S. Department of Justice - Law Enforcement Assistance Administration, National Prisoner Statistics - Admissions and Releases, 1970. Washington, D.C.: National Criminal Justice Reference Service, 1970.

    Since prison admissions are given only for states, it is assumed that:

    $C_i^j = (p^i/p) \cdot C_i$ where C_i^j is the number of court admissions to prison for the ith offense from city j, C_i is the total state court admissions for offense i, p is the state population and p^1 is the population of city j.

All cities in a given state are assigned the average sentence length (by crime) for the state.

5. Criminal Justice System Expenditures are obtained from: U.S. Department of Commerce - Bureau of Census. Criminal Justice Expenditure and Employment, 1969-70. Washinton, D.C.: Government Printing Office, 1971.

6. All other variables: U.S. Department of Commerce, City and County Data Book. Washington, D.C.: Government Printing Office, 1972.

7. Data and Correction for Underreporting: The sample consists of all U.S. cities with a population of 100,000 or more in 1970. Uniform Crime Reports provide information on reported offenses, arrests, and value of stolen goods, while prison sentence lengths and court admissions to prison data are obtained from the National Prisoner Statistics.

A central problem in all research involving UCR data is the fact that offense data is on reported crimes only. For crimes with victims, however, the true crime rate can be approximated by the ratio of the reported offense rate to the probability that an offense is reported given a victimization. A logit function is estimated for the odds in favor of reporting a commercial robbery or burglary, a personal robbery or larceny, and household burglary and auto theft. Independent variables include such characteristics of the crime as the arrest rate and the value of stolen goods, and of the victims as the race, sex or age. From a sample of 28 cities initially participating in the early National Crime Panel Survey studies, coefficients of the logit function are estimated using two stage least squares.

An aggregation scheme is employed to combine, for example, commercial and personal robbery victimization report probabilities to compute a composite robbery report probability. The model is then used to simulate victimization reporting probabilities for all cities with a population of 100,000 or more.

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