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ECONOMIC FACTORS IN JUVENILE CRIME

by

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TO TOMOYO
MY LOVELY WIFE

ABSTRACT

Although property crime has previously been discussed in a number of empirical papers, property crime by juveniles has been ignored despite the fact that the larger proportion of property crime is committed by juveniles.

This paper is an empirical exploration of the relationship between economic factors and arrest rates for four types of crime: robbery, burglary, larceny, and motor vehicle theft for juveniles under 16 and between 16-19 years of age. Two sets of data have been used. First, 1971 cross-sectional data for the United States and second, a pooled cross-sectional time-series for the five boroughs of New York City for the 1970-1980 period.

Results of this paper indicate that economic factors are important in determination of property crime among juveniles. The results also indicate that probability of being arrested has strong deterrent effects on the number of offenses committed by juveniles. Income factors indicate higher incidence of property crime in areas with higher income inequality. Also, economic factors indicate that a higher expected return to crime increases the number of offenses. Urban areas show a higher rate of property crime which might reflect the existence of slums and also the higher concentration of wealth and business activities in metropolitan areas.

Findings of this paper suggest that an increase in expected cost of punishment would be an effective policy tool in reduction of property crime. A long run solution, however, calls for an increase in the availability of legal earning opportunities in terms of both quality and quantity work.

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First, I would like to express my deep gratitude to the supervisor and chairman of my dissertation committee, Professor Michael Grossman. His advice and help made the most difficult years of my life exciting and fruitful. His concern for me was beyond belief. For the past few years, I have always been confident that he was on my side ready to sacrifice his time and energy to solve my academic and even personal problems.

I would like to thank the other members of my committee, Professor [illegible] Edwards and Harold Hochman, each of whom contributed to this work in their own special way.

I am indebted to my colleague and friend, Michael Massourakis, who has always offered me his valuable professional insight and support.

Most of all, I want to thank my parents for all the sacrifices they endured for my own sake. It is with great regret that I did not complete my dissertation, before the death of my father. However, I do hope that my mother will experience a little bit of happiness in the midst of gloomy circumstances.

This dissertation is dedicated to my wife, Tomoyo, who has been a great wife and friend to me and so patiently tolerated my anxiety and stress in the past years. Without her support, this dissertation could not have been possible to be completed.

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Chapter I

INTRODUCTION

Traditionally, sociologists and criminologists have approached criminal behavior as the outcome of irrational forces which cannot be subjected to theoretical analysis within the framework of economic rationalism. Consequently, rehabilitation was viewed as the only crime deterring policy worth of consideration. Joel Meyer expresses this traditional view in the following statement:

> Certainty of punishment and detection may deter the normal person who thinks about his actions and consequences, but the criminal mind does not operate like a normal mind. The criminal often acts irrespective of the consequences, learning little from experience and living for the present.[1]

An alternative to this traditional approach appeared in the 1960's with the introduction of the economic model of crime which assumes that the individual is rational. The rationality of the individual does not imply that the potential offender is able to perform sophisticated calculations, nor does the model assume perfect knowledge or complete and correct calculations. The attribution of rationality to the individual does imply, however, that when considering behavioral options, a potential offender uses information about the costs and benefits attached to various

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[1] Meyer, Joel. "Criminology and Police Science." Journal of Criminal Law, (1968).

alternatives. Crime in this model becomes just another manifestation of economic behavior involving choices and thus subject to scientific examination within the framework of economic theory.

The foundation of the economic model of crime rests on the traditional approach to the supply of labor as a problem of allocation of time between leisure and work, *i.e.*, different types of <u>legitimate</u> activities. In the economic model of labor supply, the individual maximizes his utility based on two constraints, income and time. Illegitimate activities in this model are ignored, probably as a result of "the attitude that illegal activity was too immoral to merit any systematic, scientific attention."[2] Parallels then emerge between the legitimate and illegitimate allocation of time. As Ehrlich states the case for the economic model of crime, "even if those who violate certain laws differ systematically in various respects from those who abide by the same laws, the former, like the latter, do respond to incentives."[3]

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[2] Becker, Gary, S. "Crime and Punishment: An Economic Approach." <u>Journal of Political Economy</u>, 78:2 (March/April 1968):169-217.

[3] Ehrlich, Isaac. "Participation in Illegitimate Activities: An Economic Analysis." <u>Journal of Political Economy</u>, 81 (May/June 1973):521-65.

Though the model itself was at the micro level (based on individual maximization of utility), the policy implications of the model were at the macro level (how police expenditure and other criminal justice inputs would bring about an optimal level of crime). For example, Becker says that the purpose of writing his article, "Crime and Punishment", was to answer questions such as how many resources and how much punishment should be used to enforce different kinds of legislation.

Gary S. Becker's work is the cornerstone of the economic model of crime. Becker essentially argues that potential criminals are similar to law abiding citizens in that they rationally maximize their own utility subject to the constraints -prices and income- that they face in the marketplace and elsewhere. In Becker's words, "some persons become criminals not because their basic motivation differs from that of other persons, but because their benefits and costs differ."[4] In Becker's view punishment is an important part of the cost consideration. Unlike the sociologists' view which focuses on rehabilitation, the economic model of crime brings punishment into the cost calculus for the potential criminal. Becker argues that the expected cost of punishment is an important factor in prevention of crime. The cost of being involved in illegitimate activities

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[4] Becker, Gary, S. "Crime and Punishment: An Economic Approach." Journal of Political Economy, 78/2 (March/April 1968):169-217.

includes not only forgone income which could have been earned in legitimate activities, but also the expected cost of punishment. The expected cost of punishment, L, is given by L=p.f, where p is the probability of punishment and f is the cost of punishment.

The relative effectiveness of p and f depends upon the attitude of the criminal towards risk. If the individual is risk neutral, both p and f have exactly the same effect. If the criminal is risk averse, the effect of f is higher than p. Finally, in the case of a risk lover, p is more effective than f. Becker believes that p is more effective than f, e.g., to catch one criminal out of 10 and sentence him to 2 years will be more effective for crime prevention than to catch one criminal out of 100 and sentence him to 20 years. In both cases, however, L (the expected cost of punishment) will be the same. Becker holds, therefore, that the criminals on average are risk lovers, and crime does not pay.[5] An estimation of costs and returns to crimes of

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[5]

$$E(U) = p\,U(Y-f) + (1-p)\,U(Y)$$

$$\frac{\partial E(U)}{\partial E(p)} = U(Y-f) - U(Y) < 0$$

$$\frac{\partial E(U)}{\partial E(f)} = -p\,U'(Y-f) < 0$$

$$-\frac{\partial E(U)}{\partial p} \cdot \frac{p}{U} = \varepsilon_p = (-U(Y-f) + U(Y))\ (p/U)$$

theft (robbery, burglary, larceny, and motor vehicle theft) have been shown in Ehrlich's empirical study which indicates that the expected net gain in burglary and larceny is positive, while the expected net gain in robbery is negative. Therefore, robbers appear to be risk lovers relative to burglars and thieves.

Although Becker was the first to systematically demonstrate the effectiveness of p over f in his economics of crime model, some earlier criminologists thought similarly. For example, in 1965 Lord Shawness commented:

> Some judges preoccupy themselves with methods of punishment. This is their job. But in preventing crime it is of less significance than they like to think. Certainty of detection is far more important than severity of punishment.[6]

In order to trace the development of the economic model of crime and to assess the present status of that model, the literature on this subject will be reviewed in two

$$-\frac{\partial E(U)}{\partial f}\cdot\frac{f}{U} = \varepsilon_f = p\ U'(Y-f)\,(f/U)$$

$$U(y) - U(Y-f)\cdot\frac{p}{U} \gtreqless pU'(Y-f)\ \cdot\frac{f}{U} \text{ or } \varepsilon_p \gtreqless \varepsilon_f$$

$$\text{or } \frac{U(Y)-U(Y-f)}{f} \gtreqless U'(Y-f)$$

The term on the left is the average change in utility between Y-f and Y. It would be greater than, equal to, or less than $U'(Y-f)$ as $U'' \gtreqless 0$.

[6] Becker, Gary, S. "Crime and Punishment: An Economic Approach." Journal of Political Economy, 78/2 (March/April 1968).

categories -general and juvenile.

1.1 GENERAL

Isaac Ehrlich's 1973 paper, "Participation in Illegitimate Activities," is important as an initial example of the use of the economic model in an empirical analysis of crime. Ehrlich's theoretical model is based on an individual who wants to maximize his utility, with income and time as the constraints. The individual's choice is to allocate a fixed amount of time (total time minus a fixed amount of time for consumption) between legitimate and illegitimate activities. Ehrlich reports the results of three cross section multiple regression analyses using FBI index crime rates for states within the U.S. for 1940, 1950, and 1960, respectively. His independent variables are a group of economic variables which have been suggested by his theoretical model. They include the legal and illegal income opportunities available to offenders, expected cost of punishment (probability of arrest, convictions, and severity of punishment), and finally, the probability of unemployment. Besides these independent variables, he introduces some other variables which are not suggested by his theory:

a. Percent of all males in the age group of 14-24.

b. percentage of nonwhites in the population.

c. Percentage of population in standard metropolitan statistical areas. Several assumptions are made and justified in order to extend the theoretical model to the aggregate level thus facilitating the use of aggregate data as indicators of individual-level phenomena. Ehrlich's findings are summarized as follows:

1. The probability of arrest and conviction has significant negative effects on the crime rate.

2. The deterrent effect of the severity of punishment has been confirmed for almost all offenses.

3. The predicted positive sign for illegal income, and the predicted negative sign for legal income have been confirmed for property offenses.

4. The remainder of the variables (except the percentage of nonwhite variable, which shows a positive sign) have indeterminate coefficients and insignificant t-values.

One major problem in Ehrlich's study is that he used available aggregate-level data with a theoretical model based on individual behavior. Ehrlich, himself points out:

> If all individuals were identical, the behavioral function, except for change in scale, could be regarded as an aggregate supply function in a given period of time.

The problem for Ehrlich, then, is that his data do not account for individual differences among people pertaining to their legitimate and illegitimate opportunities.

Contrasting to Ehrlich's model of crime, which assumes independent utility functions, Danziger and Wheeler[7] argue for interdependency of utility functions. They hold that the relative level of legitimate returns is an essential factor in the economic model of crime. Therefore, they include in their model not only the gap in absolute income of individuals, but also a measure of the gap in relative income. Their theoretical model is based on wealth maximization. Using a sample of 57 large SMSA's for the period of 1960-1961, Danziger and Wheeler concluded that an increase in income resulting from economic growth would lead to higher crime rates if the distribution of income is held constant. To decrease the crime rates, therefore, one can choose harsher punishment or redistribute income. Which of these policies should be chosen depends on the social welfare function which Danziger and Wheeler do not discuss.

The argument of Danziger and Wheeler that the envy of the poor for the rich is one of the reasons for crimes committed by the poor against the rich may be plausible. However, it is empirically difficult to prove. A poor person has a lower opportunity cost of being put in prison than does a wealthy person, and hence the potential profit to commit crime is higher for the poor. Separating this effect from the envy effect discussed by Danziger and Wheeler, however,

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[7] Danziger, Sheldon and Wheeler, David H. "The Economics of Crime: Punishment or Income Redistribution." Review of Social Economy, 33 (Oct. 1975).

would be statistically very difficult.

Although most of the economic analyses of crime have been based on individual theory of maximization of utility by using aggregate data, Ann Witte uses a sample of data collected at North Carolina prison.[8] Witte, building on the theoretical work of Block and Heineke (1975) as well as Becker and Ehrlich, finds some support for the deterrent value of punishment implied in the economic model of crime. Witte collects data from a study of the post-release activities of 641 men imprisoned in North Carolina in 1969 or 1971. Her results show that certainty and severity of punishment are negatively associated with criminal activity and that certainty of punishment has a greater deterrent effect than severity of punishment. Witte believes that drug addiction among her sample group interfered with proving the negative relationship between legitimate opportunities and crime rate.

I think a major problem with individual data used by Witte is the non-random nature of her sample. Nonrandom sampling provides estimates of theoretical structures which clearly cannot be used for inferences concerning members of society who have not already revealed their preferences for criminal activities.

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[8] Witte, Ann, P. "Estimating the Economic Model of Crime with Individual Data." The Quarterly Journal of Economic, 94 (February 1980):57-84.

1.2 JUVENILE

Belton M. Fleisher (1956) completed one of the earliest empirical studies in the economics of teenage crime. He tried to demonstrate the effects of the economic factors -unemployment and income- on juvenile crime. According to Fleisher's model, juveniles activities are determined by three factors: (a) benefits, (b) costs, (c) tastes, whether legitimate or illegitimate. In his model, supply and demand determine juvenile behavior. He defines supply and demand in the following way:
"demand which shows the tendency or propensity of people to commit delinquent acts", and by supply of offense, he means "the number and value of opportunities for the commission of such acts." Because his discussion is about juvenile crime, his data are age specific. He used arrest rates and court data which show the age of offenders. Fleisher used multiple regression analysis in order to separate the effects of economic factors from sociological and taste factors.

Fleisher uses two sets of data in his analyses: cross-sectional and time- series.[9] The focus of the latter

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9 His cross-sectional analyses use three sets of data which are as follows:
a. Court appearances of males aged 12-16 during the years 1958-1961 for the census tract communities in Chicago.
b. Court appearances of males 12-16 for 45 suburbs of Chicago

was the effect of unemployment on delinquency, while the focus of the former was the effect of income on juvenile delinquency. Fleisher's model predicts a positive correlation between unemployment rate and juvenile delinquency. If the unemployment rate goes up, not only will the legitimate earning opportunities for youth go down but also the juvenile's family income will decrease, both of which results would lead to an increase in delinquent acts. He also included some other factors in order to find the true effect of unemployment on juvenile crime. He used a dummy variable to distinguish war and peace periods and a trend variable to eliminate the long-term factors influencing actual criminality.

In Fleisher's cross-sectional analyses, which focus on the effect of income, he separated the demand effect of income from the supply effect. In order to separate these two effects, the families have been ranked according to their incomes and divided into quartiles. The mean income of the second lowest quartile (MEINC2) has been used as a proxy for legitimate earnings. The mean income of the highest quartile (MEINC4) has been used as a proxy for

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with population of 10,000 or more during 1958-1961.
c. Arrest statistics for 101 cities of the U.S. with population of over
25,000 or more during 1958-1961.
His time-series analyses is based on two sets of data:
a. Uniform Crime Reports for the U.S. (1932-1961).
b. Data published by the cities of Boston, Chicago
Cincinnati through approximately 1932-1961.

illegitimate earning opportunities. Suppose crime (Y) is a linear function of income and some other variables:

$$(1)\ Y = a + b\ MEINC2 + c\ MEINC4 + . + .$$

If we add to and subtract from the right hand side of this equation c MEINC2, we will get

$$(2)\ Y = a + (b + c)\ MEINC2 + c\ (MEINC4 - MEINC2) + . + .$$

Fleisher called the coefficient of the mean income of the poor families (which are expected to be highly delinquent) the demand effect of income. The coefficient of the absolute income gap between rich and poor, (c), was termed the supply effect of income. Fleisher argues that the sign of c has to be positive; as the absolute income gap between rich and poor (MEINC4 - MEINC2) goes up, holding MEINC2 constant, the illegitimate opportunities for delinquents would increase leading to higher criminal activity. The sign of (b + c) is ambiguous. This ambiguity results from a predicted negative sign for the coefficient of MEINC2, b, in equation (1). In equation (1), when the income of the poor goes up, so do both the legitimate earning opportunities and the opportunity costs of becoming involved in illegitimate activities. Therefore, an increase in MEINC2 would bring about a decrease in crime commited by the poor.

Fleisher adds to the above-mentioned economic factors, in his cross-sectional analyses, the following variables:

a. The proportion of females over fourteen years of age who are either separated or divorced (SPDVFM).

b. A mobility variable which is the proportion of the population over five years of age that resided in a different county five years prior to the census.

c. The race factor which is the non-white proportion of the population.

d. The proportion of owner-occupied dweling units.

e. Median number of years of schooling of the adult population.

In his time-series analyses, Fleisher finds a significant positive relationship between crime rate and unemployment for young juveniles. His war variable (a dummy variable equal to 1 for war time and zero otherwise) shows positive effects for juveniles and negative effects for adults. The positive effect of the war variable is expected because of lower parental supervision during war time. Alongside this war variable, Fleisher includes a time-trend variable to account for changes such as growing number of agencies reporting crimes to the F.B.I.'s Uniform Crime Reports, or improvements in police efficiency in arresting offenders over time. This time-trend variable shows significant positive correlation with crime.

To summarize Fleisher's results, in both his time-series and cross-sectional analyses the effect of unemployment on juvenile crime has been confirmed though in the latter the effect is less significant. Income variables show the expected signs, i.e., if income of the poor goes up, crime decreases; if the income gap widens, crime increases. The significance of taste variables and family structure are sensitive to the model specification. Fleisher claimed, however, that his purpose was to estimate the impact of economic variables rather than sociological factors. In general, the race variable does not show significant t-values, but the mobility and north-south dummy both show significant correlation with crime. The dummy variable which separates northern states from southern states shows lower degree of criminality in the southern states than in the northern states.

Singell's results differ from those of Fleisher. Singell (1967) tried to find the effect of unemployment on juvenile delinquency by using two sets of data, cross-sectional and time-series. In his cross-sectional investigation, he used census tract data for Detroit for the year 1961. He estimated the supply of offense function with delinquency as a function of unemployment in linear and double log forms. His dependent variable was the total contacts with the Youth Bureau of the Detroit Police Department divided by the age specific population. Although he found a positive relationship between the unemployment rate and delinquency, the t-values were found to be insignificant. Fleisher on the other hand found the t-values significant. Singell assumes homogeneity of the census tract population and thus uses only unemployment as the explanatory variable. This assumption remains questionable, however. The unemployment coefficients might be biased in that the dependent and independent variable might be affected by a third variable excluded in Singell's model. A set of socioeconomic variables, for example, might interact with each other producing a positive correlation between unemployment and delinquency.

Singell claimed that median family income should have a very high correlation with other socioeconomic factors. Therefore, he categorized his cross-sectional data according to median family income and ran separate simple regressions for each category. These results showed unemployment to be insignificant and, thus, inconsistent with his hypothesis which assumes unemployment to be a direct cause of delinquency. Using the same categorization with his time-series data for the same geographic area during the period 1950 through 1961, he showed a positive relationship between the unemployment rate and delinquency, though t-values were still insignificant. Unlike Singell's cross-sectional analysis, the time-series results show a very low R-squared for both linear and double log forms. He accounts for the poor results in his time-series analysis by citing the following two reasons:

a. Unavailability of data for youth unemployment.

b. Prolonged periods of youth unemployment resulting in youths not even considering a legitimate job and, therefore, not counted as unemployed.

Despite the weakness of evidence, Singell concludes that a decrease of one percent in unemployment would lead to a decrease in delinquency rates from one-fourth to one-sixth of 1 per cent.

Weicher (1970) redefined Fleisher's family structure variable with the implication of rendering Fleisher's economic variables insignificant. The 74 census tract communities in Chicago, which Fleisher himself singled out as the most useful data, were selected by Weicher in his study. Weicher introduced FAMILY, the ratio of persons less than 18 years of age who are living with both parents to all persons under 18 years, where Fleisher had used SPDVFM, the proportion of females over fourteen years of age who are separated or divorced. Fleisher introduced SPDVFM to represent the proportion of broken families in the community equating broken families with less parental supervision and guidance. Weicher claims that a better variable for indicating broken homes would be FAMILY, which could be calculated directly from census data. The statistical results after substitution of FAMILY for SPDVFM show that unemployment and income of the highest quartile (MFINC4) are not significant anymore. FAMILY by itself, however, does show a significant effect on juvenile delinquency.

Weicher, like Fleisher, also analyzed delinquency within Chicago on the basis of subgroups of communities stratified by SPDVFM. Weicher's results show that the incidence of delinquency is higher for the subgroup with lower SPDVFM. Therefore, Weicher concluded that economic variables are significantly related to delinquency only where delinquency itself is relatively unimportant. The explanation is that for the high SPDVFM subgroup, unemployment is likely to be a normal phenomenon, therefore, it does not represent a deviation of current income from normal income to the same extent as it does in the low SPDVFM subgroup. Weicher's results provide no basis to show any "effect of income on delinquency".

An article written in 1975 by Phillips, Votey, and Maxwell addresses the issue of the relative merits of the unemployment rate as compared to the labor force participation rate as a measure of economic opportunities and, hence, as a predictor of crime. Their theoretical model is based on the concept of minimization of the cost of crime to community. Their data set pertains to California counties for the year 1966. They argue that labor force participation as well as unemployment must be considered when relating labor market opportunities for youth to their arrest rates. The reason is that youth have low labor force participation rates and, therefore, the unemployment rate has less weight because a considerable fraction of youth is out of the labor force. Another important reason for considering youth labor force participation rate is that the unemployment rate reflects the cyclical and short-run conditions in the labor market, where participation rate capture secular changes, including the influence of past unemployment. On the other hand, the problem with this approach is that due to a high degree of multicollinearity between labor force participation and unemployment, t-values are insignificant. Therefore, relative significance of each variable is unknown. The relatively large R-squared in their equations causes the authors to conclude that "changing labor market opportunities are sufficient to explain increasing crime rates for youth" in the U.S. during the period 1952-1967. Another problem with this analysis is its failure to explain why both the labor force participation rate for women and their crime rates have been increasing over time.[10]

Juvenile crime has been ignored for the most part by economists since the empirical work of Fleisher despite the fact that statistics indicate that a larger proportion of

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[10] Actually, however, the economic model of crime indicates that the relationship between crime rates and labor force participation for women is ambiguous. If LFPR for women increases because of a higher legal wage, more time would be spent at legal activities (substitution effect). Therefore, a negative sign for LFPP could be predicted. On the other hand, if labor force participation is higher due to low marginal utility out of housework activities, more time would be allocated to market work leaving more time for both legitimate and illegitimate activities (scale effect).

property crimes is due to juveniles.

In this study, an attempt is made to improve the economic model of crime as determining the economic factors affecting juvenile crime. Not only will data from the 1970's be used, allowing a comparison with Fleisher's sample of the 1950's and 1960's, but also the model will explicitly incorporate time for schooling as a relevent to juvenile variable with respect to their time allocation.

Chapter II

THEORETICAL MODEL

We assume each individual has an expected utility function given by equation (1).

(1) $E(U) = (1-p)\ U\ (Y1,tc) + p\ U\ (Y2,tc)$

where Y1 is income when not apprehended

Y2 is income when apprehended

p is probability of being apprehended

F is the discounted value of punishment

tc is consumption time (fixed)

tw is work time

tl is time spent in legal activities

ti is time spent in illegal activities

ts is time for schooling

Let T be the total amount of time. Since tc is being held constant the amount of time available for work is fixed and therefore:

$$T - tc = tw + ts = tl + ti + ts$$

Let us also assume that the wage rate in the legal market (Wl) and wage rate in the illegal market (Wi) are constant. Hence:

(2) $Y1 = Wl.tl + Wi.ti + R(ts)$

and

(3) $Y2 = Y1-F = W1.t1 + Wi.ti - F + R(ts)$

Where R is the present discounted value of net return to schooling.

If we substitute equation (2) and (3) into (1)

(4) $E(U)=(1-p)\ U1[Wi.ti+W1.t1+R(ts)] + p\ U2[Wi.ti +W1.t1-F+R(ts)].$

(5) $$\frac{\partial E(U)}{\partial ti} = (1-p)U'1(Wi-W1)+pU'2(Wi-f-W1)=0$$

(6) $$\frac{\partial E(U)}{\partial ts} = (1-p)U'1(r-W1)+pU'2(r-W1)=0$$

Where $U'_1 = \dfrac{\partial U}{\partial Y1}$ $\quad U'2 = \dfrac{\partial U}{\partial Y2}$

First order-condition is:

(7) $$-\frac{W1 - Wi}{W1 - Wi - f} = \frac{p\ U'2}{(1-p)\ U'1}$$

The left hand side is the slope of the opportunity boundary which shows the rate at which income can be transferred between the two states of the world. The right hand side is the slope of the indifference curve which shows the rate at which the individual is willing to make such a transfer. Also note that condition for equation (7) holds if

(8) $Wi - Wl < f$[11] Where $f = \frac{\partial F}{\partial ti}$

Otherwise regardless of the attitudes of the individual toward risk, he would become specialized in crime.[12]

The first-order condition also gives us the following result:

(9) $r = Wl$

Where r is the derivative of S with respect to ts. The equation (9) gives us the equilibrium value of time for schooling (ts). In addition to ts, however, the marginal return to schooling would be also affected by the time spent in illegal activities because the probability of carrying a criminal record will be higher. Therefore, expectations of

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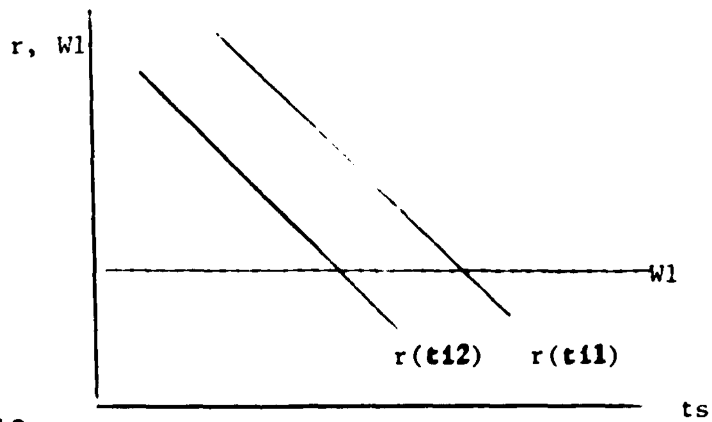
[11] One of the assumptions of this model is that the second derivative of punishment with respect to ti, F", is positive. In other words, punishment increases with an increasing rate. The rationale for such an assumption is that as an individual becomes more involved in criminal activities, the probability of getting involved in more serious crime goes up. An individual, for example, might start his criminal activities with grand larceny and as time passes he might get involved with more serious crimes like burglary or robbery.

[12] The second-order condition will be satistified if the principal minors of the Hessian determinants of the second partial derivaties alternate in sign. A necessary but not sufficient condition is that

$(1-p)U''(Wi-Wl) + pU''(Wi-Wl-f) + pU'(-F'') < 0$

If the individual is a risk averse, then U"1,U"2<0 and since F">0, the first principal minor would become negative. If the individual is a risk-neutral U"1,U"2=0, and U'2>0, the first principal minor would become gainful legal employment must be lower implying a lower marginal return to schooling function (see Figure 1). Under downward shift of the marginal return to schooling function, the individual will be willing to continue allocating the same amount of time to schooling if the legal wage was lower so that the opportunity costs of school attendance would diminish to match the lower expected return out of schooling due to employment impediments that his criminal record entail. On the other hand, with the legal wage fixed, the equilibrium amount of time for schooling will be lower.



where ti1<ti2

FIGURE 1

In this case even for a given value of W1 (the legitimate wage rate), an increase in ti will result in a lower allocation of time for schooling by an individual.

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negative again. In the case of a risk-lover $U''1, U''2>0$, therefore, the first principal minor would become negative if the value of $-pU'2F''$ would dominate

$$(1-p)U''1(Wi-W1) + pU''2(Wi-W1-f)$$

If $(1-p)U''1(Wi-W1)+pU''2(Wi-W1-f)>-F''pU'2$ there would be a corner solution, and the risk-lover would become specialized in either legitimate or illigitimate activities.

Considering the first-order condition, the offense function for an individual could be developed as:

$$(11)\ \ln C = a_0 + a_1 \ln Wi + a_2 \ln Wl + a_3 \ln f + a_4 \ln p + a_5 \ln r + U1$$

where C=crime rate per a given period of time

Based on equation(9), we assume time for schooling as a loglinear function of Wl and r

$$(12)\ \ln S = b_0 + b_1 \ln Wl + b_2 \ln r + U2$$

Now solving for r in equation(12), we obtain equation(13)

$$(13)\ \ln r = b_2^{-1} \ln S - b_0 b_2^{-1} - b_1 b_2^{-1} \ln Wl - b_2^{-1} U2$$

or (14) $\ln r = \gamma_1 \ln S - \gamma_2 - \gamma_3 \ln Wl - \gamma_1 U2$

Substituting (14) into (11):

$$(15)\ \ln C = a_0 + a_1 \ln Wi + a_2 \ln Wl + a_3 \ln f + a_4 \ln p$$
$$a_5\gamma_1 \ln S - a_5\gamma_3 \ln Wl - a_5\gamma_1 U2\ U1$$[13]

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[13] One assumption is that U1 and U2 are not mutually correlated. If, on the other hand, covariance of U1 and U2 is not zero, the system is called a system of seemingly unrelated regression equations. The reason for a non zero covariance between U1 and U2 could be that those individuals with a tendency for crime might have a taste against schooling. This negative correlation between U1 and U2 could be the cause for another source of biasdness for the estimated coefficients in the reduced form of offense function (see A. Zellner, "Estimators of Seemingly Unrelated Regressions: Some Exact Finite Sample Results." Journal of the American Statistical Association, Vol. 58, December 1963).

Since $a_5<0$, $\gamma_1>0$, we expect time for schooling to be negatively related to the crime rate. Further, ln S is positively related to U2 because $b_2>0$, this implies that the Cov $(\ln S, -a_5\gamma_1 U2+U_1)>0$.[14]
Therefore,

$$\beta^* = \beta + \mathrm{COV}$$

Where β^* is the actual estimation of the partial elasticity of the crime rate with respect to S, and β is the true partial elasticity of S. Given the Covariance of S and error term is positive and , this introduces simultanous equations bias which biases the impact of S toward zero. The important point of this conclusion is that because the covariance of S and the error term $(-a_5\gamma_1 U2+U1)$ is positive we may obtain insignificant partial elasticity for the S variable. However, it may indeed be that the true parameter is statistically significant. In essence, under the above

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[14] Proof: $\mathrm{COV}(\ln S, -a_5\gamma_1 U2+U1) =$

$E(\ln S-\overline{\ln S})[(-a_5\gamma_1 U2+U1)-\overline{(-a_5\gamma_1 U2+U1)}] =$

$E[\ln S(AU2+U1)-\ln S\,\overline{(AU2+U1)}-\overline{\ln S}(AU2+U1)+\overline{\ln S}\,\overline{(AU2+U1)}] =$

Where $A = -a_5\gamma_1>0$

$E\ln S(AU2+U1)-\ln S(0)-\overline{\ln S}(AU2+U1)+\overline{\ln S}(0) =$

$E\ln S(AU2+U1)-\overline{\ln S}\,E(AU2+U1) = E\ln S(AU2+U1)$

Since $E(\ln S.\ U1)=0$, therefore,

$E\ln S(AU2+U1) = A\,E\ln S(\ln S, U2)$. Since both A and $E(\ln S, U2)$ are positive, therefore, $\mathrm{Cov}(\ln S, -a\ U2+U1)>0$.

condition, the probability of making a type II error, i.e., S is statistically significant when it is not, becomes zero.

If we assume all individuals are identical, the aggregate supply of offense will be the same as an individual's, but with a different scale. Therefore, the aggregate supply of offense could be assumed to be a multiplicative function of the following form:

$$(16)\quad O/N = B^{\beta^0} \cdot (A/O)^{\beta^1} \cdot Wi^{\beta^2} \cdot Wl^{\beta^3} \cdot S^{\beta^4}$$

where O/N is the offense rate

A/O is the probability of being arrested

Wi is the illegitmate wage rate

Wl is the legitimate wage rate

S is time for schooling

B is a vector of sociological variables not included in the model

If we multiply both sides of equation (16) by A/O, we have:

$$(17)\quad A/N = B^{\beta^0} \cdot (A/O)^{1+\beta^1} \cdot Wi^{\beta^2} \cdot Wl^{\beta^3} \cdot S^{\beta^4}$$

Instead of offense rate, the arrest rate is now the dependent variable since the age should be known in our analyses.

The difference between equation (17) and (16) is only in terms of the elasticity of probability of being arrested, but all other variable coefficients would be unchanged.

Suppose absolute value of the elasticity of p in equation (16) is less than one, then elasticity of p in equation (17) would be positive which means as probability of being arrested goes up, everything else being held constant, arrest rate will go up. In general,

$$A/N = B^{\beta 0} \cdot (A/D)^{\gamma} \cdot Wi^{\beta 2} \cdot Wl^{\beta 3} \cdot S^{\beta 4}$$

Note that the theory predicts a negative sign for p in equation (16) but the sign of p in equation (17) is ambiguous.

Chapter III

DATA

This study uses two sets of data: first, cross-sectional data for 50 states of the U.S. for the year 1971, and second, pooled cross-sectional time-series data for five boroughs of New York City for the period 1970-1980.

A. Cross-Sectional Data for the United States:

The dependent variable in this set of data consisting of 50 observations for the year 1971 is "arrest rate" for four types of property crimes (robbery, burglary, larceny, and motor vehicle theft). The F.B.I. keeps the arrest records for only 10 years prior to the current year. Therefore, "arrest rate" data refer to 1971. Most of the data for the explanatory variables of the model were collected from the 1970 census. Information on variables like age or income distribution, which are not available on an annual basis, was gathered from the census. Since variables of that kind are unlikely to change drastically from year to year, the blending of census 1970 data with crime statistics of 1971 can be defended adequately.

B. Pooled Cross-Sectional Time-Series Data for New York City: The cross-sectional time-series data for the five boroughs of New York City (Bronx, Brooklyn, Manhattan, Queens, and Staten Island) for the period of 1970-1980, yield 55 observations. There are no data available for arrests prior to 1970 for New York City. Therefore, by using cross-sectional time-series data, we are able to augment the number of observations over the alternative of using time-series data only. Another advantage is that "since cross-section for different years are pooled, the specification incorporates variations in independent variables among counties at a moment in time as well as variations over time. Thus, it mitigates the multicollinearity problems that almost certainly would arise in time- series".[15]

The F.B.I. provided unpublished 1971 arrest data for the cross-sectional study. Arrest rate data for New York City have been collected from unpublished data sources prepared for the F.B.I.'s Uniform Crime Report by the New York City Police department. Dependent variables are arrest rates (for both the U.S. and New York City) rather than offense rates. Consequently, the real offenses committed by juveniles most likely are being underestimated for the following reasons:

1. Police might be reluctant to arrest juveniles.
2. One perpetrator might commit many crimes.

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[15] Jacobowitz, et al. "Variation in Infant Mortality Rates among Counties of the United States: The Roles of Public Policies and Programs." Demography, no.4 (November 1981).

3. Crimes might not be reported. Nifelski shows in his study, for example, that "in delinquency cases, the system is a filter where, of every 500 possible juvenile arrests, it is estimated that there are two hundred police contacts resulting in 100 arrests, of these, only 40 youths are taken in, only twenty appear before a judge, and only 2 or 3 are sent to correctional facilities."[16]

In offense data (crimes reported to the police), the characteristics of offenders are unknown. Consequently, economic factors which shape the environment in which juvenile offenders operate, remain unknown. Although individual data, cohort data, or court data might be used, the first two are simply not available. Court data, which could be easily obtained are inferior to the arrest data which will be used in this study (For example, Fleisher used court data as a part of his juvenile crime analysis). Arrest data are superior to court data because of such problems as plea bargaining in the disposition of property crimes in the judicial system. A study by the Vera Institute of Criminal Justice[17] shows that even those offenders who reach the court are not going to be prosecuted for what they have done. Most of the time, due to

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[16] Nifelski, Paul. "Confronting Youth Crime." us. American Journal of Sociology, (1964):209.

[17] Vera Institute of Criminal Justice, Felony Arrests: Their Prosecution and Disposition in NYC's Courts, New York, 1977.

congestion in the system, offenders accept a lesser charge so as to avoid the time consuming trial. Both criminals and prosecutors gain from this bargain. In a sample of 369 felonies[18] in 1973 in New York City, for example, 30% were immediately dismissed and the remaining defendants, all but two, were allowed to plead guilty to reduced charges in robbery cases. In the case of burglary from the same sample, 25% were dismissed and 94% of undismissed burglary charges were reduced to misdemeanors or less. In the case of less serious crimes, such as grand larceny, most of defendants were allowed to plead guilty to misdemeanor charges. This considerable under-reporting of crime could lead to biased results if under-reporting is correlated with any of the explanatory variables.

Independent variables which have been used are more or less the same for both analyses (the U.S. and New York City). A list of variables and their sources have been given in Table 1 and Table 10.

In dealing with the data used in this study, several modifications had to be made. For the New York City analysis, yearly data for all independent variables have been available except for Black ratio which has been estimated for the years between 1970 and 1980 based on census data for 1970 and 1980.

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[18] Felonies are crimes carrying a maximum sentense of more than a year in prison .

In all aggregate studies to find a good proxy for legitimate and illegitimate income opportunities presents a difficulty. Indeed, at times, the measure used as a proxy for legitimate income in one study is used as a proxy for illegitimate income in another. In this study whereas aid to families with dependent children has been used as a proxy for legitimate earning opportunities in the New York City analysis, the percent of families living below poverty level has been used in the cross-sectional analysis. Real per capita income has been used as a proxy for illegitimate earning opportunities in the New York City analysis while median income has been used in the cross-sectional analysis.

Data for real per capita income have been collected from the City and County Data Book of 1977. The years 1978 through 1980 have not been available. Therefore, I projected the last three years based on the trend of per capita income.

Civilian unemployment rate has been used in the analysis for juvenile delinquents under 16 in both sets of data as a proxy for the deviation of income of the families of these juveniles from its normal level in order to investigate the impact of the economic conditions of the parents on juvenile behavior. However, teenage unemployment can be used as a variable affecting crime since most of teenagers (16-19) are in the labor force. Due to the lack of data for teenage unemployment for the U.S. analysis, I utilized information on teenage unemployment for the available years, 1977-1980 after the following modification:

$$TEENUN_{1971} = \sum_{i=1977}^{1980} (TEENUN_i / UNEMPL_i) . \; UNEMPL_{1971}$$

where TEENUN is the unemployment rate for teenagers and UNEMPL is the civilian unemployment rate. Fluctuations of teenage unemployment as well as of unemployment in minority groups might be greater than fluctuations in the average civilian unemployment rate. Not making the unemployment rate age specific might be misleading because the impact of unemployment on teenage crime will be underestimated. In the case of the New York City analysis, however, due to the total lack of data for teenage unemployment, the civilian unemployment rate has been used as a proxy for teenage unemployment.

Chapter IV

CROSS-SECTIONAL RESULTS FOR THE U.S.

In this section, cross-sectional results for the U.S. are presented, discussed and evaluated. Table 1 contain the definitions and Table 2 shows the mean and standard deviation of all the variables used in the analysis.

The arrest function has been estimated as follows:

$$ARijk = \alpha_0 + \alpha_1 (UNEMPL) + \alpha_2 (DIVORC) + \alpha_3 (MEDIN) + \alpha_4 (LOWIN) + \alpha_5 (BLKR) + \alpha_6 (SMSR) + \alpha_7 (DUM) + \alpha_8 (ATTENR) + \alpha_9 (PROAR) + U$$

A short explanation for each of the independent variables entering our arrest function follows:

1. Unemployment rate (TOTUN) has been introduced into the equation because any increase in this variable would present a deviation of income from normal earnings. Therefore, ceteris paribus, we would expect a positive sign for unemployment unless the individual is not in the labor force.

2. Median income (MEDIN) has been introduced as a measure for illegitimate earnings. The theory of economics of crime predicts a positive relationship between this variable and crime rates. The justification for this prediction is based

TABLE 1

List of Variables

Variable Name	Source	Definition
Dependent Variables)		
ROB1MR	1	Arrests for robbery per 10,000 population for males under 16
BUR1MR	1	Arrests for burglary per 10,000 population for males under 16
LAR1MR	1	Arrests for larceny per 10,000 population for males under 16
MVT1MR	1	Arrests for motor vehicle theft per 10,000 population for males
ROB2MR	1	Arrests for robbery per 10,000 population for males 16-19.
BUR2MR	1	Arrests for burglary per 10,000 population for males 16-19
LAR2MR	1	Arrests for larceny per 10,000 population for males 16-19
MVT2MR	1	Arrests for motor vehicle theft per 10,000 population for males 16-19
Explanatory Variables)		
UNEMPL	2	Civilian unemployment rate for 1971 for all ages
DIVORC	2	Divorce rate (per cent) for 1971
MEDIN	3	Median income of families 1971
LOWIN	3	Percent of families who live on poverty 1970
BLKR	3	Number of blacks per 10,000 population.
SMSR	4	Number of people who live in metropolitan areas per 10,000 population

DUM	see text	Regional dummy variable equal to one for southern states, zero otherwise
TEENLF	2	Labor force participation rate for males 16-19
TEENUN	see text	Estimated teenage unemployment for 1971
LFTOTF	2	Labor force participation rate of all females age 16 and over for 1971
ATTENR	2	Daily school attendence per 10,000 registration
PROARR	1	Number of robbery arrests per 10,000 robbery complaints.
PROARB	1	Number of burgalry arrests per 10,000 burglary complaints.
PROARL	1	Number of larceny arrests per 10,000 larceny complaints.
PROARM	1	Number of motor vehicle theft arrests per 10,000 motor vehicle theft complaints.

[a]
1 = F.B.I.'s Headquarter in Washington D.C., unpublished data, 1971.

2 = Statistical Abstract of the U.S. 1973.

3 = Bureau of the Census, Population census of 1970 and 1980.

4 = F.B.I.'s Uniform Crime Report, 1971

TABLE 2

Summary Statistics of Variables

Dependent Variables)

	MEAN	STANDARD DEVIATION
ROB1MR	.87	1.25
BUR1MR	3.67	.65
LAR1MR	4.38	.64
MVT1MR	2.31	.81
ROB2MR	2.95	1.02
BUR2MR	4.65	.47
LAR2MR	5.13	.43
MVT2MR	3.77	.61
EXPLANATORY VARIABLES:		
UNEMPL	1.69	.26
TEENUN	2.63	.25
TEENLF	3.65	.11
LFTOTF	3.71	.06
DIVORC	1.20	.48
MEDIN	9.1	.16
LOWIN	2.36	.40
SMSR	7.84	2.96
PROARR	8.09	.39
PROARB	7.24	.31
PROARL	8.24	.27
PROARM	7.29	.43

on the idea that as income in the society goes up, we expect an increase in the income of victims or an increase in expected return to illegitimate earnings opportunities which gives more incentive to a potential offender to commit more crime.

3. The race factor (BLKR) has been included because blacks as a minority group in the society face certain kinds of discrimination and on average earn less income and therefore, the possibility of getting involved in illegitimate activities is higher.

4. The divorce rate is introduced as a proxy for family structure, since it has psychological, economic and sociological impacts on juvenile behavior. An economic consequence of divorce is the family's decreased income due to the loss of one wage earner. Even though a measure of income is also included in the model, this does not necessarily mean that the income effect of broken families is being held constant.

5. The daily school attendance rate (ATTENR) for public schools has been used in our equations as a proxy for time for schooling. As we discussed in the theoretical model, a negative correlation between this variable and crime rate is to be expected (see Chapter II).

6. Probability of Arrests (PROAR) has been included as an independent variable. In the theoretical model (Chapter II), it was shown that an absolute value of less than one

for the elasticity of arrest rate with respect to probability of being arrested implies a deterrent effect in the offense functions. Since offenses, committed by juveniles, are not available the average probability of being arrested for each type of crime has been used as a proxy for both age groups.

7. The urbanization factor (SMSP) is expected to have a positive correlation with crime. In general, states with a high degree of urbanization are less exposed to crime. In general, in a rather traditional society, we expect juveniles to be more under the parental supervision and to be more attached to the norms of the society. We also can expect higher rates of crime in urban areas due to a higher concentration of people and industrialization, both of which might cause some psychological and sociological problems.

8. A dummy variable (DUM) separates the northern states from the southern states to see if there is any taste difference between the North and the South. The regional dummy variable is given the value of one for southern states, and zero otherwise. Southern states in the sample are Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Texas, and Virginia. The impact of omitted variables specific to a geographic region may be reflected in the coefficient of the dummy variable. Therefore, a significant coefficient for the DUM does not necessarily indicate a taste difference between the North and the South.

Two sets of equations have been estimated. The first set refers to males under 16 for each type of property crime (robbery, burglary, grand larceny, and motor vehicle theft). The second set refers to males between 16-19. Table 3 and Table 4 present results of the arrest functions for males under 16 and 16-19 years of age, respectively. Overall, the sample of 50 states yields the following results:

1. The unemployment rate does not show significant results for any property crimes among juveniles under 16. The estimated coefficient of the unemployment rate for juveniles 16-19, is not statistically significant either; 2. The "demand effect" of income on crime, as measured by the coefficient of LOWIN, shows positive correlation with arrest rate. The coefficients, however, are not statistically significant for all types of crime; 3. The "supply effect" of income on crime estimated by the coefficient of MEDIN, shows significant positive relationship with arrest rates. All t-values are statistically significant for both age groups; 4. The estimated net effect of race is statistically insignificant; 5. SMSA as a measure of urbanization shows significant positive correlation with arrest rate; 6. The daily school attendence rate, ATTENR, is statistically insignificant for all types of crime except for robbery among juveniles 16-19. ATTENR coefficients for juveniles 16-19 are mostly negative and robbery has a specially large coefficient; 7. The divorce rate as a an indicator of family

structure shows significant positive effects on crime especially among teenagers; 8. Finally, the dummy variable, DUM, is insignificant. Its negative coefficient, however, implies less criminality in the South as compared to the North.

Results of arrest functions show that t-values of unemployment, except for robbery among juveniles under 16, are insignificant. All coefficients of unemployment (except in motor vehicle theft among juveniles under 16 and burglary and motor vehicle theft among juveniles 16-19) show negative correlation with arrest rates. This insignificant and negative relationship between unemployment rate and arrest rates might has been caused by the income factors. The income variables employed in our empirical investigation (measured income) are proxies for normal income. The unemployment rate measures the deviation of income from trend. Since measured income is being held constant, this would lead to negative correlation between unemplcyment and normal income and, thus, to a negative coefficient for unemployment if the effect of normal income on delinquency was strong relative to the effect of unemployment and if the transitory component of income was large relative to the normal component.[19] Another reason why the partial effect of

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[19] Fleisher argued this point in his cross-sectional analysis after he observed some negative coefficients for unemployment. This point has been shown by Fleisher as follows: Denote measured and transitory income by the subscripts m and t, respectively.

TABLE 3

REGRESSION COEFFICIENTS
U.S. ANALYSIS
LOG ESTIMATION
JUVENILES UNDER 16

	ROB1MR	BUR1MR	LAR1MR	MVT1MR
UNEMPL	-.8 (1.8)*	-.27 (1.0)	-.04 (.1)	.04 (.1)
DIVORC	-.06 (.2)	.34 (2.6)**	.17 (1.2)	.43 (2.8)***
MEDIN	7.2 (3.9)***	4.3 (3.9)***	3.2 (2.7)***	4.8 (3.8)***
LOWIN	1.09 (1.2)	1.1 (2.2)**	1.04 (1.95)*	.85 (1.4)
BLKR	.24 (2.0)**	.07 (1.0)	.03 (.4)	.03 (.4)
SMSP	.12 (3.0)***	.05 (2.3)**	.03 (1.4)	.09 (3.5)***
ATTENR	-3.7 (.8)	.54 (.1)	3.1 (1.0)	.31 (.09)
DUM	-.51 (1.1)	-.25 (.9)	-.52 (1.79)*	-.25 (.8)
PROAR	-.26 (.9)	.56 (3.1)***	1.1 (4.2)***	.37 (2.0)**
C	-32 (.6)	-48 (1.75)*	-65 (2.2)**	-50 (1.5)
F-STATISTIC (9, 40)	11.5	8.1	6.5	9.8
R-SQUARED	.72	.64	.59	.68

Absolute values of t-statistic are in parantheses.

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 4

REGRESSION COEFFICIENTS
U.S. ANALYSIS
LOG ESTIMATION
JUVENILES 16-19

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
TEENUN	-.10 (.3)	.06 (.3)	-.08 (.5)	.04 (.1)
MEDIN	6.9 (6.5)***	1.3 (1.97)*	1.4 (2.3)**	3.3 (4.0)***
LOWIN	1.6 (3.2)***	.02 (.08)	.15 (.5)	.43 (1.2)
BLKP	.26 (3.7)***	.07 (1.7)*	.01 (.4)	.08 (1.56)
SMSR	.12 (5.2)***	.04 (2.6)**	.02 (1.95)*	.04 (2.5)**
ATTENR	-5.2 (1.9)*	-.06 (.03)	1.1 (.7)	-.86 (.4)
DUM	-.27 (1.0)	-.21 (1.2)	-.27 (1.71)*	-.31 (1.5)
DIVORC	.20 (1.6)	.23 (2.8)***	.24 (3.2)***	.19 (1.89)*
PROAR	.39 (2.3)**	.65 (4.8)***	.63 (4.6)***	.44 (3.6)***
C	-21 (.7)	-13 (.7)	-25 (1.5)	-24 (1.1)
F-STATISTIC (9, 40)	27	12	12.2	14.3
R-SQUARED	.85	.73	.73	.76

Absolute values of t-statistic are in parantheses.

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

the teenage unemployment rate does not appear significantly different from zero could be, as Ehrlich says, "that variations in unemployment rate across states reflect considerable variation in voluntary unemployment due to the search for desirable employment."

The coefficient of median income (MEDIN), as a proxy for illegitimate earning opportunities indicates that a significant positive relationship exists between MEDIN and crime in all equations between the two age groups. LOWIN, as a proxy for measuring poverty and income inequality in each state, shows a positive relationship with arrest rate. The coefficients for LOWIN are significant for burglary and larceny among juveniles under 16 and for robbery among juveniles 16-19.

Among the other variables, the divorce rate exhibits significant positive correlation with almost all types of crime among juveniles 16-19. Among juveniles under 16, however, it is only significant for burglary and motor

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$$Y = a + b\,(MEINC2m - MEINC2t) + c\,(MEINC4m - MEINC4t) + d\,(TOTUN) + U$$

when MEINC2 is the income of lower class families and MEINC4 is the income of upper class families. Assume that MEINC2t and MEINC4t are linearly related to TOTUN (unemployment rate) as follows:

$$MEINC2t = -\,e2\ TOTUN$$
$$MEINC4t = -\,e4\ TOTUN$$

Then

$$Y = a + b\,MEINC2m + c\,MEINC4m + (be2 + ce4 + d)\,TOTUN + U$$

Therefore, however theory predicts a negative sign for d, still the coefficient of TOTUN could be negative if the absolute value be2 is bigger than (ce4 + d).

vehicle theft. The statistically significant coefficients for divorce rate support the sociologically-based theories of delinquency where the family is considered to be of major importance in delinquency formation. It should be noted, however, that divorce could be the result of economic factors as well. For example, some studies show that among those of lower socioeconomic status, there is a greater incidence of marital dissatisfaction.[20] Also other studies claim that youths in homes without fathers have less knowledge of the labor market.[21] This interaction between divorce (broken homes) and economic variables, therefore, could cause a vicious circle, i.e., a decrease in employment opportunities can cause lower income in turn causing more broken homes leading back to fewer legal employment opportunities for juveniles.

SMSR, which measures the degree of urbanization in each state, shows a significant positive relationship with arrest rates for all types of crime with the exception of larceny for juveniles under 16.

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[20] Rainwater, et al. The Moynihan Report and the Politics of Controversy, Cambridge, Mass.: MIT Press, 1967.

[21] In his study Bullock found that Chicanos in Los Angeles had greater access to factory jobs than Blacks partly because they were more likely to have fathers present in the households (see for more detail, Paul Bullock, Aspiration vs. Opportunity: Careers in the Inner City Ann Arbor: Institute of Labor and Industrial Relations, University of Michigan, 1969).

It is likely that, to a considerable extent our SMSR variable reflects the incidence of slums on crime in more industrialized states. It has been demonstrated that slums tend to create serious personality and adjustment problems for their inhabitants, and therefore, slums tend to breed crime. Some other reasons for this significant positive relationship between the dependent variable, arrest rate, and SMSR, could be the results of, as Ehrlich says, "more accessibility to (lower direct costs of engaging in) various criminal activities due to the concentration of business activity, the massive communication networks, and the density of the population in metropolitan areas." I, also believe that larger police forces in SMSA's may lead to more arrests.[22]

The race variable, BLKR, shows significant t-values for robbery and burglary among juveniles 16-19 and only for robbery among juveniles under 16. Even though all coefficients of this variable show positive correlation with crime rates, its impact is relatively small for all types of

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[22] It is expected that more urbanized areas will have higher per capita police expenditure, therefore, SMSR to some degree represents the effects of the omitted police variable. For a given locality total crime is consist of unreported and reported. If additional policeman will result more prevention and detection of crime, the sign for police could be positive, since increase in detection would cause a positive relationship between police and arrest rate. Because SMSR is expected to be highly correlated with police variable, we can expect SMSR's positive relationship with the arrest rate will be reenforced.

property crimes except for robbery. In addition to inferior legitimate opportunities among blacks, their specific labor market difficulties could be underestimated when the overall unemployment rate is used. An unemployment rate specific to the given sub-population, should reflect discouraged and underemployed workers which are ignored in conventional statistics of unemployment.

The regional dummy variable (DUM) has a negative relationship with arrest rate for all types of crime. Larceny for both age groups is the only property crime which has a significant t-value for DUM. The negative sign of the coefficient of DUM indicates lower arrest rates in the South as compared to the North. Some omitted variables might explain this result. The existence of a more traditional society, however, with stronger family structure in the South, could also provide an explanation. A comparison of results between the DUM and the SMSA suggests that urban differences are more important factors in the determination of crime than regional differences.

Elasticities of the offense rate with respect to the probability of being arrested have been estimated and shown in Table 5.

Results of this table show that the coefficients of probability of being arrested are significantly less than one, except in the case of larceny among juveniles under 16.

TABLE 5

	ESTIMATED ELASTICITIES OF PROBABILITY OF BEING ARRESTED IN OFFENSE FUNCTION	ESTIMATED T-VALUES
ROB1MR	-1.26	4.5***
BUR1MR	-0.34	1.6
LAR1MR	+0.10	0.3
MVT1MR	-0.63	3.3***
ROB2MR	-0.6	3.6***
BUR2MR	-0.36	2.64**
LAR2MR	-0.36	2.48**
MVT2MR	-0.56	4.48***

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

These results indicate that, if the probability of being arrested increases, offense rates among males under 16 and among males 16-19 will significantly decline. The significant negative correlation between offenses and the probability of being arrested implies that the demand for commiting crime is downward sloping just as the demand for any other commodity. If the relative price of any commodity rises less will be consumed. Thus, if we raise the cost of commiting a crime, fewer crimes will be committed.[23]

None of the coefficients of ATTENP shows any significant t-statistics, except in the case of robbery for the group 16-19 years of age. F-values also do not show significant results for ATTENP coefficients (see Table 6). This insignificance can be attributed to the biasdness of the estimated coefficient as explained in chapter II.
If ATTENP would be dropped out of the equation (see Table 37 and 38), results would remain more or less the same in terms of t-values and magnitude of the coefficients.

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[23] Most of the economics of crime studies indicate that punishment does deter crime, e.g., Leibowitz (1965), Ehrlich (1975), Phillips and Votey (1972). All these studies using both cross-sectional and time-series conclude that punishment deter property crime as well as violent crime such as rape and murder. Although theoretically the deterrent effect of expected punishment could be high, in practice the perceived probability of being arrested by an individual criminal might be lower than the true probability. Therefore, increasing the knowledge of the potential criminal with regard to the true probability of being arrested should decrease the likelihood that the potential criminal would choose to commit a crime.

TABLE 6

F-TEST FOR THE CONTRIBUTION OF
ATTENR IN EXPLAINING CRIME
U.S. DATA

	F-VALUE
UNDER 16)	
ROB1MR	1.6
BUR1MR	0.0
LAR1MR	1.1
MVT1MR	0.0
16-19)	
ROB2MR	3.3*
BUR2MR	0.0
LAR2MR	0.0
MVT2MR	0.0

* SIGNIFICANT AT 5% LEVEL.

As discussed in chapter I, Phillips and Votey argued that labor force participation rate should be included in the supply of offense function to reflect both the secular changes including the influence of past unemployment rates and the considerable fraction of youth who are out of the labor force. Table 7 shows the results of equations including labor force participation rate for males 16-19, TEENLF. None of the coefficients of TEENLF are significant.

Unlike Fleisher's cross-sectional analysis results, the above findings indicate that the partial effects of unemployment rate on the juvenile crime rate are insignificant. Income factors, on the other hand, carry the expected positive signs which have been confirmed in Fleisher's study. The divorce rate as a proxy for family structure, unlike Fleisher's findings, shows statistically significant correlation with crime. Although the coefficients of the regional dummy variable are negative, as in Fleisher's, the t-values are not significnat, unlike Fleisher's. For the race variable, while Fleisher found insignificant t-values for all types of crime, this study shows statistical significance for both age groups, and for burglary among juveniles 16-19. Even though the t-values are found to be significant, however, their impact is found to be very small.

TABLE 7

REGRESSION COEFFICIENTS
LOG ESTIMATION (U.S DATA)
JUVENILES 16-19

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
TEENUN	-.24 (.8)	.09 (.5)	-.0005 (.003)	.10 (.4)
MEDIN	7.1 (6.7)***	1.3 (1.87)*	1.3 (2.1)**	3.3 (3.9)***
LOWIN	1.4 (2.9)***	.06 (.2)	.28 (.9)	.55 (1.4)
BLKR	.26 (3.8)***	.09 (1.75)*	.01 (.4)	.08 (1.5)
SMSR	.12 (5.3)***	.04 (2.6)**	.02 (1.96)*	.04 (2.5)**
ATTENR	-5.2 (1.96)*	-.09 (.05)	1.0 (.6)	-.69 (.4)
DIVORC	.26 (1.97)*	.21 (2.5)**	.20 (2.7)***	.16 (1.5)
TEENLF	-1.0 (1.4)	.25 (.5)	.59 (1.59)	.43 (.7)
DUM	-.23 (.8)	-.22 (1.2)	-.31 (1.95)*	-.33 (1.5)
PROAR	.46 (2.4)**	.64 (4.7)***	.54 (4.4)***	.44 (3.5)***
C	-18.9 (.7)	-13 (.7)	-26 (1.6)	-25 (1.2)
F-STATISTICS (10, 39)	25	10.6	11.7	12.8
R-SQUARED	.86	.73	.75	.76

ABSOLUTE VALUES OF T-STATISTIC ARE IN PARANTHESES.

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

The cross-sectional analysis in this paper, in general, indicates that MEDIN contributes the most to an explanation of the property crime rate, followed by the probability of being arrested and urbanization variables. The lack of significance of the other variables, could be the result of undetected multicollinearity.

Chapter V

RESULTS FOR NEW YORK CITY

This chapter presents the Ordinary Least Squares regressions of the New York City data for the period of 1970-1980. The dependent variable is arrest rates categorized by different property crimes (robbery, burglary, larceny, and motor vehicle theft) and age (under 16 and 16-19). The log estimation of arrest functions is in the following form:

$$AR_{ijk} = a_0 + a_1(PROAR) + a_2(TOTUN) + a_3(REALIN)$$
$$a_4(ASSISR) + a_5(DIVRTE) + a_6(BLKPT) + a_7(ATTENP)$$
$$+ a_8(TIME) + a_9(D2) + a_{10}(D3) + a_{11}(D4) + a_{12}(D5) + U$$

when AR is the arrest rate for property crimes. The i subscript refers to the ith time period, j refers to the jth age group, and k refers to the kth type of crime. All variables are in the log form except the time trend (TIME) and the dummies (D2, D3, D4, and D5) differentiating the intercept of the five boroughs of New York City.

The Variables:

Table 8 lists all symbols for the variables used in our equation for New York City and provides a short description of each of the variables. Table 9 includes mean and standard deviation of dependent and independent variables.

TABLE 8

LIST OF VARIABLES FOR NYC ANALYSIS

Name OF VARIABLES	Source	Definition
DEPENDENTS VARIABLES)		
RM1R	1	Arrests for robbery per 10,000 population for males under 16
BM1R	1	Arrests for burglary per 10,000 population for males under 16
LM1R	1	Arrests for Larceny per 10,000 population for males under 16
MVTM1R	1	Arrests for motor vehicle theft per 10,000 population for males under 16
RM2R	1	Arrests for robbery per 10,000 population for males 16-19
BM2R	1	Arrests for burglary per 10,000 population for males 16-19
LM2R	1	Arrests for larceny per 10,000 population for males 16-19
MVTM2R	1	Arrests for motor vehicle theft per 10,000 population for males 16-19
INDEPENDENT VARIABLES)		
TOTUN	2	Civilian unemployment rate for all ages
REALIN	3	Real per capita income
ASSISR	8	Per capita aid to families with dependent children
DIVRIR	4	Number of divorces per 10,000 population
BLKRT	5	Number of blacks per 10,000 population

ATTENR	7	Average daily school attendence per 10,000 registration.
DROPR	6	Drop-out rate for 9-12 grades
D2, D3 D4, D5	see text	Dummy Variables to differentiate intercepts of the five boroughs of New York City
PROARR	1	Number of robbery arrests per 10,000 robbery complaints.
PROARB	1	Number of burglary arrests per 10,000 burglary complaints.
PROARL	1	Number of larceny arrests per 10,000 larceny complaints.
PROARM	1	Number of motor vehicle theft arrests per 10,000 motor vehicle theft complaints.

[a]

1 = New York Police Headquarters, unpublished arrest records prepared for F.B.I.

2 = U.S. Department of Labor, unpublished data , and Employment Review, July 1976.

3 = City and County Data Book, 1977

4 = Vital Statistics of the U.S., Department of Health, Education and Welfare.

5 = Bureau of the Census, Population Census of 1970 and 1980.

6 = The State Education Department, Bureau of Educational Data.

7 = New York State Statistical Yearbook 1979/80.

8 = New York State, Department of Social Services, Monthly Reports.

TABLE 9

Descriptive Statistics of Data

	MEAN	STANDARD DEVIATION
RM1R	4.5	.67
BM1R	4.6	.49
LM1R	3.2	.93
MVT1MR	3.5	.34
RM2R	5.1	.90
BM2R	5.2	.59
LM2R	3.8	1.0
MVTM2R	4.6	.50
TOTUN	1.98	.34
ASSISR	-.54	1.35
REALIN	8.75	.25
BLKPT	2.85	.58
DIVRTF	3.1	.45
ATTENR	8.71	.24
DROPR	2.30	.31
PROARR	7.78	.22
PORARR	16.94	.32
PROAPL	6.82	.41
PROARM	6.93	.51

Besides the independent variables already discussed in the preceding cross-sectional analysis(e.g., unemployment rate, divorce rate, and attendence rate), the following variables have been introduced for the pooled cross-sectional time-series analysis:

1. Aid to families with dependant children (ASSISR) has been used as a proxy for legitimate earnings. The reason for using ASSISR instead of LOWIN which was used in the cross-sectional analysis is that data on the distribution of income for the period of 1970-1980 are not available. Therefore, ASSISR has been utilized as the best available proxy for legitimate earning opportunities.

2. Real per capita income (REALIN) has been used instead of MEDIN as a proxy for illegitimate earning opportunitiesis due to the lack of data on median income for the period of 1970-1980 for New York City.

3. A time trend (TIME) has been used in order to eliminate the effects of some variables which are not included in the model and have been affecting crime over time, for instance, increase in the efficiency of police in apprehension of criminals in the past years. Another important reason for using a time trend is that, in the last few years, the white population has been moving out of New York City. The percent of blacks in the population, therefore, has been increasing. At the same time, crime rates in New York City have been also rising due to an overall increase in crime

for the United States as a whole. If we do not include a time trend, the coefficient of the race variable might be overestimated.

4. Four dummy variables (D2, D3, D4, and D5) have been introduced to differentiate the intercepts of the five boroughs of New York City as follows:

when D2 = equals one for Brooklyn, zero otherwise

D3 = equals one for Manhattan, zero otherwise

D4 = equals one for Queens, zero otherwise

D5 = equals one for Staten Island, zero otherwise

The preliminary results for the New York City analysis are shown in Table 18 and Table 19 for juveniles under 16 and juveniles 16-19, respectively. Because the New York City study is a cross-sectional time-series analysis, the homogeneity of data in terms of intercepts could be questioned. In order to test the homogeneity of the data sample, the following procedure has been employed:

If we assume that all boroughs have the same intercepts, the constrained function could be represented in the following form:

$$Y = a_0 + a_1 X_1 + a_2 X2 + \dots + a_n X_n + U1$$

when Y is the arrest rate, X_1 through X_n are the socioeconomic variables and U is an error term. If we add four dummies, the unconstrained equation becomes:

$$Y = a_0 + a_1 X_1 + \dots + a_n X_n + a_{n+1} D2 + a_{n+2} D3 + a_{n+3} D4 + a_{n+4} D5 + U$$

Results of the above analysis of variance are shown in table 10.[24]

As the results of Table 10 show, all F-values are significant except for BM1R and MVIM2R. These significant F-values indicate that the intercepts of each of the five boroughs are different. Therefore, dummies should be included in the model.

Estimated arrest functions for males under 16 and 16-19 years of age have been shown in Table 11 and Table 12, respectively. In equations where autocorrelation was detected the parameters have been reestimated using the Cochrane-Orcutt technique (see appendix A for more details).

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[24] The F-value is calculated as follows:

$$F_{(k-r,\ n-k)} = \frac{\dfrac{(ESS_u - ESS_c)}{(k-1)}}{\dfrac{(USS_u)}{n-k}}$$

where
ESS = Explained sum of squares of the unconstrained equation.
ESS = Explained sum of squares of the constrained equation.
USS = Unexplained sum of squares of the unconstrained equation.
K-r = Degrees of freedom in the unconstrained minus degrees of freedom in the constrained.
n-k = Total number of observations less the degrees of freedom in the unconstrained equation.
The above formula ultimately reduces to:

TABLE 10

ANALYSIS OF VARIANCE
NEW YORK CITY DATA

	F-VALUE
RM1R	5.5**
BM1R	0.0
LM1R	4.8**
MVTM1R	12.0**
RM2R	5.8**
BM2R	4.6**
LM2R	4.1**
MVTM2R	1.66

* SIGNIFICANT AT 5% LEVEL.
** SIGNIFICANT AT 1% LEVEL.

TABLE 11

REGRESSION COEFFICIENTS
NEW YORK CITY DATA
LOG ESTIMATION
JUVENILES UNDER 16

	RM1R	BM1R	LM1R	MVTM1R
PROAR	.22 (1.5)	.60 (2.8)***	.14 (.7)	.84 (7.5)***
TOTUN	.12 (1.0)	-.07 (.5)	.45 (1.5)	.21 (1.3)
ASSISR	.005 (.4)	.01 (.8)	-.02 (.5)	.006 (.2)
REALIN	-.11 (.3)	.19 (.5)	.96 (.8)	2.1 (3.6)***
DIVRTE	-.71 (2.6)**	-.59 (1.88)*	.06 (.07)	.06 (.1)
BLKPT	-.28 (.5)	.44 (.6)	.50 (.6)	1.2 (3.0)***
ATTENR	.41 (.4)	.35 (.3)	2.3 (1.4)	1.74 (1.6)
TIME	.07 (2.0)**	.02 (.4)	.12 (1.3)	.02 (.4)
D2	.09 (.2)	-.03 (.07)	.68 (1.0)	.44 (1.2)
D3	.7 (1.0)	.19 (.2)	2.1 (1.4)	-.23 (.3)
D4	-.5 (1.0)	-.10 (.1)	.19 (.2)	1.1 (2.5)**
D5	-2.1 (2.3)**	-.07 (.06)	-.25 (.1)	3.3 (4.1)***
C	3.0 (.3)	-3.3 (.3)	-35.0 (1.5)	-41.7 (3.3)***
F-STATISTIC	17.6	4.0	28.3	12.4
D - W	1.79	1.66	2.36	1.86
R-SQUARED	.85	.57	.89	.78

Absolute values of t-statistic are in parantheses.

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 12

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
MALES 16-19

	RM2R	BM2R	LM2R	MVIM2R
PROAR	-.30	.04	.31	.09
	(.8)	(.1)	(1.3)	(.4)
TOTUN	.24	.35	.17	-.09
	(.8)	(1.1)	(.4)	(.3)
ASSISR	.03	-.007	.02	-.009
	(.8)	(.1)	(.4)	(.2)
REALIN	3.7	4.5	5.0	4.0
	(3.3) ***	(4.1) ***	(3.4) ***	(3.5) ***
DIVPIE	-.55	-.65	-.82	-.10
	(.6)	(.8)	(.8)	(.1)
BLKPT	.09	.43	-.74	.25
	(.1)	(.5)	(.7)	(.3)
ATTENR	3.1	3.1	4.5	3.2
	(1.5)	(1.6)	(1.5)	(1.5)
TIME	.19	.20	.37	.13
	(2.0) **	(2.2) **	(3.0) ***	(1.3)
D2	.55	.47	1.0	.46
	(.8)	(.7)	(1.2)	(.6)
D3	.46	-.54	.87	-.21
	(.3)	(.3)	(.4)	(.1)
D4	-1.0	-1.0	-1.1	-.51
	(1.1)	(1.1)	(1.0)	(.6)
D5	-1.3	-.62	-2.5	-.47
	(.9)	(.4)	(1.4)	(.3)
C	-52.7	-63.0	-74	-60.2
	(2.2) **	(2.9) ***	(2.6) **	(2.5) **
F-STATISTIC (12, 42)	20.4	10.6	23.7	5.8
D - W	2.00	2.00	1.89	1.94
R-SQUARED	.85	.75	.87	.62

Absolute values of t-statistic are in parantheses.
* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

A positive relationship between unemployment and crime has been predicted by economists for individuals who are in the labor force, but the sign of unemployment for the juveniles under 16 is ambiguous for the following reasons:

a. Income effect. As unemployment goes up, parents' income will decline. Juveniles under 16 years of age are expected to be living with their parents. Consequently, an increase in unemployment will affect juveniles' income indirectly and, thus, lead to more juvenile crime. More specifically, for juveniles from lower income families, i.e., usually families where the wage earner is an unskilled, blue-collar worker, fluctuations in the unemployment rate are more significant. The reason is that during recessionary periods fluctuations of unemployment rate among blue-collar (mostly unskilled labor) are much higher than among skilled labor. Therefore, the family income of potential offenders from lower income families would be relatively more affected leading to an increase in blue-collar crime(robbery, burglary, larceny, and motor vehicle theft).

b. The quality of parental supervision. Some studies predict a negative sign for unemployment among juveniles

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$$F_{(k-r,\ n-k)} = \frac{(R_u^2 - R_c^2) \ / \ (k-1)}{(1-R_u^2) \ / \ (n-k)}$$

The subscripts u and c denote unconstrained and constrained equations respectively.

under 16. For example, Glaser,[25] argues that, during the periods of high unemployment, the amount of time available to unemployed parents for supervision might increase leading to lower juvenile crimes. The major criticism of Glaser's argument is that even if the amount of time for parental supervision increases during a period of unemployment, the quality of supervision might decrease. We can expect an unemployed person to have the psychological problems of frustration and depression which would lead to reduce the quality of supervision. Another criticism of Glaser's argument is that during recessionary periods the amount of time for parental supervision might even decrease since some parents who would ordinarily be at home, i.e., not part of the labor force, would be required to enter the job market and to spend increased time looking for jobs to compensate for the loss of income of the parent who had usually been the wage earner. So in the families of potential juvenile offenders both quality and quantity of parental supervision might decrease during periods of unemployment.

Since the theory cannot determine the sign of unemployment rate on crime committed by juveniles under 16, empirical studies would be helpful in clarifying the sign of the unemployment rate. The empirical work using aggregate data suggests that increased unemployment, particulary

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[25] Glaser, Daniel, et al. "Crime, Age, and Unemployment." American Sociological Review, 24:5 (October 1959):679-86.

juvenile unemployment, will lead to moderately higher overall crime rates.[26] The New York City analysis in this study shows that a positive correlation exists between unemployment and arrest rates. The t-values, however, are insignificant for both age groups. Although the civilian unemployment rate is not age specific, it is being used in this study as a proxy for the unemployment rate among juveniles between 16 to 19 years old, since age specific data are not available for that group. The same civilian unemployment rate is a relevant independent variable in this study for juveniles under 16 since it represents their parents' unemployment rate. One problem with using this civilian unemployment rate for juvenilies 16-19 is that the fluctuations in that rate do not reflect all the severity of

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[26] Studies using individual data provide greater insight into the nature of the relationship between unemployment and crime. Empirical studies by Vera institute (Sviridoff, M. and J.W. Thompson, *Linkages Between Employment and Crime: A Qualitative Study of Rikers Releases*, Working Paper, Vera Institute of Justice) and Rand (Petersilia, J. et al. *Criminal Careers of Habitual Felons*, Santa Monica, Calif.: The Rand Corporation 1972.) suggest that the nature of the relationship depends on the type of crime and type of individual. Sviridoff and Thompson identify four distinct types of relationship between unemployment and crime:

a. Offenders who alternate between employment and crime.

b. Offenders who mix employment and crime. These individuals use their legitimate job as a front, as do fences and drug dealers.

c. Offenders involved in white-collar crimes or employee theft need legitimate jobs which make crime possible.

d. Offenders who are firmly committed to crime as their primary means of support.

For the group b and c, unemployment makes criminal activity more difficult. For group d, unemployment rate teenage unemployment which is usually higher. Therefore, the impact of unemployment on property crimes among juveniles 16-19 might be

Unfortunately, the aggregate data do not give a measure of job quality. Having simply more legal job opportunities does not necessarily indicate more attraction to legal activities, because a large number of workers might experience low quality jobs with a high degree of insecurity. Studies utilizing individual data have been able to provide a better proxy for job quality (the wage an individual receives).

Aid to families with dependent children (ASSISR) does not show any significant effect on crime. Our proxy for illegitimate earning opportunities (REALIN) shows significant positive correlation with all types of crime for males 16-19 and for only motor vehicle theft among juveniles under 16. The unemployment rate shows a positive relationship with the arrest rate of juveniles under 16. The income effect of unemployment is likely to dominate the negative effect of the increase in the amount of time available for parental supervision due to being unemployed.

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is irrelavant, and only those criminals who are in group a (alternate between employment and crime) can be expected to react significantly to a change in unemployment rate.

Focusing on unemployment and income for a given level of income, unemployment is shown to be an insignificant determinant of the property crime rate whereas, given the rate of unemployment, income is indeed significant. Hence, the property crime rate among juveniles is high not because of the degree of unemployment, but because of the degree of poverty.

The sociological factors (divorce rate, race factor, and dropout rate), which have been introduced into the model, do not show any significant effects on property crime.

One important finding is that the estimated arrest functions reveal a significant negative correlation between the offense rate and the probability of being arrested. As discussed earlier in the theoretical model, the relationship between probability of being arrested and offense rates could be negative as long as the elasticity of the arrest rate with respect to the probability of being arrested is negative and/or the absolute value is less than one. The elasticities of offense rates with respect to the probability of being arrested are shown in Table 13.

All the elasticities of offense rates with respect to the probability of being arrested have a negative sign. All except two (EM1R and MVTM1R) show significant t-statistics.

TABLE 13

ELASTICITY OF OFFENSE FUNCTIONS
WITH RESPECT TO PROAR
NEW YORK CITY DATA

UNDER 16)	ELASTICITY	ABSOLUTE VALUES OF T-STATISTIC
PM1R	-.78	5.5***
BM1R	-.40	1.90*
LM1R	-.85	4.7***
MVTM1R	-.15	1.6
16-19)		
RM2R	-1.30	3.6***
PM2R	-.96	2.9***
LM2R	-.69	3.0***
MVTM2R	-.91	4.3***

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

The strongest result in the New York City analysis is that expected punishment in the form of probability of being arrested serves to deter crime. Therefore, we may be fairly certain of the deterrent effect of punishment and that the economic model of crime is useful to explain the behavior of criminals. The strong deterrent effect of probability of punishment does not necessarily imply that crime should be reduced only through increasing the probability of punishment. If the expected punishment for one type of crime goes up, reduction in that crime might occur due to substitutability among different crimes. In such a case, an increase in the other types of property crime will be observed. Therefore, as an example, if punishment for robbery is raised to death penalty, the number of robberies might decrease though the number of murders might increase. Robbers might think that to kill their victims would not increase the expected punishment, assuming robbery carries the maximum punishment, but would decrease the likelihood of being arrested since identification of the criminal by the victim is not possible.

Although pooling of data in cross-sectional time-series can increase the degree of freedom, the problem of multicollinearity is prevalent due to inclusion of dummies differentiating the intercepts of the boroughs. Therefore, to detect the partial effects caused by each variable would be difficult. The total effect caused by all explanatory variables, however, might be very significant. In the New York City analysis, for example, the goodness of fit is 89% for LM1R. The t-statistics, however, are insignificant (see Table 11). Table 16 (simple correlation matrix) also indicates a very high simple correlation between some of these dummies and other independent variables. D3, for example, has a simple correlation of 0.83 with REALIN and also -0.83 with ATTENR. Thus, the evidence indicates that the problem of multicollinearity might be significant in the New York City analysis. An insignificant t-value, therefore, is not sufficient evidence for believing that the variable is not important in determination of crime.

The results in terms of the R-squared indicate that larceny has the best fit, followed by the robbery for both age groups. In the cases of burglary and motor vehicle theft, however, motor vehicle theft for juveniles under 16 shows a better fit as compared to the burglary for juveniles 16-19. As discussed in the Analysis of Variance, dummies should be included in order to find unbiased estimates of the coefficients for all explanatory variables The possibility of multicollinearity might be reduced by eliminating the DIVPTF variable showing no significant t-statistics and no significant F-values. The DIVPTF variable shows a very high correlation with TOTUN (0.80) and with the time trend variable (0.80) causing multicollinearity.

Results after elimination of DIVRTF have been shown in Table 26 and Table 27. In these equations parameters have been reestimated when the autocorrelation problem has been observed. Comparison of results before and after exclusion of DIVRTF does not show any significant change in the values of t-statistics except when PROPR for RM1P becomes statistically significant or when BLKPT for RM1R also become statistically significant.

Since all the equations were estimated in the loglinear form, the estimated coefficients represent the elasticity of response of arrest rate to changes in the independent variables. The highest elasticities in most of the regressions are associated with the elasticities of offense rate with respect to probability of being arrested for juveniles under 16. In equations for juveniles 16-19, partial elasticity coefficients of REALIN and ATTENR are in the elastic range with the coefficient of REALIN being the most elastic.

Chapter VI

SUMMARY AND CONCLUSION

The effects of economic factors on juvenile crime for two age groups (under 16 and between 16-19) has been the subject of this study. Ordinary Least Squares was used for the U.S. as a whole in a cross-sectional analysis and for New York City in a pooled cross-sectional time-series. Our results indicate: (1) In general, both analyses show insignificant partial elasticities for unemployment in the determination of property crime; (2) Income factors carry signs consistent with the theoretical model. Proxies especially for illegitimate earning opportunities show statistically significant positive correlation with property crime. Results for the U.S. indicate that MEDIN, specifically, contributes the most to the explanation of the property crime; (3) The predicted partial elasticities of offense rate with respect to the probability of being arrested show significant negative values for both age groups for both samples; (4) The divorce rate exhibits significant positive correlation with property crime in the cross-section. The New York City analysis, however, does not fully support the above conclusion except in cases of robbery and burglary among juveniles under 15. This significant correlation between divorce and crime might result from the absence of father role model in broken homes in addition to lower levels of income which broken families might experience; (5) The race variable, in general, is insignificant and has a very small elasticity in cases with significant t-values; (6) the southern states have a lower crime rate as compared to the northern states. Stronger family ties providing higher parental supervision in addition to stronger attachment to norms and values could be the reason of low crime rates in the South; (7) A strong positive relationship exists between the urbanization factor and arrest rate showing a higher property crime rate in urban areas. Positive and significant partial elasticities for the SMSR variable might reflect the incidence of slums and also greater accessibility of various criminal activities due to the concentration of business in metropolitan areas. Economic factors are significant in the determination of juvenile property crime. These economic factors, however, cannot be considered more important than sociological factors. Radzinowicz summarizes these thoughts as follows:

> Economic factors are still a major factor in the etiology of crime. They are so by their direct impact and by their indirect influences over many other social circumstances and moral attitudes.[27]

The nature of aggregate data limits the appropriate measurement of unemployment among teenagers. Age specific data, if it were available, would be a more accurate

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[27] Radzinowicz, Leon. "Economic Pressures." In Leon Radzinowicz and Marvin E. Wolfgang (eds.), Crime and Justice, 2nd ed., New York, Basic Books, 1977.

measure. Even if it were available, however, it would not be a true measurement of unemployment among teenagers since it would reflect neither those who dropped out of the labor force due to discouragement nor the factor of job quality. Further studies investigating the effects of more comprehensive unemployment measures on juvenile crime would be beneficial.

An increase in legitimate earning opportunities appear to be more effective in reducing juvenile property crime over time than an increase in expected punishment. Although an increase in expected punishment is shown in this study to deter property crime, to see this factor as the solution would be misleading. Besides the cost of increasing expected punishment becoming prohibitive to the society, the fact of substitutability among property crimes makes that solution ineffective. If the relative expected cost of punishment in one type of crime is increased, simply a shift to another type of crime would result. A more effective policy, then, should concentrate on increasing legitimate earning opportunities.

Instead of simply considering the magnitude of elasticities of economic factors in relation to crime, consideration should also be given to the cost of manipulating these economic factors. Further cost-benefit analyses, therefore, in the area of juvenile crime would be beneficial to determine not only effective but also efficient policies in fighting crime.

Appendix A

COCHRANE-ORCUTT ITERATION TECHNIQUE

Using Durbin-Watson Statistics, autocorrelation has been detected in some equations. The autocorrelation could have been caused because of

a. inertia. Due to the pooled cross-sectional time-series data for New York City, variables have cyclical variations. Therefore, successive observations are likely to be interdependent.

b. the manipulation of raw data. For example, since yearly data for the black population's share in total population have not been available, annual data were generated under the assumption of a constant yearly growth rate as between the census years 1970 and 1980.

> This averaging introduces smoothness into the data dampening the fluctuations....therefore.... This smoothness may itself lead to a systematic pattern in the disturbances.[28]

Equations with the problem of autocorrelation have been corrected by the Cochrane-Orcutt technique which is as follows:

1. Obtain ordinary least squares estimates of

$$Y_t = a + b X_t + E_t$$

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[28] Gujarati Damodar, Basic Econometrics, McGraw Hill Co., 1978.

and calculate the residuals $\hat{E}1\ \hat{E}2 \ldots \hat{E}n$. Use these to get the "first round" estimate of p, say, $\hat{p}$

$$\hat{p} = \frac{\sum \hat{E}_t \cdot \hat{E}_{t-1}}{\sum \hat{E}_t} \quad (t=2,3,\ldots,n)$$

2. Construct new variables $(Y_t - \hat{p}Y_{t-1})$ and $(X_t - \hat{p}X_{t-1})$ and obtain ordinary least squares estimates of

$(Y_t - X_{t-1}) = a^* + b(X_t + X_{t-1}) + Ut$

where $a^* + a(1-p)$. These "second round" estimate which may be called a and b, lead to "second round" residuals $\hat{\hat{E}}1 \ldots \hat{\hat{E}}n$.

$$\hat{\hat{p}} = \frac{\sum \hat{\hat{E}}_t \cdot \hat{\hat{E}}_{t-1}}{\sum \hat{\hat{E}}_{t-1}} \quad t=2,3,\ldots,n$$

3. Construct new variables $(Y_t - \hat{\hat{p}}Y_{t-1})$ and $(X_t - \hat{\hat{p}}X_{t-1})$ and then proceed as in step 2[29]

These steps are to be followed untill the values of the estimators converge.

Because data are cross-sectional time-series, there are four gaps which exists in the data, therefore, Durbin-Watson cannot be calculated as usual. For New York City data, a new version of the TSP software package, 3.5c, have been

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[29] Kmenta Jan., Elements of Econometrics, the Macmillan Co., New York, 1971.

used which considers these four gaps (see Appendix C).

Appendix B

PROPERTY CRIME DEFINITION

1. Robbery: robbery is the taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.

2. Burglary: the uniform crime report program defines burglary as the unlawful entry of a structure to commit a felony or theft. The use of force to gain entry is not required to classify an offense as burglary. Burglary in this program is categorized into three subclassifications : forcible entry, unlawful entry where no force is used, and attempted forcible entry.

3. Larceny: larceny is the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. It includes crimes such as shoplifting, product - picking, purse - snatching, thefts from motor vehicles, thefts of motor vehicle parts and accessories, bicycle thefts, etc. in which no use of force, violence, or fraud occurs.

4. Motor Vehicle Theft: In UCR, motor vehicle theft is defined as as the theft or attempted theft of a motor vehicle. This definition excludes the taking of a motor

vehicle for temporary use by those persons having lawful access.

Appendix C

C

The preliminary results for the New York City analysis have been shown in Table 18 and Table 19.

C.0.1 Problem of Autocorrelation

The Durbin-Watson statistics indicate that a problem of autocorrelation exists in some of the equations. Since data are pooled cross-sectional time-series, Durbin-Watson statistic cannot be calculated in the ordinary way. There are 55 observations, 11 for each borough. Therefore, at four places in the data, the last observation of a particular borough preceeds the first observation of the following borough. The Durbin-Watson statistic is defined as:

$$d = \frac{\sum_{t=2}^{n} (e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

Using the above formula, the last disturbance term of the first borough would be subtracted from the first disturbance term of the second borough in the caluculation of Durbin-Watson statistic. This mixing of data would happen at four data points. In order to avoid this, four imaginary gaps have been given to the data between each borough. The latest version of the TSP software package (TSP 3.5c) has been used for the correct calculation of Durbin-Watson. The same technique of using four imaginary gaps has been employed to avoid problem of mixing the disturbance terms when data have been corrected for autocorrelation.

Table 18 and 19 both show significant F-statistics and also very large R-squared. As we discussed in the chapter IV, the dummies differentiating intercepts of five boroughs should be included. Although t-values of intercepts show significant results, inclusion of dummies make them insignificant. Results of equations after adding dummies (D2, D3, D4, D5) are shown in Table 17 and Table 20. The inclusion of dummies increased not only the Durbin-Watson statistic (see Table 22), but also the intercepts of equations among juveniles under 16, became statistically insignificant. The poor levels of significance of the intercepts for juveniles under 16, probably indicate that no important variables were excluded from the model specification.

C.0.2 Problem of Heteroskedasticity

Given that the data used in this study are cross-sectional, the problem of heteroskedasticity must be considered. Alternatively stated, the off-diagonal elements of the variance-covariance matrix of the disturbance term are varying in size with an independent variable. One reason to consider heteroskedasticity is that in states with a greater population the average property crime is high and, therefore, the variation around this level could be higher as compared to states with a lower level of population. Hence the variance of the disturbance term in states with a greater population might be positively correlated to the SMSP variable which by itself is highly related to the level of population. To test whether or not the heteroskedasticity exists, the Gleiser[30] test has been done. The procedure is as follows:

a. Ordinary Least Squares estimation of equations have been used to get the disturbance terms .

b. The SMSP variable has been regressed on the square of the disturbance terms. The beta coefficients and t-statistics of the SMSR have been shown in Table 14. As the results of this Table indicate, no heteroskedasticity exists. Therefore, the Ordinary Least Squares regression coefficients are BLUE. In other words, regression coefficients are not only unbiased, but also efficient.

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[30] Kennedy, Peter. A Guide to Econometrics, The MIT Press, Mass.:1980.

TABLE 14

TEST FOR HETEROSKEDASTICITY
U.S. DATA
ERROR TERMS REGRESSED ON SMSR

	Coefficient	T-statistic
ROB1MR	.01	.5
BUR1MR	.01	.7
LAR1MR	.02	1.0
MVT1MR	.01	.9
ROB2MR	-.008	.7
BUR2MR	-.0005	.09
LAR2MR	.004	.9
MVT2MR	-.005	.8

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

Appendix D

STATISTICAL APPENDIX

TABLE 15

SIMPLE CORRELATION MATRIX

U.S. ANALYSIS

	TOTUN	TEENUN	TEENLF	DIVRTE	LOWIN	MEDIN	BLKRT	SMSR	ATTENR	DUM	PROARR	PROARB	PROARL	PROARM
TOTUN	1.0	.84	.04	.04	-.29	.37	-.13	-.15	.03	-.28	-.09	-.06	-.16	-.1
TEENUN		1.0	-.17	-.004	-.07	.18	.16	-.006	-.11	-.45	.20	.18	-.27	-.2
TEENLF			1.0	.17	-.60	.57	-.17	.01	.02	-.45	.20	.18	.25	.15
DIVRTE				1.0	.10	-.06	.06	-.09	.14	.08	.12	.05	.07	.21
LOWIN					1.0	-.90	.36	.01	-.35	.80	-.15	-.14	-.08	0.0
MEDIN						1.0	-.16	-.04	-.49	-.68	.10	.16	.10	.05
BLKRT							1.0	.37	-.48	.58	-.28	-.03	-.14	-.3
SMSR								1.0	-.32	.13	-.01	.003	.05	-.1
ATTENR									1.0	-.13	.14	-.11	-.07	.12
DUM										1.0	-.21	-.20	-.20	-.1
PROARR											1.0	.79	.51	.49
PROARB												1.0	.68	.40
PROARL													1.0	.42
PROARM														1.0

TABLE 16

SIMPLE CORRELATION MATRIX

NEW YORK CITY ANALYSIS

	TOTUN	ASSISR	REALIN	DIVRTE	BLKRT	ATTENR	TIME	PROARR	PROARB	PROARL	PROARM	D2	D3	D4	D5
TOTUN	1.0	-.18	.06	.80	.61	-.32	.56	-.29	.38	.52	.40	.29	.28	-.07	-.5
ASSISR		1.0	.02	-.15	-.39	.03	.01	.30	-.13	-.17	-.27	-.20	-.04	-.15	.43
REALIN			1.0	.18	-.16	-.86	-.10	-.36	-.61	-.09	-.02	-.39	.83	.13	-.0
DIVRTE				1.0	.53	-.48	.81	-.31	.22	.52	.36	.12	.41	-.05	-.4
BLKR					1.0	-.01	.11	-.40	.46	.55	.73	.41	.22	-.11	-.9
ATTENR						1.0	-.18	.39	.50	.02	-.46	.01	-.83	.02	.08
TIME							1.0	-.02	.24	.32	-.03	0	0	0	0
PROARR								1.0	.45	.20	.03	-.06	-.3	-.4	.58
PROARB.									1.0	.76	.58	.23	-.30	-.4	-.2
PROARL										1.0	.71	.03	.17	-.24	-.4
PROARM											1.0	.10	.40	-.4	-.6
D2												1.0	-.2	-.2	-.2
D3													1.0	-.2	-.2
D4														1.0	-.2
D5															1.0

TABLE 17

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
NOT CORRECTED FOR AUTOCORRELATION
JUVENILES UNDER 16
DUMMIES ARE INCLUDED

	RM1R	BM1R	LM1R	MVTM1R
PROAR	.65 (4.3)***	1.12 (7.2)***	.14 (.7)	.84 (7.5)***
TOTUN	.49 (4.0)***	.34 (2.3)**	.45 (1.5)	.21 (1.3)
ASSISR	.008 (.4)	.02 (1.3)	-.02 (.5)	.006 (.2)
REALIN	-.22 (.4)	.02 (.05)	.96 (.8)	2.1 (3.6)***
DIVRTE	.19 (.5)	-.08 (.2)	.06 (.07)	.06 (.1)
BLKRT	1.12 (3.2)***	1.1 (3.2)***	.50 (.6)	1.2 (3.0)***
AITENR	.61 (.7)	.52 (.5)	2.8 (1.4)	1.74 (1.6)
TIME	-.01 (.4)	-.001 (.04)	.12 (1.3)	.02 (.4)
D2	-.11 (.4)	.06 (.2)	.58 (1.0)	.44 (1.2)
D3	.90 (1.4)	.59 (.9)	2.1 (1.4)	-.23 (.3)
D4	.40 (1.0)	.68 (1.68)*	.19 (.2)	1.1 (2.5)**
D5	.46 (.7)	1.5 (2.4)**	.09 (.07)	2.3 (3.2)***
C	-9.0 (.9)	-12.1 (1.2)	-35.0 (1.5)	-41.7 (3.3)***
F-STATISTIC (12, 42)	93	42.3	28.3	12.4

D - W	1.76	1.53	2.36	1.86
R-SQUARED	.96	.92	.89	.78

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 18

REGRESSION COEFFICIENTS
NEW YORK CITY DATA
LOG ESTIMATION
JUVENILES UNDER 16

	RM1R	BM1R	LM1R	MVTM1R
PROAR	.69 (5.2)***	1.1 (10)	.29 (1.5)	.43 (3.9)***
TOTUN	.30 (2.2)**	.26 (1.91)*	.24 (.7)	.39 (.02)
ASSISR	.01 (1.70)*	.03 (1.70)*	.01 (.3)	-.02 (.9)
REALIN	.7 (1.97)*	.48 (1.97)*	1.1 (1.92)*	.69 (1.86)*
DIVRTE	.36 (5.0)***	-.36 (1.0)	.39 (.4)	-.39 (.6)
BLKRT	1.0 (7.0)***	.35 (2.6)**	.89 (2.7)***	.02 (.1)
ATTENR	.90 (3.3)***	.01 (.05)	.14 (.1)	.82 (1.99)*
TIME	-.005 (.1)	.04 (1.2)	.05 (.5)	.06 (1.0)
C	-24.9 (5.8)***	8.5 (2.1)**	-14.5 (1.4)	-12.9 (2.1)**
F-STATISTIC (3, 46)	103	56	31	6.7
D - W	1.48	1.16	1.66	0.97
R-SQUARED	.94	.94	.84	.53

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 19

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
JUVENILES 16-19

	RM2R	BM2R	LM2R	MVTM2R
PROAR	.54 (1.72)*	.76 (2.7)***	.52 (2.3)**	.15 (.9)
TOTUN	.25 (.7)	.29 (.8)	.23 (.5)	.07 (.2)
ASSISR	.06 (1.3)	.03 (.8)	.05 (1.0)	.003 (.09)
REALIN	2.3 (3.7)***	1.6 (2.9)***	2.6 (3.5)***	1.9 (3.7)***
DIVRTE	-.32 (.3)	-.92 (1.1)	-.39 (.3)	-.14 (.1)
BLKRT	1.28 (3.7)***	.78 (2.4)**	1.0 (2.66)**	.50 (1.77)*
ATTENR	.65 (1.0)	.29 (.4)	.28 (.3)	1.4 (2.5)**
TIME	.10 (1.1)	.15 (1.78)*	.12 (1.74)*	.08 (1.0)
C	-29.0 (2.8)***	-18.1 (1.96)*	-29.7 (2.3)**	-28.4 (3.3)***
F-STATISTICS (8, 45)	21	10.4	27.9	7.6
D - W	1.65	1.75	1.47	1.92
R-SQUARED	.78	.64	.82	.56

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 20

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
JUVENILES 16-19

	RM2R	BM2R	LM2R	MVTM2R
PROAR	-.30 (.8)	.04 (.1)	.31 (1.3)	.09 (.4)
TOTUN	.24 (.8)	.35 (1.1)	.17 (.4)	-.09 (.3)
ASSISR	.03 (.8)	-.007 (.1)	.02 (.4)	-.009 (.2)
REALIN	3.7 (3.3) ***	4.5 (4.1) ***	5.0 (3.4) ***	4.0 (3.5) ***
DIVRTE	-.55 (.6)	-.65 (.8)	-.89 (.8)	-.10 (.1)
BLKRT	.09 (.1)	.43 (.5)	-.74 (.7)	.25 (.3)
ATTENR	3.1 (1.5)	3.1 (1.6)	4.5 (1.5)	3.2 (1.5)
TIME	.19 (2.0) **	.20 (2.2) **	.37 (3.0) ***	.13 (1.3)
D2	.55 (.8)	.47 (.7)	1.0 (1.2)	.46 (.6)
D3	.46 (.3)	-.54 (.3)	.87 (.4)	-.21 (.1)
D4	-1.0 (1.1)	-1.0 (1.1)	-1.1 (1.0)	-.51 (.6)
D5	-1.3 (.9)	-.62 (.4)	-2.5 (1.4)	-.47 (.3)
C	-52.7 (2.2) **	-63.0 (2.9) ***	-74 (2.6) ***	-60.2 (2.5) **
F-STATISTIC (12, 42)	20.4	10.6	23.7	5.8
D - W	2.00	2.00	1.89	1.94
R-SQUARED	.85	.75	.87	.62

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 21

REGRESSION COEFFICIENTS
LOG ESTIMATION
U.S. ANALYSIS
DUM IS NOT INCLUDED

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
TEENUN	-.13	.04	-.10	-.003
	(.4)	(.2)	(.6)	(.006)
MEDIN	7.0	1.41	1.52	3.5
	(6.5)***	(2.0)**	(2.3)**	(4.1)***
LOWIN	1.42	-.11	-.03	.28
	(3.1)***	(.3)	(.1)	(.7)
BLKR	.23	.05	-.01	.04
	(3.7)***	(1.3)	(.3)	(.9)
SMSR	.12	.04	.02	.04
	(5.2)***	(2.64)**	(1.8)*	(2.5)**
AITENR	-5.6	-.29	.88	-1.2
	(2.1)**	(.1)	(.5)	(.6)
DIVORC	.20	.23	.24	.19
	(1.62)	(2.8)**	(3.2)***	(1.9)*
POPAR	.39	.67	.72	.42
	(2.3)**	(5.0)***	(4.8)***	(3.4)***
C	-18	-11	-22	-21
	(.6)	(.6)	(1.3)	(.9)
F-STATISTICS (9, 40)	30.3	13.2	12.8	15.3
R-SQUARED	.85	.72	.71	.74

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 22

DURBIN-WATSON STATISTICS AFTER
CORRECTION FOR AUTOCORRELATION
NEW YORK CITY DATA
LOG ESTIMATION

UNDER 16)	WITHOUT DUMMIES	WITH DUMMIES
RM1P	1.95	1.79
RM1R	1.72	1.66
LM1P	2.06	2.09
MVTM1R	1.87	2.00
16-19)		
RM2R	2.01	2.00
RM2P	2.04	2.06
LM2P	2.16	2.18
MVTM2R	2.03	2.08

TABLE 23

REGRESSION COEFFICIENTS
LOG ESTIMATION (U.S. DATA)
UNEMPL IS NOT INCLUDED

	ROB1MR	BUR1MR	LAR1MR	MVT1MR
DIVORC	-.09 (.4)	.33 (2.6)**	.17 (1.3)	.43 (2.8)***
MEDIN	6.3 (3.4)***	4.03 (3.9)***	3.1 (2.8)***	4.8 (4.0)***
LOWIN	.83 (1.0)	1.04 (2.1)**	1.03 (1.98)*	.86 (1.53)
BLKR	.26 (2.1)**	.07 (1.0)	.03 (.4)	.03 (.4)
SMSR	.13 (3.0)***	.05 (2.3)**	.03 (1.4)	.09 (3.5)***
ATTENR	-3.8 (.7)	.57 (.2)	3.1 (1.1)	.30 (.09)
DUM	-.45 (.9)	-.23 (.8)	-.53 (1.8)*	-.26 (.8)
PROAR	-.16 (.5)	.70 (3.3)***	1.1 (4.4)***	.37 (2.0)**
C	-25 (.5)	-47 (1.66)*	-65 (2.2)**	-51 (1.62)
F-STATISTICS (8, 41)	11.7	9.03	7.54	11.3
R-SQUARED	.69	.63	.59	.58

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 24

REGRESSION COEFFICIENTS
LOG ESTIMATION
LFTOIF IS INCLUDED

	ROB1MR	BUR1MR	LAR1MR	MVT1MR
UNEMPL	-.10	-.17	-.03	.04
	(2.4)**	(.6)	(.1)	(.1)
DIVORC	-.02	.32	.17	.43
	(.1)	(2.5)**	(1.2)	(2.7)***
MEDIN	8.3	3.9	3.1	4.8
	(4.4)***	(3.4)***	(2.5)**	(3.5)***
LOWIN	.95	1.1	1.04	.85
	(1.1)	(2.3)**	(1.93)*	(1.4)
BLKR	.25	.07	.03	.03
	(2.1)**	(.9)	(.4)	(.4)
SMSR	.11	.05	.36	.09
	(2.9)***	(2.4)**	(1.4)	(3.4)***
ATTENR	-3.8	.61	3.1	.30
	(.8)	(.2)	(1.0)	(.09)
DUM	-.38	-.29	-.52	-.25
	(.9)	(1.0)	(1.76)*	(.7)
LFTOIF	-2.9	1.0	.08	-.06
	(1.94)*	(1.1)	(.08)	(.06)
PROAR	-.23	.69	1.1	.38
	(.9)	(3.3)***	(4.1)***	(2.0)**
C	-29	-50	-55	-50
	(.6)	(1.80)*	(2.2)**	(1.5)
F-STATISTIC (10, 39)	11.4	7.5	5.7	9.6
R-SQUARED	.74	.65	.59	.58

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 25

NEW YORK CITY DATA
COCHRANE-ORCUTT ITERATION TECHNIQUE
LOG ESTIMATION

	FINAL VALUE OF RHO	T-STATISTICS FOR RHO	NUMBER OF ITERATION
WITH DUMMIES)			
RM1R	.60	5.3***	17
BM1R	.72	7.5***	20
LM1R	-.21	1.5	4
MVTM1R	.03	.2	1
RM2R	-.06	.4	3
BM2R	-.10	.7	3
LM2R	.01	.1	3
MVTM2R	.003	.02	3
WITHOUT DUMMIES)			
RM1R	.69	6.8***	16
BM1R	.76	8.5***	14
LM1R	.13	.98	2
MVTM1R	.70	7.0***	11
RM2R	.20	1.5	4
BM2R	.12	.90	3
LM2R	.24	1.7*	3
MVTM2R	.11	.84	5

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 26

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
DIVRTE IS NOT INCLUDED
JUVENILES UNDER 16

	RM1R	BM1P	LM1R	MVTM1P
PROAR	.37 (2.3)**	1.0 (5.4)***	.15 (.8)	.85 (7.9)***
TOTUN	.26 (2.0)**	.21 (1.4)	.45 (1.61)	.22 (1.4)
ASSTSR	.008 (.1)	.02 (1.0)	-.02 (.5)	.006 (.3)
REALIN	-.05 (.1)	.28 (.6)	.97 (.8)	2.2 (3.8)***
BLKRT	.55 (1.2)	1.0 (2.1)**	.50 (.6)	1.2 (3.0)***
ATTENR	1.0 (1.0)	.59 (.5)	2.8 (1.4)	1.71 (1.66)
TIME	.01 (.9)	.003 (.1)	.13 (3.0)***	.02 (1.2)
D2	.09 (.2)	.03 (.09)	.68 (1.0)	.44 (1.2)
D3	1.0 (1.4)	.47 (.5)	2.0 (1.4)	-.24 (.3)
D4	.34 (.9)	.70 (1.7)*	.17 (.2)	1.0 (2.6)**
D5	-.39 (.6)	1.3 (1.5)	.06 (.05)	2.3 (3.4)***
C	-9.0 (.8)	-14.6 (1.1)	-34.6 (1.5)	-41.5 (3.4)***
F-STATISTIC (11, 43)	41	14	31.6	13.8
D - W	1.71	1.54	2.3	1.85
R-SQUARED	.96	.92	.89	.78

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 27

REGRESSION COEFFICIENTS
LOG ESTIMATION
NEW YORK CITY DATA
DIVRTE IS NOT INCLUDED
JUVENILES 16-19

	RM2R	BM2F	LM2R	MVT2MR
PROAR	-.32 (.8)	-.002 (.007)	.39 (1.67)*	.08 (.4)
TOTUN	.19 (.6)	.30 (1.0)	.43 (1.1)	-.10 (.3)
ASSISR	.03 (.7)	-.01 (.2)	.002 (.05)	-.009 (.2)
REALIN	3.6 (3.3)***	4.4 (4.1)***	4.6 (3.1)***	4.01 (3.6)***
BLKPT	.09 (.1)	.43 (.5)	-.55 (.5)	.25 (.3)
ATTENR	3.4 (1.8)*	3.5 (1.88)*	3.7 (1.2)	3.2 (1.66)
TIME	.14 (3.2)***	.13 (3.3)***	.27 (4.7)***	.12 (2.8)***
D2	.61 (.9)	.51 (.7)	.82 (.9)	.46 (.6)
D3	.59 (.4)	-.47 (.3)	.70 (.3)	-.19 (.1)
D4	-.88 (1.0)	-.88 (1.0)	-.88 (.7)	-.48 (.6)
D5	-1.0 (.7)	-.27 (.2)	-.34 (.9)	-.41 (.3)
C	-56 (2.4)**	-66 (3.1)***	-72 (2.3)**	-60 (2.6)**
F-STATISTIC (11, 43)	22	11.6	19.9	6.5
D - W	2.09	2.00	2.01	1.98
R-SQUARED	.85	.74	.86	.62

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.

*** SIGNIFICANT AT 1% LEVEL.

TABLE 28

REGRESSION COEFFICIENTS
LOG ESTIMATION (U.S. DATA)
INCLUDES UNEMPL INSTEAD OF TEENUM

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
UNEMPL	-.21	.05	-.09	-.09
	(.8)	(.3)	(.6)	(.4)
MEDIN	7.05	1.3	1.4	3.5
	(6.6)***	(1.95)*	(2.3)**	(4.2)***
LOWIN	1.64	.02	.16	.52
	(3.3)***	(.07)	(.5)	(1.3)
BLKR	.26	.08	.01	.08
	(3.7)***	(1.79)*	(.3)	(1.4)
SMSR	.12	.04	.02	.04
	(5.2)***	(2.67)**	(1.9)*	(2.5)**
ATTENR	-5.2	-.10	1.2	-.89
	(1.9)*	(.05)	(.7)	(.4)
DIVRTE	.21	.23	.24	.19
	(1.67)*	(2.8)***	(3.3)***	(1.93)*
DUM	-.30	-.20	-.29	-.31
	(1.1)	(1.1)	(1.8)*	(1.5)
PROBR	.38	.64	.68	.42
	(2.2)**	(4.8)***	(4.7)***	(3.4)***
C	-22	-12	-25	-25
	(.8)	(.7)	(1.6)	(1.2)
F-STATISITCS (9, 40)	27.6	12.03	12.3	14.4
R-SQUARED	.86	.73	.73	.76

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 29

REGRESSION COEFFICIENTS
LOG ESTIMATION (U.S. DATA)
JUVENILES UNDER 16
DUM IS NOT INCLUDED

	ROB1MR	BUR1MR	LAR1MR	MVT1MR
UNEMPL	-.80	-.25	.01	-.06
	(1.8)*	(.9)	(.03)	(.1)
DIVORC	-.05	.34	.17	.43
	(.2)	(2.6)**	(1.2)	(2.8)***
MEDIN	7.3	4.3	3.1	4.8
	(3.9)***	(3.9)***	(2.5)**	(3.8)***
LOWIN	.73	.94	.65	.67
	(.9)	(2.0)**	(1.3)	(1.2)
BLKR	.18	.04	-.02	.005
	(1.69)*	(.6)	(.3)	(.06)
SMSR	.12	.05	.03	.09
	(3.0)***	(2.3)**	(1.3)	(3.5)***
ATTENR	-4.3	.28	2.7	-.01
	(.9)	(.1)	(.9)	(.004)
PROAR	-.25	.69	1.2	.37
	(.8)	(3.4)***	(4.5)***	(2.0)**
C	-26	-46	-60	-47.8
	(.5)	(1.6)	(2.0)**	(1.5)
F-STATISTIC (8, 41)	12.7	9.1	6.6	11.1
R-SQUARED	.71	.64	.55	.68

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 30

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
LOG ESTIMATION
INCLUDES DROPR INSTEAD OF ATTENR
JUVENILES 16-19

	RM2R	BM2R	LM2R	MVTM2R
PROAR	-.45 (.9)	-.003 (.008)	.39 (1.5)	-.36 (1.1)
TOTUN	.16 (.4)	.35 (.9)	.47 (1.1)	-.36 (.9)
ASSISR	.01 (.3)	-.02 (.4)	-.01 (.2)	-.13 (.3)
REALIN	3.1 (2.6) **	4.1 (3.6) ***	4.0 (2.8) ***	3.7 (3.3) ***
BLKPT	-.04 (.03)	.49 (.4)	-.85 (.6)	.7 (.6)
DROPR	-.23 (.5)	-.26 (.4)	-.19 (.2)	-.04 (.06)
TIME	.10 (2.2) **	.10 (2.3) **	.23 (4.5) **	.06 (1.4)
D2	-.54 (2.1) **	-.68 (2.3) **	-.38 (1.2)	-.80 (3.0) ***
D3	-1.6 (1.76) *	-2.7 (2.9) ***	-1.7 (1.6)	-2.2 (2.7) ***
D4	-2.0 (2.0) **	-1.9 (2.0) **	-2.1 (1.9) *	-1.5 (1.68) *
D5	-2.3 (1.1)	-1.2 (.6)	-3.1 (1.3)	-1.2 (.6)
F-STATISITC (11, 38)	11.0	5.6	15.2	3.5
D - W	1.99	2.00	1.69	2.04
R-SQUARED	.79	.65	.83	.53

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 31

REGRESSION COEFFICIENTS (NEW YORK CITY)
CORRECTED FOR AUTOCORRELATION
LOG ESTIMATION
JUVENILES UNDER 16

	RM1R	BM1R	LM1R	MVTM1R
PROAR	.22	.60	.09	.82
	(1.5)	(2.8)***	(.5)	(5.1)***
TOTUN	.01	-.004	.09	.03
	(1.0)	(.2)	(2.6)**	(1.7)*
ASSISR	.005	.01	-.03	.01
	(.4)	(.8)	(.9)	(.7)
REALIN	-.13	.19	.83	2.1
	(.4)	(.5)	(.6)	(3.5)***
DIVRTE	-.70	-.57	.21	.04
	(2.6)**	(1.8)*	(.2)	(.1)
BLKPT	-.30	.51	.56	1.8
	(.6)	(.7)	(.7)	(4.0)***
ATTENR	.38	.38	.04	2.5
	(.4)	(.4)	(.3)	(2.1)**
TIME	.07	.01	.08	.01
	(2.0)**	(.3)	(.9)	(.3)
D2	.08	-.03	-.09	.65
	(.2)	(.8)	(.1)	(1.6)
D3	.73	.22	.66	.52
	(.9)	(.2)	(.4)	(.6)
D4	-.53	-.05	-.41	1.7
	(1.0)	(.08)	(.4)	(3.3)***
D5	-2.1	-.07	-.25	3.3
	(2.3)**	(.06)	(.1)	(4.1)***
C	5.1	-6.4	-19	-58
	(.4)	(.5)	(.7)	(4.1)***
D-W	1.77	1.70	2.02	1.94
R-SQUARED	.81	.42	.90	.71

Absolute values of t-statistics are in parentheses.

* SIGNIFICANT AT 10% LEVEL.

** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 32

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
CORRECTED FOR AUTOCORRELATION
LOG ESTIMATION
JUVENILES 16-19

	RM2R	BM2R	LM2R	MVTM2R
PROAR	-.46	.06	.38	-.09
	(1.0)	(.1)	(1.5)	(.3)
TOTUN	.02	.05	.07	-.01
	(.4)	(1.4)	(1.4)	(.3)
ASSISR	.03	.04	.004	-.001
	(.7)	(.1)	(.08)	(.02)
REALIN	4.2	4.9	4.5	4.4
	(3.2)***	(4.0)***	(2.9)***	(3.6)***
DIVRTE	-.81	-.91	-.40	-.38
	(.9)	(.9)	(.3)	(.4)
BLKRT	-.02	.72	-.56	.54
	(.2)	(.7)	(.4)	(.5)
ATTENR	5.0	4.8	3.6	4.9
	(2.1)**	(2.2)**	(1.2)	(2.0)**
DROPR	-.04	-.01	-.01	-.01
	(.6)	(.3)	(.1)	(.2)
TIME	.26	.24	.41	.16
	(2.3)**	(2.3)**	(2.2)**	(1.5)
D2	1.1	.97	.79	.91
	(1.4)	(1.3)	(.8)	(1.1)
D3	1.6	.54	.79	1.03
	(.9)	(.4)	(.3)	(.6)
D4	-.09	-.48	-.99	-.06
	(.7)	(.4)	(.6)	(.05)
D5	-1.5	.27	-1.9	.07
	(.6)	(.01)	(.7)	(.03)
C	-71	-83	-67	-82
	(2.4)**	(3.1)***	(1.8)*	(2.8)***
R-SQUARED	.80	.71	.83	.51

D-W	2.01	2.08	2.20	2.08

Absolute values of t-statistics are in parentheses.

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 33

REGRESSION COEFFICIENTS
U.S. DATA
LOG ESTIMATION
ECONOMIC VARIABLES ARE INCLUDED
JUVENILES UNDER 16

	ROB1MR	BUR1MR	LAR1MR	MVTM1R
TOTUN	-1.2	-.34	-.07	-.07
	(2.3)**	(1.1)	(.1)	(.1)
MEDIN	9.0	4.7	4.9	4.95
	(4.5)***	(4.9)***	(3.8)***	(3.8)***
LOWIN	1.4	1.1	.75	.75
	(1.88)*	(2.8)***	(1.4)	(1.4)
PROAR	-.50	.72	.37	.37
	(1.4)	(3.1)***	(1.87)*	(1.87)*
C	-78.7	-47	-47.2	-47.2
	(3.9)***	(4.5)***	(3.6)***	(3.6)***
F-STATISTIC (4, 45)	11.5	11.3	11.2	11.2
R-SQUARED	.50	.50	.50	.50

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 34

REGRESSION COEFFICIENTS
U.S. DATA
JUVENILES 16-19
ECONOMIC FACTORS ARE INCLUDED

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
TEENUN	-.01	.08	-.10	.01
	(.03)	(.3)	(.5)	(.07)
MEDIN	8.8	1.83	1.38	3.92
	(5.1)***	(2.4)**	(2.2)**	(4.6)***
LOWIN	2.4	.15	-.06	.53
	(3.5)***	(.5)	(.2)	(1.57)
C	-85	-17	-13	-36
	(4.9)***	(2.4)**	(2.2)**	(4.2)***
F-STATISITC (4, 45)	9.5	14.0	18.6	19.5
R-SQUARED	.46	.55	.62	.63

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 35

REGRESSION COEFFICIENTS
NEW YORK CITY ANALYSIS
JUVENILES UNDER 16

	RM1R	BM1R	LM1R	MVTM1R
PROAR	.48 (3.1)***	1.05 (6.5)***	.08 (.4)	.80 (6.9)***
TOTUN	.49 (3.7)***	.32 (2.1)**	.42 (1.5)	.17 (1.0)
ASSISR	.003 (.2)	.01 (.8)	-.02 (.6)	-.002 (.009)
REALIN	-.08 (.1)	.07 (.1)	.69 (.6)	2.0 (3.2)***
TIME	.02 (2.0)**	.009 (.7)	.10 (4.0)***	.03 (2.2)**
D2	-.28 (3.3)***	-.09 (.8)	-.22 (1.1)	-.06 (.5)
D3	.17 (.5)	-.03 (.08)	.13 (.1)	-1.5 (3.5)***
D4	-.55 (2.8)***	-.21 (.8)	-.96 (2.0)**	-.17 (.6)
D5	-1.4 (9.1)***	-.32 (1.5)	-1.4 (3.4)***	-.08 (.3)
C	.82 (.2)	-3.8 (.8)	-4.4 (.4)	-19 (3.7)***
F-STATISTIC (9, 45)	102	46	37	12
D - W	1.01	1.14	2.25	1.31
R-SQUARED	.95	.90	.88	.70

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 36

REGRESSION COEFFICIENTS
NEW YORK CITY DATA
JUVENILES 16-19
ECONOMIC VARIABLES ARE INCLUDED

	RM2R	BM2P	LM2P	MVTM2P
PROAR	-.47 (1.4)	-.15 (.4)	.19 (.8)	-.01 (.06)
TOTUN	.16 (.5)	.31 (1.0)	.07 (.2)	-.13 (.4)
ASSISR	.02 (.7)	-.01 (.4)	.02 (.3)	-.01 (.3)
REALIN	3.1 (2.9) ***	4.0 (3.7) ***	4.2 (2.9) ***	3.4 (3.2) ***
TIME	.09 (3.6) ***	.10 (4.0) ***	.20 (5.9) ***	.08 (3.3) ***
D2	-.50 (2.7) ***	-.64 (2.9) ***	-.39 (1.5)	-.58 (3.1) ***
D3	-1.6 (2.2) **	-2.9 (3.5) ***	-1.7 (1.6)	-2.2 (3.0) ***
D4	-1.9 (4.5) ***	-2.2 (4.4) ***	-1.8 (3.0) ***	-1.5 (3.7) ***
D5	-2.0 (5.6) ***	-1.9 (4.5) ***	-1.1 (3.9) ***	-1.7 (4.2) ***
C	-18 (2.0) **	-28 (3.3) ***	-34 (3.0) ***	-24 (2.7) ***
F-STATISTICS (9, 45)	26	13.0	30.3	7.4
D - W	1.78	1.67	1.58	1.75
R-SQUARED	.84	.72	.85	.59

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 37

REGRESSION COEFFICIENTS
ATTENR IS NOT INCLUDED
JUVENILES UNDER 16
U.S. DATA

	ROB1MR	BUR1MR	LAR1MR	MVT1MR
TOTUN	-.84 (1.8)*	-.28 (1.0)	-.05 (.1)	.04 (.1)
DIVRTE	-.06 (.2)	.34 (2.7)***	.18 (1.3)	.43 (2.8)***
MEDIN	7.2 (3.9)***	4.3 (4.0)***	3.2 (2.7)***	4.9 (3.8)***
LOWIN	1.1 (1.3)	1.1 (2.2)**	1.0 (1.96)*	.85 (1.4)
BLKRT	.28 (2.5)**	.06 (1.0)	-.001 (.02)	.03 (.4)
SMSR	.13 (3.5)***	.05 (2.3)**	.03 (1.2)	.09 (3.6)***
DUM	-.56 (1.2)	-.25 (.9)	-.49 (1.69)*	-.25 (.8)
PROAR	-.27 (.9)	.66 (3.2)***	1.0 (4.0)***	.37 (2.0)**
C	-66 (3.7)***	-43 (4.1)***	-35 (3.2)***	-48 (3.9)***
F-STATISTIC (8, 41)	12.9	9.4	7.1	11.4
R-SQUARED	.71	.64	.58	.68

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

TABLE 36

REGRESSION COEFFICIENTS
U.S. DATA
ATTENR IS NOT INCLUDED
JUVENILES 16-19

	ROB2MR	BUR2MR	LAR2MR	MVT2MR
TEENUN	-.08	.06	-.09	.04
	(.2)	(.3)	(.5)	(.2)
MEDIN	6.9	1.3	1.4	3.3
	(6.3)***	(1.99)*	(2.3)**	(4.0)***
LOWIN	1.6	.02	.15	.48
	(3.2)***	(.08)	(.5)	(.48)
BLKR	.31	.07	.005	.09
	(4.7)***	(1.95)*	(.01)	(1.8)*
SMSR	.13	.04	.02	.04
	(5.4)***	(2.7)***	(1.8)*	(2.6)**
DIVRTE	.20	.23	.24	.18
	(1.5)	(2.8)***	(3.3)***	(1.89)*
DUM	-.34	-.21	-.26	-.33
	(1.2)	(1.2)	(1.6)	(1.59)
PROAR	.38	.65	.67	.44
	(2.2)**	(4.9)***	(4.6)***	(3.6)***
C	-70	-13	-14	-32
	(6.5)***	(2.0)**	(2.3)**	(4.0)***
F-STATISTIC (8, 41)	28.1	13.8	13.8	16.4
R-SQUARED	.84	.73	.73	.76

* SIGNIFICANT AT 10% LEVEL.
** SIGNIFICANT AT 5% LEVEL.
*** SIGNIFICANT AT 1% LEVEL.

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