THE EFFECTS OF SOCIO-STRUCTURAL, ECONOMIC, AND RACE CONSIDERATIONS ON RATES OF PROPERTY CRIME IN THE UNITED STATES, 1958-93

DISSERTATION

Presented to the Graduate Council of the
University of North Texas in Partial
Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

By

Roy W. Ralston, B.A., M.A.

Denton, Texas

May, 1996

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This study investigates changes in rates of property crime in the United States from 1958 to 1993. Predictor variables include changes in rates of economic factors (inflation, technological/cyclical/frictional unemployment), arrest rates for property crimes disaggregated by race (ARPCDR), interaction of ARPCDR and technological unemployment, alcohol offenses, interaction of alcohol offenses and poverty, drug abuse violations, and interaction of drug abuse violations and poverty. Changes in poverty, population growth, and police presence are employed as control variables. The Beach-McKinnon Full Maximum-Likelihood EGLS AR1 Method (accompanied by residual analysis) is used to test seven hypotheses. Significant positive effects upon changes in aggregate property crime rates are found for five predictors: (a) inflation, (b) cyclical unemployment, (c) frictional unemployment, (d) the

interaction of white arrest rates and technological unemployment, and (e) the interaction of rates of alcohol offenses and poverty.

To explain changes in property crime rates, further research should decompose aggregate rates particularly those pertaining to the economy. Also, the relationship between the interaction of poverty and drug abuse violations, at the aggregate level, and changes in property crime rates should be clarified.

This research has important policy implications related to the impact of social, economic, and educational issues on mainstream society and its criminal elements. Law makers should consider this type of research in all macro and micro-oriented policies.

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CHAPTER I

INTRODUCTION

Property crime in the United States remains an enigma facilitating continuing epidemics of victimizations and the apprehension associated with it. Auto theft, burglary, and larceny continue to occur with alarming frequency impacting the lives of thousands of innocent citizens every day. Even during periods of decline (large or small) in rates of property crime, Americans should not become complacent for surely future increases are to follow (just as they have in the past) when certain situations manifest themselves.

In an effort to understand the nature of the factors impacting property crime, diverse perspectives have been advanced over time. However, upon review of the literature, several common factors can be identified which logically impact the rates of property crime in the United States, lending themselves to unique modes of inquiry. Though many such factors have been defined over time, issues related to the structural predisposition of American society (poverty, alcohol offenses, drug abuse violations), economy (inflation and unemployment), and race lend fundamental insight into the phenomenon of property crime.

Grounding In Classical Theory:

Considering the orientation suggested above, a theoretical premise grounded in *social disorganization* and *anomie* theory is essential. In relation to social disorganization, environmental influences (Morris 1958) (lack of gainful employment opportunities, poverty, etc.) received attention as causes of crime as early as the 19th century but consequently fell prey to individualistic explanations only to be revitalized early this century. Primary concepts in social disorganization include: (a) the notion that deviant behavior accompanies the breakdown of conventional institutional controls, and (b) such breakdowns inhibit the ability of individuals, groups, organizations, etc., to collectively address common problems (Shoemaker 1990).

From this perspective, concentric zones were believed to emanate from inner-city areas (Burgess 1967). These areas were seen as fostering higher rates of deviance (Shaw, Zorbaugh, McKay and Cottrel 1929). This focus gave rise to the Chicago School of sociology and originated the American orientation to ecological analysis (Park 1936).

The premise described above parallels to significant degrees the concept of *anomie.* However, while social disorganization addresses institutional concerns, anomie is oriented toward more societal concerns. In particular, anomie is thought of as a construct:

> refer(ing) to inconsistencies between societal conditions and individual opportunities for growth, fulfillment, and productivity within a society. The term *anomia* is used to refer to those who experience personal frustration and alienation as a result of anomie within a society (Shoemaker 1990, p. 99).

Two major theoretical developments in the anomie tradition were undertaken by Emile Durkheim and Robert Merton.

In *The Division of Labor in Society* (1893), Emile Durkheim conceptualized society as evolving from an undifferentiated society governed by the collective conscience (heavily dependent upon ritual) characterized by similarity among parts. This state was termed mechanical solidarity. However, with industrialization and increasing population density, society was bound to differentiate with concord founded upon differences (necessitating interdependence) reflective of organic solidarity. Accompanying the division of labor inherent in such a process, increasing individualism would decrease the propensity for societal regulation of individual desires. To maintain balance, Durkheim believed that the function of occupational associations would evolve to guide and constrain individual actions serving much the same function as guilds had historically in Europe. However, he set forth the fact that crime is a natural phenomenon in all societies, but would not constitute a pathology until the rates of deviance exceeded rates of conformity.

Merton's emphasis on anomie focused on discrepancies between goals and the legitimate means of achieving those goals available to societal members. For instance, in the United States, economic success is the primary goal (throughout society), consistent with its capitalist underpinnings. However, Merton (1968) argued that the means of achieving this success (education, occupational training, individual fiscal planning, etc.) are not evenly distributed in American society. In response to such conditions, a society's members would manifest varying modes of adaptation, to include: (a) initial conformity in accepting institutionalized means, (b) innovation in accepting cultural goals but rejecting institutionalized means,

(c) ritualism in rejecting cultural goals but accepting institutionalized means, (d) retreatism in rejecting both cultural goals and institutionalized means, and (e) rebellion in rejecting both cultural goals and institutionalized means while wishing to replace both with new systems (Merton 1968). As would be apparent, Merton's theory has also come to be known as the *means-ends theory* (Curran and Renzetti 1994).

A very important, related concept is that of *opportunity structure* which constitutes the availability of legitimate opportunities to succeed within any one social structure (Shoemaker 1990). Moreover, consequent developments in relation to opportunity structures identified *differential opportunity structures* (Cloward and Ohlin 1960). To be deviant, the behavioral inclinations must be present but illegitimate opportunity structures must also be present (to manifest deviant behavior through). It is in such environments that deviant behavior is learned and channels for the manifestation of such behavior utilized. "(N)eighborhoods in which crime flourishes as a stable, indigenous institution are fertile criminal learning environments for the young" (Cloward and Ohlin 1960, p. 148) who will become tomorrow's adult deviants.

This theoretical foundation has influenced much contemporary criminological research. Structurally, factors such as economic indicators (to include unemployment and inflation), racial composition, poverty levels, population growth/ density, and police presence have frequently been incorporated as predictors of crime (Smith, Devine and Sheley 1992; Cantor and Land 1985; Devine, Sheley and Smith 1988; Patterson 1991; Smith and Jarjoura 1988; Carroll and Jackson 1983; Jacobs 1982). Economic frustration motivates criminality and inhibits communal deterrence capacities contributing to changes in crime rates (Devine, Sheley and Smith 1988). In addition, structural/institutional studies of race have also found positive effects on crime evidenced by disparate arrest rates between majority and minority populations (Smith and Jarjoura 1988; Patterson 1991; Smith, Devine and Sheley 1992). However, recent evidence suggests that majority members of the population may have a lower threshold at which worsening economic conditions spur criminality (Smith, Devine and Sheley 1992).

Further, high levels of poverty influence the commission of crimes out of frustration and/or self-sustenance (Sviridoff and Thompson 1983). Poverty situations are compounded by population growth and increases in population density intensifying competition for valued social resources (Curran and Renzetti 1994; Denq and Altenhofel 1995). In the process, conventional control mechanisms are broken down (Wirth 1938) contributing to increases in crime.

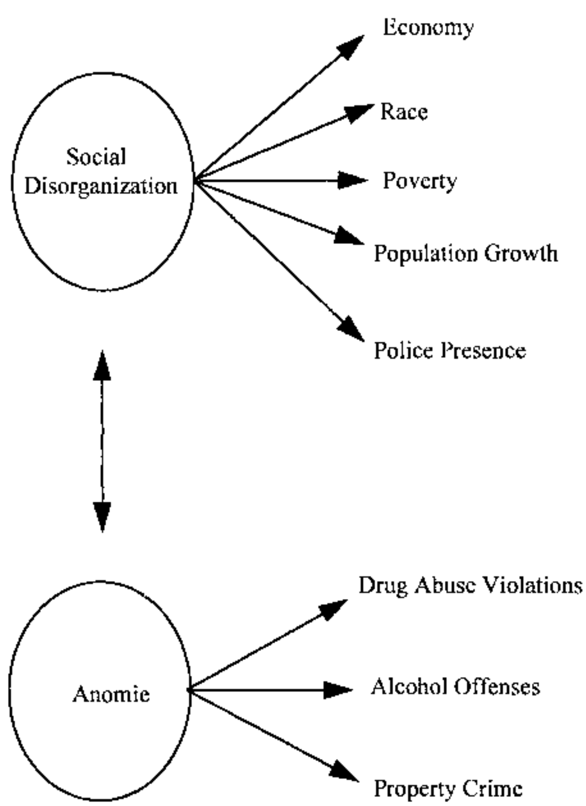
Consequently, and as part of a society's organization, the absence or presence of police officers impact crime (Swimmer 1974). Changes in the proportion of available police officers may produce changes in the: (a) number of recorded crimes, (b) deterrence effects of present activities, and (c) ability of police forces to solve crimes and apprehend suspects (Tulder 1992; Wilson and Boland 1978). Such is also important in theories of social control. However, in the present case, the focus is on the degree to which institutional change in law enforcement capacities affects fluctuations in crime. Thus, inclusion under the auspices of social disorganization is appropriate.

From an anomie perspective, involvement with drugs and alcohol and the commission of crimes manifest themselves as a partial function of conflict between *societal conditions* and *opportunities* for individual growth. Personal frustration and alienation (Shoemaker 1990) operate to increase deviant acts. Occurring in the absence of effective individual control, these deviant acts can take the form of addictive behaviors such as excessive alcohol consumption or drug abuse. Being conditioned to significant degrees by the experience of poverty, such operates to increase crime (Currie 1985; Harrison and Gfroerer 1992; Waller 1981; Murdoch, Pihl and Ross 1990). Figure 1 (p. 9) illustrates the theoretical premise under which each of the above factors are incorporated. The double-ended arrow between social disorganization and anomie reflects the closeness of association between the concepts.

Hence, fundamental theoretical paradigms have been presented relating to the causes and explanation of crime. As certain institutional and/or means-ends issues relegate varying individuals to isolated segments of society, they become separated, to varying degrees, from mainstream capitalist economic life. Consequently, the propensity to undertake alternative means of sustenance (i.e., property crime) or incorporate alternative patterns of behavior (such as drug or alcohol use/abuse) exacerbates criminal activity. This is fundamental in terms of the life experiences of those concerned (Felson and Van Dijk 1993).

Figure 1

Indicators of Social Disorganization and Anomie



Theoretical Developments And Present Trends In Research:

The theoretical premise developed above is most basic to criminological research and provides a straightforward framework within which to study crime. Upon such a foundation, much research has been conducted laying the framework for fruitful research including the development of new theories and applications. This section briefly addresses the work being conducted in the study of property crime in terms of: (a) theoretical developments and applications, (b) social attributes of interest within such theoretical perspectives, (c) units of analysis studied, and (d) methods of analysis employed.

The theoretical tenets previously introduced are some of the most heavily used classical theories of crime. However, more recent theoretical developments and applications of other classical perspectives should be noted in order to properly place the current effort in context. Routine activity/opportunity theories are initially addressed followed by a brief account of recent Marxian application.

Since the late 1970's, much research has been extended to a perspective "variously called routine activity, lifestyle, or opportunity theory" (Bennett 1991, p. 147).

This perspective views crime as a partial function of increased residential mobility and is interested in the ways victimization may be increased or decreased. This theory proposes that as residential mobility increases, suitable targets increase. As the density of suitable targets increases, the presence of effective guardianship may decrease. Criminal motivation then acts as a third component in the process of crime commission (Cohen and Felson 1979; Garfalo 1987).

Measures of residential activity are pertinent within the confines of this theory. The first generation of studies testing this perspective investigated aggregate phenomena such as labor force participation, etc. (Lynch and Cantor 1991). In this regard, Cantor and Land (1985) supported the following: (a) a negative partial relationship between the level of aggregate unemployment and detrended fluctuations (changes) in burglary and larceny-theft; and (b) a positive partial relationship between fluctuations (changes) in unemployment and fluctuations (changes) in burglary and larceny-theft. The former supported criminal opportunity effects while the latter criminal motivation. Studies such as those conducted by Bennett (1991) (involving 52 countries between the years 1960-1984) traverse national boundaries promoting cross-national attention and expansion of the theory into an international context. Such studies effectively support the importance of economic factors in the study of property crime.

The next generation of studies incorporating this perspective advocated behaviorally-oriented measures at more disaggregated levels such as neighborhoods and communities, though such measures are more difficult to obtain (Lynch and Cantor 1992). In one such study, Lynch and Cantor operationally define and measure criminal opportunity via area attributes such as location and design of housing, time spent at home during day/night, degree of social disorganization present, etc. The results indicated that these types of predictors varied across the type of crime considered. None of the environmental design attributes were significant, while the other ecological and behavioral attributes differed by the type of crime being considered.

Aggregate measures do not completely address the complete range of considerations encapsulated in routine activity/opportunity perspectives. Aggregation is argued to "wash out" many important individual differences between smaller areas that impact crime differently at those levels (Lynch and Cantor 1992). Such should be considered if the issues guiding the research revolve around neighborhood or community interests, etc. (such as local legislation). Nonetheless, the density level of motivated offenders can be measured by structural attributes such as the proportion of unemployed adults (Lynch and Cantor 1992; Cantor and Land 1985).

Further, radical theory draws upon the classical Marxian interpretation of society and extends it to crime. This perspective proposes that: (a) most behavior is a product of class struggle, (b) capitalism is responsible for the class division, (c) the bourgeoisie attempt to suppress the proletariat, and (d) crime is committed by the proletariat in response to the oppression from the bourgeoisie. Certainly, the notion of class conflict is a central concept as is the application of surplus labor (labor in excess of what is needed to replace wages) (Shoemaker 1990).

This extra labor provides surplus value to the owners of production. For Marx (1967), "the rate of surplus value is...an exact expression for the degree of exploitation of labour-power by capital, or the labourer by the capitalist" (p. 218). Following from this position, many recent studies have focused on this type of problem. Among recent efforts, Lynch, Groves, and Lizotte (1994) demonstrate that surplus value is significant in predicting property crime (as well as other types of crime). This conclusion was also supported by Lynch (1988) in a domestic, national time-series study (1950-1974).

Current research efforts incorporate all of the aforementioned as well as other phenomena that can be supported by other theoretical perspectives. With this in mind, it is important to note that the intent of the research questions guiding a project greatly influences the theoretical tenets drawn upon, units of analysis chosen, variable operationalization, and the analytical methods employed. Further consideration regarding current trends in research practices will help place the current study in the appropriate context.

In relation to property crime, studies have spanned the distance between micro issues such as the self (Caspi, Moffitt, Silva, Stouthamer-Loeber, Krueger and Schmutte 1994; Spunt 1993) to more aggregated phenomenon at the following levels; (a) neighborhood (Patterson 1991; Smith and Jarjoura 1988), (b) city (Neapolitan 1994; Liu and Bee 1983; Carroll and Jackson 1983), (c) county (Kposawa, Breault and Harrison 1995), (d) SMSA (Standard Metropolitan

Statistical Areas) (Jacobs 1982), (e) state (Chamlin and Cochran 1995) and (f) national (Lynch, Groves and Lizotte 1994; Smith, Devine and Sheley 1992; Devine, Sheley and Smith 1988; Cantor and Land 1985). Much of the research has been conducted cross-sectionally, but a rich collection of time-series issues have been examined (Lynch, Groves and Lizotte 1994; Smith, Devine and Sheley 1992; Devine, Sheley and Smith 1988; Cantor and Land 1985; Liu and Bee 1983; Bennett and Basiotis 1991). This attention has also been extended to a cross-national context (Pyle and Deadman 1994) further supporting the use of time-series data in the study of property crime. However, sound studies at the national or city level appear to be more abundant in relation to property crime.

In terms of quantitative methods, the majority of property crime studies (both cross-sectional and time series) rely on statistical techniques subsumed under the General Linear Model. Cross-sectionally, the majority of studies are based on OLS regression or a specialized case of its application (such as ANOVA/ANCOVA, MANOVA/MANCOVA, etc.) (Osborn, Trickett and Elder 1992). Some attention has been extended to path modeling and ultimately to LISREL (Hakim, Spiegel and Weinblatt 1984). In a time-series context, the majority of studies have incorporated AR1 regression techniques or OLS models incorporating lagged endogenous variables (Smith, Devine and Sheley 1992; Devine, Sheley and Smith 1988; Cantor and Land 1985; Lynch 1988).

Further, several reputable time-series studies have been conducted with annual, aggregate data (Cantor and Land 1985; Devine, Sheley and Smith 1988; Smith, Devine, and Sheley 1992). While the existence and ease of access to national, aggregate data certainly facilitate its use, it is very important in investigating the impact of varying aggregate economic and social phenomena on crime rates (Cantor and Land 1985; Devine, Sheley and Smith 1988; Smith, Devine, and Sheley 1992). The findings from this type of research are fundamental to the appropriate legislation of national economic and social policy (U.S. Congress 1978).

Rationale And Contribution Of The Present Study:

With the aforementioned serving as an abbreviated statement of the current orientation to property crime, the rationale and contribution of the current study can be more fully appreciated. Certainly, the primary theories being incorporated (social disorganization and anomie) represent some of the most universally accepted classical theories of crime. However, it is shown that application at each stage of this investigation incorporates new approaches never before attempted in the study of property crime *over time*, and most appropriately (as a starting point) should be addressed from a theoretical perspective grounded in institutional concerns (social disorganization) and pressures toward deviant behavior (anomie). This is consistent with the nature of Messner and Rosenfeld's idea of institutional anomie (Chamlin and Cochran 1995).

One such innovation focuses on the use of annual unemployment rates in the prediction of crime. The more complex issues regarding aggregate unemployment rates (in a time-series context) have merely investigated the effects of the aggregate rate and the differenced series on changes in property crime (Devine, Sheley and Smith 1988; Smith, Devine and Sheley 1992; Cantor and Land 1985). However, this study decomposes the unemployment series (1958-1993) into the three components; technological, cyclical, and frictional unemployment. These components represent the full dynamics of the annual series with each meaningful within the context of economic theory.

This strategy fundamentally changes the nature of the consideration of unemployment and its impact on crime. Indeed, the issue becomes much more complicated. The more simple conceptions posed by studies such as Cantor and Land (1985) relative to differenced vs. synchronous rates of unemployment and their effects on property crime are no longer so straightforward. Preliminary application of a structurally-oriented theory such as social disorganization provides the necessary structural premise. It offers a usable sociological platform to investigate the effects of the varying components of the unemployment rate based in an institutional (i.e., economy) context. In the process, totally new and unique information relating unemployment to property crime can be presented. Further, inflation may be placed in this context. Although Devine, Sheley and Smith (1988) place inflation in the context of criminal motivation (routine activity), it certainly can be included with social disorganization as an inhibitor of the economy (a *major* institution).

Another unique aspect of the study is the incorporation of interactions within a time-series context which also uniquely contributes to the criminological literature. Interaction of the upward trend in unemployment and race (two institutional concerns) is investigated. This tests the degree to which disaggregated arrest rates (based on race) are conditioned by upward trends in unemployment *over* *time*. Further, the interactions of poverty with alcohol offense rates and rates of drug abuse violations (anomie related concerns) is investigated. This tests the degree to which aggregate changes in the rates of alcohol offenses and drug abuse violations are conditioned by changes in rates of poverty *over time*. Although interactions have been tested in a cross-sectional (and even cross-national) sense (Stack 1984), no evidence has been uncovered for their use in any time-series analysis relative to property crime.

Accordingly, at each step of the analytical process, unique approaches are being applied which have consequences for the theories chosen to support the effort. Many times, very unique and different approaches are more difficult to place in context than mere replications of previous attempts. Such is the case with this study. Considering the uniqueness of the use of economic and interaction variables in this time-series analysis, a theoretical grounding in social disorganization and anomie is appropriate. A strength of any research project is to illustrate fundamentally different approaches, never before employed, within the context of appropriate theories to include classical perspectives in the same vein in which radical theory is currently employed via Marxism. Such efforts have the potential to demonstrate that work within classical perspectives is not concluded which may provide additional insight into the development and evolution of new theories (as well as a better understanding of the classical ones). This fact supports the uniqueness and contribution of the present study.

Definition Of Terms:

Consistent with the above considerations set within the theoretical framework of social disorganization and anomie, the following variables constitute the basis of this study. Following identification of each variable is the definition guiding interest in this work:

(A) Property Crimes - Property offenses known to police in the United States to include:

(1) Burglary (breaking and entering) - "The unlawful entry of a structure to commit a felony or theft. Attempted forcible entry is included" (U.S. Bureau of Justice Statistics, Department of Criminal Justice 1994, p. 705).

(2) Larceny (theft excluding motor theft) - "The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples

are thefts of bicycles or automobile accessories, shoplifting, pocket-picking, or the stealing of property or article which is not taken by force and violence or by fraud. Attempted larcenies are included. embezzlement, 'con' games, forgery, worthless checks, etc., are excluded" (p. 705).

(3) Motor vehicle theft - "The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on the surface and not on rails. Specifically excluded from this category are motorboats, construction equipment, airplanes, and farming equipment" (p. 705).

(B) Inflation - Upward movements of the absolute price level (Byrns and Stone 1987). The annual rate of inflation in the United States.

(C) Unemployment - "A condition that occurs when an individual wants work but is without a job" (Byrns and Stone 1987, p. 772). Unemployment rate is, "The percentage of workers who are not working but who are looking for work" (Hall and Taylor 1991, p. 8) per 100,000 inhabitants in the United States.

(1) Technological unemployment is the upward trend in an annual series of unemployment rates.

(2) Cyclical unemployment is the annual cycles of unemployment rates in an annual series of unemployment rates.

(3) Frictional unemployment is unemployment arising from imperfect knowledge of workers relative to job openings at times when they lose jobs (Byrns and Stone 1987). It is partially realized in the *error* in predicting successive periods of unemployment.

(D) Drug Abuse Violations - Drug abuse violations in the United States are defined as "state and local offenses relating to the unlawful possession, sales, use, growing, and manufacturing of narcotic drugs. The following drug categories are specified: Opium or cocaine and the derivatives (morphine, heroin, codeine); marijuana; synthetic narcotics - manufactured narcotics that cause true addiction (Demerol, methadone); and dangerous non-narcotic drugs (barbiturates, Benzedrine)" (U.S. Bureau of Justice Statistics, Department of Criminal Justice 1994, p. 705).

(E) Alcohol Offenses - Rates of arrests (per 100,000 population) for alcohol related offenses in the United States to include:

(1) Driving under the Influence - "Driving or operating any vehicle or common carrier while drunk or under the influence of liquor or narcotics" (p. 705).

(2) Liquor Laws - "State or local liquor law violations, except 'drunkenness and 'driving under the influence.' Federal violations are excluded.' (p. 705).

(3) Drunkenness - "Offenses relating to drunkenness or intoxication. Excluded is 'driving under the influence' (p. 705).

(4) Disorderly Conduct - "Breach of the Peace" (p. 705).

(5) Vagrancy - "Vagabondage, begging, loitering, etc." (p. 705).

(F) Poverty - The percent of individuals of all races in the United States living under poverty level as of March 1 of each year (1958-1993).

(G) Population Growth - Percent change in total, annual United States population as of July 1 for each year (1958-1993).

(H) Police Presence - The average number of city police employees per 100,000 inhabitants in the United States (1958-93).

Research Questions:

Based upon the preceding review and delineation of factors believed to impact property crime from social disorganization and anomie perspectives, the following research questions are explicitly offered as guiding issues in this study:

(A) What is the impact of changes in rates of inflation on changes in rates of property crimes known to police?

(B) What is the impact of changes in rates of technological, cyclical, and frictional unemployment on changes in the rates of property crimes known to police?

(C) What is the impact of changes in the interaction of technological unemployment and race on changes in the rates of property crimes known to police?

(D) What is the impact of changes in the interaction of poverty and rates of alcohol offenses on changes in the rates of property crimes known to police?

(E) What is the impact of changes in the interaction of poverty and rates of drug abuse violations on changes in the rates of property crimes known to police?

(F) What is the impact of changes in the rates of poverty on changes in the rates of property crimes known to police?

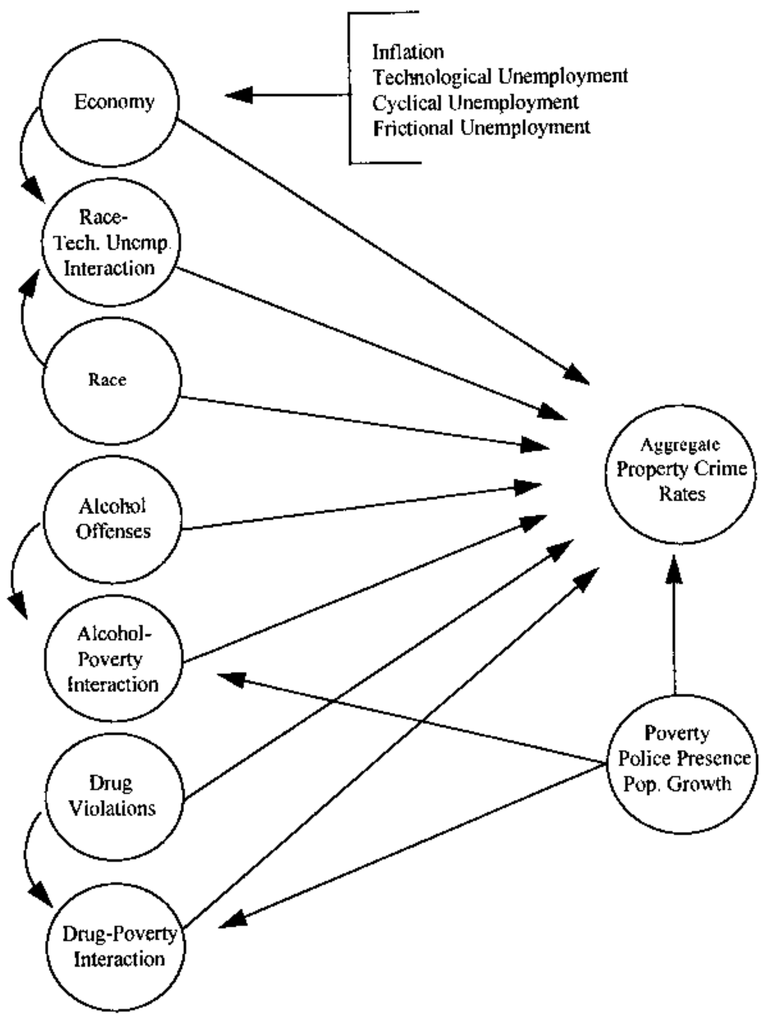
(G) What is the impact of changes in the rates of population growth on changes in the rates of property crimes known to police?

(H) What is the impact of changes in the rates of police presence on changes in the rates of property crimes known to police?

Figure 2 (p. 26) illustrates the interrelated nature of these questions.

Figure 2

A Model of the Relationship Between Social Disorganization, Anomie and Aggregate Property Crime Rates



Predictors Of Property Crime:

Economic Factors

The aim of this work is the exploration of property crime within the context introduced above. As a starting point, Devine, Sheley and Smith (1988) advocate the inclusion of inflation in any model incorporating macroeconomic considerations as they relate to the explanation of crime rates (both property and violent). The basic notion is that crime rates rise with increases in inflation, because "hard times motivate criminal behavior and...inhibit the capacity of communities to deter crime" (p. 410). Thus, following from this precedent, higher inflation rates facilitate higher rates of property crime.

Unemployment is another factor often employed in studying crime in general to include property crime (Currie 1985; Hartnagel and Krahn 1989; Howsen and Jarrell 1985; Lessan 1991). Though unemployment has been investigated relative to several types of crime, there is a general (though not majority) consensus that rates of unemployment do affect rates of property crime (Smith, Devine and Sheley 1992; Hagan 1993; Howsen and Jarrell 1987; Stack and Krohn 1978; Skogan and Lurigio 1992; Allan and Steffensmeier 1989).

With particular reference to the study of unemployment and crime rates (both property and violent), many researchers (Cantor and Land 1985; Devine, Sheley and Smith 1988; Smith, Devine and Sheley 1992) advocate the investigation of the effects of *changes* in unemployment rates on *changes* in crime rates. Such an approach recognizes the impact of changes in certain structural rates and the consequent effects on property crime rates and is applied across the expanse of explanatory factors incorporated herein. Hence, structural questions are posed in terms of how changes in certain explanatory rates impact changes in property crime rates.

Relatively little attention has been extended to the impact of differing types of unemployment (i.e., cyclical vs. frictional vs. seasonal vs. structural) on property crime. The majority of the aforementioned studies focused predominantly on aggregate, annual unemployment data taking less than full advantage of the total dynamics of the series. However, monthly data has occasionally been employed across crimes (Rahav 1982; Corman and Joyce 1990) providing opportunity for considerations of seasonal and cyclical effects.

With this said, annual data prevent exploration of seasonal unemployment. However, of particular interest are the concurrent, individual effects of structural, cyclical, and frictional unemployment. Structural unemployment occurs when individual job skills cannot be matched with virtually any available jobs. Technological differentiation is a structural change which tends to displace workers by rendering their job skills obsolete. Further, over the course of varying life histories, individuals may not acquire any marketable skills (Byrns and Stone 1987; Clark, Theis, Wilson and Barr 1990). What happens when a worker is displaced (by technology, depletion of natural resources crippling specific industries, etc.) and is unable to find a job for which they are capable? After a certain length of time, they fall out of the unemployment fact finding picture. They are no longer counted among the unemployed when they stop looking for jobs.

How important would such a fact be in determining who would be most predisposed to the commission of property crime? It would appear to be of ultimate importance. Indeed, in a time series study (1958-1987), Smith, Devine, and Sheley (1992) postulate that:

> upward trends in unemployment appear to increase the motivation to engage in property crime among all groups, including older and majority-status groups that were assumed to be better insulated from the effects of unemployment. (p. 565)

As processes such as technological innovation deplete blue-collar job markets, many argue that we can expect higher than normal unemployment rates throughout the next several decades (Byrns and Stone 1987; Clark, Theis, Wilson and Barr 1990). Those structurally displaced, therefore, constitute an upward trend in unemployment which impacts property crime rates. Even though current efforts to record unemployment do not address structural unemployment, the positive trend observed over the past three decades in overall unemployment rates captures significant aspects of the phenomenon and shall be termed *technological unemployment* henceforth in this study. Consequently, this informs the hypothesis of a positive relationship between changes in the upward trend in unemployment (technological unemployment) and changes in the rates of property crimes.

A general business recession produces cyclical unemployment as a consequence of downward turns in the business cycle. However, not all groups are equally affected by this cyclical phenomenon. Professional and technical workers suffer much less from cyclical unemployment than do blue-collar, service, manufacturing, construction workers, etc. (Byrns and Stone 1987; Clark, Theis, Wilson and Barr 1990). Thus, many potential workers may experience periods of cyclical unemployment (as in the case of blue-collar workers in general) on the way to being structurally unemployed. Conceptually, after battling periods of cyclical unemployment, those who become structurally unemployed may be even more predisposed (due to exacerbated financial distress) to the commission of property crime. Hence, this informs the hypothesis that changes in the level of annual cycles of unemployment is positively related to annual changes in the rates of property crimes.

Finally, frictional unemployment addresses that portion of society currently between jobs and is a by-product of normal business activity. As workers get terminated, laid-off, or quit, turnover in the unemployed occurs with the process continuing on and on as no-one possesses perfect knowledge about job openings, etc. (Byrns and Stone 1987; Hall and Taylor 1991; Clark, Theis, Wilson and Barr 1991). Thus, there are always workers frictionally unemployed, those between jobs. Perhaps, those frictionally unemployed become more predisposed to property crime as an economic option as the period of unemployment increases. Thus, this informs the hypothesis of a positive relationship between changes in rates of frictional unemployment and changes in the rates of property crimes.

Race

Though direct evidence for the use of race as employed in this study has not been discovered by this author, this study shows that consideration of the arrest rates of whites and blacks is significant in investigating rates of property crime. In terms of race in general, many argue that race must be incorporated in some way in models studying crime (Sommers and Baskin 1992; Peterson and Krivo 1993). Such researchers argue that studies that do not include considerations of race produce deceptive results. Indeed, in the case of violent crime, some argue that crimes must be disaggregated by race (with particular reference to African-Americans) (Peterson and Krivo 1993; Harer and Steffensmeier 1992).

In their study of crime and unemployment across age and race categories, Smith, Devine, and Sheley (1992) suggest that "controls for age and race qualify only partially at the aggregate level, at least for the crimes and era addressed in (their) analysis" when considering unemployment as a predictor of property crime (p. 565). In their study (as in the present one), race was operationally defined as the disaggregated arrest rates with the comparison being made between the two rates (whites vs. blacks). Based on their findings, the researchers suggested that whites might be influenced to greater degrees by changes in unemployment rates than their black counterparts indicating that "whites may have a lower threshold at which economic hardship spurs criminal activity" (p. 565). This statement is tested via the separate interactions of technological unemployment and white and black property crime arrest rates. Whites (as compared to their counterparts) are believed to be motivated to commit more property crimes during upward trends in unemployment. Again, this is tested via interaction of technological unemployment and white property crime arrest rates. Such informs the hypothesis of a positive relationship between changes in this interaction (white arrest rates/technological unemployment) and changes in property crime rates. This relationship is also believed to outweigh (by far) the significance of its counterpart interaction (black arrest rates/technological unemployment) which should not be significant in the context of the setting established in this study.

Socio-Structural Factors

Harrison and Gfroerer (1992) indicate that drug use (particularly cocaine) is a strong predictor of being booked for a criminal offense. Waller (1981) agrees that drug usage in the U.S. partially impacts crime rates. In addition, Skogan and Lurigio (1992) believe that drug problems are more pronounced in minority communities impacting, to some degree, the rates of crime in those areas. Much the same can be said for alcohol. Cookson (1992) has reported a high correlation between self-reports of delinquency and prior convictions and habitual use of alcohol with much the same being offered by other researchers (Welte and Miller 1987; Gerson and Preston 1979). Cordilia (1985) found that drinking prior and at the time of offense were not strongly associated with professional property crime impacting, instead, the commission of unplanned, high-risk crime.

Of importance in the hierarchy of variables suggested thus far, Currie (1985) suggests that recurrent bouts with unemployment tend to lead to drug and alcohol use.

Indeed, Hartnagel and Krahn (1989) support this contention in their study on high-school dropouts, postulating that "current unemployment and an unstable work history are most related to crime and drug use, except for violent crime" (p. 416). Further, Speckart and Anglin (1986) have postulated that drug dealing is also a very important factor exacerbating the narcotic/property crime relationship.

In unique manner, the effects of changes in alcohol and drug abuse violation rates on changes in property crimes rates are tested via *interactions with poverty.* Such an approach allows investigation of the degree to which poverty conditions the use of/involvement with alcohol and/or drugs. This is most consistent with perspectives founded upon the belief that deviant subcultures form in poverty stricken populations. It should be noted, however, that the concept of interactive effects is reciprocal between the variables constituting the interactive product (Cohen and Cohen 1983). Thus, this informs the hypotheses that separate interactions of poverty and rates of alcohol offenses and poverty and drug abuse violations produce positive changes in property crime rates, respectively.

Established Socio-Structural Controls

Review of the literature revealed several socio-structural factors of interest in terms of statistical control. Among these controls are poverty, population growth, and police presence. Though various controls exist which could arguably be included in the model, it is believed that a cogent set has been chosen.

In their study on public housing and the concentration of poverty (employing separate equations for each estimate), Massey and Kanaiaupuni (1993) found that housing projects since the 1950's have been targeted toward poor, black neighborhoods. As a consequence, housing projects dramatically increased the concentration of poverty within these respective communities. In effect, many more African-Americans have been placed within an environment providing many more interactions with the poor as opposed to any other socioeconomic group impacting their definition/perception of social relations. Neapolitan (1994) states that the effects of poverty are more pronounced in areas of high population concentration (impacting everyone, regardless of race, who experiences it). However, there have been mixed results in studies incorporating varying operational definitions and measurements of "poverty". Both positive and negative effects have been identified in studies incorporating variables similar in nature and measurement to the present study (Devine, Sheley and Smith 1988).

In addition to measures of poverty, research on crime has also incorporated measures of inequality in relation to property crime (Stack 1984; Patterson 1991). Indeed, Patterson reviews in excess of 10 studies on the poverty/inequality/crime relationship finding inconsistent results. In relation to violent crime, Blau and Blau (1982) found inequality to be a more significant predictor than poverty. Consequently, these findings were supported by Blau and Golden (1986). Conversely, in a cross-national context, Stack (1984) does not find significant effects of inequality on property crime. Indeed, he proposes that, "(t)he results generally indicate that neither inequality nor the interaction between inequality and egalitarian culture exerts independent effects on property crime" (p. 229).

Conversely, several studies including Smith and Jarjoura (1988) and Sampson and Groves (1989) note conditional effects (i.e., depending on the level) of poverty on crime. Indeed, this is most consistent with the intent of testing interactions (as advocated herein).

Further, it appears that the absolute nature of poverty (compared to the relative nature of inequality) which most comprehensively influences the context in which the majority of the underclass comes to understand/define reality and the relations, appropriate activity, etc., pertaining thereto. When all is said and done, concentrations of poverty are at the heart of the matter. Inequality may produce conflict between the majority and minority, but poverty creates the context within which "deviant" orientations (i.e., drug/alcohol use) can develop. Accordingly, poverty is incorporated in this study instead of inequality in order to test its conditional effects on alcohol offenses and drug abuse violations, as they operate to influence property crime rates.

In relation to population growth, much attention has been placed on investigating the impact of higher degrees of population density on property and violent crime (South 1987; Peterson and Krivo 1993; Neapolitan 1994; Choldin and Roncek 1976; Joubert and Forsyth 1989). It has been found that greater population size and density (impacted to varying degrees by immigration/migration) (South 1987) increase property crime for many of the reasons already discussed, including institutional stress. Thus, a measure of population growth is a viable candidate in studying property crime while sharing a positive relationship (in terms of change) with changes in property crime rates.

A solid consensus regarding the impact of police presence on crime as a deterrent is lacking. Several different measures of police presence have been investigated including per capita police expenditures (Victor 1977), size of available police force (Swimmer 1974), etc. Victor suggests that, as expenditures increase, the level of known crime increases positively impacting imprisonment rates (particularly during times of high unemployment and inflation) (Lessan 1991). Further, Swimmer believes that an increase in the number of police officers decreases crime rates (realized through greater probability of arrest). Likewise, Howsen and Jarrell (1987) found that presence of police, level of poverty, and the unemployment rate (among other factors) were all significant predictors of property crimes. However, varying studies over time (extending into the present) such as that conducted by Wellford (1974) have failed to establish a relationship between varying measures of police presence and rates of crime. However, to the degree that a relationship exists between changes in police presence and changes in rates of property crimes, it should be positive.

Assumptions/Limitations/Delimitations:

Naturally, one assumption underlying this study is that a majority of the most relevant factors impacting property crime have been included in the model via incorporation as control or predictor variables. Two variables that were not included in the model were gender and age. Gender is particularly valuable in assessing differences in the propensity to commit violent crime among males and female of differing races (Sommers and Baskin 1992). Further, property crime is increasing among females. However, the vast majority is still committed by males (Sheley 1985). As a consequence, gender was not included in the model.

Further, the effects of age are not included in this model. The effects of age on differing crime rates have been studied for some time indicating males in the later teens and early to mid-20's are the more predisposed groups to commit street crimes, and do indeed, commit the majority of these crimes (Brahce and Bachand 1989; Chilton 1987; Stahura and Sloan 1988). However, as alluded to earlier, Smith et al., (1992) propose that controlling for "age and race qualify only partially the findings at the aggregate level" (p. 565) in their model focusing on the relationship between unemployment and crime (after controlling for inflation, police presence, poverty, and criminal opportunity). Further, Devine et al., (1988) found that representation of the most crime-prone group of males (those 16 to 29 years of age) was multicollinear with the rate of inflation in their study (which also utilized aggregated, national, annual data) and was not significant in its logged form (while being only marginally significant in its original unit of measure). Thus, in the interest of a parsimonious model, a measure of age has not been included.

Two limitations also present themselves in regard to the present study. First, the length of the time series is 36 years. The reason for this is that in 1958 the Federal Bureau of Investigation instituted major changes in the collection procedures of the *Uniform Crime Report* rendering data from previous periods suspect (Smith et al. 1992; Wolfgang 1963).

Further, the dependent variable is operationalized as the rate of property crimes known to police, when in fact, there are surely property crimes that are committed that are not known to police. Such is to be expected. Hence, the most a researcher can do is attempt to obtain the most widely used and accepted measure of the phenomenon of interest. It is believed that this has been achieved in this study.

Finally, a delimitation of the study revolves around the fact that property crime is operationalized as an overall measure of burglary, larceny, and auto theft. Consequently, the three property crimes are not investigated individually. The reason behind this methodological fact is the attempt to escape increases in Type I error (i.e., the probability of finding something that is not there) associated with prediction of a series of dependent variables from an identical series of independent variables (Tabachnick and Fidell 1989). Though such practices are common in the criminological literature, the focus of this study is on the estimation of a parsimonious model oriented to the general prediction of property crime.

CHAPTER II

METHODOLOGY

The following sections describe the steps taken in operationalizing and measuring the factors believed to be important in assessing the premise of property crime in the United States.

Unit Of Analysis:

Societal units of analysis (Babbie 1992) are employed in this study via annual, national rates/data relative to the phenomena of interest. Extreme care is taken prior to, during, and after analysis to avoid erroneous errors relative to "ecological fallacies" (p. 96). As pointed out by Robinson (1950), the pitfall of the ecological fallacy involves misdirected attempts to draw conclusions regarding individual behavior based upon some aggregated data when the "ecological correlation...(based on a *grouping* of people)... is almost certainly not equal to its corresponding individual correlation" (p. 357). As Babbie (1992) points out:

> Although the patterns observed among variables may be genuine, the danger here lies in drawing unwarranted

> assumptions about the cause of those patterns (of behavior) - assumptions about the individuals making up the groups. (p. 97)

Unguided extrapolations can produce horrific theoretical pitfalls. Indeed, for many years, the social sciences have been plagued by these types of fallible deductions (Robinson 1950) with evidence of the phenomenon readily apparent in the criminological literature. Many studies can be located which base individually-oriented causal statements on some type of aggregate data (SMSA, city, county, state, national, etc.). However, this present study is conducted and articulated with strict reference to aggregate phenomena without extension to the prediction of any one individual's behavior. All factors are measured on a national level, and interpretation remains within the context of the influences of certain aggregate phenomena on other aggregate phenomena.

Operationalization

The following provides operational definitions following from the previous definition of terms.

Dependent Variable

As previously noted and explicitly defined, the dependent variable in this study is property crime consisting of three dimensions: burglary, larceny, and motor vehicle theft. Arson is not considered. This variable is measured as the rate (per 100,000 inhabitants) of property crime offenses known to police. The data were extracted from the *Sourcebook of Criminal Justice Statistics, 1993* (U.S. Bureau of Justice Statistics, Department of Criminal Justice 1994) for the years of 1960-1992. The data for 1958, 1959, and 1993 were extracted from the appropriate volumes (1959, 1960, and 1994, respectively) of the Federal Bureau of Investigation's (1959-1994) *Uniform Crime Reports (UCR)*. Consistent with the approach of Smith, Devine and Sheley (1992), the present analysis is initiated from 1958 (the year major changes in *UCR* collection procedures were instituted).

As subsequently addressed, the aggregate rate of the three property crimes is used. This does not allow individual investigation of the three property crimes separately, but it protects against inflation of Type I error (the probability of finding something that is not there) which is to be found in many studies employing successive regression equations (involving identical independent variables) to predict a series of dependent variables (such as the separate property crimes). Though such a practice is common in the literature, it is not undertaken here for the reasons related to Type I error. Finally, as previously mentioned, focus is placed on changes in such rates. Accordingly, the dependent variable is first-differenced.

Independent Variables

The primary variables of interest (predictor variables) are addressed initially followed by similar discussion of the variables utilized as established socio-structural controls. In each case, focus is placed on the effects of changes in the predictor/control variables on changes in the rates of property crimes know to police (to be fully discussed in the methods section). Hence, the independent variables are first-differenced.

Predictor Variables

Inflation is measured as the annual percent change in the consumer price index for all items during the period of study. The data was obtained from the *Statistical Abstracts of the United States* (U.S. Bureau of the Census, Department of Commerce 1959-1994) and the *Historical Statistics of the United States* (U.S. Bureau of the Census, Department of Commerce 1975). As previously set forth, the variable was first differenced to assess the impact of changes in rates of inflation on changes in rates of property crime.

Unemployment provides an important foundation for this study. This variable is operationally defined as national, annual, average unemployment rates (per 100,000 inhabitants) as reported by the U.S. Bureau of Labor Statistics, Department of Labor (1959-1994) as reported in the *Handbook of Labor Statistics.* These annual figures provide the basis for the next step.

Following from the above, a time series can be classically decomposed into its constituent elements; trend and cyclical, seasonal, and irregular (error) components (Bowerman & O'Connell 1993). Consequently, based on the annual data described above, trend and cyclical components are derived based on a multiplicative model (Value = Trend x Cycle x Seasonality x Random) which has been found to accommodate a wider range of forecasting situations than an additive approach (Value = Trend + Cycle + Seasonality + Random) (Hintze, 1991a). As the data are annual, no seasonal component is generated.

The cyclical component is derived as described above. Next, the aggregate unemployment rate is regressed on the cyclical component and the residuals saved. The trend component (technological/structural unemployment) is then represented as the third moving average of the residuals.

The trend is operationally defined in this manner due to the fact that once the classically decomposed deterministic trend is first-differenced, its variance is reduced to zero negating its use in a regression equation. However, the trend based on the moving averages exhibits greater variation in its movement upward and permits first-differencing (remaining consistent with the intent of the study).

The cyclical component represents the annual cycles of unemployment (cyclical unemployment) as it accompanies changes in the business cycle (again looking at it from a standpoint of annual figures). The cyclical component is represented by the cyclical component obtained via classical decomposition of the whole unemployment rate. The variable is then first-differenced. Though the cyclical effects may not be as profound with annual data as it would be with monthly or quarterly data, the cyclical component nonetheless provides unique information relative to the impact of changes in annual cycles (up and down) of employment as it impacts changes in rates of property crime on a year-to-year basis.

Frictional unemployment is represented by the residuals realized when regressing the aggregate unemployment rate on the classically decomposed trend and cyclical components. This component contains the error involved in predicting unemployment based on its deterministic trend and cyclical patterns. Thus, it is an error term in that sense which represents something meaningful. Of the four types of unemployment defined by economic theory; (a) the trend component represents technological/structural unemployment and (b) the cyclical component represents cyclical unemployment. There is no seasonal variation as the data are annual. Hence, one type remains, frictional unemployment, which the aforementioned error term is intended to represent to a significant degree. For when the trend and cyclical patterns are removed from the unemployment rate, what must remain, to a significant degree, are those individuals who are between jobs. Again, the variable is first-differenced allowing for the investigation of changes in frictional unemployment and changes in the rates of property crimes.

Race is incorporated in this analysis via the arrest rates of whites and blacks for property crimes. As noted by Smith, et al. (1992), "arrest data are the only source of national, time-series information that allows for an analysis of the relationships among...race, unemployment, and crime" (p. 556). Hence, first-differenced arrest rates for property crimes across whites and blacks serve as the base components to interact with technological unemployment (i.e., first-differenced white arrest rates X first-differenced technological unemployment; first-differenced black arrest rates X first-differenced technological unemployment).

The level of alcohol use in U.S. society is operationally defined and measured via rates of arrests (per 100,000 population) for alcohol-related offenses (to include the offenses as previously defined). For the years of 1972-1992, the data were obtained from the *Sourcebook of Criminal Justice Statistics* (U.S. Bureau of Justice Statistics, Department of Criminal Justice 1993). For the years of 1958-1971 and 1993, the data were extracted from the 1959-1972 volumes of the *UCR* (Federal Bureau of Investigation 1959-1993).

In similar fashion, the level of drug activity is operationalized as arrest rates (per 100,000 inhabitants) for drug abuse violations (as previously defined). Data for this series were obtained from the *Sourcebook of Criminal Justice Statistics* (U.S. Bureau of Justice Statistics, Department of Criminal Justice 1994) for the years of 1965 to 1992. The data for the years 1958-1964 and 1993 were extracted from the 1959-1965 and 1994 volumes of the *UCR*, respectively.

Control Variables

Three control variables are utilized in this study; (a) poverty, (b) population growth, (c) police presence. Though many such controls could be chosen, it is believed that a cogent set has been delineated. These variables were operationalized and measured as follows.

Poverty has been measured many different ways in the literature (number of individuals on public relief, number of individuals per room per dwelling, etc.) (Smith, et al. 1992; Corman & Joyce 1990). In this present study, a straightforward measure is incorporated with poverty (as previously defined) being operationalized as the percentage of individuals living below poverty level. The data for poverty were extracted from the *Statistical Abstracts of the United States* (U.S. Bureau of the Census, Department of Commerce 1959-1994) for the period of this study. The variable is first-differenced.

The rate of population growth (as previously defined) is another logical factor to include in a study of property crime in the United States. This variable is operationally defined as the percent change in total, annual United States population from one year to the next. The data for population growth were extracted from the *Statistical Abstracts of the United States* (U.S. Bureau of the Census, Department of Commerce 1959-1994) for the period of this study. The variable is first-differenced.

Finally, police presence is incorporated as the final control variable in this study. With regard to this variable, as the number of city police officers per 100,000 inhabitants were not available until the mid-1960's, this variable is operationalized as the number of city police employees per 100,000 inhabitants. The data are extracted from the appropriate volumes of the *UCR* 1959-1994 (for the years of 1958-1993). The variable is first-differenced.

Research Hypotheses:

The following hypotheses are reiterated with regard to the preceding literature review and discussion describing the relationship between varying independent variables and property crime. With regard to the expected relationships stated at the end of each of the sections discussing the respective independent variables, the following hypotheses are offered:

1. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in inflation rates and changes in rates of property crime.
2. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, technological unemployment rates and changes in rates of property crime.
3. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, cyclical unemployment rates and changes in the rates of property crime.
4. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, frictional unemployment rates and changes in the rates of property crime.
5. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in the interaction of technological unemployment and white

arrest rates for property crime and changes in the rates of property crime.

6. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in the interaction of poverty and rates of alcohol offenses and changes in the rates of property crime.

7. After controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in the interaction of poverty and drug abuse violations rates and changes in the rates of property crime.

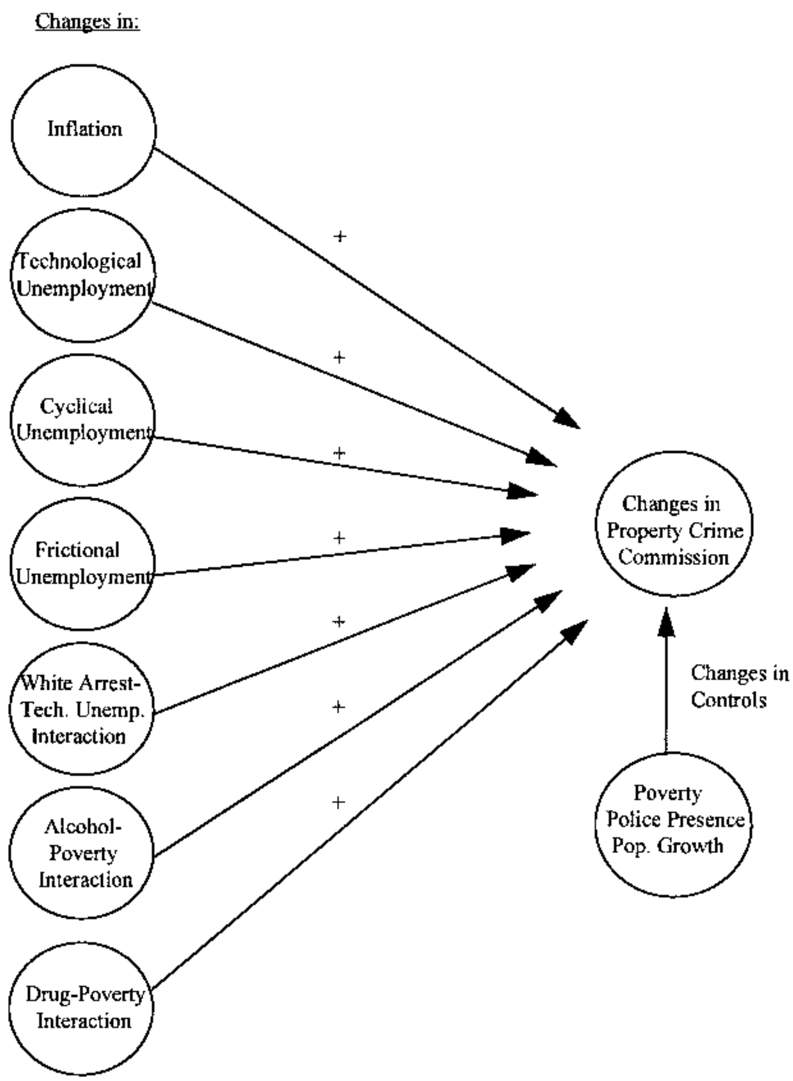
Figure 3 (p. 55) illustrates these hypotheses.

Methods Of Analysis:

This study is a longitudinal study designed to permit an analysis of observations over an extended period of time (Babbie 1992). Basically, the nature of varying series is used to predict property crime in the United States during the period of 1958-1993. Initially, a brief description of the movement of the varying series over time is accompanied by illustration of each series' first-differenced counterpart.

Figure 3

Proposed Effects



Multivariate time-series techniques are then employed. An Estimated Generalized Least Squares (EGLS) method is used to model the effects of time and its impact on the error term of the proposed model. The need for alternative regression-based techniques to analyze time-series data is necessitated by the fact that, in an OLS context, a fundamental assumption is commonly violated.

Such mis-specifications revolve around violations of the nonautoregressive assumption. In such cases, one error term tends to influence another error term in the future. The consequence of autocorrelation is manifested via invalidated significance tests (though the least-squares parameters are still unbiased). In such cases, "significance tests will be much more likely to indicate that a coefficient is statistically significant, when in fact it is not" (Lewis-Beck 1990).

This autocorrelation can be of a first-order nature (i.e., the error term for time period one influences the error term for period two, and so on) though a distinction between the error term and residuals is called for. Basically, the error term cannot be observed, and is therefore distinguished from the residual. The error term is relative to the "true regression model" with the residuals arising from the estimation procedure (Ostrom 1990). For the nonautocorrelation assumption to be met, the residuals must be "randomly scattered about the regression line" (p. 10).

Positive autocorrelation presents itself when positive values of the error term tend to be followed by positive values or when negative values are followed by negative values (Bowerman and O'Connell 1993; McCleary and Hay 1980). Positive autocorrelation is most common in the social sciences. In terms of crime rates (which all exhibit definite secular trends), this means that a value at any particular year is followed by a higher value the next facilitating positive autocorrelation (where a positive error term is followed by another positive error term, or vice versa).

As Ostrom (1990) points out, "each disturbance is equal to a portion ([when] p is less than 1.0 in absolute value) of the preceding disturbance term plus a random variable" (p. 17). The problem is that this confounds estimated variances of the parameters which invalidates the denominator of the *t*-statistic, in turn, invalidating the *t*-statistic itself analytically confounding the establishment of causal relationships. As a consequence, it is vital to test the null hypothesis of nonautocorrelation of any parameters produced via regression techniques (Ostrom 1990).

Autocorrelation can take the form of first-order (as previously described when one error term influences the next one in sequence, the second then influences the third, and so on). EGLS procedures, in general, are based upon the assumption that the serial autocorrelation is of the first-order. Unless the value of $|p|$ (the magnitude of the autoregressive process) is quite small (< 0.30), procedures such as the Cochrane-Orcutt, Prais-Winsten, or the Beach-McKinnon maximum likelihood method perform better than Ordinary Least Square (OLS) procedures (Greene 1992).

A test for first-order autocorrelation is the Durbin-Watson d statistic. A value of 2.00 reflects no first-order autocorrelation. Values closer to 4.00 indicate negative first-order autocorrelation, while values closer to 0 indicate the presence of positive first-order autocorrelation. Tables of critical values are used to evaluate the significance of any one value of d (Kanji 1993).

A Beach-McKinnon maximum likelihood EGLS procedure is utilized in this study. As an EGLS approach, for a given model and series, this method estimates the parameters that most likely produced the observed data. Further, the approach is based on iterative algorithms enhancing the performance of the estimates. With times series of less than 50 data points (as in the present case), many researchers recommend this or others types of AR1 approaches as opposed to ARIMA or other time series methods (Roberts 1984; Cook and Campbell 1979).

As previously noted, all variables are first differenced. First differencing ($z_t = y_t - y_{t-1}$, where t = 2...n) (Bowerman and O'Connell 1993) can be effectively employed to facilitate stationarity of a series (in terms of a series' mean and variance). Smith et al., (1992), used the first-difference of crime rates as dependent variables in their study suggesting that this captures the essence of change.

In relation to the effects of unemployment and changes in unemployment on changes in crime rates, such is advocated by "virtually all aggregate-level theories linking economic distress to crime rates" (Smith et al. 1992, p. 558). They go on to estimate equations with OLS procedures while applying EGLS-AR1 models to equations reflecting autocorrelation (via the magnitude of the Durbin-Watson statistic). However, at least one equation still maintained an unacceptable Durbin-Watson statistic.

As the authors note, this facilitates stationarity of the series (Smith et al. 1992; Cantor and Land 1985; Devine, Sheley and Smith 1988) permitting the estimation of a model which may be represented as:

> Δ (Delta) $c_t = a + b_1 u_t + b_2 \Delta u_t + e_t$
>
> where $\Delta\ c_t$ = the change in the crime rate at year *t*; u_u = the unemployment rate in year *t*; Δu_t = the change in the unemployment rate in year *t*; *a*, b_1, b_2 = constants to be estimated; and *e* = the error term (p. 558).

Indeed, in their 1988 article in the *American Sociological Review*, Devine et al., advocate this type of approach in the study of crime rates and the series relevant to its predictions.

In this present study, the dependent variable (property crime rates known to police) is first-differenced. This enables the assessment of the impact of changes in the predictor variables as they relate to changes in the rates of property crimes known to police on a year-to-year basis after removing the effects of the changes in the control variables. Consequently, the variables are entered into the regression equation initiated by the control variables. See step 1 in the equation below for illustration of this method.

Following the suggestion of Devine et al. (1988), unemployment and inflation are considered of primary importance. Thus, the economic set (inflation; technological, cyclical, and frictional unemployment) are entered on the second step. The race set is entered third to assess the effects of the interactions with technological unemployment (entered on the previous step). The alcohol set is entered fourth to determine the interactive effects of alcohol offense rates and poverty. Finally, the drug set is entered to assess the interactive effects of drug abuse violations and poverty. The alcohol set is entered prior to the drug set due to the more frequent commission of alcohol offenses. The following formula illustrates this approach:

$$
\begin{array}{ll}
\text{step 1} & \Delta c_t = a + b_1\Delta x_{1t} + b_2\Delta x_{2t} + b_3\Delta x_{3t} \\
\text{step 2} & \qquad + b_4\Delta x_{4t} + b_5\Delta x_{5t} + b_6 x_{6t} + b_7\Delta x_{7t} \\
\text{step 3} & \qquad + b_8\Delta x_{8t} + b_9\Delta x_{9t} + b_{10}\Delta x_{10t} + b_{11}\Delta x_{11t} \\
\text{step 4} & \qquad + b_{12}\Delta x_{12t} + b_{13}\Delta x_{13t} \\
\text{step 5} & \qquad + b_{14}\Delta x_{14t} + b_{15}\Delta x_{15t} + e
\end{array}
$$

where Δc_t = the change in the rates of property crimes known to police at year t; Δx_{1t} to Δx_{3t} = the changes in poverty, population growth, and police presence at year t, respectively; Δx_{4t} to Δx_{7t} = the changes in the rates of inflation; technological, cyclical, and frictional unemployment, respectively; Δx_{8t} and Δx_{9t} = the changes in white and black arrest rates for property crimes (which is ignored in favor of the respective interactions), respectively; Δx_{10t} and Δx_{11t} = the changes in the interactions of white and black arrest rates and technological unemployment, respectively; Δx_{12t} and Δx_{13t} = the changes in rates of alcohol offenses (to be ignored in favor of the poverty interaction) (Jaccard, Turrisi and Wan 1990) and changes in the interaction of rates of alcohol offenses and poverty, respectively; Δx_{14t} and Δx_{15t} = the changes in rates of drug abuse violations (to be ignored in favor of the poverty interaction) and changes in the interaction of rates of drug abuse violations and poverty.

The coefficients a, b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, b_{11}, b_{12}, b_{13}, b_{14}, b_{15} = parameters to be estimated, and e = the error term. Residual analysis addresses all assumptions stressing those particularly relative to the use of regression in a time series context (i.e., the residuals are normally distributed, are nonautocorrelated, are homoscedastic, and uncorrelated with the error term). After presenting the initial results, the equation is re-estimated excluding the set of control variables due to their dismal performance taking advantage of the degrees of freedom they represent.

In terms of methodological difficulties, multi-collinearity (high intercorrelation among predictor variables) has commonly been found to confound studies of crime. This also applies to some time series analyses (Devine et al. 1988). Multicollinearity exists when two independent variables are very nearly linear combinations of one another resulting in correlations of .90 and above (Tabachnick and Fidell 1989).

This causes logical and statistical problems. The logical problem is manifest in the fact that perhaps two highly related variables are measuring some latent commonality. In such a case, perhaps only one should be in the equation (or the two factored).

The statistical difficulty is manifested in the fact that matrix inversion is rendered unstable and impossible in the case of singularity (perfect association) (Tabachnick and Fidell 1989). Finally, the common variance of the collinear variables is manifest in the regression constant making it appear that the variables in question explain nothing or very little of the dependent variable (Cohen and Cohen 1983).

In addition to zero-order correlations, the variance inflation factor (VIF) can be used to detect multicollinearity. The VIF for b_j is $1/1-R^2_j$. A VIF of 10 is equivalent to a correlation in excess of .90 (Bowerman and O'Connell 1993). Thus, VIF's in the area of 6 to 7 should be considered evidence of sufficient collinearity to raise concern (Draper and Smith 1981).

In a cross-sectional context, one method which addresses multicollinearity is ridge regression. However, as Tabachnick and Fidell (1989) note:

> Ridge regression is a controversial procedure that attempts to stabilize estimates of regression coefficients by inflating the variance that is analyzed...Although originally greeted with enthusiasm, serious questions about the procedure have been raised [as early as the 1970's] (pp. 130-131).

Finally, ridge regression lacks the facility to address autoregression (to be subsequently addressed) which confounds the vast majority of time series data.

Alternatively, and preferably, principal component analysis (PCA) (Dunteman 1989) or factor analysis (Tabachnick and Fidell 1989) can be used to defeat multicollinearity in a regression context. For instance, the components generated in PCA are orthogonal to one another (Dunteman 1989) allowing the incorporation of more than one component without the worry of multicollinearity. However, the challenge is interpreting what each component represents based upon the loadings of the constituent variables. Ultimately, this may lead an investigator to the development of latent variable models (Cohen and Cohen 1983).

A special case of multicollinearity exists when testing interactions in a regression context (cross-sectional or time series). Much more often than not, interactions are multicollinear with its constituent elements, as it is a product of those elements (Cohen and Cohen 1983; Jaccard Turrisi and Wan 1990). However, methodologically, the interpretation of interactions poses no problems.

First, *significant* main effects can be initially interpreted without the interaction in the equation. Then the interaction term can be entered and interpreted consistent with Cohen and Cohen's (1983) advocacy of hierarchical regression techniques. If significant, the interaction accounts for an effect over and above that of its constituent elements. However, if neither of the main effects are significant, it is entirely appropriate to enter the whole set (constituent elements and the interaction) and interpret only the significant interaction (which is undertaken in this work) (Jaccard, Turrisi and Wan 1990).

In the present study, the only significant main effect across the range of interactions tested was changes in black arrest rates which promoted little interest in the context of the present study. In the case of race, the issue of interest is the degree to which arrest rates are *conditioned* by technological unemployment. Accordingly, the question of whether one should enter the main effects, interpret them, and then enter the interaction or enter the whole set at once and interpret only the interaction is moot.

Further, in this study, the only VIF's that indicate sufficient degrees of multicollinearity to raise concern are those associated with the race\technological unemployment set of variables. These VIF's range from 6.1 to 9.4 and are to be expected, as the interactions are products of other variables in the set. However, interpretation is appropriately undertaken as noted above and supported by the relevant literature.

Other than this instance, the VIF's of the other variables (including the interaction sets) are of no consequence. These VIF's range from 1.1 to 1.8 upon hierarchical entry into the equation with the exception of drug abuse violations on the last step of the first fully-partialled equation. However, even the VIF of 2.7 in this case is no cause for alarm. For as advocated by Cohen and Cohen (1983), hierarchical entry of the variable sets with interpretation on the margin is an appropriate strategy to employ in cases such as this especially when incorporating interactions in the analysis.

Finally, fifteen regressors are numerous considering the length of the series. However, the independent variables are entered in sets protecting against inflation of Type I (alpha) error (i.e., the probability of finding something that is not there) (Cohen and Cohen 1983). Accordingly, each respective hypothesis is interpreted on the margin (i.e., at the step the variable set in question enters the equation). Further, type II (beta) error is addressed via power analysis across sets (Hintze 1991b; Cohen and Cohen 1983) to assess the probability of committing error in failing to reject a false, null hypotheses (Cohen and Cohen 1983).

CHAPTER III

FINDINGS

This chapter sets forth the findings of this study. Initially, each of the respective series is graphically and statistically described to better inform the reader of the movement (changes) of the respective series over time. Following is the actual presentation of the time series regression results via the AR1 hierarchical model as previously defined.

Description Of The Series:

Each of the time series (1958-1993) in this study is graphically illustrated. These illustrations reflect both the actual and stationary (i.e., differenced) change-score series. Accompanying each of these illustrations is a brief description of the general movement of the respective series over time. Meaningful interpretation of each series is facilitated by depiction of its average change. In addition, the greatest positive and negative changes (identified by year) for each of the series are provided. This helps the reader to better understand the dynamics of each of the series of data over the last 36 years.

Figure 4 reflects the movement of rates of property crime known to police during the period of interest. The series exhibits a definite secular trend with highs occurring in the late 1970's and early 1980's. The average change of the series was +87.92. The greatest change increase (+652.30) in the series occurred in 1974, with the greatest negative change (-395.10) occurring in 1983.

Figure 4

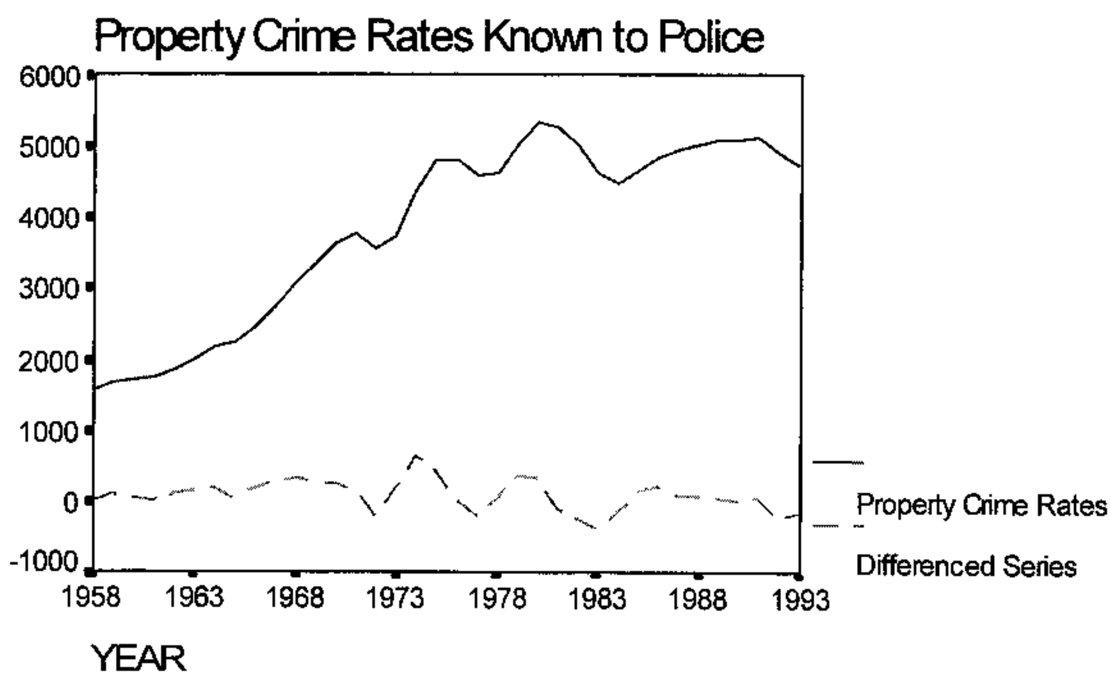


Figure 5 reflects the movement of the percent of the population living below poverty level during the period of interest. The series exhibits a downward trend stabilizing in the early 1970's while increasing temporarily in the early 1980's before leveling off again. The average change of the series was -0.26. The greatest change increase (+1.30) in the series occurred in 1980, with the greatest negative change (-2.60) occurring in 1966.

Figure 5

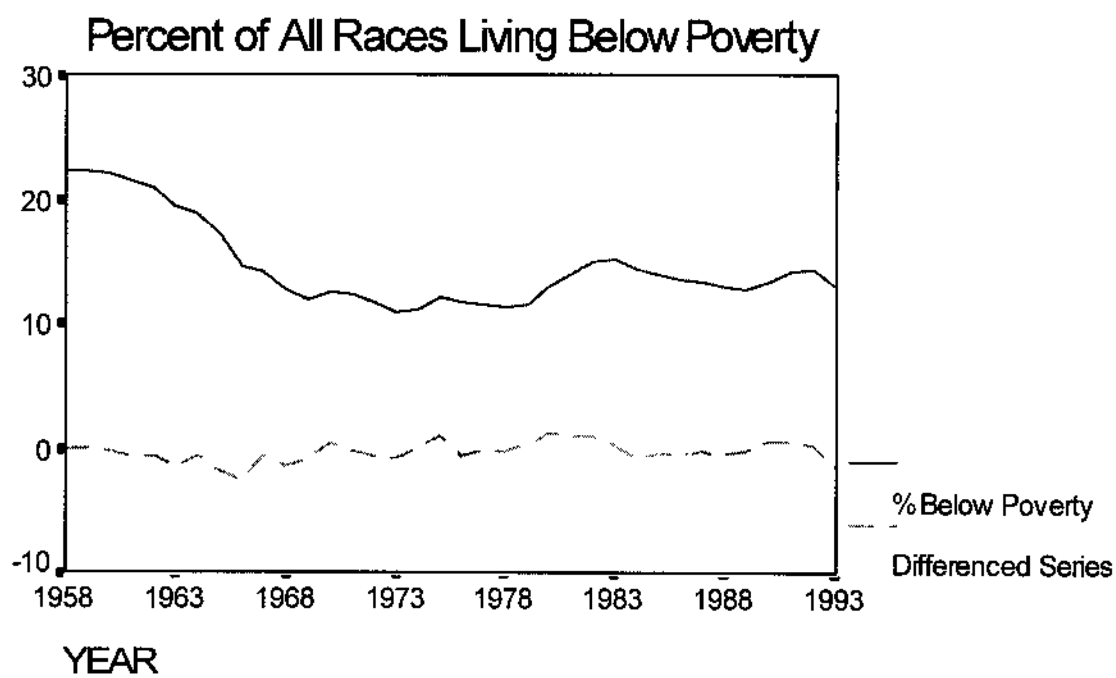


Figure 6 reflects the movement of the percent change in the annual population of the United States during the period of interest. The series exhibits a downward movement stabilizing in the late 1960's and early 1970's. The average change in the percent change in population is -0.02. The greatest change increase (+0.19) occurred in 1970, with the greatest negative change (-0.21) occurring in 1981.

Figure 6

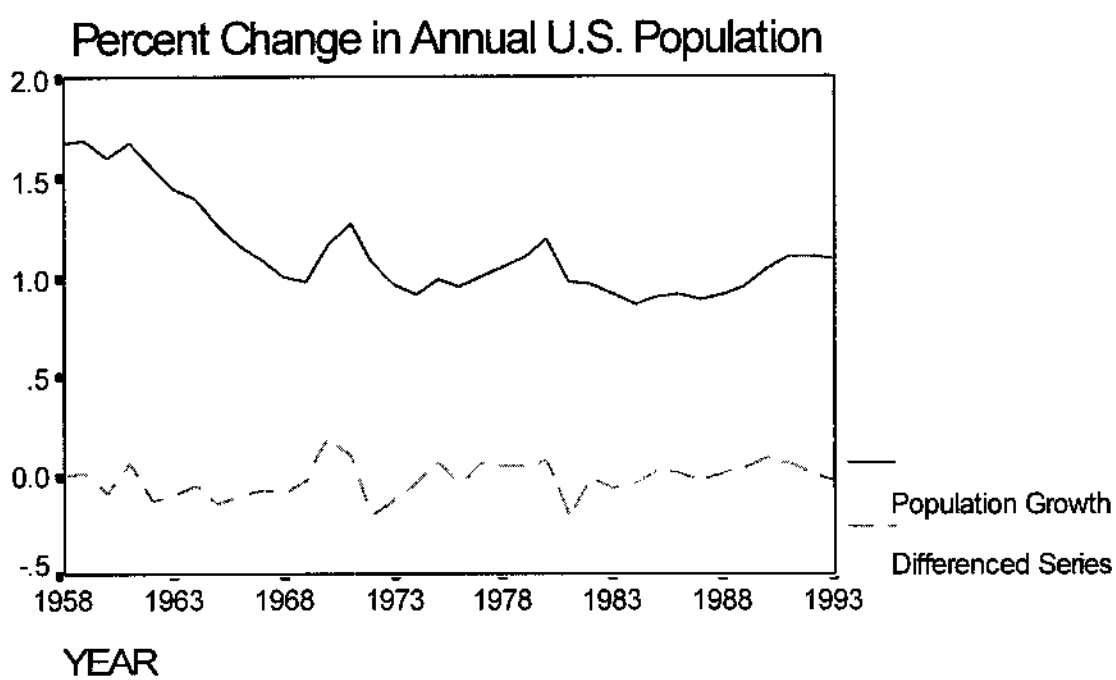


Figure 7 reflects the movement of the number of city police employees per 100,000 inhabitants during the period of interest. The series exhibits a slight upward trend, as gradually, more police employees (including officers) have been added to city departments across the country. The average change of the series was +0.03. The greatest change increase (+0.10) occurred for numerous years throughout the series. There was no decrease in the series as each subsequent observation was at least as large as its predecessor.

Figure 7

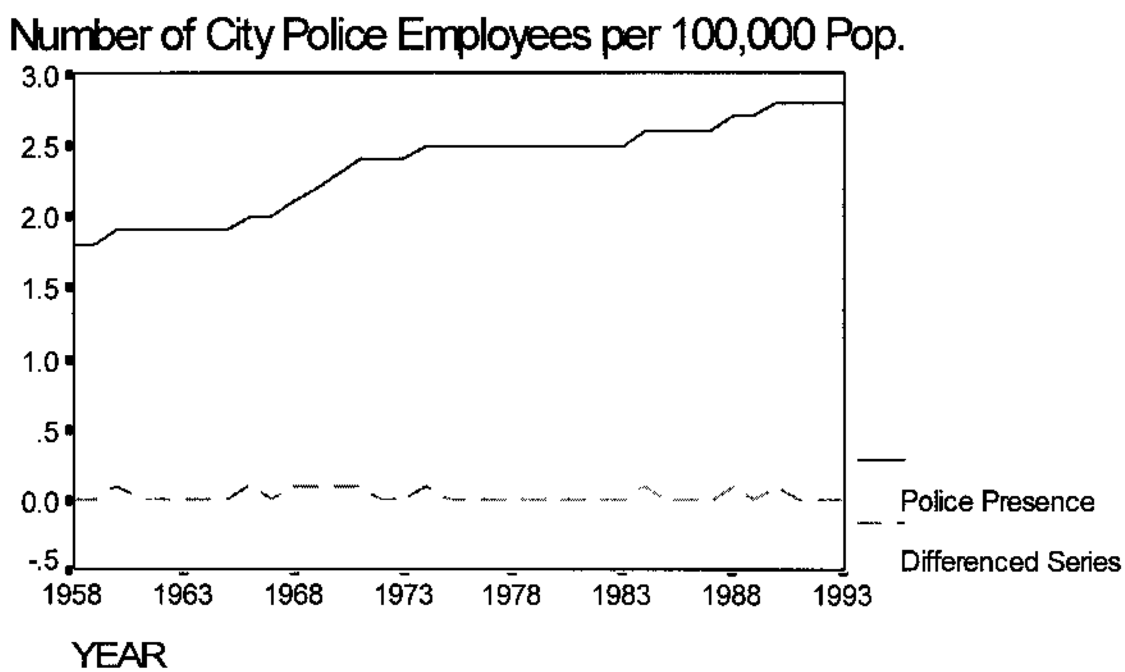


Figure 8 reflects the movement of the annual percent change in the consumer price index during the period of interest. The series exhibits relative stationarity over its course with greatest ranges in the 1970's. The average change of the series was +0.008. The greatest change increase (+4.80) occurred in 1974, with the greatest negative change (-4.10) occurring in 1982.

Figure 8

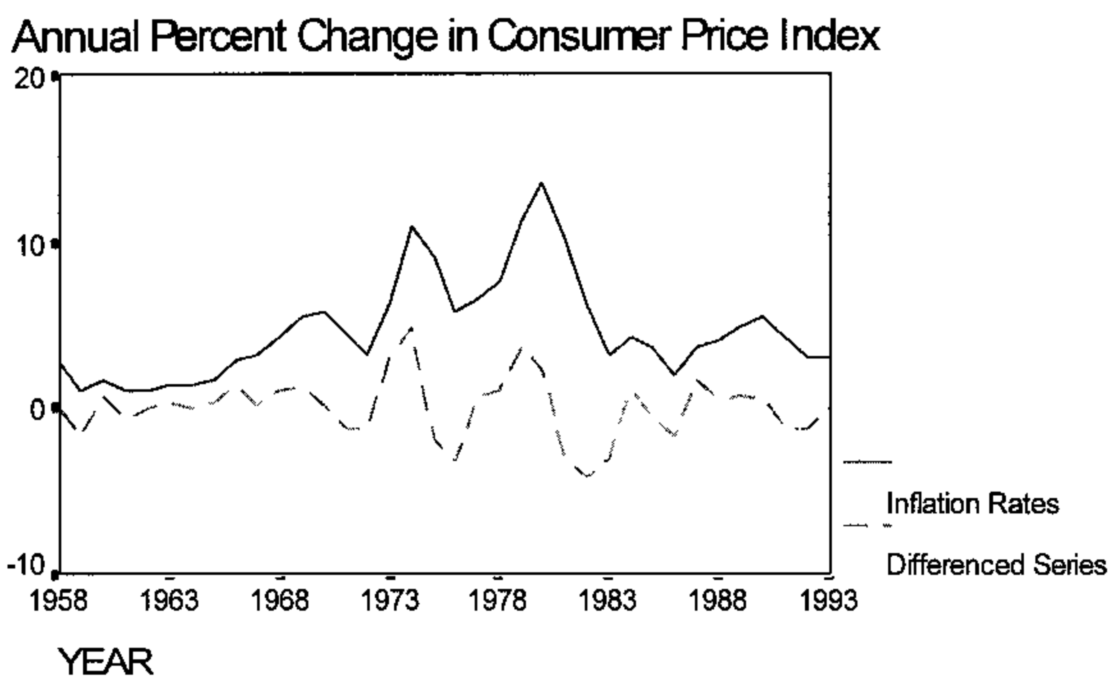


Figure 9 reflects the movement of technological/ structural unemployment during the period of interest. Naturally, the series exhibits a strong, positive secular trend. Remembering that this variable is represented by moving averages, it starts its climb upward from approximately -1.40. The average change of the series was +0.07. The greatest change increase (+0.16) occurred in 1964, with the greatest negative change (-0.01) occurring in 1989. Note that the detrended series maintains sufficient variability for use in regression analysis.

Figure 9

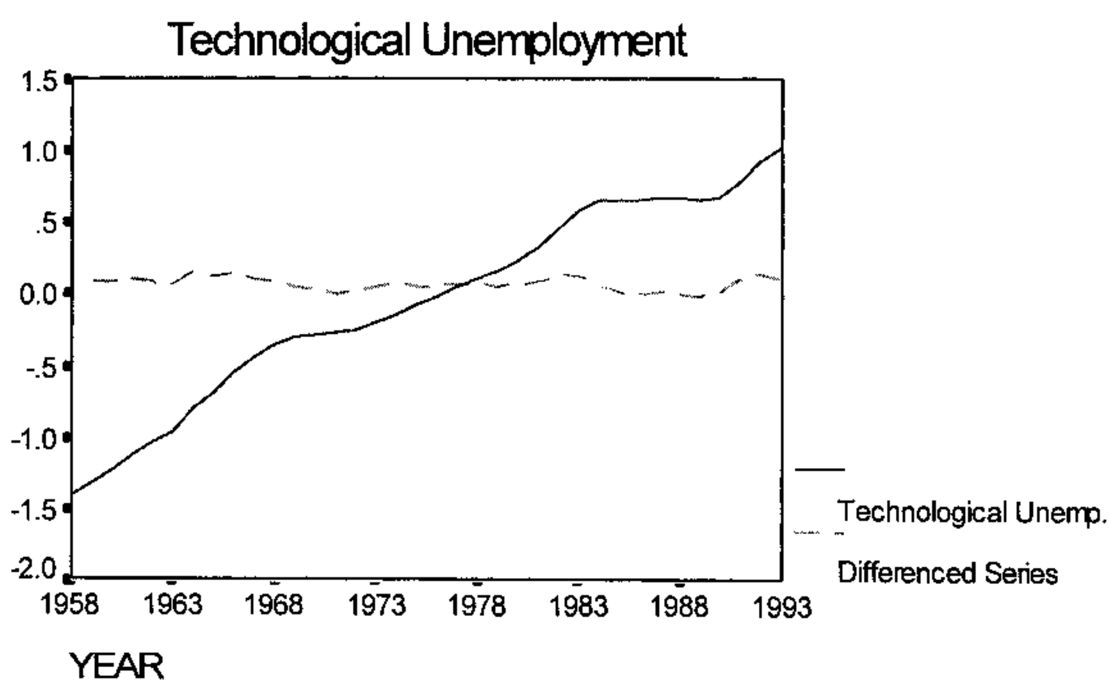


Figure 10 reflects the movement of cyclical unemployment during the period of interest. The series exhibits relative stationarity (prior to differencing). The average change of the series was -0.01. The greatest change increase (+0.48) occurred in 1975, with the greatest negative change (-0.33) occurring in 1984.

Figure 10

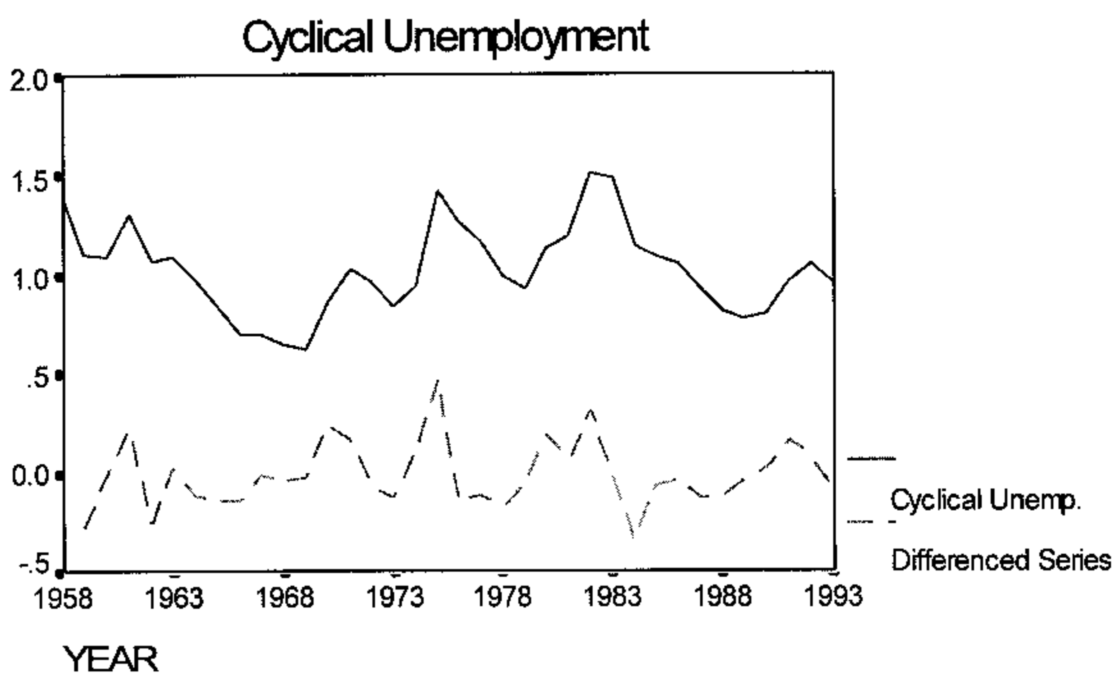


Figure 11 reflects the movement of frictional unemployment during the period of interest. The series exhibits relative stationarity mirrored to a significant degree (with exception of its earliest most parts) by the differenced series. The average change of the series was +0.01. The greatest change increase (+0.29) occurred in 1959, with the greatest negative change (-0.18) occurring in 1961.

Figure 11

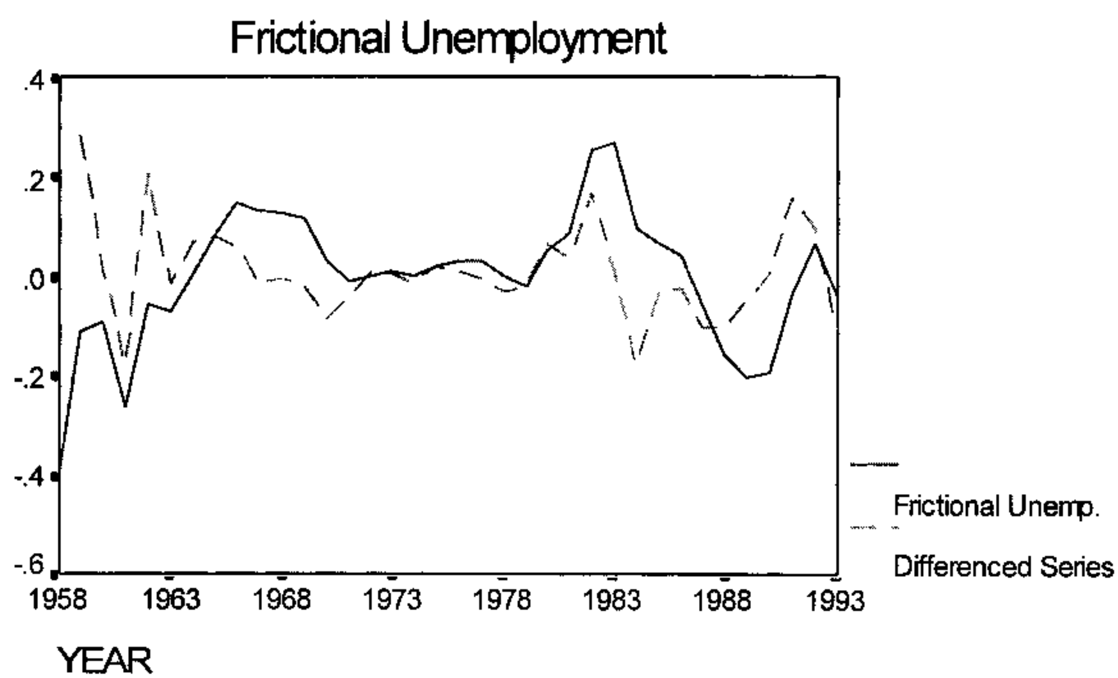


Figure 12 reflects the movement of property crime arrest rates for whites during the period of interest. The series has risen overall in establishing an average change of +21.03. The most dramatic changes occurred during the 1970's. The greatest change increase (+334.80) occurred in 1974, with the greatest negative change (-156.80) occurring in 1976.

Figure 12

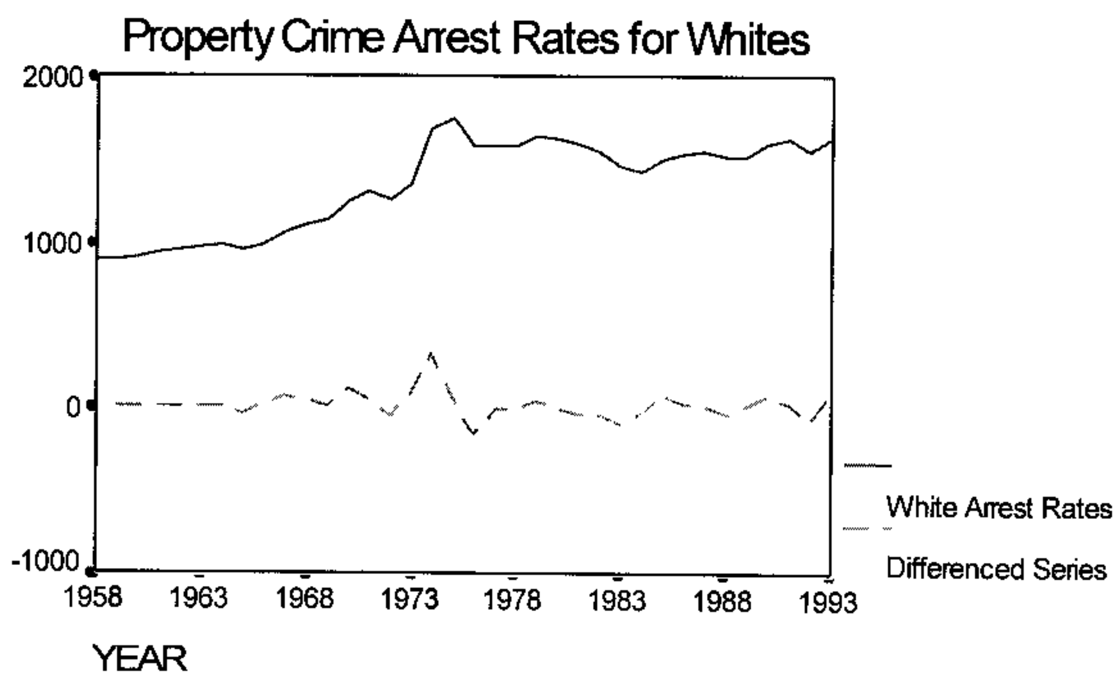


Figure 13 reflects the movement of rates of property crime arrest rates for blacks during the period of interest. The series exhibits slightly more variability than do similar rates for whites. The average change for the series (+40.53) was nearly double of those for whites. The greatest change increase (+62.50) occurred in 1974 (the same year as those for whites), with the greatest negative change (-410.85) occurring in 1975.

Figure 13

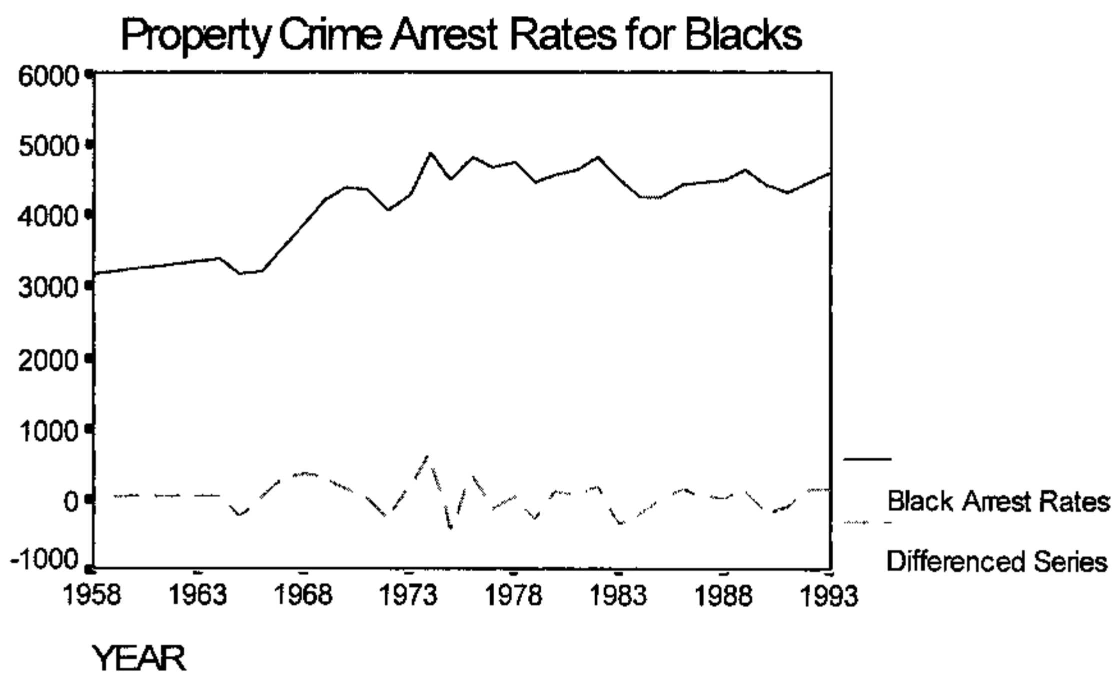


Figure 14 reflects the movement of the arrest rates for alcohol-related offenses. The series exhibits relative stationarity even prior to differencing. The average change of the series was +12.61. The greatest change increase (+387.32) occurred in 1959, with the greatest negative change (-257.45) occurring in 1984.

Figure 14

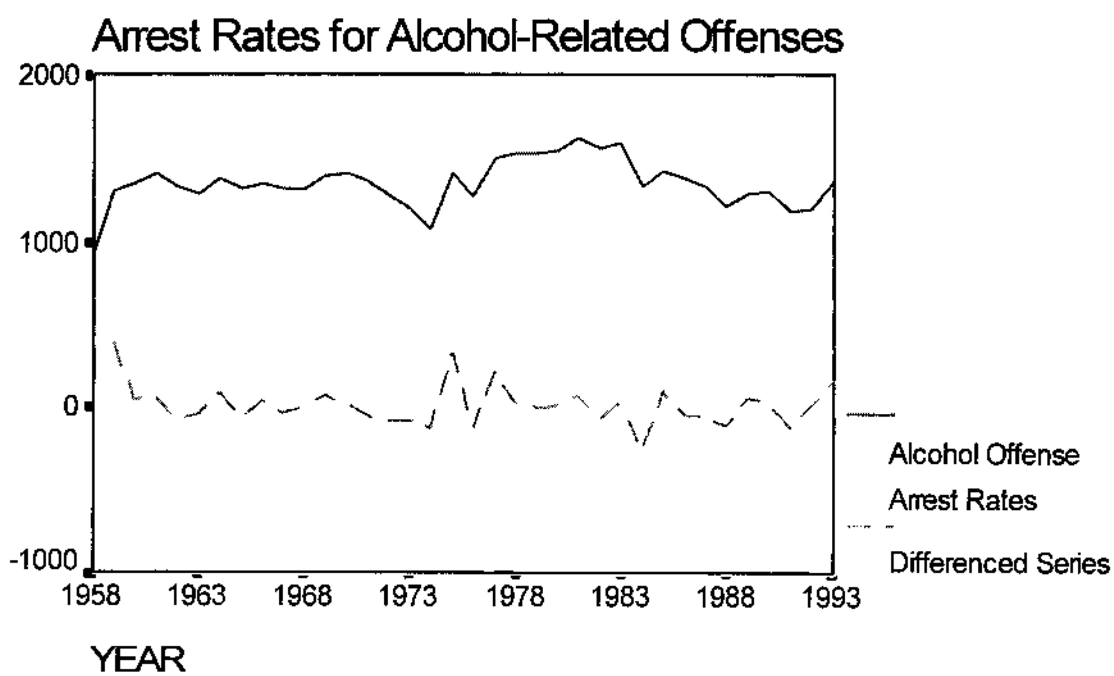
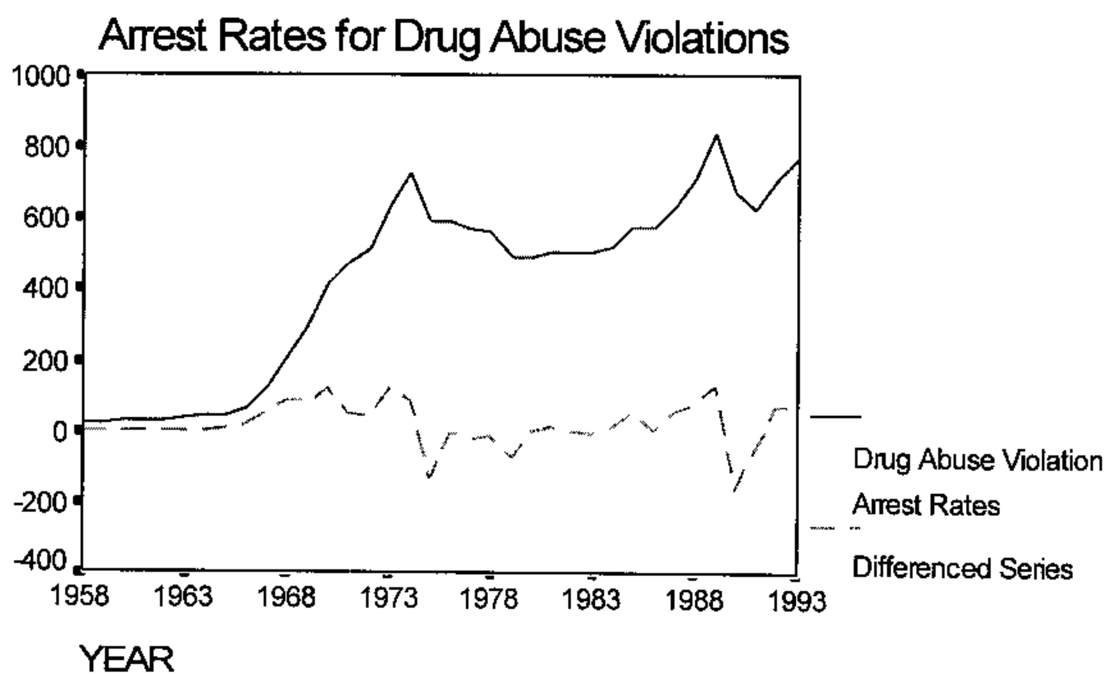


Figure 15 reflects the movement of arrest rates for drug abuse violations during the period of interest. Such violations were nearly non-existent through the mid-1960's, before skyrocketing in the late 1960's and early 1970's before leveling off and increasing again in the late 1980's. The average change of the series was +20.78. The greatest change increase (+130.50) occurred in 1989, with the greatest negative change (-161.30) occurring in 1990.

Figure 15



Findings:

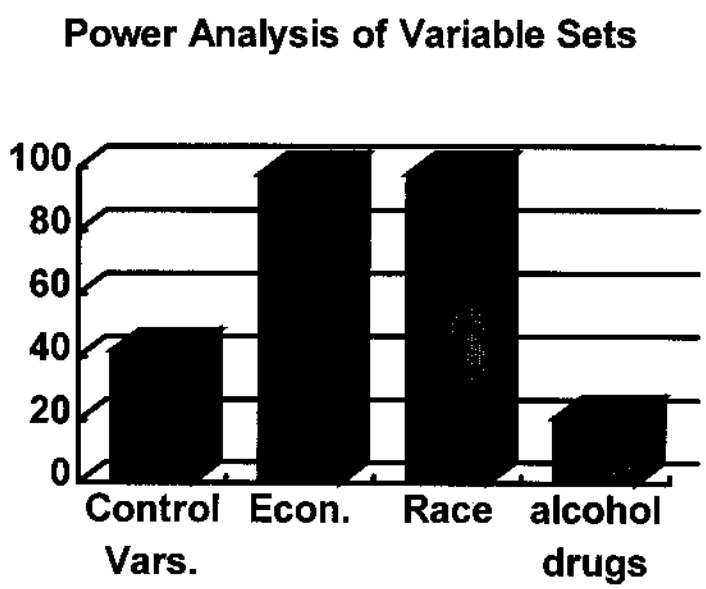
This section sets forth the descriptive and inferential results of this study. Initially, the results of a power analysis of the variable sets are described, followed by discussion of the appropriate OLS and AR1 maximum likelihood models. The hypotheses are formally tested at that time.

Power Analysis

As outlined by Cohen and Cohen (1983), a power analysis was performed using the computer package, Power Analysis and Sample Size (PASS) (Hintze 1991b). This is accomplished by drawing inference (relative to the probability of rejecting the null hypothesis) from the sample size, number of variables in each set, and the respective sequential, Prais-Winsten adjusted-R^2's resulting from hierarchical regression on the criterion. Power is defined as the probability of rejecting the null hypothesis, or 1 - beta (the probability of rejecting the null hypothesis when it is false) (Cohen and Cohen 1983). As alpha risk (i.e., finding something that is not there) increases, power increases. As the sample size increases, power increases. Finally, the larger the population effect or departure from the null hypothesis, the greater the power of a test (Cohen and Cohen 1983).

Sufficient power (i.e., the probability that a statistical test will be significant) is defined as .80 (Cohen and Cohen 1983). Although power analysis is generally carried out in the planning stages of research to identify necessary sample sizes (Hintze 1991b), it was undertaken post hoc in this case to assess the impact of the relatively short series (36 years) upon which this study is necessarily founded. Figure 16 reflects the results of this analysis.

Figure 16



The power estimates were derived (in a multiple regression context) for each variable set while controlling for all the other variable sets using the adjusted R^2's obtained from hierarchical Prais-Winsten set regression. Hence, across the sets, the economic and race sets exhibited the most power with coefficients exceeding 0.995 at .05. Following Cohen and Cohen (1983), the decimal is omitted henceforth and is referred to as whole numbers between one and 100. Thus, these two sets exhibited power of 99. Comparatively, the control set's power was 42, while the combined set of drugs and alcohol reflected power of 21. Both of the latter power ratings are too low (less than .80 probability of rejecting the null hypothesis). Such was surely observed in the case of the controls variables; however, economy and race suppressed an alcohol interaction into significance.

Time-Series Regression

The variables were entered into regression equations in the order previously specified (controls, economy, race, alcohol, drugs). For each step, OLS and EGLS AR1 maximum likelihood results are presented. Primary attention is extended to; (a) the extent to which the non-autocorrelation assumption was met, (b) the significance of coefficients in white-noise models, and (c) the magnitude and meaning of coefficients of interest (i.e., those for variables being tested as their set is entered into the equation). In all cases, assuming that first-order autocorrelation is acting upon the equation, the Durbin-Watson statistic is the major determinant in testing the previously set forth hypotheses via EGLS estimates. The Ljung-Box Q-statistic (LBQ) series is a second method of autocorrelation evaluation, though primary weight is extended to the OLS Durbin-Watson statistic, as it is a most common method for assessing first-order autocorrelation in regression analysis (Bowerman and O'Connell 1993). It should be noted that at each step, the OLS residuals meet all assumptions, except non-autocorrelation, to include homoscedasticity and normal distribution as evidenced by the Lagrange Multiplier Statistic ($p > .05$) and the Wilk-Shapiro Statistic ($WS > 97$), respectively. Further, multicollinearity was assessed via the variance inflation factor (VIF) and presented no difficulties (i.e., $VIF < 6.00$) with the exception of the sets containing interactions. Finally, hypotheses are tested on the margin, which is to say that each hypothesis is tested at the point where the respective variable (contained in the variable set) is entered into the equation.

Each set is tested (at the point where it enters the model) for its significance as a whole via a MLE chi-square statistic based on the difference between log-likelihood estimates of each step. The formula for this statistic is 2 x (LLN-LLO), where LLN is the log-likelihood of the first set and LLO is the log-likelihood of the second set. This tests the significance of the second set. The degrees of freedom are the number of variables in the second set (Roberts 1984, Cook and Campbell 1979). For the first set, the statistic was computed with LLN representing the log-likelihood of the equation represented by only the constant.

Further, an approximation of the OLS R^2 is undertaken based on the EGLS ML AR1 estimates of the log-likelihood (LLN and LLO) via McFadden's rho^2. The formula for this statistic is LLN-LLO/LLN. The test of significance is the same as that for set significance (Roberts 1984, Cook and Campbell 1979). McFadden's rho^2 (predicated upon reduction of the log-likelihood) measures the percentage decrease in the log-likelihood as sets are entered with larger rho^2's indicative of better fitting sets of predictors. It should be noted that each equation beginning with entry of the economy set was highly significant.

Table 1 reflects the results from the first OLS equation containing only the control variables (as denoted by the box specifying set entry).

Table 1

OLS Regression Results

Step 1

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	56.99		1.33	.19	
Poverty	-11.14	-.04	-0.22	.83	1.4
Population Growth	412.87	.17	0.86	.40	1.3
Police Presence	1253.32	.27	1.52	.14	1.1

R^2 = .109
Adjusted R^2 = .026
Residual Mean Square = 44760.2
F-ratio for equation = 1.31
P-value = .29

Residuals
Autocorrelation: Durbin-Watson Statistic = 0.93 (autocorrelated)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic chi^2 = 3.701, p = .30

The equation is not significant, and reflects significant, positive autocorrelation (Durbin-Watson = 0.98). Such autocorrelation may be a result of exclusion of pertinent predictors (Bowerman and O'Connell 1993) and may fatally confound the equation.

Table 2 (p. 89) reflects the LBQ series for this equation and also measures autocorrelation. Each Q-statistic is accompanied by its *p*-value and calculated to the maximum lag (34). However, only the first 20 are reflected which is an appropriate cut-off point (Bowerman and O'Connell 1993). Distributed as a chi-square statistic, no autocorrelation exists when $p > .05$. As reflected in Table 2, the LBQ series further substantiates autocorrelation as $p < .05$ at each lag.

Accordingly, the model was ran as an EGLS maximum-likelihood (ML) AR1 model. The results of this procedure are reflected in Table 3 (p. 90). The Durbin-Watson is still inconclusive as substantiated by the LBQ series. Accordingly, nothing can be said of the sole effects of the controls, except that they are not significant. Neither the set nor the reduction in the log-likelihood was significant with reference to the set of control variables.

Table 2

Ljung-Box Q-statistic Series - OLS Step 1		
Lag	Ljung-Box Q	Probability
1	10.190	.001
2	11.157	.004
3	17.990	.000
4	18.649	.001
5	22.747	.000
6	30.960	.000
7	31.988	.000
8	33.340	.000
9	35.618	.000
10	35.618	.000
11	39.549	.000
12	42.459	.000
13	42.839	.000
14	45.992	.000
15	47.173	.000
16	47.444	.000
17	48.068	.000
18	49.744	.000
19	52.181	.000
20	52.759	.000

Ljung-Box Q > 30 at 20 lags with significant lags indicating autocorrelation.

Table 3

EGLS Maximum-Likelihood AR1 Results Step 1			
Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	69.55	1.00	.32
Poverty	24.55	0.53	.60
Population Growth	617.60	1.71	.09
Police Presence	892.12	1.52	.13

Autocorrelation: Durbin-Watson Statistic = 1.34
Set Significance: MLE chi-square = 7 w/3df (not sig. at .05)
Log-L Reduction: McFadden's rho^2 = .01 (not sig. at .05)

See Table 4 (p. 91) to review the LBQ series for this first EGLS ML AR1 equation. Autocorrelation is definitely observed. The *p*-values are less than .05 throughout the first 20 lags.

Table 5 (p. 92) reflects OLS entry of the economy set of variables. At this point, the Durbin-Watson statistic (1.57) is indeterminate meaning that we can neither accept nor reject the presence of autocorrelation though the LBQ series (see Table 6, p. 94) suggests a white-noise error process. However, based on the indeterminacy of the Durbin-Watson statistic, a consistent, conservative orientation, calls for the interpretation of the EGLS estimates to test the economy hypotheses.

Table 4

Ljung-Box Q-statistic Series - EGLS Step 1		
Lag	Ljung-Box Q	Probability
1	3.997	.046
2	6.640	.036
3	17.862	.000
4	19.252	.001
5	23.995	.000
6	32.474	.000
7	33.127	.000
8	35.822	.000
9	40.130	.000
10	40.140	.000
11	44.876	.000
12	49.113	.000
13	49.368	.000
14	51.934	.000
15	52.258	.000
16	52.407	.000
17	52.450	.000
18	52.931	.000
19	53.822	.000
20	53.850	.000

Ljung-Box Q > 30 at 20 lags with significant lags indicating autocorrelation.

Table 5

OLS Regression Results

Step 2

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	159.14		2.76	.01	
Poverty	-71.84	-.28	-1.52	.14	2.1
Population Growth	69.81	.03	0.18	.86	1.6
Police Presence	294.11	.06	0.44	.66	1.3
Inflation	74.91	.67	4.66	.00	1.3
Tech. Unemployment	-1383.92	-.30	-1.94	.06	1.5
Cyclical Unemployment	680.94	.53	3.17	.00	1.8
Frictional Unemployment	850.64	.39	2.42	.02	1.6

R^2 = .574
Adjusted R^2 = .464
Residual Mean Square = 25231.7
F-ratio for equation = 5.20
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.57 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic chi^2 = 4.01, p = .78

Table 7 (p. 95) reflects the EGLS maximum-likelihood AR1 results. The set was significant (MLE chi^2 significant at .001) while reducing the log-likelihood by 6%. Hypothesis one stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in inflation rates and changes in rates of property crime. This hypothesis was supported. Change in inflation was a significant predictor of changes in property crime (t-ratio = 3.66, $p < .01$). For each unit increase in the change scores of inflation, 60.01 more property crimes (per 100,000 inhabitants) are known to police, on the average.

Hypothesis two stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, technological unemployment rates and changes in rates of property crime. This hypothesis was not supported (t-ratio = -1.52, $p = .13$). All that can be said is that when controlling for the variables of interest in this study, changes in the levels of technological unemployment, acting conjunctively with the other economy variables, is not a significant predictor of changes in property crime rates. However, it is shown that this facet of the economy is fundamentally important due to its interactive effect on other predictors of property crime.

Hypothesis three stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, cyclical unemployment rates and changes in the rates of property crime. This hypothesis was supported. Change

Table 6

Ljung-Box Q-statistic Series - OLS Step 2		
Lag	Ljung-Box Q	Probability
1	1.333	.248
2	1.702	.427
3	2.203	.531
4	4.496	.343
5	6.361	.273
6	6.375	.382
7	6.383	.496
8	6.514	.590
9	6.562	.683
10	8.036	.625
11	9.797	.549
12	11.744	.466
13	14.618	.332
14	16.482	.285
15	16.855	.328
16	17.504	.354
17	18.553	.355
18	18.776	.406
19	19.144	.448
20	19.778	.472

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

in cyclical unemployment was a significant predictor of changes in property crime (t-ratio = 2.22, $p < .05$). For each unit increase in the change scores of cyclical unemployment, 459.61 additional crimes (per 100,000 inhabitants) are known to police, on the average.

Table 7

EGLS Maximum-Likelihood AR1 Results

Step 2

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	157.46	2.24	.03
Poverty	-29.49	-0.62	.54
Population Growth	233.55	0.62	.53
Police Presence	332.74	0.56	.58
Inflation	60.01	3.66	.00*
Tech. Unemployment	-1189.88	-1.52	.13
Cyclical Unemployment	459.61	2.22	.03**
Frictional Unemployment	676.08	2.14	.03**

* significant at .01   ** significant at .05

Autocorrelation: Durbin-Watson Statistic = 1.81
Set Significance: MLE chi^2 = 28 w/4df (sig. at .001)
Log-L Reduction: McFadden's rho^2 = .06 (sig. at .001)

Hypothesis four stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in annual, frictional unemployment rates and changes in the rates of property crime. This hypothesis was supported. Change in frictional unemployment was a significant predictor of property crime. For each unit increase in the change scores of frictional unemployment, 676.08 additional property crimes (per 100,000 inhabitants) are known to police, on the average.

Table 8 (p. 97) reflects the LBQ series for this equation. A white-noise process is indicated accompanied by an improved Durbin-Watson statistic, 1.81. Such continues throughout this work.

Table 9 (p. 98) reflects the results of the OLS equation incorporating the race set of variables (containing the race/technological unemployment interactions). Again, the Durbin-Watson statistic was inconclusive, although the LBQ Series (see Table 10 p. 99) indicates a random error process. Following the precedent established upon entry of the control and economy variables, an EGLS ML AR1 model was estimated at this step. Table 11 (p. 100) reflects the results from this procedure. The set was significant (MLE chi^2 significant at .025) in reducing the log-likelihood by an additional 3%.

Table 8

Ljung-Box Q-statistic Series - EGLS Step 2		
Lag	Ljung-Box Q	Probability
1	0.210	.647
2	0.687	.709
3	1.370	.713
4	3.354	.500
5	8.210	.145
6	8.310	.216
7	8.685	.276
8	9.089	.335
9	10.147	.339
10	11.706	.305
11	12.339	.339
12	16.298	.178
13	17.868	.163
14	19.711	.140
15	19.720	.183
16	21.847	.148
17	22.850	.154
18	23.497	.172
19	23.501	.216
20	23.735	.254

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 9

OLS Regression Results Step 3					
Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	154.42		2.74	.01	
Poverty	-36.00	-.14	-0.79	.44	2.3
Population Growth	154.16	.06	0.42	.68	1.6
Police Presence	197.52	.04	0.31	.75	1.3
Inflation	47.41	.42	2.38	.03	2.3
Tech. Unemployment	-1215.94	-.26	-1.80	.07	1.6
Cyclical Unemployment	539.22	.42	2.39	.03	2.3
Frictional Unemployment	772.33	.34	2.32	.03	1.6
White Arrest Rates	-0.82	-.30	-0.84	.41	9.4
Black Arrest Rates	0.46	.47	1.65	.11	6.1
White/Tech. Unemp. Int.	23.21	.63	1.79	.09	9.2
Black/Tech. Unemp. Int.	-4.66	-.37	-1.23	.11	6.7

R^2 = .693
Adjusted R^2 = .546
Residual Mean Square = 21360.2
F-ratio for equation = 4.72
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.46 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.99
Heteroscedasticity: Lagrange Multiplier Statistic
chi^2 = 12.24, p = .35

Hypothesis five stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in

Table 10

Ljung-Box Q-statistic Series - OLS Step 3		
Lag	Ljung-Box Q	Probability
1	1.670	.196
2	2.204	.332
3	2.486	.478
4	2.500	.645
5	3.324	.650
6	3.330	.766
7	4.940	.667
8	5.459	.708
9	5.461	.792
10	5.714	.839
11	9.190	.604
12	9.385	.670
13	12.191	.512
14	13.704	.472
15	14.055	.521
16	14.889	.533
17	15.680	.547
18	16.509	.557
19	16.733	.608
20	17.284	.634

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 11

EGLS Maximum-Likelihood AR1 Results Step 3			
Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	160.40	2.18	.03
Poverty	9.04	0.20	.84
Population Growth	246.99	0.74	.46
Police Presence	303.68	0.57	.57
Inflation	33.47	1.83	.07
Tech. Unemployment	-1257.16	-1.68	.09
Cyclical Unemployment	355.45	1.80	.07
Frictional Unemployment	581.80	2.08	.04
White Arrest Rates	-0.48	-0.57	.57
Black Arrest Rates	0.36	1.69	.09
White/Tech. Unemp. Int.	16.92	1.68	.09**
Black/Tech. Unemp. Int.	-3.13	-1.09	.27

** significant at .05 (one-tailed test)

Autocorrelation:	Durbin-Watson Statistic - 1.70
Set Significance:	MLE chi^2 = 12 w/4df (sig. at .025)
Log-L Reduction:	McFadden's rho^2 = .03 (sig. at .025)

the interaction of technological unemployment and white arrest rates for property crime and changes in the rates of property crime known to police. This hypothesis was supported. With entry of the white and black interactions, only the change in the level of the white arrest rates/ technological unemployment interaction was found to be a significant predictor of changes in property crime (t-ratio = 1.79, $p < .05$ on one-tailed test). This interaction provides a significant effect over-and-above that of the insignificant constituents of its product. For a unit change in technological unemployment, the slope of changes in property crime rates on changes in white arrest rates increases by 16.92 known offenses (Jaccard, Turrisi and Wan 1990). Whites commit more crimes. The interactions accounted for practically all of the 3% reduction in the log-likelihood with the entry of the set. These results indicate that changes in rates of white property crime arrests are conditioned/influenced by changes in levels of technological unemployment (and formally, vice-versa) (Cohen and Cohen 1983), as they act conjunctively to influence changes in the rates of property crime. Table 12 (p. 102) reflects the LBQ series for this equation. Again, autocorrelation was not indicated. The Durbin-Watson statistic improved to 1.70 compared to its OLS counterpart.

Table 13 (p. 103) reflects the results of the OLS equation upon entry of the alcohol, alcohol/poverty interaction set. Again, the OLS Durbin-Watson statistic continues to be inconclusive, though random error is suggested by the LBQ series (see Table 14, p. 104). Again, following established procedures, Table 15 (p. 105) reflects the results of the EGLS ML AR1 model at this point.

Table 12

Ljung-Box Q-statistic Series - EGLS Step 3		
Lag	Ljung-Box Q	Probability
1	0.734	.392
2	2.392	.302
3	2.952	.399
4	2.980	.561
5	6.080	.299
6	6.347	.385
7	6.610	.471
8	7.185	.517
9	7.467	.589
10	8.043	.625
11	10.335	.501
12	12.054	.441
13	12.914	.454
14	14.667	.401
15	15.282	.431
16	15.354	.499
17	16.228	.508
18	17.549	.486
19	17.655	.546
20	17.729	.605

Ljung-Box Q < 30 at 20 lags indicating white noise.

Table 13

OLS Regression Results

Step 4

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	97.57		1.98	.06	
Poverty	-59.53	-.23	-1.56	.13	2.4
Population Growth	536.05	.22	1.55	.14	1.4
Police Presence	51.62	.01	0.10	.92	2.1
Inflation	42.88	.38	2.53	.02	2.5
Tech. Unemployment	-698.57	-.15	-1.20	.24	1.7
Cyclical Unemployment	395.49	.32	2.07	.05	2.5
Frictional Unemployment	758.29	.34	2.70	.04	1.7
White Arrest Rates	-0.66	-.24	-0.80	.43	9.4
Black Arrest Rates	0.57	.58	2.42	.02	6.3
White/Tech. Unemp. Int.	22.57	.61	2.07	.05	9.4
Black/Tech. Unemp. Int.	-3.88	-.31	-1.23	.23	6.7
Alcohol Offenses	0.09	.05	0.44	.66	1.4
Alcohol/Poverty Int.	0.97	.42	3.53	.00	1.5

R^2 = .808
Adjusted R^2 = .690
Residual Mean Square = 14607.9
F-ratio for equation = 6.81
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.70 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Test
chi^2 = 18.4, p = .14

Table 14

Ljung-Box Q-statistic Series - OLS Step 4		
Lag	Ljung-Box Q	Probability
1	0.666	.415
2	0.889	.641
3	1.197	.754
4	1.223	.874
5	1.313	.934
6	2.043	.916
7	2.043	.957
8	6.315	.612
9	7.027	.634
10	7.315	.695
11	7.381	.767
12	8.218	.768
13	12.048	.524
14	12.102	.598
15	15.780	.397
16	17.176	.374
17	17.625	.413
18	17.684	.477
19	18.444	.493
20	18.472	.556

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 15

EGLS Maximum-Likelihood AR1 Results

Step 4

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	98.17	1.82	.07
Poverty	-46.87	-1.19	.23
Population Growth	486.95	1.47	.14
Police Presence	100.60	0.19	.85
Inflation	36.49	2.15	.03
Tech. Unemployment	-713.59	-1.16	.25
Cyclical Unemployment	350.55	1.91	.06
Frictional Unemployment	715.14	2.68	.00
White Arrest Rates	-0.54	-0.68	.50
Black Arrest Rates	0.55	2.50	.01
White/Tech. Unemp. Int.	22.06	2.22	.03
Black/Tech. Unemp. Int.	-3.77	-1.32	.19
Alcohol Offenses	0.08	0.40	.69
Alcohol/Poverty Int.	0.90	3.32	.00*

* significant at .01

Autocorrelation: Durbin-Watson Statistic - 1.93
Set Significance: MLE chi^2 = 12 w/2df (sig. at .005)
Log-L Reduction: McFadden's rho^2 = .03 (sig. at .005)

The set was significant (MLE chi^2 significant at .005) while accounting for 3% reduction in the log-likelihood. Hypothesis six stated that, after controlling for changes in poverty, population growth, and police presence, there is a direct/positive relationship between changes in the interaction of poverty and rates of alcohol offenses and changes in rates of property crime. This hypothesis was supported. Change in the level of the poverty/alcohol interaction was found to be a significant predictor of changes in rates of property crime (t-ratio 3.32, $p < .01$). For each unit increase in the change in poverty, the slope of changes in property crime rates on changes in alcohol offense rates increases by 0.97 known offenses (Jaccard, Turrisi and Wan 1990). The interaction accounted for practically all of the 3% reduction in the log-likelihood. These results indicate that changes in poverty conditions or influences changes in alcohol offenses (and formally, vice-versa) (Cohen and Cohen 1983) as they operate conjunctively to influence changes in the rates of property crime.

As before, the Durbin-Watson increased to 1.93 (compared to its OLS counterpart). Further, the LBQ series indicated a random error component. See Table 16 (p. 107) for the LBQ series for the equation.

Table 17 (p. 108) reflects the results of OLS estimation after inclusion of the final variable set. The Durbin-Watson statistic was inconclusive, while the LBQ series (see Table 18, p. 109) appeared to exhibit a white-noise process. Neither the set nor any of the variables were significant. As before, an EGLS ML AR1 model was

Table 16

Ljung-Box Q-statistic Series - EGLS Step 4		
Lag	Ljung-Box Q	Probability
1	0.045	.832
2	0.553	.758
3	0.828	.843
4	0.846	.932
5	1.141	.950
6	1.571	.955
7	1.797	.970
8	5.322	.723
9	5.568	.782
10	5.606	.847
11	5.717	.892
12	7.452	.826
13	11.365	.580
14	11.638	.635
15	13.994	.526
16	14.560	.557
17	14.732	.615
18	14.736	.680
19	15.273	.705
20	15.387	.754

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 17

OLS Regression Results

Step 5

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	127.88		2.31	.03	
Poverty	-76.33	-.30	-1.87	.07	2.8
Population Growth	369.54	.15	1.01	.33	2.4
Police Presence	60.97	.01	0.11	.91	1.4
Inflation	47.03	.42	2.73	.01	2.6
Tech. Unemployment	-960.33	-.21	-1.55	.14	1.9
Cyclical Unemployment	437.11	.34	2.22	.04	2.6
Frictional Unemployment	670.47	.30	2.33	.03	1.8
White Arrest Rates	-0.46	-.17	-0.56	.58	9.9
Black Arrest Rates	0.71	.71	2.63	.02	8.1
White/Tech. Unemp. Int.	18.56	.50	1.62	.12	10.5
Black/Tech. Unemp. Int.	-4.13	-.32	-1.27	.22	7.1
Alcohol Offenses	0.14	.08	0.69	.50	1.6
Alcohol/Poverty Int.	0.90	.39	3.21	.00	1.6
Drug Abuse Violations	-0.74	-.22	-1.40	.17	2.7
Drug/Poverty Int.	0.33	.07	0.54	.59	1.6

R^2 = .826
Adjusted R2 = .689
Residual Mean Square = 14613.4
F-ratio for equation = 6.03
P-value = .00

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.74 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic
chi^2 = 21.5, p = .12

Table 18

Ljung-Box Q-statistic Series OLS Step 5		
Lag	Ljung-Box Q	Probability
1	0.565	.452
2	0.764	.682
3	0.769	.857
4	0.820	.936
5	0.937	.967
6	1.210	.976
7	1.543	.981
8	4.858	.773
9	5.581	.781
10	6.692	.754
11	6.849	.811
12	8.543	.741
13	9.486	.735
14	9.510	.797
15	13.832	.538
16	15.120	.516
17	16.346	.499
18	16.351	.568
19	16.457	.627
20	16.663	.675

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

estimated for this step. Table 19 reflects the results of this procedure.

Table 19

EGLS Maximum-Likelihood AR1 Results Step 5			
Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	124.20	2.06	.04
Poverty	-57.66	-1.35	.18
Population Growth	370.20	1.09	.27
Police Presence	-2.13	-0.01	.99
Inflation	40.69	2.34	.02
Tech. Unemployment	-888.77	-1.38	.17
Cyclical Unemployment	367.21	1.94	.05
Frictional Unemployment	634.73	2.34	.02
White Arrest Rates	-0.41	-0.51	.61
Black Arrest Rates	0.72	2.82	.00
White/Tech. Unemp. Int.	18.80	1.84	.07
Black/Tech. Unemp. Int.	-4.46	-1.52	.13
Alcohol Offenses	0.12	0.59	.56
Alcohol/Poverty Int.	0.84	3.06	.00
Drug Abuse Violations	-0.76	-1.41	.16
Drug/Poverty Int.	0.14	0.22	.82

Autocorrelation: Durbin-Watson Statistic = 1.94
Set Significance: MLE chi^2 = 4 w/2df (not significant)
Log-L Reduction: McFadden's rho^2 = .00

Neither the set nor the rho^2 were significant (MLE chi^2 not significant).

Hypothesis seven stated that after controlling for changes in poverty, population growth, and police presence, there is a direct\positive relationship between changes in the interaction of poverty and rates of drug abuse violations and changes in the rates of property crime. This hypothesis was not supported. This study does not support the notion that poverty conditions aggregate drug activity or involvement. Perhaps, such an interaction would be more significant in relation to violent crimes and other crimes facilitated by lack of physical constraint, etc. Table 20 (p. 112) reflects the LBQ series for the equation at this point. Due to variable insignificance, the issue of autocorrelation is moot.

Thus, five of the seven hypotheses were supported in the preceding analysis. At this point, it was decided to replicate the analysis without consideration of the control variables. The following articulates the results of this exercise. Discussion of the results relative to the respective hypotheses is abbreviated, as the results are consistent (in nature and direction) with those discussed previously.

Table 20

Ljung-Box Q-statistic Series - EGLS Step 5		
Lag	Ljung-Box Q	Probability
1	0.041	.839
2	0.462	.794
3	0.467	.926
4	0.467	.977
5	0.480	.993
6	0.500	.998
7	0.507	.999
8	3.061	.930
9	3.074	.961
10	3.656	.962
11	4.118	.966
12	5.758	.928
13	6.593	.922
14	6.704	.946
15	9.535	.848
16	10.113	.861
17	10.833	.865
18	10.901	.898
19	11.003	.924
20	11.227	.939

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 21 reflects OLS results for the economy set. As before, the Durbin-Watson statistic was inconclusive, though the LBQ series exhibited *relatively* random error (see lag one). See Table 22 (p. 114) for the equation's LBQ series.

Table 21

OLS Regression Results

Step 1

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	161.70		3.13	.00	
Inflation	79.48	.71	5.19	.00	1.2
Tech. Unemployment	-1040.13	-.22	-1.60	.12	1.2
Cyclical Unemployment	499.28	.39	3.02	.00	1.1
Frictional Unemployment	619.90	.28	1.92	.06	1.3

R^2 = .528
Adjusted R^2 = .465
Residual Mean Square = 25197.1
F-ratio for equation = 8.37
P-value = .00

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.31 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic
chi^2 = 2.14, p = .71

Table 23 (p. 115) reflects the results of EGLS ML AR1 estimation at this point. As before, the hypotheses relative to changes in rates of inflation and cyclical and frictional unemployment were supported: (a) inflation, t-ratio 4.38, $p < .01$; (b) cyclical unemployment, t-ratio

Table 22

Ljung-Box Q-statistic Series OLS Step 1		
Lag	Ljung-Box Q	Probability
1	3.960	.047
2	4.037	.133
3	4.163	.244
4	4.744	.315
5	6.575	.254
6	6.589	.361
7	6.697	.461
8	6.698	.570
9	6.731	.665
10	10.468	.400
11	11.432	.408
12	12.961	.372
13	14.616	.332
14	17.543	.228
15	17.802	.273
16	19.809	.229
17	19.891	.280
18	20.000	.333
19	20.069	.390
20	20.332	.437

Ljung-Box Q < 30 at 20 lags but with a significant lag indicating slight autocorrelation.

Table 23

EGLS Maximum-Likelihood AR1 Results

Step 1

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	172.41	2.61	.01
Inflation	64.51	4.38	.00*
Tech. Unemployment	-1190.83	-1.60	.11
Cyclical Unemployment	450.01	2.99	.00*
Frictional Unemployment	572.75	2.07	.04**

*significant at .01 **significant at .05

Autocorrelation: Durbin-Watson Statistic = 1.94 (no *AC*)
Set Significance: MLE chi^2 = 32 w/4df (sig. at .001)
Log-L reduction: McFadden's rho^2 = .07 (sig. at .001)

2.99, $p < .01$; and (c) frictional unemployment, t-ratio 2.07, $p < .05$.

For each unit increase in the change scores of inflation, 64.01 (compared to 60.01 in the previous set of equations) more property crimes (per 100,000 inhabitants) are known to police, on the average. Further, for each unit increase in the change scores for cyclical unemployment, 450.01 (compared to 459.61 previously) more property crimes (per 100,000 inhabitants) are known to police, on the average. Finally, for each unit increase in the change scores for frictional unemployment, 572.75 (compared to 676.08 previously) more property crimes (per 100,000 inhabitants) are known to police, on the average. See Table 24 for the white-noise LBQ series for this equation.

Table 24

Ljung-Box Q-statistic Series - EGLS

Step 1

Lag	Ljung-Box Q	Probability
1	0.094	.759
2	0.252	.882
3	0.702	.873
4	1.905	.753
5	7.058	.216
6	7.142	.308
7	7.488	.380
8	7.775	.456
9	8.247	.509
10	11.763	.301
11	11.873	.373
12	15.447	.218
13	18.021	.157
14	20.573	.113
15	20.939	.139
16	23.603	.099
17	24.556	.105
18	25.227	.119
19	25.260	.152
20	25.870	.170

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 25 reflects the OLS results after adding the race set to the equation.

Table 25

OLS Regression Results

Step 2

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	158.32		3.14	.00	
Inflation	47.68	.42	2.54	.02	2.3
Tech. Unemployment	-1103.73	-.24	-1.84	.08	1.3
Cyclical Unemployment	466.80	.37	2.62	.01	1.6
Frictional Unemployment	644.75	.29	2.21	.04	1.4
White Arrest Rates	-0.82	-.30	-0.90	.37	8.7
Black Arrest Rates	0.50	.50	1.86	.07	6.0
White/Tech. Unemp. Int.	24.37	.66	2.07	.04	8.2
Black/Tech. Unemp. Int.	-5.01	-.39	-1.40	.17	6.5

R^2 = .681
Adjusted R^2 = .583
Residual Mean Square = 19637.7
F-ratio for equation = 6.93
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.38 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.99
Heteroscedasticity: Lagrange Multiplier Test
chi^2 = 5.41, p = .71

As before, the Durbin-Watson statistic (1.38) is indeterminate. However, Table 26 (p. 118)reflects a

Table 26

Ljung-Box Q-statistic Series - OLS Step 2		
Lag	Ljung-Box Q	Probability
1	2.36	.125
2	2.56	.227
3	2.82	.420
4	3.05	.550
5	3.59	.609
6	3.61	.729
7	4.74	.691
8	5.11	.745
9	5.31	.806
10	6.69	.754
11	8.81	.639
12	8.91	.710
13	11.01	.610
14	12.67	.552
15	12.85	.614
16	13.37	.646
17	13.82	.680
18	14.65	.686
19	14.87	.731
20	15.32	.758

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

relatively clean LBQ series except for a somewhat low *p*-value at lag 16 which should not cause worry due to the extreme length of the lag (even if it were significant).

As previously established, the EGLS ML AR1 model was interpreted. See Table 27 for a display of the results.

Table 27

EGLS Maximum Likelihood AR1 Results

Step 2

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	165.38	2.60	.00
Inflation	38.80	2.22	.03
Tech. Unemployment	-1293.11	-1.87	.06
Cyclical Unemployment	432.64	2.67	.00
Frictional Unemployment	589.17	2.32	.02
White Arrest Rates	-0.36	-0.45	.65
Black Arrest Rates	0.35	1.72	.09
White/Tech. Unemp. Int.	16.05	1.66	.09**
Black/Tech. Unemp. Int.	-2.96	-1.07	.28

**significant at .05 (one-tailed test)

Autocorrelation: Durbin-Watson Statistic = 1.76
Set Significance: MLE chi^2 = 14 w/4df (sig. at .01)
Log-L Reduction: McFadden's rho^2 = .03 (sig. at .01)

The effects of the interaction of white property crime arrest rates/technological unemployment remained relatively constant compared to the previous set of equations (b = 16.05 compared to 16.92 previously, t-ratio = 1.66, $p < .05$ on a one-tailed test). Table 28 (p. 120) reflects the LBQ series for the equation indicating a white-noise error process in conjunction with the Durbin-Watson statistic increasing to 1.76.

Table 28

Ljung-Box Q-statistic Series - EGLS

Step 2

Lag	Ljung-Box Q	Probability
1	0.392	.532
2	1.681	.431
3	2.330	.507
4	2.365	.669
5	5.693	.337
6	5.701	.457
7	6.505	.482
8	7.008	.536
9	7.041	.633
10	8.250	.604
11	9.809	.548
12	11.006	.528
13	13.161	.435
14	14.828	.390
15	14.894	.459
16	14.991	.525
17	15.903	.531
18	18.237	.440
19	18.252	.506
20	18.657	.544

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 29 reflects the OLS results for the equation incorporating the alcohol/poverty interaction set.

Table 29

OLS Regression Results

Step 3

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	113.04		2.41	.02	
Inflation	48.26	.43	2.87	.00	2.4
Tech. Unemployment	-929.27	-.19	-1.63	.12	1.6
Cyclical Unemployment	471.96	.37	2.52	.02	2.3
Frictional Unemployment	658.08	.29	2.38	.03	1.6
White Arrest Rates	-0.47	-.17	-0.59	.56	9.0
Black Arrest Rates	0.58	.60	2.45	.02	6.2
White/Tech. Unemp. Int.	19.21	.52	1.78	.09	9.0
Black/Tech. Unemp. Int.	-4.25	-.33	-1.35	.19	6.6
Alcohol Offenses	0.17	.10	0.92	.37	1.3
Poverty	-42.67	-.16	-1.18	.25	2.1
Alcohol/Poverty Int.	0.82	.35	3.17	.00	1.3

R^2 = .785
Adjusted R^2 = .682
Residual Mean Square = 14951.1
F-ratio for equation = 7.64
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.66 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic chi^2 = 9.41, p = .58

As before the Durbin-Watson statistic was inconclusive though the LBQ series was more favorable (see Table 30).

Table 30

Ljung-Box Q-statistic Series OLS Step 3		
Lag	Ljung-Box Q	Probability
1	0.864	.353
2	2.274	.321
3	2.450	.484
4	2.653	.617
5	2.755	.738
6	3.588	.732
7	3.964	.784
8	5.627	.689
9	5.634	.776
10	5.647	.844
11	5.661	.895
12	7.215	.843
13	12.888	.456
14	13.474	.490
15	16.893	.325
16	17.466	.356
17	17.700	.408
18	17.725	.474
19	17.973	.524
20	18.374	.563

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 31 reflects the results of the EGLS ML AR1 model for this equation.

Table 31

EGLS Maximum-Likelihood AR1 Results

Step 3

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	112.24	2.12	.03
Inflation	40.77	2.44	.02
Tech. Unemployment	-897.46	-1.46	.14
Cyclical Unemployment	425.82	2.42	.02
Frictional Unemployment	632.38	2.41	.02
White Arrest Rates	-0.39	-0.49	.62
Black Arrest Rates	0.55	2.53	.02
White/Tech. Unemp. Int.	19.52	1.99	.04
Black/Tech. Unemp. Int.	-3.89	-1.38	.17
Alcohol Offenses	0.13	0.71	.48
Poverty	-29.59	-0.80	.43
Alcohol/Poverty Int.	0.78	3.00	.00*

*significant at .01

Autocorrelation: Durbin-Watson Statistic = 1.88
Set Significance: MLE chi^2 = 10 w/3df (sig. at .025)
Log-L Reduction: McFadden's rho^2 = .02 (sig. at .025)

Once again the set was significant with the interaction of alcohol and poverty carrying the weight (b = 0.78 compared to 0.90 previously, t-ratio = 3.00 compared to 3.32 previously, $p < .01$). Hence, this further substantiates an interactive effect between poverty and alcohol offenses.

With the Durbin-Watson statistic increasing to 1.88 (from the OLS result of 1.66), the LBQ series (see Table 32) presents a white-noise error component.

Table 32

Ljung-Box Q-statistic Series - EGLS

Step 3

Lag	Ljung-Box Q	Probability
1	0.127	.722
2	1.740	.419
3	1.860	.602
4	2.051	.726
5	2.541	.770
6	3.408	.756
7	3.442	.841
8	4.976	.760
9	5.091	.826
10	5.287	.871
11	5.287	.916
12	7.693	.809
13	13.244	.429
14	13.952	.453
15	19.572	.345
16	16.639	.409
17	16.819	.467
18	17.065	.519
19	17.308	.569
20	17.507	.620

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Table 33 reflects the OLS results after adding the drug and poverty interaction set to the equation.

Table 33

OLS Regression Results

Step 4

Predictors (1st differences)	Coefficient	Beta	T-ratio	P-value	VIF
Constant	145.89		2.89	.00	
Inflation	51.43	.46	3.14	.00	2.4
Tech. Unemployment	-1170.17	-.25	-2.05	.05	1.7
Cyclical Unemployment	495.34	.39	2.68	.02	2.4
Frictional Unemployment	586.49	.26	2.17	.04	1.7
White Arrest Rates	-0.30	-.11	-0.38	.71	9.3
Black Arrest Rates	0.74	.75	2.85	.00	8.0
White/Tech. Unemp. Int.	15.50	.42	1.43	.17	9.7
Black/Tech. Unemp. Int.	-4.38	-.34	-1.39	.18	7.0
Alcohol Offenses	0.21	.12	1.12	.28	1.4
Alcohol/Poverty Int.	0.80	.34	3.13	.00	1.4
Drug Abuse Violations	-0.93	-.27	-1.86	.08	2.4
Poverty	-70.54	-.27	-1.81	.08	2.6
Drug/Poverty Int.	0.42	.08	0.72	.48	1.6

R^2 = .816
Adjusted R^2 = .703
Residual Mean Square = 13991.3
F-ratio for equation = 7.18
P-value = .000

Residuals
Autocorrelation: Durbin-Watson Statistic = 1.75 (indeterminate)
Normal Distribution: Wilk-Shapiro Statistic = 0.98
Heteroscedasticity: Lagrange Multiplier Statistic
chi^2 = 15.90, p = .25

As previously encountered, the Durbin-Watson statistic is inconclusive, though the LBQ series (see Table 34) suggests a white-noise error process.

Table 34

Ljung-Box Q-statistic Series

OLS Step 4

Lag	Ljung-Box Q	Probability
1	0.477	.490
2	1.440	.487
3	1.579	.664
4	1.725	.786
5	1.755	.882
6	2.179	.903
7	3.362	.850
8	5.720	.679
9	5.723	.767
10	6.578	.765
11	6.886	.808
12	9.185	.687
13	10.435	.658
14	10.450	.729
15	13.954	.529
16	14.670	.549
17	15.758	.541
18	15.765	.609
19	15.767	.673
20	15.768	.731

Ljung-Box $Q < 30$ at 20 lags with no significant lags indicating white noise.

Table 35 reflects the results for the final EGLS ML AR1 equation after incorporating the drug/poverty interaction set.

Table 35

EGLS Maximum-Likelihood AR1 Results

Step 4

Predictors (1st differences)	Coefficient	T-ratio	P-value
Constant	139.16	2.50	.02
Inflation	45.63	2.76	.00
Tech. Unemployment	-1067.44	-1.75	.08
Cyclical Unemployment	438.25	2.49	.02
Frictional Unemployment	573.19	2.21	.03
White Arrest Rates	-0.33	-0.42	.67
Black Arrest Rates	0.76	3.05	.00
White/Tech. Unemp. Int.	16.77	1.70	.09
Black/Tech. Unemp. Int.	-4.69	-1.64	.11
Alcohol Offenses	0.19	0.99	.32
Alcohol/Poverty Int.	0.76	2.96	.00
Drug Abuse Violations	-0.92	-1.82	.07
Poverty	-51.22	-1.27	.21
Drug/Poverty Int.	0.24	0.41	.68

Autocorrelation: Durbin-Watson Statistic = 1.90
Set Significance: MLE chi^2 = 4 w/2df (not significant)
Log-L Reduction: McFadden's rho^2 = .00 (not significant)

The set was not significant; therefore, the same conclusions and statements previously put forth relative to this set stand. Nonetheless, see Table 36 (p. 128) for the EGLS ML AR1 residual correlations.

Table 36

Ljung-Box Q-statistic Series - EGLS Step 4		
Lag	Ljung-Box Q	Probability
1	0.082	.774
2	1.601	.449
3	1.764	.623
4	1.846	.764
5	1.846	.870
6	1.918	.927
7	2.37	.937
8	4.10	.848
9	4.424	.881
10	4.971	.893
11	6.008	.873
12	8.166	.772
13	9.427	.740
14	9.568	.793
15	12.231	.661
16	12.401	.716
17	13.209	.722
18	13.217	.779
19	13.224	.827
20	13.229	.867

Ljung-Box Q < 30 at 20 lags with no significant lags indicating white noise.

Hence, the equation has been re-estimated in the absence of the control variables as initially specified (though poverty was entered at the appropriate stage to test the respective interactions). Overall, the equation performed as well and better than the equation containing the controls. These findings suggest that changes in population growth and police presence are not fundamental to the study of property crime at the aggregate level (at least when operationalized as they were in this study during the specified period).

CHAPTER IV

IMPLICATIONS AND CONCLUSION

In its entirety, this study established fundamental facts relative to the effects of changes in the economy, race and technological unemployment, and the interaction of alcohol offenses and poverty on changes in rates of property crime (in the context of 1958-1993 annual data). Hypotheses were set forth postulating positive relationships between changes in the rates of inflation, technological, cyclical, and frictional unemployment. Via EGLS maximum-likelihood AR1 modeling, all hypotheses were supported with the exception of technological unemployment (which was not significant).

Further, hypotheses regarding the interactive effects of race (white) and technological unemployment as well as alcohol offenses and poverty proved to be significant predictors of property crime. However, the interaction between changes in rates of drug abuse violations and rates of poverty was not significant. Consequently, five of seven hypotheses were supported.

The hypotheses regarding the economy are fundamental to understanding the dynamics of crime over time. As previously suggested, inflation is a vital predictor of property crime and should, as suggested by Devine, Sheley and Smith (1988), be included in all models investigating the effects of changes in economic conditions on changes in property crime rates. Upward pressures on prices do facilitate positive changes in property crime rates as a partial function of criminal motivation. Such systemic imbalance "motivate(s) criminal behavior...[and]...inhibits capacit(ies)...to deter crime" (Devine, Sheley and Smith 1988, p. 408).

As a consequence, anomie is facilitated and the polity's ability to deter and control crime is diminished (Devine, Sheley and Smith 1988). The importance of inflation (and its structural implications) supports the social disorganization and anomie perspective, as it was developed in this case. It also supports other perspectives noting the role of criminal motivation (such as routine activity theory) in the commission of property crime. Hence, legislation, such as monetary policy, (Byrns and Stone 1987) offering valid approaches to maintaining lower levels of inflation should be supported, at least with reference to, its effect on property crime.

In addition, changes in rates of cyclical and frictional unemployment performed nearly as well as inflation. Both were significant predictors of changes in property crime. Increases in cyclical unemployment fluctuations positively contribute to fluctuations in property crime rates. As the business cycle turns downward and fluctuations in cyclical unemployment grow larger, a logical consequence is increased property crime rates. As an attribute of the economy, these findings support the inclusion of this structural element in studies of property crime, particularly with reference to social disorganization and anomie perspectives.

With reference to levels of annual, cyclical unemployment, further study needs to assess the effects of annual, cyclical patterns of other economic factors on property crime. Such efforts should incorporate measures of surplus value (perhaps through measures such as GDP, etc.) via radical theory. Extension of the method to other types of crime (such as violent crime) is also be warranted. As a more comprehensive understanding of the effects of varying economic, cyclical patterns across varying types of crime is achieved, policy decisions can become more informed and equipped to address domestic property crime.

The finding regarding frictional unemployment is very interesting. As defined in this study, this element reflected that portion of the unemployment rate representing those workers currently between jobs. The positive finding in this case suggests that current institutional efforts (unemployment insurance programs, job training, etc.) are not maximally dampening the impact that "between-job" unemployment has on property crime.

It would appear that this group of workers would be subject to the effects of the length of frictional unemployment. Perhaps the effects of frictional unemployment grow more acute (in terms of impacting property crime rates) as shorter periods of frictional unemployment for certain groups extend (for whatever reason) into longer periods. An important question would be, at what point does this extension move workers from frictional unemployment to technological unemployment predisposing whites to higher probabilities of property crime commission? Such are fundamental structural questions needing further examination if policy concerns relative to property crime are to be well informed.

The positive signs do not support the notion that increased guardianship (from a routine activity perspective) decreases crime commission by decreasing criminal opportunity. During periods of higher unemployment (frictional or cyclical) more people would be present in their neighborhoods and would suggest a negative relationship, as posited by Cantor and Land (1985).

It should be noted again that a negative sign was observed for technological unemployment though it was not significant (p = .13/2 = .065 on a one-tailed test). If the coefficient was significant at .05, this would have supported the negative effect of unemployment on crime rates via opportunity effects suggested by Cantor and Land (1985). However, as it was not significant, the only effects that support the routine activity perspective in this study are the positive effects of frictional and cyclical unemployment. This is consistent with the argument made by Cantor and Land that criminal motivation is probably observed via lagged consideration of unemployment on crime while the effects of criminal opportunity are more synchronous. Future work on the model constructed in this study should also consider the use of contemporaneous values of the economic indicators employed.

It was further hypothesized that there would be a significant, interactive effect between changes in white arrests rates for property crime and changes in rates of technological unemployment as it impacted changes in property crime rates. With the coefficient being positive (as hypothesized) and significant compared to its insignificant black counterpart, Smith, Devine and Sheley's (1992) assertions that (a) upward trends in unemployment impact all group's equally to include majority groups, and (b) that whites are less insulated (than generally believed) to the effects of unemployment are partially supported. In contrast to their notions, the current research suggests that upward trends in unemployment impact whites more than blacks. Thus, consistent with their statements, whites are less insulated from the effects of unemployment than previously believed.

This finding strongly suggests that economic dysfunction/systemic imbalance (partially captured via unemployment figures) impacts the majority far greater than the minority. These are fundamental issues to be understood in institutional studies of race and its relation to property crime. Being more closely associated with the capitalist infrastructure from the beginning, criminal motivation (from a routine activity perspective) is necessarily increased among the majority (whites). Further, in the presence of a statistically significant negative effect of technological unemployment (which was *not* the case in this instance), this interaction could be seen as increasing property crime rates even during periods of decreased criminal opportunity.

Such facts are fundamental in any legislation oriented toward deterring the property crimes of burglary, auto-theft, and larceny. Accordingly, any legislation on the topic should consider directives, options, etc., which dampen the impact of unemployment on the at-risk white population, as it relates to the commission of property crime. For instance, in areas of high unemployment among poor whites, re-directed efforts at the expansion of job training programs and education are very important. Such would also impact blacks in the areas, but in terms of the impact of rising unemployment on rates of property crime, whites are impacted the most. Finally, current governmental efforts extended to expansion of unemployment insurance (or similar programs) should be viewed as an important tool (due for further investigation) in the possible curtailment of property crime.

The interactive effect of rates of alcohol offenses and poverty was also hypothesized to impact rates of property crime. Again, this hypothesis was supported with a positive coefficient. These results suggest that rates of alcohol offenses are conditioned by, or dependent upon, the level of poverty. As noted throughout, interactions are symmetrical, though deviance theory would tend to support the position articulated herein (i.e., focusing on the conditioning of alcohol offenses by poverty).

Poverty, as a structural element, does condition rates of alcohol offenses at the national level in the context of property crime. Though the property crimes were not investigated separately due to reasons of Type I error, these findings challenge the notion that alcohol consumption is related only to spontaneous property crimes. Perhaps such would hold true for those testing positive for alcohol upon apprehension (Cordilia 1985), but it fails to account for the effects that extreme alcohol use has on lifestyles in general (even during sober moments) that might be reflected in consideration of more professional property crimes. Indeed, such considerations would occur within the context of poverty conditioning alcohol use. Over time, this profoundly effects groups' general orientations to the opportunity structures they encounter, promoting some to undertake alternative modes of action (such as property crime). Within the context of the present study, these findings provide indisputable support for the interactive use of poverty rates and rates of alcohol offenses in the study of fluctuations in annual, aggregate property crime rates. Indeed, such greatly illustrates the interrelation between the two concepts of social disorganization and anomie as applied in the present case.

Confirming the relationship between alcohol offenses and poverty, these results should also be considered in all efforts oriented toward reducing alcohol use/involvement and/or poverty. Alcohol education programs which define the impact of inappropriate alcohol consumption or involvement at the macro as well as micro-levels are fundamentally important. Certainly, rates of group activity were under scrutiny in this study, but it is individual action which changes lives.

Further, efforts at reducing poverty should continue to be pressing topics in all national, legislative forums. The results of this study again substantiate (in a unique manner) the effects of poverty on crime (property crime in the present case) and its relation to anomie (i.e., rates of alcohol offenses). Living in poverty impacts aggregate levels of group behavior regardless of race. However, while a higher proportion of blacks live in poverty (compared to whites), it would be at this group (blacks) that primary efforts in reducing poverty should be directed just as primary efforts relative to technological unemployment were extended to consideration of whites. For what impacts one group, may not necessarily impact the other equally.

Finally, the interaction of changes in the rates of drug abuse violations and poverty was tested as a positive predictor of changes in rates of property crime. This hypothesis was not supported. Consequently, this does not support the notion that the rate of drug abuse violations is conditioned by, or depends on the level, of poverty (at least for the variables as measured from 1958-1993). As previously offered, this relationship should be tested in the context of violent crime, to include robbery.

Further, to the degree that activities such as drug dealing are a partial function of economic inequality, the interactive effect of inequality and rates of drug abuse violations might prove significant in predicting changes in property crime. As inequality increases and opportunity structures constrict, rates of alternative modes of action (i.e., drug dealing) should increase drug abuse. This might positively impact fluctuations in property crime rates and is worthy of further research.

Thus, a unique study of the causes of property crime has been undertaken. The depth and breadth of the majority of variable sets is impressive. Indeed, while controlling for changes in poverty, population growth, and police presence, five of seven hypotheses were supported. In fact, the latter two (race/technological unemployment and alcohol/ poverty sets) were actually significant after controlling for the effects of the economy set and the economy/race sets, respectively, in addition to inclusion of the explicitly defined control variables in the first series of equations. Such provides support for the hierarchical ordering of the variable sets in terms of their entry into the equation taking full advantage of suppressive relationships.

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