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OCCUPATION, RACE, UNEMPLOYMENT AND CRIME IN A DYNAMIC SYSTEM

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ABSTRACT

In this paper, the relationship between unemployment and property crime is investigated in the context of dynamic system by using quarterly time series data for the United States during the period of 1973 (I) - 1981 (IV).

The results of Granger's causality tests indicate that unemployment by occupation (white and blue collars) is significantly associated with robbery, which is the most serious property crime. Unemployment by race (white, black, and Hispanic) also supports the above finding. In general, the linkage between unemployment rate and property crime seems to become stronger as the degree of seriousness of crime increases. The findings of the dynamic system show that blue collar, Hispanic, and black unemployment rates have persistently positive effects on robbery. Therefore, these above findings suggest that any attempt to reduce property crime through alleviation of unemployment would most efficiently be directed towards specific categories of the labor force.

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OCCUPATION, RACE, UNEMPLOYMENT AND CRIME IN A DYNAMIC SYSTEM

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In the 1960s, economists[1] attempted for the first time to explain property crime[2] as the outcome of economic behavior on the part of the individual. Being a rational economic agent, the criminal is in a position to evaluate relative prices reflecting costs and benefits of various legal and illegal activities and, thus, to choose an optimum utility-maximizing "basket." Since then, economic incentives and disincentives have been emphasized as policy tools in fighting crime as opposed to rehabilitation which is the main concern of other social scientists.

In the last two decades, a considerable amount of theoretical analysis and empirical investigation has been done on the relationship between unemployment and crime. A review of the literature can be found in Freeman (1982), Long and Witte (1981), and Thompson et al. (1981). The main focus of those studies has been to explore the effects of employment opportunities on property crime, even though other socio-economic variables were included in an attempt to ensure proper model specification.[3]

The unemployment has the expected impact on property crime more or less consistently across all time-series studies though the consensus is weaker with respect to the findings of cross-sectional studies (Freeman 1982). A careful evaluation of these studies reveals that, despite the high plausibility of the claim that unemployment may be the key factor behind property-related criminal activity, only a moderate link between unemployment and property crime exists.[4] A major methodological problem of these approaches has been the use of a static rather than a dynamic model. The advantage of the latter is that it may show not only the correlation but also the duration of lagged effects of unemployment on property crime.

In this paper, dynamic time-series techniques developed by Granger (1969) and Sims (1980) are employed. Because of high expected collinearity between time and some economic variables, and limited degrees of freedom, the unemployment rate is adopted as the only explanatory variable in addition to the lagged dependent variable. The following relationships are investigated in this study: First, total unemployment and property crime (total and each kind of property crime separately); second, unemployment rates by occupation (white and blue collars) and different kinds of property crime; and third, race-specific unemployment rates (white, black, Hispanic) and various categories of property crime. The period of analysis extends from the first quarter of 1973 to the fourth quarter of 1981. The relative crime rates for the United States used in this paper are the ones released in the 1982 Uniform Crime Reports of the Federal Bureau of Investigation.[5] Data on unemployment rates are collected from unpublished records of the Bureau of Labor Statistics.

Section I describes the statistical techniques involved in the Granger's causality test and the dynamic representation of a system. Section II reports the empirical results. Finally, section III gives a summary of the findings of this paper.

I. STATISTICAL TECHNIQUES OF CAUSALITY TEST AND DYNAMIC SYSTEM

Granger (1969) defines causality between two stationary stochastic time series, U(t) and X(t), within a set of information in the universe, as follows: A time series U causes another time series X if the current value of X is more accurately predicted by using the information which includes at least the own-past series of X and the past series of U, than by using the information which excludes the past series of U.[6]

By using a logarithmic specification, we estimate the following linear model:

$$\hat{X}_i(t) = \hat{a}_0 + \sum_{s=1}^{n} \hat{a}_i(s) X_i(t-s) + \sum_{j=1}^{m} \sum_{s=1}^{n} \hat{b}_j(s) U_j(t-s)$$

$$+ \sum_{k=2}^{4} \hat{c}_k D_k + \hat{d}\, T, \qquad \ldots\ldots (1)$$

where $\hat{a}_0$, $\hat{a}_i$, $\hat{b}_j$, $\hat{c}_k$, and $\hat{d}$ are least-square estimates; X_i represents proprety crime while U_j represents unemployment rate; D_k are quarterly dummy variables; and T is a linear time trend. In order to identify the Granger's causality from U_j to X_i in equation (1), the null hypothesis is that the set of parameters $b_j(s)$, s=1,...,n, should be zero if there is no Granger's causality from U_j to X_i.[7]

With respect to dynamic relationships between X_i and U_j in equation (1), the estimated coefficients on successive lags include complicated cross-equation feedback and, therefore, the summing of distributed lagged coefficients, e.g., the sum of $b_j(t-s)$, $s=1,\ldots,n$, is quite misleading (Sims 1980). As suggested, we estimate the moving average representation (MAR) of the system.[8]

Let $\hat{Z}(t)$ represent the best linear forecast of $Z(t)$ based on its past series $Z(t-s)$, $s > 0$, where $Z(t)$ is an q x 1 vector stationary stochastic time series. Then, the innovation in $Z(t)$ is defined as follows:

$$V(t) = Z(t) - \hat{Z}(t), \quad \ldots\ldots (2)$$

where $V(t)$ is serially uncorrelated and is also a linear combination of current and past values of $Z(t)$ for all t. Then, $Z(t)$ can be expressed as a linear combination of current and past innovations $V(t-s)$, $s \geq 0$. However, if components of V are contemporaneously correlated, it is not possible to partition the variance of Z into components accounted for by each innovation. Therefore, an orthogonalizing transformation to V is required to obtain the identity matrix $M(t) = T\,V(t)$, where T is a lower triangular matrix with zero elements above the diagonal, and which makes the covariance matrix $M(t)$ the identity matrix. The final equation to estimate is as follows:

$$Z(t) = \sum_{s=0}^{\infty} F(s)T^{-1} M(t-s). \qquad ..... (3)$$

The components of the matrix function $F(s)T^{-1}$ represent the k+1 step-ahead forecast Z_i, accounted for by the innovation in Z_j (Eckstein et al. 1981). Then, a particular i-th equation of Z(t) is expressed as follows:

$$Z_i = \sum_{j=1}^{q} \sum_{s=0}^{k} f_{ij}(s) \; M_{ij}(t-s), \qquad ..... (4)$$

where f_{ij} is the i-th equation's components of $F(s)T^{-1}$ for j=1,...,q; and M's are the normalized innovations in variables in the system. In particular, the sum of f_{ij}^2 from s=0 to s=k for the j-th component represents the part of error variance in the k=1 step-ahead forecast of Z_i, accounted for by the innovation in Z_j at s=0 (Eckstein et al. 1981). Consequently, the proportion of k quarters ahead forecast error variance in Z_i due to typical random shocks of one standard deviation in the innovation Z_j is expressed as follows [9]:

$$\rho^2_{ij}(k) = \frac{\sum_{s=0}^{k} f_{ij}^2(s)}{\sum_{j=1}^{q} \sum_{s=0}^{k} f_{ij}^2(s)}. \qquad ..... (5)$$

II. EMPIRICAL RESULTS

II-1. Granger's Causality Tests

Granger's causality tests for property crimes and unemployment rates are performed using quarterly time series data for the United States during the period of 1973(I) - 1981(IV). The F-statistics of the results of four lag distributions in a logarithmic specification are reported in Tables 1 through 3.

Summarizing the empirical evidence, the following observations emerge. First, our results largely support the significance of the lag distributions of each property crime in the determination of its own behavior. Second, total unemployment is shown to Granger-cause total property crime and robbery, burglary and motor vehicle theft in particular, at various significance levels. Third, white collar and blue collar unemployment are both significant in affecting robbery whereas Granger's causality could not be detected with respect to other types of property crime with the exception of motor vehicle theft where the impact of blue collar unemployment appears stronger. Fourth, unemployment by race-specific group is significant in Granger-causing robbery leaving other property crimes unaffected. Fifth, black and Hispanic unemployment seem to exert a stronger influence on robbery than white unemployment. And, sixth, black unemployment is the only type of unemployment significantly shown to Granger-cause burglary besides robbery.

The general picture emerging out of these results seems to indicate that Granger's causality between unemployment and property crime becomes stronger as the degree of seriousness of the crime increases and as the incidence of unemployment discriminates against blue collar, and non-white groups.

GRANGER'S TEST OF CAUSALITY

TABLE 1

Period 1973(I) - 1981(IV) F-Statistics (d.f.) = (4,23)

Independent Variable	Dependent Variable TPC	ROB	BUR	LAR	MOT
OWN LAGS	48.17***	7.56***	15.73***	20.59***	2.49*
TU	3.81**	6.96***	2.77*	2.08	4.63***

Note. * Significant at α = 10% ** Significant at α = 5%
*** Significant at α = 1%

TPC: Total Property Crime
ROB: Robbery
BUR: Burglary
LAR: Larceny
MOT: Motor Vehicle Theft
TU : Total Unemployment Rate

TABLE 2

Period 1973(I) - 1981(IV) F-Statistics (d.f.) = (4,19)

Independent Variable	Dependent Variable ROB	BUR	LAR	MOT
OWN LAGS	2.47*	8.58***	20.73***	3.04**
WHC	4.92***	0.26	0.41	1.34
BLC	4.70***	1.29	0.90	2.30*

Note. * Significant at α = 10% ** Significant at α = 5%
*** Significant at α = 1%

WHC: White Collar Unemployment Rate
BLC: Blue Collar Unemployment Rate

GRANGER'S TEST OF CAUSALITY
(continued)

TABLE 3

Period 1973(I) - 1981(IV) F-Statistics (d.f.) = (4,10)

Independent Variable	Dependent Variable ROB	BUR	LAR	MOT
OWN LAGS	18.00***	7.58***	4.29**	1.34
WU	2.63*	1.02	0.17	0.41
BU	3.75**	3.68**	0.59	1.01
HU	3.72**	1.41	0.67	0.68

Note. * Significant at α = 10% ** Significant at α = 5%
*** Significant at α = 1%

WU : White Unemployment Rate
BU : Black Unemployment Rate
HU : Hispanic Unemployment Rate

II-2. Dynamic Relationships between Robbery and Unemployment

In the Granger's causality tests, we concluded that serious property crimes are most likely to be related to unemplyment, while the relationship between unemployment and less serious property crimes appears rather weak. Therefore, in this section, only robbery, being the most serious property crime, has been investigated in its relationship to unemployment categorized by occupation and race.

Responses of robbery to positive random shocks of one standard deviation in the innovation in blue collar unemployment are shown in chart 4 - A. The innovation in blue collar has persistently positive effects on the robbery variable at all quarters except the third quarter (k=3). As the chart indicates, an increase in blue collar unemployment does not increase robbery much during the first year (k=1 through 4). However, the effects of blue collar unemployment on robbery become stronger during the second year. On the contrary, the responses of robbery to typical random shocks in the innovation in white collar unemployment are not positive at all quarters except the second, third, and fourth quarters, shown in chart 4 - B.

The charts in Table 5 present the responses of robbery to Hispanic, black, and white unemployments. In chart 5 - A, the innovation in Hispanic unemployment generates positive effects on the robbery variable. The peak of robbery is reached in the middle of the first year. The responses of robbery to black unemployment follow the similar pattern to those described for Hispanic unemployment (chart 5 - B). Again, the innovation in white unemployment does not show positive effects on the robbery variable (chart 5 - C).

Table 6 reports the results of dynamic relationships between property crime and total unemployment rate, which show the percentage of error variance of the dependent variable (total and each property crime) accounted for by the innovation in total unemployment rate (TU).

In Table 6 - 1, the total property crime (TPC) in the United States has 37 percent of its variance accounted for by total unemployment rate in the first quarter, 50 percent in the fourth quarter, and 60 percent in the seventh quarter. As more future quarters are forecasted, the variance of total property crime tends to be explained more by the total unemployment rate. The results for each property crime treated separately in Tables 6 - 2 through 6 - 5 reveal the same pattern as explained for the total property crime in Table 6 - 1. Therefore, the results of Table 6 indicate that the total unemployment rate is a strong determinant of the fluctuations of property crime in the long run.

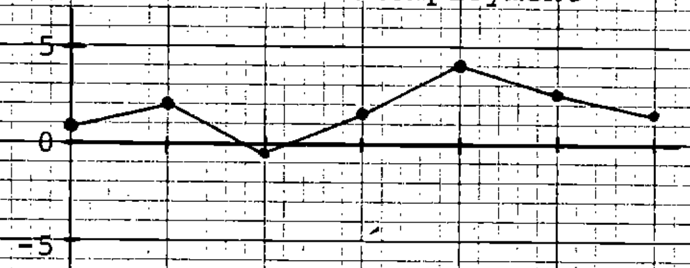
To summarize, there exist dynamic relationships between property crime and unemployment rate. Above all, blue collar, Hispanic, and black unemployment rates show significantly positive effects on robbery. On the other hand, white collar and white unemployment rates do not show positive effects on robbery. Thus, the average overall unemployment rate hides the existing differences with respect to the impact of unemployment suffered by specific groups on property crime and robbery in particular. One might argue that it is not unemployment per se which causes property crime to increase, but rather the prolonged structural unemployment that hits blue collar, Hispanic, and black workers in general. However, persistently high unemployment rates for these groups may weaken the legitimacy of legal earning activities and consequently push these people towards economic crime. On the other hand, the duration and frequency of unemployment among white collar and white workers are small in general and, therefore, these people are less likely to get involved in economic criminal activities.

TABLE 4

Responses of Robbery Variable to Positive Shocks of One Standard Deviation in Blue Collar Unemployment and White Collar Unemployment Innovations

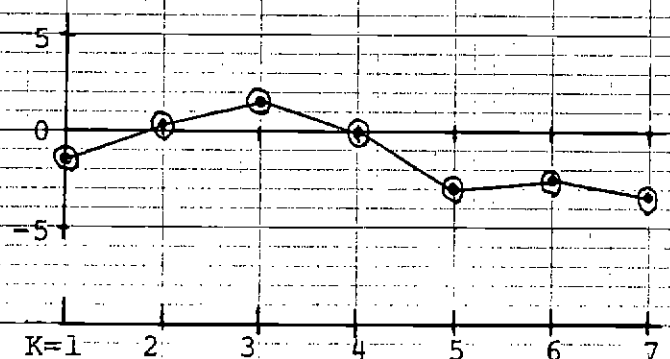
4 - A

Blue Collar Unemployment



4 - B

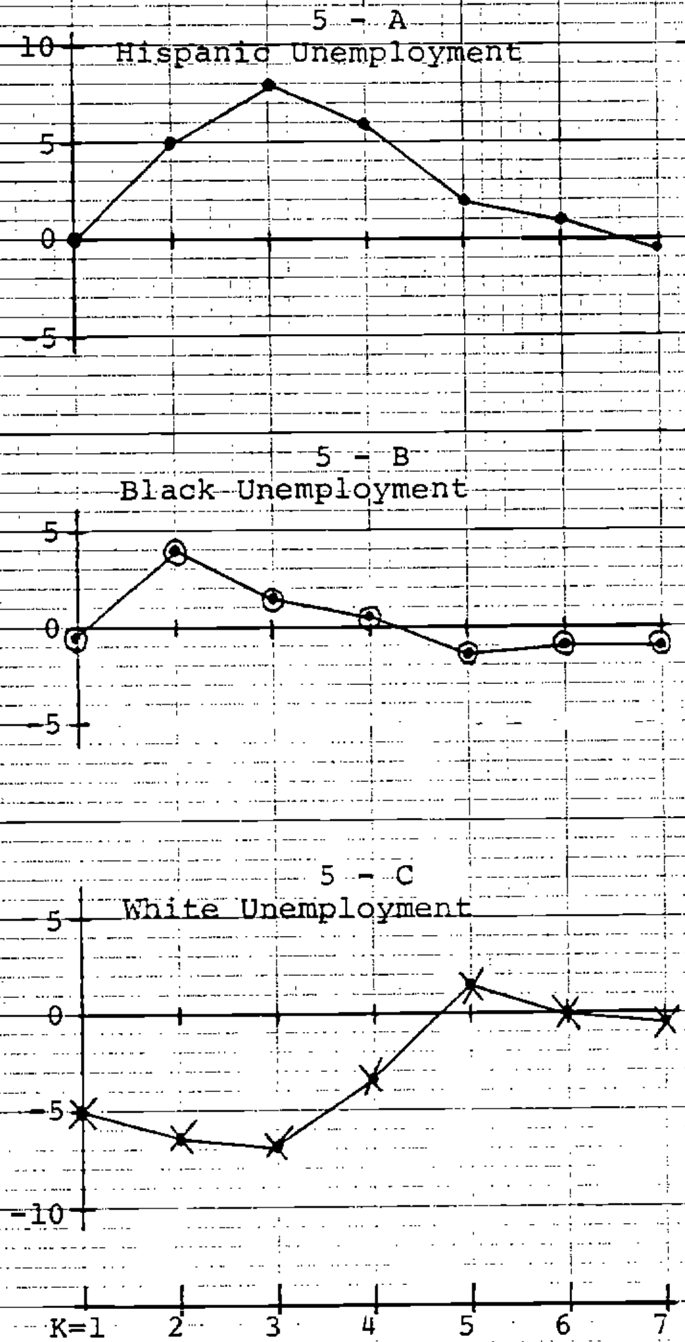
White Collar Unemployment



Note. Vertical values are $f_{ij}(s)$ in equation 4.

TABLE 5

Responses of Robbery Variable to Positive Shcoks of One Standard Deviation in Hispanic Unemployment, Black Unemployment, and White Unemployment Innovations



Note. Vertical values are $f_{ij}(s)$ in equation 4.

TABLE 6

Decomposition of Variance: Proportion of Forecast Error Variance 1, 4, and 7 Quarters Ahead Produced by Each Innovation

6 - 1

Response in	K	Innovation in TU	TPC
TPC	1	0.37	0.63
	4	0.50	0.50
	7	0.60	0.40

6 - 2

Response in	K	Innovation in TU	ROB
ROB	1	0.58	0.42
	4	0.55	0.45
	7	0.70	0.30

6 - 3

Response in	K	Innovation in TU	BUR
BUR	1	0.26	0.74
	4	0.28	0.72
	7	0.42	0.58

6 - 4

Response in	K	Innovation in TU	LAR
LAR	1	0.51	0.49
	4	0.51	0.49
	7	0.54	0.46

6 - 5

Response in	K	Innovation in TU	MOT
MOT	1	0.27	0.73
	4	0.31	0.69
	7	0.38	0.62

Note. K represents the k-th quarer ahead forecast. The period studied is 1973 (I) - 1981 (IV).

TU : Total Unemployment Rate
TPC: Total Property Crime
ROB: Robbery
BUR: Burglary
LAR: Larceny
MOT: Motor Vehicle Theft

III. SUMMARY

The purpose of this study has been first to investigate the relationship between the property crime rate and the unemployment rate in the United States, and then to find dynamic correlations which might exist between these variables.

The results of Granger's causality tests indicate that unemployment by occupation (white and blue collars) is significantly associated with robbery. Unemployment by race (white, black, and Hispanic) also supports the above finding. In general, the linkage between unemployment rate and property crime seems to become stronger as the degree of seriousness of cirme increases. The findings of the dynamic system show that blue, Hispanic, and black unemployment rates have significantly positive effects on serious property crimes, i.e., robbery.

As a concluding remark, unemployment rates are important for the determination of property crime. It is unemployment in specific groups in the society which is crime-related. Therefore, any attempt to reduce crime through alleviation of unemployment would most efficiently be directed towards specific categories of the labor force (blue, black, and Hispanic workers).

FOOTNOTES

* International Monetary Fund in Washington, D.C., ** Montclair State College of New Jersey, and *** Brooklyn College of the City University of New York, and National Bureau of Economic Research. The authors are listed in alphabetical order and are equally responsible for the content of this paper.

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[1] Here one should mention the pioneering work of Ehrlich (1973, 1974) and the path-breaking innovations in economic analysis of Becker (1968).

[2] Property crime is a general term referring to robbery, burglary, larceny, and motor vehicle theft.

[3] For example, Ehrlich (1973) uses the following variables:
a) Economic variables
   i. legal and illegal income opportunities.
   ii. expected cost of punishment.
b) Demographic variables
   i. percentage of males aged 14-24 in the population.
   ii. percentage of nonwhites in the population.
   iii. percentage of population in Standard Metropolitan Statistical Areas (SMSAs).

[4] However, Phillips, Votey, and Maxwell (1972) found relatively large R-squares in their equations. Therefore, they concluded that changing labor market opportunities are sufficient to explain increasing crime rates in the United States.

[5] The relative crime rate is obtained by setting the crime rate in the first quarter of 1972 equal to 100 as a base in the 1982 Uniform Crime Reports.

[6] "Causality" in Granger's model means "linear causality between variables within a given set of information in a universe." See Granger (1969), p.430. Blinder (1982) states that "Granger-causation has nothing to do with causation in the usual sense... It means that X adds to the ability to predict Y, no more and no less [pp.15-16]."

[7]The assumptions of the linearity between X(t) and U(t), and the set of information consisting of X(t) and U(t) would give spurious results of the Granger's causality tests, if there is a third variable which is causally and linearly related with X(t) and U(t) but being not included in the set of information.

[8]The rest of this section draws heavily on Sims (1978 and 1980) and Eckstein et al. (1981).

[9]Equation (5) follows Eckstein et al. (1981).

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