

Inequality and Crime

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INEQUALITY AND CRIME

Morgan Kelly*

Abstract—This paper considers the relationship between inequality and crime using data from urban counties. The behavior of property and violent crime are quite different. Inequality has no effect on property crime but a strong and robust impact on violent crime, with an elasticity above 0.5. By contrast, poverty and police activity have significant effects on property crime, but little on violent crime. Property crime is well explained by the economic theory of crime, while violent crime is better explained by strain and social disorganization theories.

I. Introduction

AMONG industrialized economies, the United States enjoys two unenviable distinctions: high inequality and high rates of crime, particularly of violent crime. This paper examines whether these two factors—inequality and crime—are linked.

That inequality increases crime rates is a prediction of the three most influential ecological theories of crime: Becker's (1968) economic theory of crime, Merton's (1938) strain theory, and the social disorganization theory of Shaw and McKay (1942). Ecological theories seek to explain variations in crime rates through the differing incentives, pressures, and deterrents that individuals face in different environments.

In the economic theory of crime, areas of high inequality place poor individuals who have low returns from market activity next to high-income individuals who have goods worth taking, thereby increasing the returns to time allocated to criminal activity. Strain theory argues that, when faced with the relative success of others around them, unsuccessful individuals feel frustration at their situation. The greater the inequality, the higher this strain and the greater the inducement for low-status individuals to commit crime. Social disorganization theory argues that crime occurs when the mechanisms of social control are weakened. Factors that weaken a community's ability to regulate its members are poverty, racial heterogeneity, residential mobility, and family instability. In this case, inequality is associated with crime because it is linked to poverty: areas with high inequality tend to have high poverty rates.

We use data for all metropolitan counties in 1991 to examine the link between crime and inequality. To distinguish the effects of inequality from those of poverty, we include several measures of deprivation—unemployment and poverty rates, percentage of nonwhite population, and percentage of female-headed families—in our crime regressions. Police expenditure per capita is used as a measure of the deterrent effect of police activity.

We find very different patterns of behavior between

property and violent crime. Both types of crime are positively influenced by the percentage of female-headed families and by population turnover, and negatively related to the percentage of population aged 16–24. However, although property crime is largely unaffected by inequality but significantly influenced by poverty and police activity; violent crime is little affected by poverty and police activity but strongly aggravated by inequality, with an elasticity in excess of 0.5. The differing effects of inequality on property and violent crime are extremely robust, with similar patterns of significance obtained whether inequality is measured using income or education, and regardless of the combination of other explanatory variables used.

In summary, then, the pattern of property crime is in line with the predictions of the economic theory of crime. However, when it comes to explaining violent crime, the role of inequality and race are in keeping with strain theory, while the significance of weak family and community ties support social disorganization theory.

The rest of the paper is as follows. Section II outlines the theories that link inequality and crime, and discusses previous empirical studies. The econometric specification of equation to be tested is given in section III. Section IV discusses the data used, and the regression results are presented in sections V and VI.

II. Inequality and Crime

The link between inequality and crime is stressed by the three main ecological theories of crime: Becker's economic theory of crime; the social disorganization theory of Shaw and McKay, and Merton's strain theory.

In the economic theory of crime—originating with Becker (1968) and developed by Ehrlich (1973), Block and Heineke (1975), and others—individuals allocate time between market and criminal activity by comparing the expected return from each, and taking account of the likelihood and severity of punishment. In these models, inequality leads to crime by placing low-income individuals who have low returns from market activity in proximity to high-income individuals who have things that are worth taking. A formal model of inequality and property crime in which individuals choose between legitimate and criminal activity can be found in Chiu and Madden (1998).

Following the emphasis in the theoretical literature, most empirical tests of the economic theory of crime have been concerned with the deterrent effects of the criminal justice system—in particular by how increased police activity and imprisonment rates reduce crime, and whether this reduction is due to deterrence or incapacitation.¹ Several studies have

¹ Notable studies include Grogger (1991), Levitt (1994, 1996, 1997), and Tauchen, Witte, and Griesinger (1994). Freeman (1996) and Ehrlich (1996) give excellent reviews.

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considered the effect on crime of inequality, albeit indirectly through the effect of low earnings on criminal activity. The pioneering study of Ehrlich (1973) uses the fraction of the population in an area earning less than half the median income as a proxy for inequality; Freeman (1983) examines the effect of unemployment on crime; and Grogger (1997), Machin and Meghir (1999), Myers (1983), Viscusi (1986), Witte (1980), and Witte and Tauchen (1994) examine the impact of earnings on criminal participation.

In contrast to the economics of crime literature, which focuses on the deterrent effects of the formal criminal justice system, social disorganization theory considers factors that diminish the effectiveness of informal social controls. Shaw and McKay (1942) and Kornhauser (1978) identified poverty, ethnic heterogeneity, and residential mobility as the three factors that weaken networks of social control and undermine the ability and willingness of communities to exercise informal control over their members. Sampson (1987) has added family stability to this list. For social disorganization theory, inequality causes crime indirectly by being associated with poverty.

In Merton's (1938) strain theory, individuals low in the social structure are frustrated by their failure to attain the material attributes of success, and this failure is more galling when they are confronted by the success of those around them. Unsuccessful individuals become alienated from society and commit crime in response. Individual alienation can arise from income inequality, or from belonging to a racial minority.

The predictions of strain and social disorganization theories have been subject to extensive but inconclusive empirical testing in the sociological literature. The influential study of Blau and Blau (1982) found a strong relationship between measured income inequality and homicide rates in large metropolitan areas in 1970. However, as the extensive survey of Land, McCall, and Cohen (1990) shows, later empirical results have been mixed, with strong collinearity between inequality and poverty, race, unemployment, and other measures of deprivation making it hard to separate the effects of inequality on crime from those of poverty.

In summary, the three ecological theories of crime are better seen as complements than substitutes, each focusing on a different facet of the relationship between crime and inequality. Social disorganization theory considers informal social deterrents to crime; strain theory focuses on pressures to commit violent crime; and the economic theory of crime, although formally able to encompass the other two theories, is concerned primarily with the incentives to commit property crime, and the deterrent effect of the formal criminal justice system.

A. Econometric Specification

Suppose that the total population of the region is N . Each individual comes across other people who are unknown to him or their property at an exponential rate δ that is an

increasing function of population density d . Density has two roles in causing crime: It increases the supply of potential victims who do not know the criminal (as in Glaeser and Sacerdote (1996)), and it reduces the chance of being caught.

At any one time, a fraction χ of the population is predisposed to commit crime if a suitable opportunity arises. These individuals may be optimally allocating time to illegitimate activities given their possible returns from all activities as in Block and Heineke (1975), or may commit crime in an impulsive and unplanned manner, as argued by Gottfredson and Hirschi (1990) and Witte and Tauchen (1994). This fraction χ of potential malefactors is a function of inequality I and the factors considered above: poverty, race, family instability, and residential mobility. These factors will be denoted by x . Situations in which an individual who is predisposed to commit crime meets with other people or their property therefore occur at exponential rate $\chi\delta N$.

Not all opportunities to commit crime are taken, however. A certain fraction $(1 - \pi)$ are judged too risky, because the probability of immediate or subsequent arrest and punishment is felt to be high. A fraction π of encounters with potential criminals result in crime, where π is diminishing in police activity p , and possibly in other factors such as community stability, in which individuals who see crimes committed against neighbors inform the police.

As a result, the number of crimes y occurring in an area is a Poisson process with expected value

$$\lambda \equiv \pi\chi\delta N. \quad (1)$$

To estimate the model, it will be assumed that there is a log-linear relationship between π , χ , δ and their determinants. It follows that

$$\begin{aligned} \log(\lambda) = & \log(N) + \beta_0 \log(d) + \beta_1 \log(I) \\ & + \beta_2 \cdot \log(x) - \beta_3 \log(p). \end{aligned} \quad (2)$$

In order to estimate this count model it is necessary to identify the variables x and p .

III. Data

This section outlines the data on crime, inequality, police activity and other variables used in estimating the above regression.

A. Crime

Our crime data are taken from the 1991 FBI Uniform Crime Reports, which comprise violent crimes and property crimes. Violent crime consists of murder and non-negligent homicide, forcible rape, robbery, and aggravated assault. Crime against property consists of burglary, larceny, and auto theft. These data are well known to suffer from

under-reporting bias, and, although they will be left-side variables in what follows, it is likely that this bias will be correlated with some of the explanatory variables, particularly those concerning poverty, education, race, and intensity of police activity.

B. Inequality

To measure income inequality, this paper uses a simple approach that is intuitive and easily implementable: the ratio of mean to median household income. Assuming income to be approximately log-normally distributed $\log(Y) \sim N(\mu_y, \sigma_y^2)$, mean income is then equal to $\exp(\mu_y + \frac{1}{2}\sigma_y^2)$, while median income equals $\exp(\mu_y)$.² The log ratio of mean to median income is $\frac{1}{2}\sigma_y^2$, allowing us to calculate a Gini coefficient (Shimizu & Crow, 1988):

$$I = 2\Phi\left(\frac{\sigma_y}{\sqrt{2}}\right) - 1, \quad (3)$$

where Φ is the normal distribution.

To distinguish the impact of inequality on crime from that of poverty, it is useful to have a measure of inequality that is derived independently of income. Such a measure is given by inequality in human capital. For each district, we have the fraction q of adults with fewer than t_q years of education, where t_q is 12 or 16. Assuming the distribution of years of education to be approximately log-normal, $\log(E) \sim N(\eta_e, \sigma_e^2)$, we have the linear relationship

$$\log(t_q) = \eta_e + \sigma_e r_q, \quad (4)$$

where r_q satisfies the equation $q = \Phi(r_q)$. Given σ_e , we can estimate a Gini coefficient for years of education from equation (3). If the assumption of log-normality is violated for either income or education, the estimated statistic will not be an exact Gini coefficient, but is still a measure of inequality.

C. Other Covariates

Although income inequality is our main concern in this paper, it is necessary to control for factors stressed by ecological theories of crime: police activity, poverty, unemployment, family structure, race, population turnover, and age composition.

The difficulty in assessing the deterrent effect of police expenditure on crime is that police activity is endogenous: areas with high crime rates have high rates of police expenditure. As a consequence, studies that ignore endogeneity find that police activity and severity of punishment have no demonstrable impact on crime (cf Cameron, 1988), while

² A priori reasons for income to be log-normal are developed in Brown and Sanders (1981). Empirically, the log-normal distribution appears to be a reasonable fit to the income distribution, outside the extreme tails (Lawrence, 1988).

studies such as Ehrlich (1973) that use instruments find a considerable negative impact. Levitt (1997) uses the ingenious instrument of electoral cycles in police recruitment as an instrument and finds an elasticity of crime with respect to police numbers of up to -1 .

Poverty is usually measured by the percentage of the population below the poverty line. Most people in poverty, however, are children, single mothers, or old people—groups with limited means to resort to crime in response to their situation. We therefore measure the poverty rate after subtracting single mothers and people under 18 or over 65. Similarly, unemployment is measured as the percentage of the civilian, male labor force that is unemployed. Using total poverty and unemployment rates gave practically identical results.

Race is a predictor of crime either through the low economic success of black males (Grogger, 1997) or the social isolation and feelings of hopelessness in black communities (Massey & Denton, 1993; Sampson & Wilson, 1995). Race is measured by the percentage of the population that is nonwhite.

High residential mobility reduces the cohesion of communities and results in lower social control. As well as increasing the number of people willing to commit crimes, it makes crime easier through increased anonymity, and less willingness among people to intervene when they see a crime being committed against a neighbor's property or person. Mobility is measured as the fraction of the population over age five who lived in a different place five years ago.

Family instability is measured by the percentage of families headed by a single female. Liberal criminologists (such as Currie (1985)) see the link from family instability to crime in the emotional disturbances suffered by children during family break-up, and the increased risk of poverty in female-headed households. The character-forming role of families is emphasized by conservatives (such as Gottfredson & Hirschi (1990)) who associate weak family structure with lack of self-control in children, leading to criminal behavior.

The last two variables used are the percentage of adults over age 25 with four or more years of college education, and the percentage of the population aged 16 to 24. College education reflects both increased economic opportunity and greater socialization, while the age variable captures the segment of the population that is most predisposed to commit crime (Cohen & Land, 1987).

D. Summary Statistics

We examine the impact of inequality on crime using urban counties as the unit of analysis. Although there are 829 metropolitan counties in the contiguous 48 states, 70% of the urban population and 80% of violent and property crime are accounted for by the largest 200. We therefore list results for

TABLE 1.—SUMMARY STATISTICS FOR CRIME RATES, PER THOUSAND POPULATION, AND EXPLANATORY VARIABLES

	All Counties		Largest 200	
	Mean	SD	Mean	SD
Violent	4.69	4.31	7.84	5.51
Property	40.32	22.94	57.07	21.33
Assault	3.1	2.74	4.5	3.15
Robbery	1.19	1.74	2.78	2.55
Murder	0.06	0.08	0.1	0.11
Rape	0.33	0.26	0.46	0.27
Burglary	10.03	6.23	13.74	6.19
Larceny	26.91	15.18	36.08	12.88
Auto	3.38	3.7	7.25	5.13
Population	228.87	465.65	671.52	793.36
Density	541.12	1255.88	1385.34	2115.44
Income Gini	34.94	5.11	36.86	4.42
Education Gini	28.28	3.15	29.06	3.03
Female Head	14.14	4.64	16.62	5.33
Nonwhite	13.81	12.74	19.44	13.18
Unemployed	5.86	2.07	6.18	2.13
Poverty	8.1	3.97	7.54	4.06
Movers	46.4	8.27	48.42	7.89
Young	13.54	3.38	13.47	2.1
College	18.15	8.13	23.27	7.12
Police	61.21	33.38	87.8	39.44

these counties separately.³ Data are taken from the 1994 *County and City Data Book*. (Definitions of variables are given in table A.1.)

Summary statistics for crime rates and explanatory variables, in levels, are given in table 1.

Simple correlations between rates of violent and property crime and the covariates, in logs, are given in table 2. Inequality is correlated with both violent and property crime, although the strongest correlation with crime is obtained with percentage nonwhite and percentage female-headed families. Among potential explanatory variables, income inequality is most strongly correlated with poverty and percentage of female-headed families, and educational

inequality is less so. Percentage of female-headed families and percentage nonwhite are strongly correlated, as are rates of poverty and unemployment.

IV. Regression Results: Exogenous Police Activity

This section reports results for the count model (1) and (2). In looking at the factors that determine crime rates, we will assume here that police expenditure is determined independently of crime rates. As section V will show, allowing police expenditure to be endogenous does not alter the results obtained materially.

Table 3 gives results of a Poisson regression of violent and property crime on income and educational inequality for all urban counties and the largest 200. To allow for possible overdispersion, standard errors are computed by a quasi-likelihood procedure (Davison & Hinkley, 1997). The residual deviance term is twice the difference between the maximum log-likelihood and the log-likelihood obtained using all explanatory variables; the null deviance is twice the difference between the maximum log-likelihood and the log-likelihood obtained using only an intercept term (Cameron & Trivedi, 1998). Coming from Poisson regressions with log explanatory variables, the estimated coefficients are immediately interpretable as elasticities.

What is most striking about table 3 is the very different behavior of violent and property crime. Both types of crime are significantly influenced by the proportion of female-headed families (with an elasticity of 1.6 for violent crime and 0.7 for property crime), population mobility (with elasticities of 1.6 and 1.3 for violent and property crime), and proportion of young people (with an elasticity of -1 for both categories). Violent crime is little affected by police activity or poverty but strongly affected by inequality, measured either by income or education, with estimated elasticities above unity. By contrast, inequality has little impact on property crime, which, as Machin and Meghir (1999) find for British data, is significantly aggravated by

TABLE 2.—CORRELATIONS AMONG VARIABLES

	Violent Rate	Property Rate	Population	Density	Income Gini	Education Gini	Female Head	Non-white	Unemployed	Poverty	Movers	Young	College	Police
Violent rate	1	0.8	0.3	0.25	0.46	0.27	0.71	0.74	0.42	0.56	0.2	0.19	-0.16	0.45
Property rate	0.83	1	0.17	0.1	0.3	0.19	0.41	0.51	0.25	0.42	0.32	0.16	-0.06	0.31
Population	0.49	0.43	1	0.46	0.23	0.24	0.24	0.35	0.11	0.06	0.02	-0.06	0.17	0.53
Density	0.41	0.35	0.67	1	0.15	0.4	0.42	0.32	0.02	-0.14	-0.34	-0.02	0.29	0.52
Income Gini	0.33	0.21	0.28	0.14	1	0.55	0.47	0.49	0.32	0.55	0.08	0.12	0.08	0.32
Educational Gini	0.27	0.16	0.09	0.27	0.43	1	0.37	0.47	0.13	0.23	-0.11	0.23	0.33	0.29
Female head	0.57	0.35	0.38	0.46	0.45	0.43	1	0.73	0.66	0.61	-0.12	0.33	-0.2	0.47
Nonwhite	0.61	0.43	0.36	0.33	0.39	0.44	0.66	1	0.35	0.48	0.21	0.34	0.01	0.52
Unemployed	0.22	0.08	0.15	-0.03	0.35	-0.01	0.46	0.11	1	0.7	-0.21	0.19	-0.58	0.22
Poverty	0.23	0.07	-0.05	-0.23	0.53	0.31	0.48	0.25	0.66	1	0.22	0.39	-0.42	0.13
Movers	0.28	0.33	0.25	0.13	0.19	0.05	0	0.32	-0.21	-0.02	1	0.19	0.19	0.05
Young	0.13	0.14	0.11	0.13	0.3	0.27	0.29	0.23	0.12	0.35	0.31	1	0.11	0.02
College	0.22	0.31	0.51	0.51	0.21	0.24	0.05	0.23	-0.34	-0.3	0.52	0.25	1	0.22
Police	0.45	0.43	0.57	0.54	0.27	0.22	0.47	0.48	0.11	0.03	0.24	0.05	0.44	1

All variables in logs. Entries below diagonal are for all counties; entries above are for largest 200.

TABLE 3.—DETERMINANTS OF CRIME: EXOGENOUS POLICE EXPENDITURE

	Income Inequality				Educational Inequality			
	All Counties		Largest 200		All Counties		Largest 200	
	Violent	Property	Violent	Property	Violent	Property	Violent	Property
Intercept	-11.7507 (0.7396)	-0.8078 (0.576)	-12.6106 (1.5291)	-0.3304 (1.2082)	-11.476 (0.7758)	0.1399 (0.5958)	-12.3127 (1.6045)	0.1865 (1.2291)
Population	1.2329 (0.0137)	0.9568 (0.0107)	1.2435 (0.0281)	0.9451 (0.0225)	1.255 (0.0138)	0.9529 (0.0105)	1.2659 (0.0283)	0.9414 (0.0221)
Density	0.0582 (0.0168)	0.0362 (0.0122)	0.0687 (0.0344)	0.0372 (0.0246)	0.0245 (0.0165)	0.0399 (0.012)	0.0339 (0.0338)	0.0404 (0.0243)
Gini	1.3346 (0.1509)	-0.1535 (0.1174)	1.3846 (0.3074)	-0.1547 (0.2378)	1.1906 (0.1583)	-0.4168 (0.123)	1.2204 (0.3229)	-0.2974 (0.2459)
Female head	1.5751 (0.0942)	0.7923 (0.0709)	1.6414 (0.1926)	0.7222 (0.1464)	1.7032 (0.0952)	0.7489 (0.0709)	1.7708 (0.1951)	0.6867 (0.1471)
Nonwhite	0.0568 (0.0391)	-0.0305 (0.0251)	0.0414 (0.0808)	-0.0384 (0.0539)	-0.0148 (0.0393)	0.0004 (0.0268)	-0.0342 (0.0812)	-0.015 (0.0575)
Unemployed	-0.0489 (0.0775)	0.0158 (0.0599)	-0.021 (0.159)	0.0258 (0.1251)	0.0505 (0.084)	-0.0234 (0.0611)	0.0868 (0.1731)	0.0049 (0.1269)
Poverty	-0.216 (0.0666)	0.3452 (0.0483)	-0.2663 (0.1368)	0.3888 (0.0988)	-0.0776 (0.0616)	0.3703 (0.0429)	-0.1169 (0.1266)	0.3943 (0.0875)
Movers	1.6043 (0.1228)	1.3384 (0.0879)	1.7587 (0.2564)	1.2716 (0.1841)	1.7753 (0.1342)	1.2299 (0.0922)	1.9383 (0.2811)	1.1985 (0.1929)
Young	-0.9055 (0.1017)	-1.0359 (0.0786)	-0.9524 (0.2079)	-1.0251 (0.166)	-1.1988 (0.0997)	-0.9752 (0.073)	-1.259 (0.2039)	-0.9707 (0.1543)
College	-0.2974 (0.0659)	0.1842 (0.0475)	-0.3075 (0.1356)	0.1857 (0.0989)	-0.186 (0.0629)	0.2206 (0.0467)	-0.1841 (0.1294)	0.2048 (0.0971)
Police	-0.0209 (0.0387)	-0.1046 (0.0341)	-0.0267 (0.0781)	-0.1128 (0.0692)	-0.0709 (0.0431)	-0.0808 (0.0345)	-0.077 (0.0875)	-0.0973 (0.0703)
Null dev.	45.511	78.009	39.869	56.525	45.511	78.009	39.870	56.525
Resid. dev.	8.102	22.493	7.365	19.901	8.298	22.228	7.578	19.792

Logistic regression results for all urban counties and largest 200. Standard errors are in parentheses. All explanatory variables are in logs. Deviances multiplied by 10^{-9} .

poverty with an elasticity of 0.3 and moderately deterred by police expenditure with an elasticity around -0.1^4

Given the tendency of households to segregate themselves by income and for crimes to be committed locally, it is notable in table 3 that the largest urban counties show the same impact of inequality on violent crime as the entire sample which is dominated by relatively small counties. In counties with large populations, high-income households are less likely to live near low-income ones, but inequality still induces violent crime. As a result, urban flight by high-income households will reduce their exposure to crime but, to the extent that they are still observed driving nice cars and shopping in expensive stores by poorer individuals, their absence will not lessen the strains that lead to violent crime.⁵

A. Robustness

Given the fairly large correlations shown in table 2 between poverty, female-headed households, and income

⁴ At the suggestion of a referee, the percentage of households at different income levels was used as an alternative to poverty, specifically the fraction of households with incomes below \$15,000 and between \$15,000 and \$25,000, corresponding to percentiles 24 and 42 of the U.S. income distribution. Both measures performed somewhat better than the poverty rate with elasticities of 0.37 and 0.21, respectively, both significant at 5%, for violent crime, and 0.55 and 0.63 for property crime over all counties, with similar results for the largest 200. However, the coefficients on inequality were unaffected by this change of variable.

⁵ For evidence on the link between crime and urban flight, see Cullen and Levitt (1997).

inequality, it is natural to ask how robust is this result that inequality strongly affects violent crime but not property crime. Although the similar pattern generated by educational inequality can increase our confidence in the validity of the finding, we must ensure that the result is not the consequence of a fortuitous combination of explanatory variables. To test robustness, we ran regressions that, from equation (2), always included population, density, and police expenditure, and looked at how the estimated coefficient of inequality changed as all 127 combinations of the remaining seven explanatory variables were used. As table 4 shows, the result is extremely robust. Income inequality is a large and significant predictor of violent crime in every regression. Educational inequality is significant less often. However, in

TABLE 4.—ROBUSTNESS OF ESTIMATED COEFFICIENTS OF INEQUALITY

	All Counties			Largest 200		
	Min.	Max.	$t > 2$	Min.	Max.	$t > 2$
Violent Crime						
Income Gini	0.76	2.73	100.0	0.88	2.72	100.0
Education Gini	-0.02	1.98	95.2	0.01	2.09	79.5
Property Crime						
Income Gini	-0.46	1.29	67.8	-0.46	1.35	46.4
Education Gini	-1.23	0.51	7.1	-0.99	0.62	0.8

Range of estimated coefficients of inequality in Poisson regressions of crime on population, density, police, and all combinations of female head, nonwhite, unemployed, poverty, movers, young, and college. Column $t > 2$ gives percentage of regressions where the asymptotic t -statistic exceeded 2.

regressions that include percentage of female-headed families—the most important single predictor of violent crime—it is always significant. By contrast, the effect of inequality on property crime varies widely depending on the choice of other explanatory variables.

An additional test of robustness was to run the model on data for the same counties ten years earlier. The results, not reported here, are almost identical to those reported in table 3: poverty had a strong impact on property crime, while the elasticity of violent crime with respect to inequality was above unity. Data for 1981 and 1991 were also combined into a longitudinal model in which the coefficients of a fixed-effects Poisson model are estimated by a simple logit procedure (Cameron & Trivedi, 1998, Section 9.3.1). However, the lack of variability in the explanatory variables between the two periods resulted in large standard errors, with population being the only significant variable in the longitudinal regressions.

As a final test of robustness, we examined the effect on the reported results of omitting counties with unusually high or low rates of reported crime. In no case did the results obtained change significantly.

B. Categories of Crime

Table 5 gives a breakdown of crime into individual categories for the largest 200 counties. The results for all urban counties are practically identical. The high elasticity of violent crime with respect to inequality is generated by the strong impact of inequality on assault and robbery. It is not possible to find a significant effect on murder, due

perhaps to the relative rarity of that crime, while the effect on rape is of the wrong sign. Although the elasticities of burglary and car theft are reasonably large, inequality has no significant effect on the components of property crime.

Property crime increases proportionately with population (and violent crime more than proportionately), while density has little effect on crime. Race, measured by the percentage of the population that is nonwhite, has a significant effect on murder, rape, and car theft. Percentage of female-headed households affects all categories of crime but is particularly strong for violent crime, and poverty affects the two smallest categories of violent crime (rape and murder) but has a significant impact on property crime, particularly burglary and larceny. Except for car theft, unemployment either has an insignificant effect or reduces crime, reflecting the presence of other measures of deprivation. Population turnover is one of the strongest predictors of crime, with an elasticity around unity for all categories of crime, while a large population of young people actually reduces crime substantially. The percentage of college educated adults is negatively related to violent crime but unrelated to property crime. Police activity has a strong deterrent effect on property crime, particularly burglary and larceny, with an elasticity of approximately -0.2 , but little impact on violent crime.

How well do the three ecological theories of crime match these results? Viewed as a theory of property crime, the economic theory of crime works well: poverty leads to crime and police activity deters it. However, the economic theory of crime is uncomfortable with violent crime: why should

TABLE 5.—DETERMINANTS OF CRIME BY CATEGORY

	Assault	Robbery	Murder	Rape	Burglary	Larceny	Auto
Intercept	-13.6081 (2.1712)	-14.2012 (1.5385)	-11.5976 (1.7299)	-2.4313 (2.929)	-2.4248 (1.2301)	0.9984 (1.5187)	-6.8164 (1.7571)
Population	1.2596 (0.0416)	1.3084 (0.0266)	1.0319 (0.0342)	0.8703 (0.0592)	0.9325 (0.0233)	0.9197 (0.0285)	1.0244 (0.0322)
Density	0.0003 (0.0482)	0.1731 (0.0347)	0.005 (0.0411)	-0.0039 (0.0598)	0.0217 (0.0246)	0.0262 (0.0306)	0.1001 (0.0383)
Income Gini	1.5459 (0.4276)	1.3946 (0.3143)	-0.333 (0.412)	-0.9793 (0.6371)	0.2085 (0.2453)	-0.5336 (0.2933)	0.3792 (0.3703)
Female head	1.4408 (0.2767)	2.0965 (0.1862)	1.2774 (0.2413)	1.2312 (0.3624)	0.7168 (0.1453)	0.7927 (0.1838)	0.4839 (0.222)
Nonwhite	0.03 (0.1115)	-0.0015 (0.0833)	0.5969 (0.1051)	0.032 (0.1379)	0.0267 (0.056)	-0.1061 (0.0647)	0.1684 (0.0899)
Unemployed	0.0538 (0.2311)	-0.1623 (0.1532)	0.3041 (0.1845)	-1.1246 (0.2994)	-0.1212 (0.1277)	-0.0756 (0.1537)	0.4451 (0.1941)
Poverty	-0.4327 (0.1873)	-0.0827 (0.1431)	0.4698 (0.1835)	1.1031 (0.2671)	0.4572 (0.1011)	0.4196 (0.1221)	0.3064 (0.152)
Movers	1.7174 (0.3595)	1.81 (0.2548)	1.2889 (0.3168)	1.262 (0.4546)	1.4104 (0.1868)	1.1738 (0.2272)	1.5126 (0.2891)
Young	-0.5397 (0.2938)	-1.7529 (0.2102)	-0.9962 (0.2785)	-0.4235 (0.4153)	-0.9969 (0.1708)	-1.1859 (0.2067)	-0.6141 (0.2437)
College	-0.3543 (0.1926)	-0.1752 (0.1359)	0.3307 (0.1731)	-0.2699 (0.2366)	-0.0651 (0.0988)	0.3287 (0.1221)	0.0264 (0.1553)
Police	0.0205 (0.118)	-0.1226 (0.0711)	-0.0443 (0.0825)	-0.1481 (0.1737)	-0.1924 (0.071)	-0.0514 (0.0864)	-0.1974 (0.1013)
Null dev.	11.055	7.97	0.006	0.032	32.425	169.189	29.514
Resid. dev.	0.416	0.119	0.000	0.007	1.165	11.199	1.193

Logistic regression results for largest 200 counties. Standard errors are in parentheses. All explanatory variables are in logs. Deviances multiplied by 10^{-9} .

individuals hurt others for no financial return unless they have some taste for violence whose origin the theory does not explain?

The role of inequality, both in income and race, in causing violent crime is in keeping with strain theory, and the importance of weak family and community ties—measured by female-headed households and population turnover—supports social disorganization theory. In summary, then, although no individual ecological theory of crime does a particularly good job of explaining all crime, between them the theories explain most of the variation in crime across different areas.

V. Regression Results: Endogenous Police Activity

The possible endogeneity of police activity leads us to use a GMM procedure to test the validity of the results reported in the previous section. Let y denote the count of crimes, X denote the right-hand variables in equation (2), Z be the set of instruments, and $\lambda = \exp(X\beta)$ be the expected number of crimes. The efficient two-step GMM estimator $\hat{\beta}$ is found by minimization of

$$(y - \lambda)' Z(Z' \Omega Z)^{-1} Z' (y - \lambda), \quad (5)$$

where $Z' \Omega Z = \sum_i (y_i - \tilde{\lambda}_i)^2 z_i z_i'$ and $\tilde{\lambda}$ is the first-round IV estimate of λ (Windmeijer & Santos Silva, 1997; Mullahy, 1998). The limiting distribution of $\sqrt{N}(\hat{\beta} - \beta)$ is asymptotically normal with expectation zero and variance equal to the limit of $(N^{-1}(X' \Lambda Z)(Z' \Omega Z)^{-1}(Z' \Lambda X))^{-1}$, where Λ is a matrix with diagonal λ .

For the potentially endogenous explanatory variable (police activity), we consider three possible instruments. The first is per capita income, because high-income areas can afford to spend more on police protection. The second is the share of non-police expenditure by local government in total county income, on the grounds that lavish spending districts will spend more on their police forces regardless of crime rates. The last potential instrument is the percentage of voters that voted against the Democrat candidate in the 1988 presidential election, because conservative voters should be inclined to support higher levels of police expenditure.

For the coefficient estimates $\hat{\beta}$ to be meaningful requires two things of the instruments Z . First, the instruments used must be orthogonal to the regression errors; secondly, the instruments must have reasonable explanatory power for the

explanatory variables X . The orthogonality of the instruments and residuals is measured by Hansen's J test of overidentifying restrictions (Davidson & MacKinnon, 1993). If some variable used as an instrument should really be included as an explanatory variable, this statistic will be significant.

The importance of the instruments having explanatory power for the variable of interest has been highlighted by Bound, Jaeger, and Baker (1995). The endogenous explanatory variable of interest here, police activity, itself depends on another endogenous variable, crime rates. We therefore use a GMM procedure to estimate police activity, and use the Newey-West (1987) D statistic for exclusion restrictions to measure the joint significance of the potential instruments.

Results for a linear model of police expenditure per crime are reported in table 6. Explanatory variables used were population, density, income inequality, movers, young, college, and the total crime rate, as well as the three variables of interest: income, expenditure share, and non-Democrat. For total crime rate, the instruments used were female head, nonwhite, unemployed, and poverty.

The insignificant J statistic indicates that these instruments are correctly omitted as explanatory variables, and the highly significant D statistic indicates that they have strong explanatory power for crime rates. A Hausman statistic is estimated from an artificial regression of residuals from a regression excluding the endogenous explanatory variable onto the predicted value of that variable from its instruments (Davidson & MacKinnon, 1993). It indicates that any endogeneity in crime rates does not have a substantial impact on estimated coefficients for the largest 200, but a significant effect for all counties. All three potential instruments are significant, although non-Democrat voters is marginal for the largest counties, and together they have strong explanatory power for police expenditure: the p value of their joint exclusion is below 0.0001 for both samples, and a regression of police expenditure on the three variables has an R^2 of 0.49 and 0.54 for all counties and the largest 200, respectively.

Having established that our instruments are reasonable ones for police activity, we report regression results for violent and property crimes in table 7, for all urban counties and for the largest 200. Using the first-stage, nonlinear instrumental-variables estimates gave practically identical results to GMM. The reported results use percentage non-

TABLE 6.—DETERMINANTS OF POLICE EXPENDITURE PER CAPITA

	Population	Income	Expenditure Share	Non-Democrat	Total Rate	J	H
All counties	-0.028 (0.0206)	1.3007 (0.1549)	0.4922 (0.0562)	-0.5969 (0.0788)	0.464 (0.0536)	0.0498	0.0000
Largest 200	0.1172 (0.0292)	1.2825 (0.2256)	0.6379 (0.0887)	-0.1735 (0.1091)	0.2379 (0.1166)	0.2037	0.3137

GMM estimates of determinants of police expenditure per capita. Standard errors in parentheses. All variables in logs. Explanatory variables not reported: intercept, density, Gini, movers, young, college. Instruments for total rate: female head, nonwhite, unemployed, poverty. J : p value of Hansen's test of over-identifying restrictions. H : p value of Hausman endogeneity test. p value of exclusion test for explanatory power of instruments for both samples: 0.0000.

TABLE 7.—DETERMINANTS OF CRIME: ENDOGENOUS POLICE EXPENDITURE

	All Counties		Largest 200	
	Violent	Property	Violent	Property
Intercept	-5.9314 (0.9913)	-2.3003 (0.694)	-6.7852 (1.4776)	-1.3564 (1.2345)
Population	1.1664 (0.0273)	1.0407 (0.03)	1.1669 (0.0371)	0.9918 (0.0311)
Density	0.0437 (0.0305)	0.0245 (0.0235)	0.0586 (0.0371)	0.0678 (0.0349)
Income Gini	0.4888 (0.2192)	0.0507 (0.143)	0.7472 (0.2921)	0.119 (0.2305)
Female head	1.2667 (0.1608)	0.7199 (0.1321)	1.3809 (0.2091)	0.6876 (0.1668)
Nonwhite	0.2285 (0.0429)	0.0653 (0.0274)	0.232 (0.0694)	0.0738 (0.0553)
Unemployed	-0.198 (0.1201)	-0.0676 (0.0943)	-0.3393 (0.1824)	0.0406 (0.1514)
Poverty	0.201 (0.0867)	0.2335 (0.0656)	0.1647 (0.1252)	0.26 (0.0844)
Movers	1.0911 (0.175)	1.2639 (0.1853)	1.1598 (0.2436)	1.3698 (0.2862)
Young	-0.7622 (0.1478)	-0.5534 (0.1572)	-0.7209 (0.2177)	-0.7926 (0.2071)
College	-0.2729 (0.0909)	0.0533 (0.0794)	-0.3816 (0.1311)	0.0791 (0.098)
Police	-0.1938 (0.1418)	-0.1089 (0.1316)	-0.2455 (0.168)	-0.3741 (0.1804)
<i>J</i>	0.7303	0.0000	0.9558	0.0008
<i>H</i>	0.3967	0.0000	0.0508	0.0595

GMM estimates of Poisson model. Standard errors in parentheses. Instruments for police expenditure: expenditure share, non-Democrat. All explanatory variables in logs. *p* value of exclusion test for explanatory power of instruments for both samples: 0.0000. *J*: *p* value of Hansen's test of over-identifying restrictions. *H*: *p* value of Hausman endogeneity test.

Democratic voters and spending share as instruments: using any two or three of the candidate instruments gave similar results. The estimated *J* statistics show that the instruments are orthogonal to the regression residuals for violent crime, but not for property crime where both income and expenditure share appear to have explanatory power for crime. In all cases except property crime in the total county group, the *H* statistic shows little difference in coefficient estimates due to endogeneity, and this can be seen by comparing the results with those for the exogenous case in table 3: inequality has a

strong effect on violent crime (the estimated elasticities are approximately halved, however) but not on property crime, although the effect of police activity on violent crime has edged closer to significance.

Figure 1 plots the actual rates of violent and property crime in the largest 200 counties against their estimated values from table 7. It is evident that the regression gives a close fit to the data in both cases.

VI. Conclusions

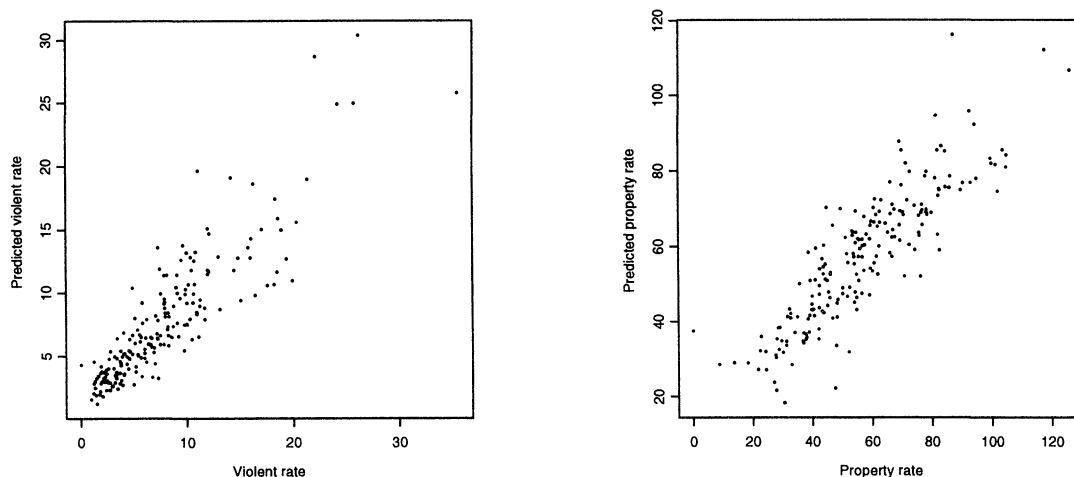
In assessing the social costs of inequality, the economics literature has tended to consider its long-run costs: lower economic growth (Persson & Tabellini, 1994) and reduced human capital formation (Bénabou, 1996; Durlauf, 1996; Kremer, 1997).⁶ This paper investigated a much more immediate cost of inequality: its impact on crime.

It showed that for violent crime the impact of inequality is large, even after controlling for the effects of poverty, race, and family composition. Although most crimes are committed by the most disadvantaged members of society, these individuals face greater pressure and incentives to commit crime in areas of high inequality.

This paper took a first step in investigating the link between crime and inequality, finding that it was not possible to reject the hypothesis that inequality causes violent crime for one data set. The natural extension of this work is to test the model, both in cross section and longitudinally, on a wider range of data, such as U.S. cities or British police-force areas. Given the relatively large geographical units analyzed here, it would be particularly interesting to examine neighborhood data to see if local inequality translates into increased levels of property crime.

⁶ The public health literature has considered the link between inequality and mortality rates. See, for instance, Kaplan et al. (1996).

FIGURE 1.—ACTUAL VERSUS PREDICTED CRIME RATES



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APPENDIX A—EXPLANATORY VARIABLES AND INSTRUMENTS

TABLE A.1.—DEFINITION OF EXPLANATORY VARIABLES AND INSTRUMENTS

Explanatory Variables	
Population	County population in 1,000s
Density	Population per square mile, 1990.
Income Gini	Gini coefficient calculated from ratio of mean to median household income, 1989.
Educational Gini	Gini coefficient calculated from percentages of population aged 25 years and over with twelve or fewer, or sixteen or more, years of education, 1990.
Female head	Percentage of families with female head, no spouse present, 1990.
Nonwhite	Percentage of population that is nonwhite, 1990.
Unemployed	Percentage of male labor force that is unemployed, 1990.
Poverty	Percentage of population aged 18 to 65, excluding single mothers, that is in poverty, 1990.
Movers	Percentage of the population aged five years and over that lived in a different house five years ago, 1990.
College	Percentage of population aged 25 years and over that has completed four or more years of college, 1990.
Young	Percentage of population aged 16 to 24 years, 1990.
Police	Police expenditure per capita 1987.
Instruments	
Expenditure share	Local government expenditure 1987, excluding police, as percentage of aggregate county income.
Income	Per capita income in 1989.
Non-Democrat	Percentage of voters that did not support the Democratic presidential candidate, 1988