Income inequality and crime: the case of Sweden[#]

by

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Abstract

The degree of income inequality in Sweden has varied substantially since the 1970s. This study analyzes whether this variation has affected the crime rate using a panel of Swedish county-level data for the period 1973–2000. We consider various measures of income inequality to evaluate which part of the distribution that matters most in determining crime rates. Our results indicate that there is a statistically significant positive effect of the proportion of the population with an income below 10 percent of median income on the incidence of property crime. Moreover, the unemployment rate has a positive effect on the incidence of the number of overall crime, auto thefts and robberies. The results look different for the violent crime category assault.

Keywords: crime, income inequality, panel data
JEL classification: D31, I32, J00, K40

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1 Introduction

Earlier research has shown that the unemployment rate affects some major crime categories, especially property crime, in Sweden.[1] Higher unemployment leads to e.g. more auto theft and burglary. But is it merely a sudden, and often time-limited, decrease in income from an unexpected unemployment spell that influences the individual's decision on whether or not to commit a crime? Considering the far-reaching consequences of detection, crime rates should be more responsive to long-term changes in labor market opportunities.

Economic theories of crime explain variations in crime rates through the varying incentives and deterrents that face individuals. Following Becker (1968), the individual chooses whether or not to engage in criminal activities by comparing the returns from those activities to the returns from working legally. Presumably the expected returns to illegal activities are to a great extent depending on the opportunities provided by potential victims and could therefore be seen as proportional to the mean income in the society. The cost of committing crime however increases with the potential legal income of the criminal through the opportunity cost of time. In a society with considerable income inequality the gap between the mean income and the potential legal income of low-skilled workers will be large and hence give incentives for people at the bottom part of the income distribution to commit crime. Being at the lower end of the income distribution must be considered as a more long-term condition than being temporarily unemployed, hence income inequality reflects long-term labor market opportunities to a greater extent than unemployment rates do.

For reviews of the literature on the link between income inequality and crime, see e.g. Bourguignon (2001), Eide (1999) and Freeman (1999). As one of the first empirical papers on the economics of crime Ehrlich (1973) analyzed the variations of crime rates across U.S. states and found a strong positive correlation between income inequality, measured by the percentage of the population with an income below one half of median income, and property crime. More recently, Gould et al (2002) use U.S. county-level data and show that the decline in wages of unskilled men can explain more than 50 percent of

[1] See Edmark (2003) and Nilsson and Agell (2003).

the increase in both violent and property crime during the 1980s and 1990s.[2] Machin and Meghir (2000) find an effect of wages of less skilled workers in the U.K. on property crime using data on police force areas for the period 1975–1996.[3] Bourguignon et al (2002) argue that criminals in Colombia are to be found among people living in households where income per capita is below 80 percent of the mean. The share of the population in that group and their mean income relative to the overall population appear to be main determinants of the variations in the property crime rate. The literature thus indicates a link between crime and income inequality. This paper studies what part of the income distribution that matters most in determining Swedish crime rates and whether this link holds for both property and violent crime.

This paper uses a new panel dataset covering all Swedish counties during the period 1973–2000. The long time period contains considerable variations in the income distribution. Figure 1 illustrates the evolution of the Gini-coefficient. From the beginning of the 1980s until today the spread of the distribution of pre-tax earnings has increased with the trend becoming even more evident in the 1990s.[4] This study analyzes whether this variation in the income distribution has affected the overall crime rate as well as specific property and violent crime rates. We consider several measures of income inequality in trying to evaluate if there is a specific part of the income distribution that matters most in determining crime rates.

[2] Other papers studying the effect of income inequality on violent crime are Demombynes and Özler (2002), Entorf and Spengler (2000), Fajnzylber et al (2002) and Kelly (2000).

[3] Also, Grogger (1998) uses individual level data and conclude that falling real wages played an important role in the increase of youth crime during the 1970s and 1980s in the U.S. Freeman (1994, 1996) discusses the role of falling real earnings of the less educated in the, despite massive imprisonment of criminals, high crime rate in the U.S. Imrohoroglu et al (2000) also conclude that increased inequality has prevented a larger decline in crime in the U.S.

[4] See e.g. Edin and Holmlund (1995) for a discussion on the evolution of wage dispersion in Sweden.

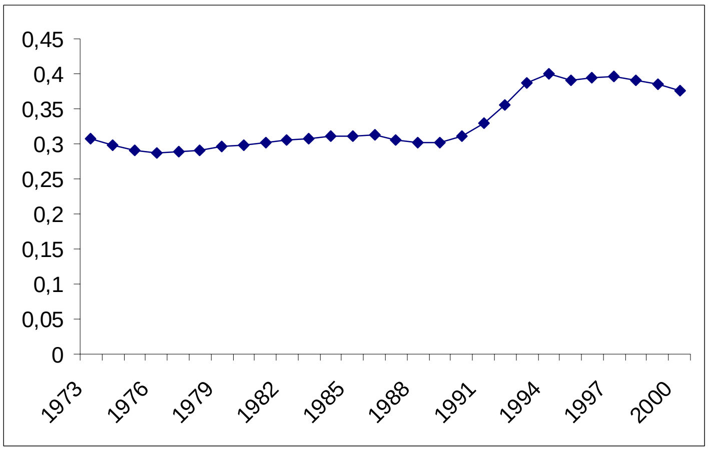

Figure 1 The Gini-coefficient using pre-tax earnings. The Gini-coefficient is the national mean of the Gini-coefficients of all counties each year. The measure is calculated using the individual earnings measure in LINDA for all men aged 25–64.

The unique aspect of this paper is that we have access to individual-level income information, which allows us to construct various measures of earnings inequality. We construct measures of the changes in the income distribution on the county-level from an individual-level register-based longitudinal dataset (LINDA), which is a representative sample covering 3.4 percent of the population annually.[5] We will consider measures of income inequality based on individual labor earnings.[6] In addition to our measures of earnings inequality, we control for various demographic and socio-economic characteristics of the county and include county and time fixed effects as well as county-specific time trends. In a sensitivity analysis we also include deterrence variables as regressors and estimate a dynamic specification.

We find that there is a statistically significant positive effect of the proportion of the population with an income below 10 percent of the median income on the incidence of property crime. The results look very different for the violent crime category assault. Moreover, the unemployment rate has a positive effect on the incidence of the number of overall crime, auto thefts and robberies

[5] The data set includes approximately 300,000 individuals each year. For details about the data set see Edin and Fredriksson (2000).

[6] It would also be of interest to consider measures of income inequality based on disposable income. Disposable income is, however, only included in LINDA since 1978, and the definition of the variable has changed numerous times.

even when controlling for the size of the low-income group separately. These results correspond to the findings in Nilsson and Agell (2003). Furthermore, our empirical findings suggest that Swedish crime rates suffer from a high degree of inertia.

The next section presents a simple model of the link between income inequality and property crime. Section 3 describes the data and the empirical specification and in section 4 the basic results on the link between income inequality and property crime are reported. Section 5 analyzes the effect of income inequality on violent crime and discusses alternative econometric specifications. The final section summarizes.

2 A simple model

In the economic theory of crime an individual chooses between legal and illegal activities by comparing the returns to these activities within the framework of the economic theory of choice under uncertainty. It is not necessarily a choice between two mutually exclusive activities but a choice of determining the optimal allocation of time between competing legal and illegal activities.

The expected returns to illegal activities depend on the opportunities provided by potential victims of crime. If criminals were unable to choose their targets the expected gain from crime would be proportional to the mean income in society. The cost of devoting time to illegal activities, however, depends on the opportunity cost of time. The opportunity cost is the returns to legal activities, which is a function of the individual's ability, education and other legitimate training. In a society with considerable income inequality the gap between the mean income and the potential legal earnings of low-skilled workers will be large and hence give incentives for people at the bottom part of the income distribution to commit crime.

A simple model may clarify the issues. Consider an individual's choice between working and committing crime to gain income during a single period. We assume that crime and legal labor market activity are mutually exclusive activities, and that the individual is faced with the option of either going to work, or to spend the period committing one crime. Let y be the individual's income from legal labor market activity, $\bar{y}$ the mean income in society, and t the expected returns to illegal activity (which is the same as the percentage loss to a victimized individual). Further, let μ_V be the risk of being victimized, μ_A the risk of apprehension for a criminal, δ the (psychic) disutility cost from being victimized, f a fine payable in case of apprehension, and κ any (psychic) disutility cost from being punished for a crime. In case the criminal is apprehended, we assume that the stolen amount is returned to the victim. Finally, we assume that all individuals are alike, except for the fact that they differ with respect to their legal labor market income, y.

Based on this notation the expected value from participating in legal activity can be written as:

$$EV_L = (1-\mu_V)U(y) + \mu_V\left[(1-\mu_A)U(y(1-t)) + \mu_A U(y) - \delta\right] \qquad (1)$$

The expected value from participating in illegal activities is:

$$EV_I = (1-\mu_A)U(t\bar{y}) + \mu_A(U(-f) - \kappa) \qquad (2)$$

In writing (1), we have assumed that criminals only steal money from law-abiding citizens, which implies that criminals do not bother about the risk of being victimized. Modifying this assumption is straightforward, but does not alter our argument.

If the expected returns from crime exceed those from legal activities the individual will engage in criminal activities. Thus depending on whether EV_L is greater or smaller than EV_I the individual will become an ordinary worker or a criminal. For our purpose it is useful to identify the individual who is just indifferent between legal market work and illegal activity. Formally, we solve for that cut-off level of labor market income y^*, which gives us equality between EV_L and EV_I. In general terms, we can define y^* as

$$y^* = f(\bar{y}, \mu_V, \mu_A, \delta, \kappa, t, f) \qquad (3)$$

Because of the simple form of the return functions (1) and (2), it follows readily that every individual with labor market income y below y^* will choose to become a criminal while everyone with income greater than y^* will choose legal labor market activity. Furthermore, it is a tedious but straightforward exercise to derive the following comparative static results:

$$\text{(i) } \frac{\partial y^*}{\partial \bar{y}} > 0 \qquad \text{(ii) } \frac{\partial y^*}{\partial \mu_v} > 0 \qquad \text{(iii) } \frac{\partial y^*}{\partial \mu_A} < 0 \qquad \text{(iv) } \frac{\partial y^*}{\partial \delta} > 0$$

$$\text{(v) } \frac{\partial y^*}{\partial \kappa} < 0 \qquad \text{(vi) } \frac{\partial y^*}{\partial t} > 0 \qquad \text{(vii) } \frac{\partial y^*}{\partial f} < 0 \tag{4}$$

Equation (4) states that the minimum expected legal income required for someone not to commit a crime (i) increases with mean income, (ii) increases with the risk of victimization, (iii) decreases with the risk of apprehension, (iv) increases with the disutility cost of being victimized, (v) decreases with the disutility cost from being punished for a crime, (vi) increases with the expected returns to illegal activity and (vii) decreases with the fine payable in case of apprehension.

Next, we let $f(y)$ be the population density function, with support over the interval $[y_{\min}, y_{\max}]$. We may define the overall number of crimes in our economy with the help of the following integral:

$$\textit{Total number of crimes} = \int_{y_{\min}}^{y^*} f(y)dy \tag{5}$$

The crime rate will depend on the relative number of people with low regular labor market incomes (i.e. the population densities in the interval between y^* and $y_{\min}$), the supply of theft-worthy goods (represented by the average income $\bar{y}$), and on e.g. deterrence variables capturing the risk and disutility of being apprehended. From a policy point of view, the model predicts that policies that improve the labor market prospects of individuals at the low-end of the ability distribution will be quite successful in reducing the crime rate.

Finally, a disclaimer is in order. Though the model conveys useful intuition, it only captures the link between income inequality and property crime. Hence, in section 5 where we consider the effect of income inequality on assault we cannot expect the results to comply with the model. Also, the model has the unrealistic implication that every agent with low labor market ability will become a criminal. However, in reality it is often the case that rich individuals commit crimes to become even richer, a phenomenon that attracts a lot of attention in the media. Thus, we do not want to link our econometric specifications very tightly to this model, but we believe that the model, in a satisfying way, serves as guidance for how to view the effect of income inequality on property crime.

3 Data and econometric specification

Our panel data set includes annual data from 21 Swedish counties for the period 1973–2000.[7] The starting point for our econometric analysis is the following model:

$$Crime_{it} = \alpha_i + \lambda_t + \gamma_i time_t + \theta I_{it} + \beta X_{it} + \varepsilon_{it} \qquad (6)$$

where $Crime_{it}$ is the log of the number of crimes reported to the police per 100,000 residents of the crime category investigated, α_i and λ_t are county and year fixed effects and γ_i is the county-specific coefficient on a linear time trend.[8] I_{it} represents our various measures of earnings inequality and X_{it} is a vector of other control variables. The estimated coefficients should be interpreted as semi-elasticities, i.e. they show the percentage change in the crime rate due to a unit change in any of the explanatory variables. All variables are weighted by the county and time specific population.

The crime data were provided by *The National Council for Crime Prevention (BRÅ)*. We focus primarily on the effect of income inequality on the overall crime rate and on three major property crime-categories: burglary, auto theft and robbery. As a sidetrack we also consider the effect of income inequality on the assault rate in section 5. Table 1 shows the descriptive statistics for the crime variables. Evidently, property crimes are far more common than violent crime. The county of *Stockholm* accounts for all the maximum-values of our crime variables whereas the counties of *Gotland*, *Blekinge* and *Jämtland* share the minimum-values.

[7] During this period there have been changes in the county-structure, in 1997 *Kristianstad* and *Malmöhus* county jointly became *Skåne* county and in 1998 *Göteborg-* & *Bohus-county, Älvsborg* and *Skaraborg* were merged into *Västra Götalands* county. We use the latter classification throughout the whole period, leaving us with 21 counties.

[8] Assuming that unobserved covariates are constant within a county for 28 years or that they are changing over time in accordance with a national time trend is restrictive. Including county-specific trends relaxes the specification and allows the trend to vary across counties. For a more detailed discussion on the issue, see Friedberg (1998) and Raphael and Winter-Ebmer (2001).

Table 1 Descriptive statistics, crime variables

Variables	Min	Max	Mean	Standard deviation
All crimes	5087	21600.8	10464.9	2835.6
Burglary	687.1	3383.4	1383.1	416.2
Auto theft	119.9	1926.3	432.8	236.5
Robbery	1.8	210.7	30.4	30.1
Assault	104.9	965.8	376	162.8

Note: The crime data was provided by *The National Council for Crime Prevention.* All crime categories are expressed as the annual incidence per 100,000 residents. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000.

Figures 2–4 show the evolution of the different crime categories during the last three decades. All crime rates have increased except the burglary rate, which has been volatile from year-to-year but not characterized by an increasing trend.

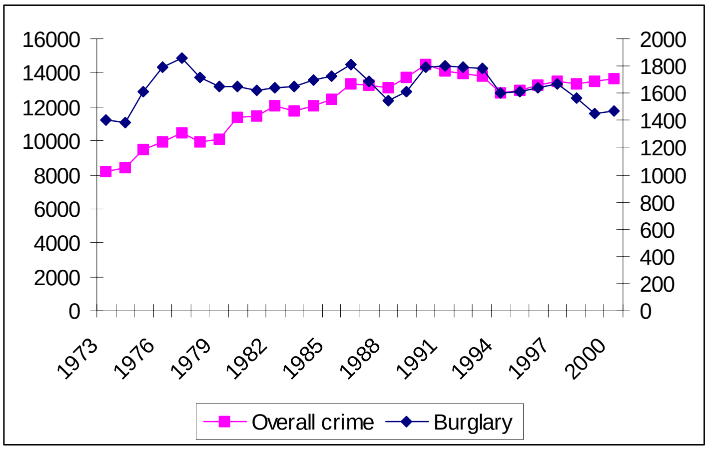

Figure 2 The total number of crimes per 100,000 inhabitants reported to the police is on the left axis and the number of burglaries per 100,000 inhabitants on the right.

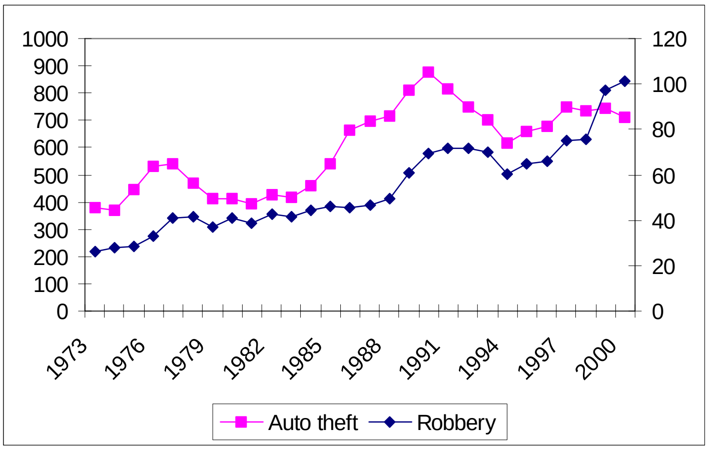

Figure 3 The number of auto thefts per 100,000 reported to the police is on the left axis and the number of robberies per 100,000 inhabitants on the right.

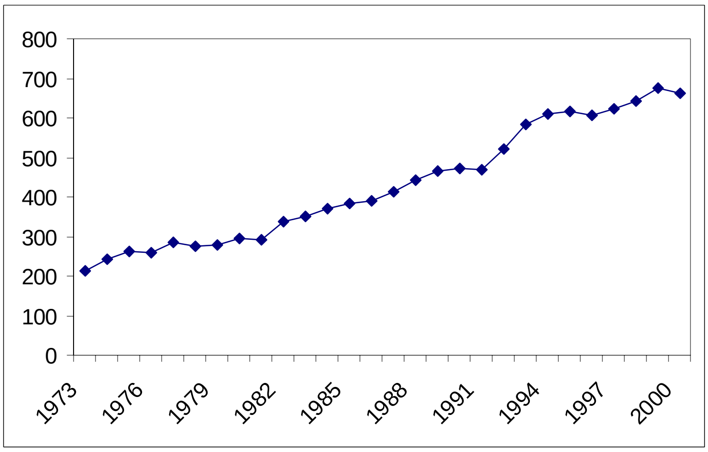

Figure 4 The number of assaults reported to the police per 100,000 inhabitants.

The data used to construct measures of the development of the income distribution are taken from the register-based longitudinal data set LINDA. The data set is a representative sample of the population starting in 1960 and it covers 3.4 percent of the population annually, which implies approximately 300,000 individuals. We focus on reported earnings of the male population in working age 25–64, giving us a sample of about 75,000 individuals per year.

The reason for only using the earnings of males is that during the relevant period there was a large shift in female labor market participation. Including the incomes of females would thus give us an inconsistent measure of earnings over time.[9]

Table 2 Descriptive statistics, income variables (annual earnings in 1980 SEK)

Variables	Min	Max	Mean	Standard deviation
10th percentile	0	28364.1	7549.06	7668.71
90th percentile	87158.65	189542.4	114070.4	13596.27
Gini-coefficient	0.258	0.459	0.330	0.045
Proportion in relative poverty:				
10 % of median income	0.045	0.214	0.115	0.039
20 % of median income	0.060	0.242	0.136	0.043
40 % of median income	0.102	0.294	0.182	0.048
Mean earnings	54341.96	101884.1	69758.94	6395.97

Note: All income variables are computed from the individual annual earnings measure included in LINDA. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. The variables are more carefully explained in Appendix.

We construct measures of the county-specific income distribution using a measure of earnings that includes sickness benefits but not pensions and unemployment insurance, given that this definition of the earnings variable is the most consistent over time.[10] Table 2 presents the descriptive statistics for our various measures of income inequality, the earnings of the 10th and 90th percentile, the Gini-coefficient, various definitions of the proportion of relatively poor and the overall mean income. Figure 5 conveys that the proportion of relatively poor increased in the beginning of the 1990s. Figure 6 presents the measures we use as proxies for the general prosperity of the area.

[9] As an alternative to using males aged 25-64 we decreased the age ceiling to 55, attempting to exclude the increasing number of individuals receiving early age retirement possibly influencing the income measures. Eliminating this age group gives us a sample of 60,000 individuals per year. However, using the smaller age group does not change the results.

[10] The measure in 1973 includes pensions but excludes sickness benefits and unemployment insurance, which makes it inconsistent with the measure during later years. We have checked whether this matters by estimating all specification using a shorter panel (1974-2000), and the results are not affected. A more detailed description of our income measures is available in Appendix.

The earnings of the 90th percentile and the mean earnings measure evolved in the same manner until the beginning of the 1990s, when the difference between them increased and the high-income group got better off compared to the rest of the population. Although we focus on the bottom part of the distribution we also take the general prosperity of the area into account, comparing the situation of the low-income group with that of the rest of the population/the high-income group. As a measure of the low-income group we use different definitions of the proportion of relatively poor residing in the county; the proportion of the population with an income below 10, 20 and 40 percent of median income. In our baseline specification the 90th percentile reflects the characteristics of the high-income group. We will also include an interaction of the low- and high-income measures, which will capture a potential effect of the two different income-groups residing in proximity to each other. We cannot predict the sign of the coefficient on this interaction. It could turn out positive if the interaction-term captures a larger supply of theft-worthy goods within reach for a large number of poor individuals to steal. It could, on the other hand, turn out negative if the rich invest more resources to protect themselves and their property when the proportion of relatively poor increases.

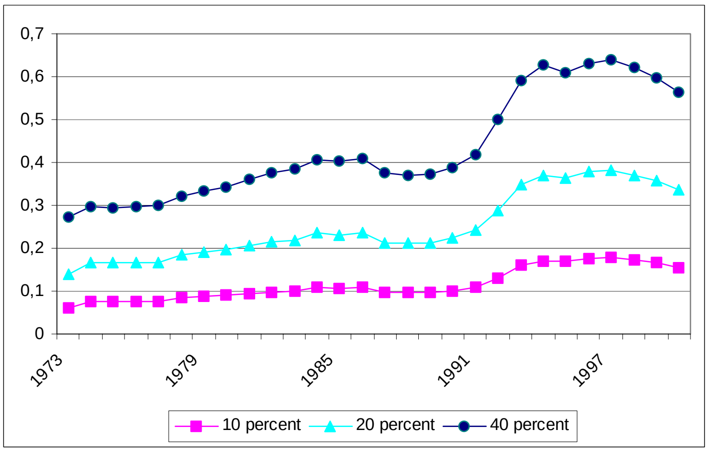

Figure 5 The relative poverty measures above are the national mean of the proportion of individuals with earnings less than 10, 20 and 40 percent of median earnings in all counties each year. The measures are calculated using the individual earnings measure in LINDA for all men aged 25–64.

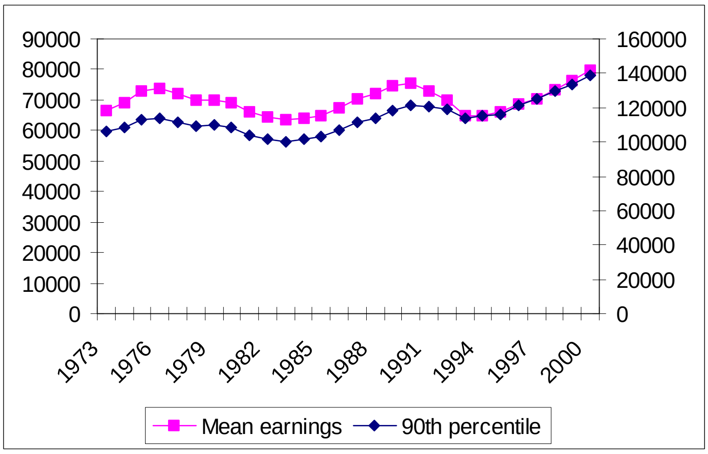

Figure 6 The earnings measures are the national means of corresponding measures in all counties each year. The measures are calculated using the individual earnings measure in LINDA for all men aged 25–64.

In addition to these income variables we also control for a possible separate effect of unemployment on crime. Nilsson and Agell (2003) identify an effect of unemployment on the incidence of overall crime, burglary and auto theft, hence excluding the unemployment rate from the analysis could lead to biased estimates. The effect of unemployment on crime is probably both a lack-of-activity effect and an income effect. Unfortunately we cannot separate the two effects, potentially causing the unemployment coefficient to capture part of the income inequality effect that we are interested in here. The inclusion of the unemployment rate in the analysis may therefore lead to under-estimated coefficients on the income distribution variables.[11]

In the analysis we control for various socio-economic and demographic factors, see Table 3. *Statistics Sweden* has provided us with data on the proportion of males aged 15–24, the proportion of foreign citizens[12] and the number of divorced individuals. The first two variables will account for the over-representation of those groups in the crime statistics and could be considered as determining the risk of being victimized. The number of divorced individuals is

[11] It should be noted that the unemployment insurance is not included in the earnings variables, hence all unemployed are registered as having zero earnings during their unemployment spell.

[12] Preferably we would include the proportion of individuals not born in Sweden but we do not have data on this before 1984. However, the two variables are highly correlated.

included to reflect the family situation for young people. Using U.S. data Levitt and Lochner (2001) find that unstable families have a strong effect on juvenile crime. Since young individuals are responsible for a disproportionate share of many crimes and since single parent households often have low incomes, not controlling for the family situation of young people might lead to omitted variable bias. All variables are more carefully explained in Appendix where also the data sources are included.

Table 3 Descriptive statistics, control variables

Variables	Min	Max	Mean	Standard deviation
Unemployment	0.008	0.128	0.042	0.025
Proportion of males aged 15–24	0.055	0.082	0.068	0.005
Proportion foreign citizens	0.006	0.100	0.039	0.020
Proportion divorced	0.020	0.103	0.059	0.017
Police officers	79.89	294.49	162.59	30.29
Clear-up rates:				
All crimes	0.11	0.35	0.210	0.038
Assault	0.21	0.57	0.357	0.071
Auto theft	0.04	0.49	0.194	0.090
Burglary	0.02	0.7	0.104	0.063
Robbery	0.06	0.82	0.287	0.111

Note: The first three variables have been provided by *Statistics Sweden*. Police officers is number of employed police officers per 100,000 inhabitants and was provided by *The National Police Board*. The clear-up rates are measured as the percentage of all reported crimes (in one specific category) that are solved the same year that they are reported. The clear-up rates were provided by *The National Council for Crime Prevention*. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000.

In the empirical specification we also include fixed effects which is equivalent to using within groups estimation, hence all variables are expressed as deviations from their county and time specific means. Besides from controlling for omitted time invariant heterogeneity these fixed effects to some extent help in solving the potential problem of measurement error. The number of recorded crimes most likely underestimates true criminal activity. If this measurement error varies systematically across counties over time our results could be biased. The empirical specification with fixed effects helps to reduce this problem by eliminating the influence of measurement errors that (a) remains constant over time, (b) varies in accordance with a general time-trend and (c) follows the county-specific time-trend.[13] The standard errors are throughout the paper robust to heteroscedasticity.[14]

4 Basic results

When studying the effect of income inequality on property crime it is not clear which part of the distribution that matters most. We focus primarily on the bottom part of the distribution, since the theory predicts that income inequality gives incentives for people at the bottom part of the income distribution to commit crime. However, we also want to control for the possibility that a greater supply of theft-worthy goods in prosperous areas may induce more property crime, as well as the possibility that prosperous areas invest more resources in crime preventing activities possibly reducing property crime.

Table 4 presents the results from three specifications where the overall crime rate is the dependent variable. The specifications use different measures of the proportion of the population living in relative poverty: the proportion of the population with an income below 10 (specification 1), 20 (specification 2) and 40 percent (specification 3) of median income. The 90th percentile reflects the characteristics of the high-income group and the interaction of the low- and high-income measures capture a potential effect of the two different income-groups residing in proximity to each other as explained above.

The coefficient on the proportion of relatively poor is significant in all specifications. The magnitude of the coefficient is smaller when a larger proportion is considered poor, suggesting that most of the effect is coming from the really low end of the income distribution. A one-percentage point increase in the proportion of the population with an income below 10 percent (40 percent) of median income would imply a 2.9 (2.0) percent increase in the overall crime rate. An increase of the 90th percentile would also raise the number of crimes, possibly reflecting the effect of a greater supply of theft-worthy goods, although the effect seems to be small. The coefficient on the interaction term shows a negative (and in two specifications statistically significant) result.

[13] See Nilsson and Agell (2003) for a more detailed discussion concerning measurement errors in Swedish crime data.

[14] We have chosen not to use the cluster-estimator since it is known to have good properties only when the number of groups is large relative to the number of units with the clusters. For a discussion on inference problems in the presence of group effects when the number of groups is small, see for example Wooldridge (2002, 2003).

We had anticipated a positive effect of the two different income-groups residing in proximity to each other when prospective criminals have access to a larger supply of theft-worthy goods. This negative coefficient could potentially be interpreted as the rich protecting themselves more when the proportion of relatively poor increases. According to the coefficient on the unemployment variable a one-percentage point drop in the unemployment rate would decrease the overall crime rate by 1.1 percent, a result in accordance with the findings of Nilsson and Agell (2003).

Table 4 Basic results, overall crime

	(1)	(2)	(3)
Relative poverty, 10 percent	2.898***		
	(1.113)		
Relative poverty, 20 percent		2.226**	
		(1.023)	
Relative poverty, 40 percent			2.004**
			(0.953)
90th percentile	4.8e-06**	4.5e-06**	4.4e-06*
	(2.3e-06)	(2.3e-06)	(2.34e-06)
Interaction	-1.6e-05*	-1.4e-05*	-9.7e-06
	(8.7e-06)	(8.1e-06)	(7.8e-06)
Unemployment	1.109*	1.103*	1.024*
	(0.618)	(0.624)	(0.623)
Males aged 15–24	0.361	1.875	1.587
	(2.527)	(2.520)	(2.543)
Foreign citizens	2.497**	2.740**	2.885**
	(1.223)	(1.227)	(1.243)
Divorced	20.337***	19.367***	19.721***
	(3.815)	(3.803)	(3.873)
Adjusted R-square	0.968	0.968	0.968

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

The coefficients on the remaining control variables also show interesting results. A one-percentage point increase in the proportion of divorced individuals would (everything else held constant) increase the overall crime rate with close to 20 percent. A corresponding change in the proportion of foreign citizens would increase the overall crime rate with 2.5 percent. At the same time, the proportion of young men seems to have no separate effect on the overall crime rate.

Although we have found some evidence of a link between income inequality and crime we cannot expect to have seen the full picture when only having considered the overall crime rate. The measure of overall crime includes many different crime categories and we do not expect economic factors to have the same effect on all of them. We will continue by studying the effect of income inequality on more specific crime categories.

Table 5 Basic results, burglary

	(1)	(2)	(3)
Relative poverty, 10 percent	5.893***		
	(1.870)		
Relative poverty, 20 percent		5.050***	
		(1.728)	
Relative poverty, 40 percent			3.978***
			(1.583)
90^{th} percentile	5.7e-06	5.9e-06	5.8e-06
	(3.9e-06)	(3.9e-06)	(4.0e-06)
Interaction	-4.8e-05***	-4.3e-05***	-3.2e-05
	(1.4e-05)	(1.3e-05)	(1.3e-05)
Unemployment	1.405	1.409	1.487*
	(0.891)	(0.897)	(0.901)
Males aged 15–24	-0.775	-0.413	-0.798
	(3.859)	(3.827)	(3.804)
Foreign citizens	-1.496	-1.431	-1.487
	(2.101)	(2.085)	(2.078)
Divorced	31.560***	30.699***	31.448***
	(6.125)	(6.188)	(6.179)
Adjusted R-square	0.927	0.927	0.926

Note: The interaction-term is an interaction of the relative poverty measure and the 90^{th} percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

Tables 5–7 show results for the same three specifications as above, with the dependent variable being the three specific crime categories auto theft, burglary and robbery. The coefficients on the different measures of the proportion of relatively poor are significant at the one-percent level for burglary and auto theft. A one-percentage point increase in the proportion of the population with an income below 10 percent (40 percent) of median income would imply a 5.9 (4.0) percent increase in the burglary rate and a 22.1 (15.8) percent increase in the number of auto thefts.

Table 6 Basic results, auto theft

	(1)	(2)	(3)
Relative poverty, 10 percent	22.140***		
	(3.456)		
Relative poverty, 20 percent		20.424***	
		(3.229)	
Relative poverty, 40 percent			15.813***
			(3.331)
90th percentile	1.9e-05***	2.1e-05***	2.0e-05***
	(6.8e-06)	(7.0e-06)	(7.8e-06)
Interaction	-0.0002***	-0.0002***	-0.0001***
	(2.8e-05)	(2.6e-05)	(2.7e-05)
Unemployment	4.666***	4.601***	4.760***
	(1.633)	(1.633)	(1.672)
Males aged 15–24	-2.908	-2.599	-2.579
	(6.278)	(6.278)	(6.424)
Foreign citizens	-5.459	-5.376	-5.268
	(3.412)	(3.452)	(3.580)
Divorced	43.087***	42.403***	40.915***
	(9.864)	(9.904)	(10.277)
Adjusted R-square	0.939	0.939	0.937

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

As for overall crime, increasing the proportion to be considered relatively poor decreases the magnitude of the coefficient. For robbery the coefficient on the proportion of relatively poor is not as precisely estimated, as for burglary and auto theft, but it still implies a 9.1 percent increase in the robbery rate following a one-percentage point increase in the proportion of relatively poor with an income below 10 percent of median income.

The 90th percentile produce positive coefficients for all the property crime categories, but it is only a significant determinant of the number of auto thefts. The positive sign on the 90th percentile coefficient possibly suggests that the 90th percentile serves as a proxy for the supply of theft-worthy goods. The interaction term displays a negative effect on the specific property crime rates as well as for overall crime.

Table 7 Basic results, robbery

	(1)	(2)	(3)
Relative poverty, 10 percent	9.140**		
	(4.149)		
Relative poverty, 20 percent		7.139*	
		(3.907)	
Relative poverty, 40 percent			3.684
			(3.603)
90th percentile	8.2e-06	7.7e-06	5.3e-06
	(6.5e-06)	(6.8e-06)	(7.0e-06)
Interaction	-6.6e-05**	-5.7e-05*	-3.4e-05
	(3.2e-05)	(3.0e-05)	(2.8e-05)
Unemployment	4.360***	4.373***	4.714***
	(1.514)	(1.530)	(1.541)
Males aged 15–24	11.057	12.329*	12.740*
	(7.207)	(7.169)	(7.196)
Foreign citizens	-2.522	-2.087	-1.900
	(2.956)	(2.943)	(2.943)
Divorced	20.230**	17.548*	17.396*
	(9.736)	(9.879)	(9.955)
Adjusted R-square	0.967	0.967	0.967

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

Concerning the link between unemployment and crime it is clear that the unemployment rate has a strong effect on the number of auto thefts and the robbery rate, where the coefficients on unemployment are significant at the one-percent level. The results imply that a one-percentage point increase in the unemployment rate would raise the number of auto thefts and the robbery rate with approximately 4.7 and 4.4 percent respectively. These results correspond to the findings in Nilsson and Agell (2003), where a one-percentage point drop in the unemployment rate is found to decrease the number of auto thefts with 3.9 percent. For burglary, on the other hand, we estimate a marginally significant coefficient on the unemployment rate of 1.5 while Nilsson and Agell (2003) report a larger coefficient of 2.8.

The proportion of men aged 15–24 seems to be a marginal determinant of the robbery rate whereas the proportion of the population that are divorced seems to be a main determinant for all the specific property crime categories considered here. The magnitude of the coefficients on the proportion of divorced individuals is surprisingly large, it seems quite implausible that a one-percentage point decrease in that proportion of the population would decrease the number of auto thefts with 40 percent, everything else held constant. There might be an upward bias in these coefficients caused by e.g. simultaneity bias. Excluding the variable from the specification does, however, not seem to alter the estimated coefficients on the earnings variables, which are our main concern. The estimated coefficients on the proportion of divorced individuals are most likely over-estimated but they nonetheless point at a potential criminogenic effect of unstable families.

To sum up, the proportion of relatively poor seems to have a strong effect on both the overall crime rate and the specific property crime categories although increasing the proportion to be considered relatively poor decreases the magnitude of the coefficient. An increase of the 90th percentile would also raise the number of crimes, possibly reflecting a greater supply of theft-worthy goods, although the effect seems to be small. Concerning the link between unemployment and crime it is clear that the unemployment rate has a strong effect on the overall crime rate as well as for the incidence of auto theft and robbery.

In this baseline specification we have chosen to compare the earnings of the people at the bottom of the income distribution with the earnings of the high-income group in an attempt to take the full distribution of earnings into account. However, it could also be of interest to compare the low-income group with the earnings in the middle of the distribution. Such a specification would be more in line with the model in line with the model in section 2. Table 8 presents the results from including the county mean income in the specification instead of the 90th percentile and the interaction term. The results for the proportion of the population in relative poverty is now weaker while all other control variables show more or less similar results. Keep in mind, however, that the mean income will, in contrast with the 90th percentile, depend on the size of the low-income group. Consequently, it seems like it is the size of the low-income group together with the earnings of the high-income group that are successful in determining property crime rates in Sweden.

Table 8 Alternative baseline specification

	Overall crime	Burglary	Auto theft	Robbery
Relative poverty, 10 %	0.547	-0.093	0.436	1.051
	(0.465)	(0.760)	(1.363)	(1.224)
Log of mean income	-0.202	-0.154	-0.634	-0.064
	(.1506)	(0.260)	(0.463)	(0.441)
Unemployment	1.187**	1.936**	6.536***	5.196***
	(0.581)	(0.874)	(1.907)	(1.620)
Males aged 15–24	2.524	-0.761	-3.556	11.166
	(2.415)	(3.773)	(6.807)	(6.985)
Foreign citizens	2.829**	-0.783	-2.741	-1.717
	(1.230)	(2.114)	(3.730)	(2.919)
Divorced	16.727***	33.925***	53.951***	23.501***
	(2.803)	(4.804)	(9.279)	(7.864)
Adjusted R-square	0.968	0.926	0.933	0.967
Observations	588	588	588	588

Note: Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

5 Alternative specifications

5.1 Income inequality and violent crime

Although the economic theory of crime primarily seems appropriate for examining the determinants of property crime we also report results for the violent crime category assault, since we find it interesting to compare the effects. Table 9 presents the results from the same specifications as in the analysis of the property crime categories. It reveals that the determinants of violent crime are quite different from those of property crime. The coefficient on the proportion of relatively poor is small, insignificant and even negative when we increase the earnings ceiling to be considered relatively poor from 10 to 20 percent of median income. The 90th percentile exhibits a negative sign compared to the positive one for property crime and the interaction term also has the opposite sign to the one reported above. The unemployment rate seems to have no effect on the assault rate, nor does the proportion of foreign citizens or the proportion of divorced individuals. The only variable included in the specification that seems to have a statistically significant effect on assault is the proportion of men aged 15–24.

Table 9 Basic results, assault

	(1)	(2)	(3)
Relative poverty, 10 percent	0.115		
	(1.598)		
Relative poverty, 20 percent		-0.134	
		(1.515)	
Relative poverty, 40 percent			-0.394
			(1.468)
90th percentile	-4.0e-06	-4.6e-06	-5.4e-06*
	(2.7e-06)	(2.8e-06)	(3.0e-06)
Interaction	1.2e-05	1.2e-05	1.3e-05
	(1.2e-05)	(1.2e-05)	(1.1e-05)
Unemployment	0.024	-0.016	-0.121
	(0.732)	(0.738)	(0.749)
Males aged 15–24	14.222***	14.819***	15.005***
	(3.441)	(3.451)	(3.489)
Foreign citizens	1.467	1.828	2.202
	(1.426)	(1.439)	(1.453)
Divorced	5.420	4.353	3.862
	(4.831)	(4.832)	(4.968)
Adjusted R-square	0.976	0.976	0.976

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

5.2 Alternative measures of income inequality

When thinking about measures of income inequality the first that comes to mind are perhaps the Gini-coefficient and some percentile quotient like the $90^{th}/10^{th}$. However, it seems that these variables are uncorrelated with the crime rate. Running similar specifications as in section 4, including fixed effects, county-specific trends and control variables but letting the Gini-coefficient or the $90^{th}/10^{th}$ percentile quotient together with mean earnings control for the income distribution, the Gini-coefficient and the percentile quotient turn out insignificant. Even when letting the Gini-coefficient and the percentile quotient be the only variables reflecting the income distribution, i.e. excluding the mean earnings measure from the specification, they give inconclusive results. However, we might not expect an overall income inequality measure like the Gini-coefficient to capture the changes in the income distribution that are most important in determining crime rates. As mentioned above, the size of the low-income group together with the earnings of the high-income group seem to matter most in determining property crime.

5.3 Deterrence variables

Examining the effect of deterrence variables on crime should be done with caution since there is a potential problem of reverse causation. For example, in a county where crime is rising there might be an increase in police hirings in an attempt to stop the increasing crime rate. Consequently, there will be a causal and positive effect of crime on the number of police officers, which will generate an upward bias in our OLS estimate of the coefficient on the police resources variable. Furthermore, an increase in the crime rate, keeping the number of police officers constant, is likely to cause a reduction in the clear-up rate. That is to say that there will be a causal and negative effect of crime on the clear-up rate causing a downward bias in the coefficient on the clear-up rate. Although there are apparent problems with drawing conclusions on how police resources and clear-up rates affect the crime rate we still include these deterrence variables in the specification to check whether the omission of them in previous sections has lead to biased coefficients on the earnings variables.

For each county *The National Police Board* provided us with data on the number of police officers per 100,000 residents and *The National Council for*

Crime Prevention provided us with data on county-level clear-up rates for different crime categories.[15]

Table 10 Deterrence variables

	Overall crime	Burglary	Auto theft	Robbery
Clear-up rate	-0.056	-0.024	-0.266	-0.061
	(0.235)	(0.070)	(0.255)	(0.078)
Police resources	6.4e-05	-0.0005	1.7e-05	0.0003
	(0.0002)	(0.0004)	(0.0005)	(0.0005)
Relative poverty, 10 %	3.290***	5.389***	20.793***	11.390***
	(1.239)	(2.030)	(3.718)	(4.278)
90th percentile	4.5e-06**	6.6e-06*	2.1e-05***	8.4e-06
	(2.3e-06)	(3.9e-06)	(7.1e-06)	(6.9e-06)
Interaction	-1.9e-05*	-4.8e-05***	-0.0002***	-8.1e-05
	(1.0e-05)	(1.5e-05)	(2.9e-05)	(3.2e-05)
Unemployment	1.048*	0.961	5.056***	3.397**
	(0.607)	(0.893)	(1.681)	(1.555)
Males aged 15–24	1.840	-2.632	-4.849	5.951
	(2.665)	(3.962)	(6.515)	(7.588)
Foreign citizens	1.009	-5.937**	-8.997**	-0.818
	(1.607)	(2.652)	(3.846)	(3.892)
Divorced	15.961***	34.820***	55.768***	11.496
	(5.162)	(7.354)	(11.665)	(13.158)
Adj. R-square	0.966	0.931	0.943	0.969
Observations	546	546	546	543

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. However, we only have access to data on the clear-up rate since 1975 for burglary and auto theft and since 1976 for assault.

Table 10 presents the result from including the crime-specific clear-up rate and the county-specific measure of police resources in the baseline specification. Briefly considering the results for the deterrence variables, it should be noted

[15] The clear-up rate is measured as the percentage of all reported crimes (in one specific category) that are solved the same year that they are reported.

that all coefficients are statistically insignificant. However, concentrating on the signs of the coefficients we find that the coefficient on police resources is negative for burglary but positive for overall crime, auto theft and robbery. Since we suspected there to be an upward bias in our OLS estimate of the coefficient on police, the negative coefficient on police for burglary most likely reflects a true negative relationship between the number of police officers and the burglary rate although we cannot determine how large the effect is.[16] The coefficients on the clear-up rate are all negative, but since we were concerned with a potential downward bias of this coefficient we cannot say anything about the relationship between the clear-up rate and the number of crimes. Focusing on the earnings variables, the results look quite similar to those presented in section 4. Consequently, the omission of deterrence variables in previous sections seems to have caused no problem with biased coefficients on our earnings variables.

5.4 Dynamics

Crime rates tend to be persistent over time. Unobserved heterogeneity and neighborhood effects can most likely explain a large proportion of this inertia.[17] By including time and area fixed effects and county-specific trends in the specification we have done our best in trying to control for unobserved heterogeneity. However, we have so far not taken peer effects into account. The existence of peer effects will result in crime rates differing from the rates predicted by the characteristics of the geographical area. The idea is that an individual's decision to become a criminal will depend on whether people in the same neighborhood commit crime. Such effects would not be captured in a standard static model and the model would therefore not be able to explain the crime rate.

One way of controlling for social interactions is to introduce dynamics into the model, i.e. include a lagged dependent variable in the specification.[18] With our panel, including 28 years, any bias from including a lagged dependent vari-

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[16] Levitt (1997) instruments the effect of police on crime with the timing of mayoral and gubernatorial elections and shows that increases in police substantially reduce violent crime but have a smaller impact on property crime. The validity of these results is however questioned in McCrary (2002).
[17] Glaeser et al (1996) emphasize the role of local social interactions in determining crime rates in the U.S.
[18] This has, for example, been done by Fajnzylber et al (1998) and Machin and Meghir (2000).

able into the specification should be minimal, see Nickell (1981). Table 11 presents the results from including a one-year lag of the county crime rate in the specification. The coefficients on the lagged dependent variable reveal a significant (at the one-percent level) persistence in county crime rates. Considering the earnings variables the coefficients are now overall smaller than in the static model. However, most results remain.

Table 11 Dynamics

	Overall crime	Burglary	Auto theft	Robbery
Lagged dep. variable	0.292***	0.403***	0.569***	0.148***
	(0.052)	(0.051)	(0.035)	(0.048)
Relative poverty, 10 %	1.813*	2.674	9.353***	7.899**
	(1.085)	(1.851)	(2.821)	(3.910)
90th percentile	3.6e-06	3.3e-06	1.4e-05***	7.6e-06
	(2.0e-06)	(3.3e-06)	(4.4e-06)	(6.2e-06)
Interaction	-9.2e-06	-2.4e-05*	-7.8e-05***	-5.9e-05**
	(8.2e-06)	(1.4e-05)	(2.2e-05)	(2.9e-05)
Unemployment	0.895	0.598	1.256	3.770***
	(0.588)	(0.794)	(1.266)	(1.508)
Males aged 15–24	0.744	-1.397	-2.096	9.161
	(2.481)	(3.568)	(5.129)	(7.267)
Foreign citizens	1.388	-1.521	-3.524	-2.283
	(1.180)	(1.890)	(2.519)	(2.922)
Divorced	16.954***	23.597***	36.782***	18.262*
	(3.770)	(5.620)	(7.660)	(9.540)
Adj. R-square	0.971	0.939	0.960	0.968
Observations	588	588	588	588

Note: The interaction-term is an interaction of the relative poverty measure and the 90th percentile. Standard errors are in parenthesis. All standard errors are robust to heteroscedasticity. In addition to the variables shown in the table, all regressions include a complete set of municipality and year effects as well as linear county-specific trends. Our complete panel consists of 588 observations for 21 counties during the period 1973–2000. ***, ** and * denote significance at the 1, 5 and 10 percent level, respectively.

The proportion of relatively poor still has a significant positive effect on both the overall crime rate, the number of auto thefts and the robbery rate. A one-percentage point increase in the proportion of the population with an income below 10 percent of median income seems to induce an increase in the overall crime rate of 1.8 percent. Although the magnitude of the coefficients on the earnings variables is smaller than in the previous section it should be noted that these coefficients only measure the short-run effect on crime. The long-run effects will be very close to the coefficients calculated above, considering the large coefficients on the lagged dependent variables.[19]

6 Conclusions

The unique aspect of this paper is that we have access to detailed income information during a long time-period, which contains considerable variations in the income distribution. The rich income data allows us to construct various measures of earnings inequality helping us to evaluate how different segments of the distribution of earnings affect crime rates.

Our main results can be summarized as follows. First, the proportion of relatively poor seems to have a strong effect on both the overall crime rate and the specific property crime categories. A one-percentage point increase in the proportion of the population with an income below 10 percent of the median income would increase the overall crime rate with 2.9 percent, the burglary rate with 5.9 percent, the number of auto thefts with 22.1 and the robbery rate with 9.1 percent, everything else held constant. Increasing the proportion to be considered relatively poor decreases the magnitude of the coefficient until the coefficients are small enough compared to the standard errors to become insignificant. Furthermore, our results indicate that it is the size of the low-income group together with the earnings of the high-income group that are successful in determining property crime rates in Sweden.

Second, there is an unambiguous link between unemployment and property crime. According to our results, a one-percentage point drop in the unemployment rate would decrease the overall crime rate, the number of auto thefts and the robbery rate with approximately 1.1, 4.7 and 4.4 percent respectively. These results are consistent with the findings in Nilsson and Agell (2003) where a one-percentage point drop in the unemployment rate is found to de-

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[19] Consider a dynamic specification where the crime rate is a function of the lagged dependent variable, income inequality (x) and other control variables (z), $y_t = \alpha y_{t-1} + \beta_1 x_t + \beta_2 z_t$. To derive the long-run effect we set $y_t = y_{t-1} = \bar{y}$ and $x_t = x_{t-1} = \bar{x}$ and get $\bar{y} = \frac{\beta_1}{1-\alpha}\bar{x} + \frac{\beta_2}{1-\alpha}\bar{z}$. Consequently, the long-run effect of a one-percentage point change in the proportion of relatively poor on the number of auto thefts would, according to our results in Table 10, be 21.7 percent, which can be compared to the coefficient 22.1 shown in Table 6.

crease the overall crime rate and the number of auto thefts with 1.2 and 3.9 percent respectively.

Third, the results look different for the violent crime category assault. The coefficient on the proportion of relatively poor is small, insignificant and even negative when we increase the earnings ceiling to be considered relatively poor from 10 to 20 percent of the median income. The unemployment rate seems to have no effect on the assault rate, nor does the proportion of foreign citizens or the proportion of divorced individuals. The only variable that seems to have an effect on assault is the proportion of men aged 15–24. Finally, the omission of deterrence variables in the baseline specification appears to have caused no problem with biased coefficients on our earnings variables. Moreover, our empirical findings suggest that Swedish crime rates suffer from a high degree of inertia.

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Appendix

A.1 Deriving the earnings measure

All earnings measures on county-level are derived using the individual earnings measure in LINDA for all men aged 25–64. The earnings measure included in LINDA has not been entirely consistent throughout the period. Since 1974 it is possible to construct a measure that is consistent the remaining period with some small corrections. 1973 we calculate earnings by adding income from employment (*A-inkomst av tjänst* + *Beskattningsbar sjöinkomst*) and income from business (*A-inkomst av jordbruk* + *A-inkomst av rörelse*). The earnings measure for the period 1974–1977 is constructed adding the same income variables, from employment and business, as for the previous period and then subtracting the sum of pensions (*Pension*), unemployment compensation (*Dagpenning vid arbetslöshet* + *KAS*), and compensation during labor market training (*Utbildningsbidrag*). 1978–2000 the earnings measure is directly available in the data with some minor adjustments.

A.2 Definitions of variables

Table A1 Definitions of crime variables

Variables	Definitions
All crimes	All crimes reported in the county during one year.
Burglary	All burglary, not including firearms.
Auto theft	All auto thefts, both attempted and completed.
Robbery	All robberies, with and without the use of firearms.
Assault	All assaults, not with fatal ending.

Note: The crime data were provided by The National Council for Crime Prevention (BRÅ).

Table A2 Definitions of earnings variables (annual earnings in 1980 SEK)

Variables	Definitions
10^{th} percentile	The county-specific 10^{th} percentile.
90^{th} percentile	The county-specific 90^{th} percentile.
Gini-coefficient	The county-specific Gini-coefficient.
Proportion in relative poverty	Proportion of the population with earnings less than 40 percent of median earnings in the county.
Mean earnings	Mean earnings in each county.

Note: All earnings measures on county-level are calculated using the individual earnings measure in LINDA for all men aged 25–64.

Table A3 Definitions of control variables

Variables	Definitions
Unemployment	The proportion unemployed of the county labor force.
Proportion of males aged 15–24	Proportion of males aged 15–24 of each county population.
Proportion foreign citizens	Proportion of the population in each county that are not Swedish citizens.
Proportion divorced	Proportion of the population in each county that are divorced.
Police officers	Number of employed police officers per 100,000 inhabitants.
Clear-up rates	The percentage of all reported crimes (in one specific category) that are solved the same year that they are reported.

Note: The data on unemployment, the proportion of males aged 15–24, the proportion of foreign citizens and the proportion divorced were provided by *Statistics Sweden. The National Police Board* provided us with data on the number of police officers per 100,000 residents and *The National Council for Crime Prevention* provided us with data on clear-up rates for different crime categories.