Scand. J. of Economics 107(2), 353–373, 2005
DOI: 10.1111/j.1467-9442.2005.00412.x

Unemployment and Crime: Is There a Connection?

*Karin Edmark**

Uppsala University, SE-751 20 Uppsala, Sweden
karin.edmark@nek.uu.se

Abstract

A panel of Swedish counties over the years 1988–1999 is used to study the effects of unemployment on property crime rates. The period under study is characterized by turbulence in the labor market—the variation in unemployment rates was unprecedented in the latter part of the century. Hence, the data provide a unique opportunity to examine unemployment effects. According to the theory of economics of crime, increased unemployment rates lead to higher property crime rates. A fixed-effects model is estimated to investigate this hypothesis. The model includes time- and county-specific effects and a number of economic and socio-demographic variables to control for unobservables and covariates. The results show that unemployment had a positive and significant effect on some property crimes (burglary, car theft and bike theft).

Keywords: Economics of crime; unemployment; panel data; fixed-effects estimation

JEL classification: *C*230; *J*290; *J*390; *J*690

I. Introduction

During the deep recession of the early 1990s, Sweden experienced its worst economic crisis since the 1930s. Unemployment rates rose dramatically and public spending on unemployment benefits soared. In addition to such direct expenses, high unemployment is costly; it keeps part of the labor force out of production and, if persistent, skills and know-how are likely to decrease. According to the theory of economics of crime that has evolved over the last decades, unemployment has yet another cost: an increase in property crime.

Although several studies have treated the effects of the massive rise in unemployment during the early 1990s, attempts at estimating the effects on crime have been rare. This study investigates the effects of Swedish unemployment on crime using county panel data for the period 1988–1999. Since the theory of economics of crime is primarily applicable to property crime,

* I have received valuable comments and advice from Matz Dahlberg, Kerry L. Papps, Antonio Rodriguez Andres and two anonymous referees.

the focus is on this aspect, while, for the sake of comparison, some estimates on violent crimes are also included.

The great variation in unemployment rates characterizing the period under study was unprecedented towards the end of the century. During the first five years of the period, unemployment rates more than quadrupled—from 2 percent in 1988 to 10.4 percent in 1993, after which they gradually declined to 6.4 percent in 1999. In comparison with other studies, these substantial swings greatly facilitate the identification of the supposed effects of unemployment on crime.

An increasing amount of empirical research on the connection between unemployment and crime has been carried out in recent years. Several of these studies use panel data; see, for example, Levitt (1996), Ahmed, Doyle and Horn (1999), Raphael and Winter-Ebmer (2001), and Gould, Weinberg and Mustard (2002) for U.S. state- and county-level investigations, Entorf and Spengler (2000) for a German state-level survey, Papps and Winkelmann (2000) for a study on regional data from New Zealand, and Rodríguez (2003) who uses Spanish region-level data. The four American studies all find support for the hypothesis that deteriorated conditions on the labor market are associated with higher property crime rates.[1] These results are, to some extent, confirmed by Papps and Winkelmann. Entorf and Spengler's results are significantly weaker, however. Their unemployment estimates for former West Germany are weak and ambiguous (even *negative* estimates are reported for some theft crimes). After German reunification, the relation between unemployment and property crime is stronger, however, and positive for all crimes. Finally, Rodríguez finds little support for the link between unemployment and overall crime.

There are also some time-series studies on unemployment and crime. Scorcu and Cellini (1998) use Italian time-series data and find unemployment to be a significant explanatory variable for theft. Schuller (1986) also finds support for the positive relation between unemployment and crime using time-series data on Sweden (for the years 1966–1982), whereas his municipality-level cross-section analysis on the average of the years 1975 and 1976 yields insignificant results.

Studies concerned with individuals often focus on youth, since younger individuals, especially young men, tend to be over-represented in criminal records. For example, Witte and Tauchen (1994) use American panel data on young men, and find that employed individuals tend to commit fewer crimes than those who are unemployed.

[1] While Raphael and Winter-Ebmer, Gould *et al.* and Levitt examine the effect of the unemployment rate on crime, Ahmed *et al.* measure the effect of changes in overall labor market conditions by constructing a measure which includes wage levels, unemployment rates and unemployment benefits.

The empirical evidence is thus ambiguous. The U.S. studies mentioned above all support the positive relation between unemployment and crime, while studies on other countries in general obtain significantly weaker results. Further research, especially from countries other than the U.S., is thus motivated. The insignificant results may be due to insufficient variation in unemployment rates. In this light, the case of Sweden during the 1990s is especially pertinent.

Our study finds that unemployment affects certain types of property crime. Based on a panel of 21 Swedish counties during the period 1988–1999, we find fairly robust evidence of a positive link between unemployment and property crime in the form of burglary and car theft, and somewhat weaker evidence regarding aggregate property crime and bike theft.

The credibility of these results is reinforced by Nilsson and Agell (2003). Using Swedish municipality-level data for the period 1996–2000, they find evidence of a positive link between unemployment and overall property crime, burglary and car theft.

II. Theoretical Framework

The Individual's Choice between Work and Crime

According to Becker (1968), the theory of the economics of crime considers crime as a type of work, i.e., as an activity that takes time and yields economic benefits. The theoretical model is foremost applicable to property crime. In the following, unless stated otherwise, "crime" therefore refers to property crime. The simple model for the supply of crime introduced here is based on the models of Ehrlich (1973) and Freeman (1999).[2]

The model describes individual n's choice between work and crime as a source of income during one period. Work and crime are regarded as alternative activities that cannot be combined.[3] In the model, W denotes the individual's wage from honest work, W_b the return from crime, A unemployment benefits and u the unemployment rate (interpreted as the probability of the individual being unemployed during the period). If the individual chooses crime, p denotes the probability that he/she is caught and S the cost of punishment. These variables are, for simplicity, assumed to be equal for all individuals, i.e., all individuals face the same wages, unemployment, etc. We also introduce an idiosyncratic psychological cost of

[2] Although the demand side is taken into account, we focus on the supply side, since it appears to be more important for the relation between unemployment and crime.

[3] Dynamic models as well as models which allow for a combination of work and crime have been developed; see, for example, Lochner (1999) or Witte and Tauchen (1994). Here, however, our simple static model is sufficient for the argumentation in this paper.

committing a crime, c_n. This cost can be positive or negative, and is assumed to be independently and continuously distributed over the population.

The individual chooses crime if the expected return from crime minus the psychological cost of committing a crime is higher than the expected return from work, i.e., if the following is fulfilled:

$$E(W_b) - c_n > E(W). \tag{1}$$

Equation (1) thus implies that crime pays, in the sense that an individual chooses to commit crime only if the expected return from crime, minus the psychological cost of committing crime, exceeds that from honest work. An increase in the LHS increases the individual's propensity to commit crime, while a higher value on the RHS increases the probability that honest work will be chosen.

$E(W_b)$, the expected return from crime, is a probability-weighted average of the return, if the individual is caught for having committed a crime, p, and not caught $(1 - p)$, respectively. If the individual chooses crime but is caught, the return, W_b, is reduced by the cost of punishment, S. The expected return from crime can thus be written as:

$$E(W_b) = (1 - p)W_b + p(W_b - S). \tag{2}$$

The expected return from work is affected by the unemployment rate and the unemployment benefit. The unemployment rate affects the individual's possibilities of becoming employed and, hence, also the expected wage, $E(W)$. If the individual is employed during the period, he/she obtains wage W, while if unemployed, he/she receives the unemployment benefit A:

$$E(W) = (1 - u)W + uA. \tag{3}$$

The restriction in equation (1) for individual n to choose crime can now be written as:

$$c_n < ((1 - p)(W_b) + p(W_b - S)) - ((1 - u)W + uA), \tag{4}$$

i.e., the psychological cost of committing a crime should be strictly less than the difference in expected return from crime and honest work. Equation (4) hence states that an individual chooses crime as long as the expected income premium of choosing crime instead of honest work is above the individual-specific threshold value, c_n.

Aggregate Supply of Crime

From equation (4), it is straightforward to derive the effects of the model parameters on the aggregate supply of crime. A higher expected income premium for crime, the RHS of equation (4), implies that the condition for choosing crime will hold for a larger number of individuals, and will hence increase the aggregate supply of crime. Assuming $W > A$ and $u < 1$ (both highly realistic assumptions), the RHS of equation (4) is increasing in W_b and u, and decreasing in W, S and A. Hence, there will be an increase in the aggregate supply of crime in response to increases in the return from crime, W_b, and unemployment, u, and a decrease in aggregate supply in response to increases in the return from honest work, W, the punishment for crime, S, and unemployment benefits, A. The expected effect of unemployment on the supply of crime is hence positive: higher unemployment makes more individuals willing to commit a crime, *ceteris paribus*.

Aggregate Demand for Crime

In order to derive the effects in a general equilibrium, the demand side also has to be taken into consideration. Aggregate demand for crime is affected by the wealth of a region, i.e., by the supply of booty. A higher income level in a region is hence equal to a higher demand for crime. This effect works in the opposite direction as compared to the supply side, where we have seen that the income level has a negative effect. The net effect of the income level from honest work on the crime rate is therefore ambiguous: a negative effect on supply, but a positive effect on demand.[4] This also has implications for the expected effects of unemployment on crime. Since high unemployment is likely to decrease the aggregate income of a region (at least if it is assumed that the unemployment-related income loss is not fully replaced by illegal income), there is a potential indirect negative effect of unemployment on the demand for crime, through the effect on aggregate income. By controlling for mean income in the econometric specification, however, we ensure that the unemployment coefficient only measures the effect on the supply of crime, and not the indirect effect on demand.

It can be concluded that the theoretical model predicts a positive link between unemployment and the supply of crime, but that there is also a potential indirect negative effect on demand, through the effect on the income level. By controlling for mean income, we can attempt to isolate the unemployment effect on the supply of crime. This implies that an unambiguously positive relation between unemployment and crime is expected.

III. Econometric Specification

On the basis of economic theory, we have derived a number of parameters to be included when specifying an econometric model for aggregate

[4] The argument regarding a positive effect of aggregate income on the demand for crime could also be applied to income from illegal activities. The demand and supply effects would then work in the same directions, however. Hence, we can expect a positive net effect of illegal income on crime rates.

crime rates: unemployment, u, honest income, $\overline{W}$ (measured as deflated average income), and the risk of getting caught, p (measured as the overall clear-up rate, i.e., the proportion of crimes solved by the police).[5,6] The parameters with bars are now in the form of region-specific means. The mean unemployment benefits, $\overline{A}$, are included in the measure of average income and therefore do not appear separately in the model. The return from crime, $\overline{W}_b$, and the cost of punishment, $\overline{S}$, are excluded due to lack of data. We also lack information on the distribution of the psychological cost of crime, c_n.

A vector π of socio-demographic variables is also added to the model (see Section IV for definitions). Region- and time-specific effects (α_i, where i denotes the region, and τ_t, where t denotes the year, respectively) are estimated to control for unobserved, county-specific effects and national shocks with a similar effect on crime rates in the counties.[7] Insofar as the effects of the omitted variables, $\overline{W}_b$, S and c_n, remain fixed over time, they are controlled for by the fixed-effects specification. In addition, they are probably at least partly incorporated in average income.[8] Previous studies generally use log-linear or log-log specifications. Here, we follow the theoretical framework of Ehrlich (1973), which suggests a log-log specification. The resulting baseline specification is given as:

$$\ln B_{it} = \alpha_i + \beta_1 \ln u_{it} + \beta_2 \ln \overline{W}_{it} + \beta_3 \ln p_{it} + \gamma' \ln \pi_{it} + \tau_t + \varepsilon_{it}. \qquad (5)$$

Our main interest lies in the effect of unemployment on crime. Can we be certain that this is measured by an estimated positive coefficient for unemployment, or do we risk that the result is biased by reverse causality, i.e., that crime also affects unemployment? The possibility of simultaneous causal effects between unemployment and crime is discussed in many of the articles referred to above.

Raphael and Winter-Ebmer (2001) consider the possibility that high or increasing crime in an area has a deterrent effect on the establishment of new industries, or even scares existing companies away, thereby restraining employment in the region. It can also be assumed that individuals with a

[5] The same measure, the overall clear-up rate, is used for all crimes. This should not be interpreted as a direct measure of the risk of getting caught for the specific crime in question, but rather as a general measure of the resources of the police and justice system. (Since the clear-up rate varies greatly among crimes, the clear-up rates for specific crimes would have to be used in order to apply p as a direct measure of the risk of getting caught.)

[6] See the Appendix for definitions of the data.

[7] Models of this type, i.e., fixed-effects models including region- and/or time-specific effects, have generally been used in previous research; see Entorf and Spengler (2000), Ahmed *et al.* (1999), Papps and Winkelmann (2000) and Gould *et al.* (2002).

[8] It is reasonable to assume that the cost of punishment is related to legal income—for example, the amount of a fine may be directly dependent on the wage level of the individual.

criminal record have fewer opportunities to find work, which may lead to lower employment in areas with many ex-criminals. Furthermore, Gould *et al.* (2002) discuss the hypothesis that companies in areas with high criminality are disadvantaged by having to pay higher wages in order to compensate their employees for the bad area.

On the other hand, Raphael and Winter-Ebmer's instrumental variable analysis (with instrumental variables for unemployment based on contracts for the defense industry and oil prices), finds support for a causal direction from unemployment to crime. Moreover, the instrumental variable estimations yield higher coefficient values than the ordinary OLS regressions, which implies that it could even be the case that the OLS regressions used in our study underestimate the effect of unemployment on crime.

Another issue concerns the likelihood of the possible effects of crime on unemployment in this context. That companies avoid areas with high criminality is a plausible assumption, but this problem is more likely to arise at the municipal rather than at the county level. Hence, there are good reasons to believe that the results of this study reflect a causal direction from unemployment to crime.

IV. Data

The data consist of a panel of Swedish counties[9] over the years 1988–1999—a period of great turbulence in the labor market. Between 1990 and 1993, the unemployment rate rose from 1.6 to 10.4 percent. The large swings in the business cycle during the period provide a unique opportunity to study the effects of unemployment on crime, especially when using a fixed-effects estimator, where the identifying variation comes from county-specific deviations from a county-specific time average in each time period. During the period under study, the average county-wise unemployment, measured as the number of unemployed per 100,000, was 5,693. The county-specific deviations from the county-specific time averages range between −4,921 and 5,137, which suggests a substantial identifying variation in the data.

Since the crime rates for the most turbulent period—the early 1990s—are only available at the county level,[10] the capacity to cover this period in the analysis is a major advantage of choosing county-level, instead of municipality-level, data. The latter would not take into account the substantial increase in unemployment that took place in the first part of the decade.

[9] There are 21 Swedish counties, each containing a number of municipalities. The smallest, Gotland county, is comprised of the municipality of Gotland; Västra Götaland is the county with the most municipalities (47).

[10] The official municipality-level crime statistics run from 1996.

The use of county-level data, as compared to data at the municipal level, has additional advantages. First, county-level data minimize the risk of biased estimates due to "the mobility of criminals", i.e., that criminals may commit crimes in areas other than their district of residence. This phenomenon is not unlikely at the municipal level—especially in large cities such as Stockholm where mobility is high and the supply of crime can differ substantially among districts. This problem may, to some extent, also arise at the county level, but certainly to a far smaller degree. Second, county-level data are less likely to be affected by simultaneity bias stemming from the influence of crime rates on unemployment in an area. Third, clear-up rates in Sweden are only available at the county level, and theory implies that this is an important analytical variable. Hence, unless other measures to capture the probability of getting caught are included, a municipality-level analysis might suffer from an omitted variable bias.

Data on crime rates were collected from the National Council for Crime Prevention. "Crime" is defined as the number of reported crimes per 100,000 individuals. If the number of reported crimes is used as a measure of the crime rate, it will not reflect the number of crimes actually committed, but only those reported. However, a Swedish study by the the National Council for Crime Prevention (2001), based on comparisons between the number of reported crimes and the number of victims, shows that, in general, the number of reported crimes mirrors changes in true crime rates relatively well.[11] As long as changes in the frequency of reporting crimes are the same in all counties, they are controlled for through the fixed-effects specification.

Since reporting a crime is a condition for receiving insurance compensation, it can furthermore be assumed that the reported number of crimes is particularly close to the true figure for property crimes. This is probably also the case for car theft and burglary, where not reporting a crime implies losing a significant amount of insurance compensation.

Property crime consists of burglary, robbery, car theft, bike theft, theft/pilfering from motor vehicles and shops respectively, and fraud.[12] The distribution of these crimes in Sweden in 1999 is shown in Figure 1. Property crime (as defined in this study) in 1999 constituted around 47 percent of total crime, while violent crime accounted for 6 percent. The

[11] Exceptions include fraud, child assault and school violence, where the report frequency seems to have changed during the 1990s.

[12] Vandalism may also be counted as a property crime, but since it does not yield any direct economic proceeds, it is omitted from this study. Correspondingly, we regard robbery as a property crime, even though it may lead to violence, since the main reason for a robbery can be assumed to be the economic benefits (otherwise, the individual could just as well commit "purely violent" crimes, such as assault or vandalism).

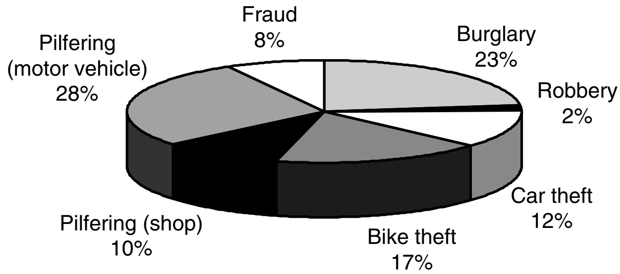

Fig. 1. The distribution of reported property crimes in Sweden, 1999

remaining 47 percent consist of offenses such as vandalism, traffic violations and drug-related crime.[13]

In addition to the factors motivated by economic theory, a number of control variables are generally included in models of crime and unemployment. The purpose is to decrease the risk that social and demographic factors will distort the results; see, for example, Schuller (1986), Ahmed *et al.* (1999), Entorf and Spengler (2000), Raphael and Winter-Ebmer (2001), and Gould *et al.* (2002). The following control variables are included in our study: the proportion of divorced persons, population density, the proportion of the population with higher education (defined as college or higher levels), the proportion of individuals on social allowance, the proportion of foreign citizens, the proportion of young men (15–24 years old), and sales of alcohol at the National Liquor Monopoly. The choice of these variables is motivated either by previous research or on theoretical grounds.

Table 1 reports descriptive statistics and the expected sign of all variables. Unless otherwise stated, the variables show the county-wise mean per 100,000 inhabitants.

V. Results

In reporting the results of the regression analysis, we focus on property crimes but, for the sake of comparison, estimates for violent crimes are also shown. The presentation of the baseline results is followed by a sensitivity analysis, which tests the robustness of the results to changes in the model specification.

---

[13] For definitions of the explanatory variables and descriptive statistics, see the Appendix.

Table 1. *Descriptive statistics and expected sign; number of observations = 252*

Variable	Average	Standard deviation	Min.	Max.	Expected sign
Aggregate property crime	5,781	1,647	2,872	12,093	
Burglary	1,425	376	764	2,656	
Robbery	38	35	10	211	
Car theft	515	275	173	1,926	
Bike theft	1,340	460	409	2,889	
Theft/Pilfering in shop	604	176	265	1,606	
Theft/Pilfering from motor vehicle	1,210	521	423	3,396	
Fraud	648	551	232	6,842	
Aggregate violent crime	564	163	276	1,103	
Murder	2	1	0	5	
Assault	489	141	248	966	
Sexual assault (excl. rape)	56	21	21	134	
Rape	18	16	3	218	
Unemployment	5,693	2,959	820	12,810	+
Clear-up rate[a]	29,996	5,514	18,000	47,000	−
Average income (SEK 1,000)	103.82	6.92	89.07	136.00	+/−
Education	18,009	3,921	11,011	31,828	−
Males 15–24	6,564	477	5,535	7,649	+
Foreign citizens	4,232	1,885	974	10,050	+
People on social allowance	6,656	1,518	3,077	10,400	+
Divorced	7,056	1,134	4,801	10,280	+
Sales of alcohol (liters)	4.1	0.8	2.4	6.7	+
Population density (persons/km^2)	41.6	54.4	2.6	278.0	+

[a]An extreme value was removed from the clear-up rate, and the number of observations for this variable is thus 251.

Property Crime

The results for aggregate property crime and seven separate crimes are reported in Table 2. The estimates were obtained by regressing equation (5), i.e., including covariates, county-specific fixed effects and year dummies. As can be seen, the unemployment coefficient is positive and significant for aggregate property crime, burglary, car theft, bike theft and fraud. The log-log specification implies that the coefficients are interpreted as elasticities. The size of the estimated coefficients thus suggests that a 1 percent increase in the unemployment rate leads to an increase in aggregate crime by 0.11 percent, in burglary by 0.15 percent, in car theft by 0.16 percent, in bike theft by 0.07 percent, and in fraud by 0.22 percent.

The unemployment coefficients are insignificant (at the 10 percent level of significance) for the remaining property crimes. Why do these crimes seem to be unaffected by unemployment? Regarding robbery, a possible explanation proposed in the literature is that the unemployed spend more time at home (at least by not going to and from work every day) and, hence,

Table 2. *Baseline specification, property crime*

Variables (in logarithms)	Aggregate property crime	Burglary	Car theft	Bike theft	Pilfering motor vehicle	Pilfering shop	Robbery	Fraud
Unemployment	0.106	0.147	0.159	0.072	0.078	0.069	−0.060	0.217
	(0.041)***	(0.062)**	(0.085)*	(0.042)*	(0.048)	(0.084)	(0.103)	(0.128)*
Clear-up rate	−0.387	−0.117	−0.212	−0.193	−0.139	0.004	−0.334	−0.762
	(0.141)***	(0.086)	(0.110)*	(0.051)***	(0.068)**	(0.102)	(0.125)***	(0.512)
Mean income	−0.386	−0.601	−1.031	−0.121	−0.873	1.631	−1.716	−3.071
	(0.668)	(0.872)	(1.262)	(0.777)	(0.908)	(1.304)	(1.755)	(2.685)
Education	−0.282	−0.408	0.281	0.038	0.125	−0.504	−0.371	−0.824
	(0.129)**	(0.166)**	(0.288)	(0.123)	(0.144)	(0.197)**	(0.373)	(0.516)
Males 15–24	0.104	0.082	0.751	0.575	−0.489	0.954	0.247	0.818
	(0.309)	(0.371)	(0.628)	(0.291)**	(0.427)	(0.460)**	(0.695)	(0.905)
Foreign citizens	0.133	0.154	−0.158	−0.390	0.571	0.036	0.429	0.465
	(0.123)	(0.181)	(0.250)	(0.106)***	(0.149)***	(0.173)	(0.283)	(0.460)
Social allowance	0.190	0.082	0.255	0.281	0.312	−0.031	0.250	−0.287
	(0.117)	(0.115)	(0.192)	(0.093)***	(0.133)**	(0.196)	(0.225)	(0.365)
Divorced	0.694	1.504	1.665	−0.309	1.678	0.054	1.320	−1.735
	(0.357)*	(0.412)***	(0.650)**	(0.300)	(0.387)***	(0.583)	(0.766)*	(1.077)
Alcohol	0.091	−0.024	0.070	−0.193	−0.180	0.649	0.441	0.079
	(0.131)	(0.133)	(0.231)	(0.153)	(0.185)	(0.208)***	(0.321)	(0.447)
Population density	−1.355	−2.307	−1.993	−2.490	−2.772	0.811	1.481	−2.228
	(0.526)**	(0.568)***	(0.833)**	(0.437)***	(0.610)***	(0.746)	(1.048)	(1.390)
Observations	251	251	251	251	251	251	251	251
R-squared	0.92	0.89	0.92	0.97	0.95	0.78	0.94	0.73

Notes: Robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%. Fixed effects and year dummies are included in all regressions. The hypotheses that all fixed effects are equal to zero and that all time effects are equal to zero are rejected for all specifications.

decreases the demand for personal robbery. (This argument holds, of course, for all crimes requiring a personal encounter.) This effect could cancel any positive effects of unemployment on the supply of crime and, hence, explain the insignificant coefficient for robbery. The insignificant results for pilfering are more difficult to explain. It may be that the economic gains from these crimes are smaller, and that the theoretical approach of viewing crime as a source of income is therefore not appropriate.

Among the covariates, the coefficients for the clear-up rate, population density and the divorce rate are significant for most of the property crimes, and the coefficients for education, young males, foreign citizens and alcohol are significant for some of the crimes. Mean income enters insignificantly for all crimes. The coefficient for population density is surprisingly large: a reduction in population density of 1 percent is estimated to yield an increase in aggregate property crime by almost 1.4 percent.

Violent Crime

Theoretical considerations regarding economic incentives for crime are not directly applicable to violent crimes. However, there are still channels through which unemployment may affect violent crimes. They may be a "by-product" of property crime, which implies that the effect of unemployment is similar to that of property crime, i.e., positive. Here, the discussion regarding diminished opportunities for personal crimes as unemployment increases is also applicable to violent crimes which, in turn, suggests a negative relation. Since the expected effect of unemployment on violent crime is not clear, we may turn to the data to examine the empirical evidence.

Violent crime is categorized as murder, assault, sexual assault (excluding rape) and rape. Table 3 shows the unemployment coefficients for these categories. Since the category "murder" is too small to be analyzed separately, it is combined with assault.

According to Table 3, the unemployment coefficient is insignificant for all violent crimes. This is not surprising, in the sense that the theory on economics and crime suggests no direct link between unemployment and violent crime. However, the insignificant unemployment coefficient may also be due to counteracting effects of unemployment, as discussed above.

Regarding the covariates, young males and alcohol consumption are estimated to have a positive effect on the number of aggregate violent crimes, as well as on murder and assault. Furthermore, education is negatively related to the number of reported crimes, while population density is negatively related to aggregate violent crime. None of the other variables is significant.

Table 3. *Baseline specification, violent crime*

Variables (in logarithms)	Aggregate violent crime	Murder and assault	Sexual (excl. rape)	Rape
Unemployment	0.066	0.056	0.037	0.366
	(0.051)	(0.052)	(0.113)	(0.227)
Clear-up rate	−0.034	−0.021	−0.048	−0.257
	(0.059)	(0.060)	(0.159)	(0.295)
Mean income	0.509	0.194	1.529	4.534
	(0.797)	(0.813)	(1.807)	(3.637)
Education	−0.324	−0.302	−0.064	−1.372
	(0.210)	(0.205)	(0.567)	(0.614)**
Males 15–24	1.084	1.223	0.356	0.059
	(0.392)***	(0.407)***	(0.819)	(1.268)
Foreign citizens	−0.056	−0.065	0.035	−0.227
	(0.110)	(0.117)	(0.306)	(0.568)
Social allowance	−0.059	0.007	−0.238	−0.399
	(0.113)	(0.117)	(0.264)	(0.499)
Divorced	−0.391	−0.259	−0.970	−1.447
	(0.388)	(0.414)	(0.833)	(1.368)
Alcohol	0.276	0.269	0.263	0.730
	(0.132)**	(0.133)**	(0.301)	(0.537)
Population density	−0.922	−0.826	−0.973	−2.591
	(0.524)*	(0.539)	(1.114)	(2.043)
Observations	251	251	251	251
R-squared	0.92	0.92	0.73	0.50

Notes: Robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%. Fixed effects and year dummies are included in all regressions. The hypotheses that all fixed effects are equal to zero and that all time effects are equal to zero are rejected for all specifications.

Sensitivity Analysis

The results reported so far suggest that unemployment has an effect on some property crimes, but not on violent crimes. However, it is important to check the sensitivity of these results to alterations in the model specification.

In a sensitivity test proposed by Raphael and Winter-Ebmer (2001), county-specific time trends are included in the regression. They argue that it is not sufficient to control for fixed effects and time dummies if some of the variation in crime rates is caused by *county-specific time trends* in unobservables. Raphael and Winter-Ebmer point to the availability of drugs and guns as examples of variables that may follow county-specific time trends. Following Raphael and Winter-Ebmer, linear and quadratic county-specific trends ($\psi_i time_t$ and $\omega_i time_t^2$, respectively) were therefore added to the baseline estimation. The resulting model is:

$$\ln B_{it} = \alpha_i + \beta_1 \ln u_{it} + \beta_2 \ln \overline{W}_{it} + \beta_3 \ln p_{it} + \gamma' \ln \pi_{it} + \tau_t + \psi_i time_t + \omega_i time_t^2 + \varepsilon_{it}. \tag{6}$$

The unemployment coefficients obtained by estimating equation (6), including only linear time trends, as well as both linear and quadratic time trends, respectively, are given in columns 2 and 3 in Table 4 (the results for the full set of covariates are reported in the Appendix). For comparison, the unemployment coefficient of the baseline specification is reproduced in the table.

The results show that, in general, the size of the coefficient on unemployment decreases somewhat when county-specific time trends are added. (The exception is the coefficient on car theft in the model with linear and quadratic trends, which increases.) The coefficient is significant at the 5 percent significance level for car theft, and at the 10 percent level for burglary and bike theft for both specifications including county-specific trends, but not for aggregate property crimes. This suggests that controlling for county-specific time trends may be important.

One problem with this approach, however, is that it greatly reduces the number of degrees of freedom. Therefore, the failure to establish a significant relation for aggregate crime, when county-specific trends are included, may be due to too few observations. Hence, it is not evident which of the specifications we should trust. In any event, the analysis indicates that the estimated unemployment effects for burglary, car theft and bike theft are not driven by county-specific trends in unobservables.

Table 4. *Unemployment coefficient for property crimes, sensitivity analysis*

Crime (in logarithms)	Baseline specification	Linear trends	Linear and quadratic trends
LnAggregate property crime	0.106	0.074	0.063
	(0.041)***	(0.045)	(0.046)
LnBurglary	0.147	0.123	0.125
	(0.062)**	(0.071)*	(0.069)*
LnCar theft	0.159	0.153	0.174
	(0.085)*	(0.074)**	(0.085)**
LnBike theft	0.072	0.061	0.058
	(0.042)*	(0.035)*	(0.033)*
LnPilfering motor vehicle	0.078	−0.005	−0.015
	(0.048)	(0.053)	(0.053)
LnPilfering shop	0.069	−0.093	−0.112
	(0.084)	(0.104)	(0.100)
LnRobbery	−0.060	−0.045	−0.003
	(0.103)	(0.133)	(0.141)
LnFraud	0.217	0.223	0.167
	(0.128)*	(0.168)	(0.185)

Notes: Robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%. Fixed effects and year dummies are included in all regressions. The regressions include the same set of covariates as the baseline specification. The hypotheses that all fixed effects are equal to zero and that all time effects are equal to zero are rejected for all specifications.

The baseline estimation yielded a surprisingly large and negative coefficient on population density. How should this be interpreted? The inclusion of fixed effects in the model specification implies that the population-density coefficient measures effects of *changes* in the population density of the counties, and not effects of population density *per se*. Hence, the negative coefficients of the baseline specification should not be interpreted as evidence of the relation between low population density and crime, but as evidence of a link between a negative *trend* in the population density of a county and the crime rate. It could be that the large and negative coefficients of the baseline specification mirror omitted county-specific factors correlated with changes in population density.

If this line of argument is correct, the coefficient on population density should change when county-specific time trends are included, since these capture the effects of such omitted variables. The following also happens: when we included county-specific time trends in the estimation, the population density coefficient goes from negative and significant for most of the crimes to positive and insignificant for most types of crime (see Tables A1 and A2 in the Appendix). Hence, it is likely that the large and negative population density coefficient obtained in the baseline specification is affected by omitted variable bias.

The robustness of the results to varying the set of covariates was also tested. The general impression is that the result regarding unemployment and crime is robust to changes in the set of covariates for aggregate property crime, burglary and car theft, while the result for bike theft is more sensitive (results not reported).

The results of testing the robustness of the results of the baseline regression for property crimes to alterations in the model specification provide strong evidence of a positive unemployment effect on certain property crimes; burglary and car theft. These are significant for all model specifications of the sensitivity analysis. Some, although weaker, evidence is also found for the effect of unemployment on aggregate crime, bike theft and fraud.

Economic Significance of the Unemployment Effect

As already indicated, we have quite a strong case for the statistical significance of the unemployment effect. But what about the economic significance? The unemployment coefficient in Table 3 implies that a 1 percent rise in the unemployment rate increases burglary by 0.15 percent and car theft by 0.16 percent. In Sweden, during the period under study, an annual average of 144,400 burglaries and 64,300 car thefts were reported. The estimated unemployment coefficients thus imply that a 1 percent increment in the unemployment rate, *ceteris paribus*, is related to approximately 217 more burglaries and 103 more car thefts. As an example, assume an increase in the unemployment rate of 1 percentage point, from 4 to 5 percentage points (i.e., an increase of 25 percent). Such an increase would, in this somewhat stylized example, give rise to around 5,400 (3.75 percent) more burglaries and around 2,600 (4 percent) more car thefts. It should be pointed out that an increase in the unemployment rate from 4 to 5 percent is by no means an unrealistic figure. During the period under study, unemployment rates spanned from 1.5 percent to 10.4 percent. Hence, our results suggest that quite common changes in the unemployment rate can have substantial effects in terms of the number of crimes.

VI. Comparison with Other Results

It is interesting to compare our results to those of similar studies. When examining separate property crimes in West German *Bundesländer*, Entorf and Spengler (2000) found that the estimated unemployment elasticities are, in general, around zero. Their analysis of reunified Germany yields elasticities that are significantly higher, however—around 1 percent for robbery and theft. Papps and Winkelmann (2000) also use a log-log model and obtain unemployment elasticities around 0.1 for total offenses and dishonesty offenses (defined as theft, fraud, car conversion, receiving and burglary) in their analysis on New Zealand data.

In our study, the corresponding elasticities for burglary and car theft—the crimes that are significant in all model specifications—are around 0.15 and 0.16, respectively, in all model specifications. For aggregate property crime, the corresponding estimate obtained in the baseline model specification is about 0.11, but it is not robust for the inclusion of county-specific time trends. Hence, the estimated elasticities in our analysis are within the interval of the estimations carried out by Entorf and Spengler and by Papps and Winkelmann.

Several studies use log-linear models, where the coefficient value should be interpreted as the percentage effect of a 1 percentage point change in the unemployment rate. In Raphael and Winter-Ebmer (2001), an increment of 1 percentage point in the unemployment rate is estimated to increase property crime by 1.6–5 percent, depending on the model specification. The highest values are obtained in models where instrumental variables were used for unemployment. Gould *et al*. (2002) estimate the corresponding effect among males without higher education (non-college) to 2.2–2.8 percent. In Levitt's (1996) study, a 1 percentage point increase in unemployment is estimated to yield around 1 percent higher property crime rates.[14] In

[14] In the above three studies, property crime is defined as burglary, theft/pilfering and motor vehicle theft.

conclusion, the estimated effect on property crime in these studies lies between 1 and 5 percent, which is well in accordance with the results of our study: an increment of approximately 3.75 percent in burglary and 4 percent in car theft as unemployment rates rise from 4 to 5 percent. Our results are also well in agreement with those of Nilsson and Agell (2003). They find that a 1 percentage point drop in unemployment causes reductions of 1.2 percent in overall crime, 2.8 in the burglary rate, and 3.9 percent in the auto-theft rate.

The literature considered in the introduction to this paper suggested that support for the unemployment effect on crime is stronger in the U.S. studies than in the other papers mentioned. Some of the variation might be explained by differences in the factors which determine severance when unemployed, such as the unemployment benefit system and the overall unemployment structure. Without a coordinated analysis, however, it is precarious to compare the relative sizes of the estimated effects. It would therefore be interesting to pool data on different countries and analyze whether differences in unemployment structure and labor market policies are reflected in the estimated relation between unemployment and crime. However, it should be noted that the results of our study, as well as those of Nilsson and Agell (2003), are more in line with the American results than with the European studies.

It should be kept in mind that the unemployment rate is not the only possible measure of the state of the labor market. Ahmed *et al*. (1999) use a broader definition of labor-market conditions when measuring their effect on crime; in addition to unemployment rates, it also includes wage levels and unemployment benefits. Such a measure might be more appropriate for the economics of crime-related applications. Future research could thus be devoted to developing a method for measuring overall Swedish labor-market conditions and their effects on crime.

VII. Conclusion

The results of the panel-data analysis indicate that unemployment has a positive effect on certain property crimes. Significant coefficients, at the 5 and 10 percent levels, are obtained for burglary and car theft for all model specifications, i.e., for the baseline fixed-effects estimation as well as when county-specific time trends are included. Varying the set of covariates does not affect these results. Bike theft is weakly significant in some, but not all, model specifications, whereas no significant effect is found for the other property crimes under consideration.

There is also some evidence on the link between unemployment and aggregate property crime, but it is sensitive to the model specification. The estimated coefficient is significant in the baseline model specification and is robust to changing the set of covariates, but turns insignificant when county-specific time trends are included. On the other hand, the fact that the estimated effect of unemployment on property crime varies across the different crimes indicates that it is not suitable to sum specific crimes into an aggregate measure when the aim is to explain crime.

Among the violent crimes, none is found to be significantly related to unemployment.

The results from studies on unemployment and crime place the cost of unemployment in a broader perspective. According to the results of this study, it seems that higher unemployment does not solely lead to expenses directly related to unemployment, but may also have indirect effects in the form of increased property crime.

Appendix

Explanatory Variables and Descriptive Statistics

All explanatory variables in this study, except the clear-up rate, average income, sales of alcoholic beverages and population density, are indicated per 100,000 people. Data on unemployment were collected from the National Labor Market Board (www.ams.se) and measures the number of people in the labor force who are "openly unemployed". The clear-up rate measures the number of solved crimes per 100,000 reported crimes on an annual basis and was collected from the National Council for Crime Prevention. Data on average income, higher education, males 15–24, divorced persons and population density are from the Statistics Sweden database (see www.scb.se). Average income is defined as average deflated pre-tax income from work in SEK1,000.[15] (The measure includes income from work, pensions, unemployment benefits and sick pay.) Higher education is defined as the number of people per 100,000 in the age interval 16–74 with college or higher education, and population density is measured as population per km^2. Data on social allowances are from the National Board of Health and Welfare and measure the number of persons benefiting from social allowances in the age group 20–64. Alcohol is defined as sales at the National Liquor Monopoly (*Systembolaget*) in liters of 100 percent alcohol per person aged 15 years and older, and the data are from the sales statistics of the National Liquor Monopoly. Data until 1998 were collected from the National Board of Health and Welfare's database, Public Health in Figures ("How Are You, Sweden?"). Data for 1999 were obtained directly from the National Liquor Monopoly.

[15] Due to changes in tax regulations that went into effect following the Swedish tax reform in 1991, the definition of average income differs before and after the reform. For the years 1988–1990, besides income from work, capital income is also included, whereas average income for the years after the reform only measures income from work. Furthermore, data prior to 1991 measure income for all people aged 20 and older, while data for subsequent years measure the income of all persons aged 16 and older. To the extent that the effects of these changes are equal between regions, they are incorporated by the time-specific effects.

Table A1. *Estimates including county-specific linear time trends, property crime*

Variables (in logarithms)	Aggregate property crime	Burglary	Car theft	Bike theft	Pilfering motor vehicle	Pilfering shop	Robbery	Fraud
Unemployment	0.074	0.123	0.153	0.061	−0.005	−0.093	−0.045	0.223
	(0.045)	(0.071)*	(0.074)**	(0.035)*	(0.053)	(0.104)	(0.133)	(0.168)
Clear-up rate	−0.326	0.007	0.109	−0.096	−0.102	0.025	−0.303	−1.020
	(0.156)**	(0.070)	(0.098)	(0.043)**	(0.065)	(0.116)	(0.140)**	(0.545)*
Mean income	−0.954	−2.159	−3.293	−1.233	−2.139	−0.099	−0.749	0.313
	(0.903)	(0.862)**	(1.203)***	(0.683)*	(1.021)**	(1.595)	(2.063)	(3.739)
Education	−0.218	−0.587	0.104	0.139	0.097	−0.347	−0.377	−0.616
	(0.108)**	(0.121)***	(0.286)	(0.131)	(0.133)	(0.211)	(0.361)	(0.535)
Males 15–24	−0.424	−0.188	−1.033	0.097	−2.218	0.581	0.650	2.969
	(0.964)	(1.311)	(1.822)	(0.744)	(1.215)*	(1.816)	(2.224)	(3.615)
Foreign citizens	0.011	0.101	0.002	−0.242	0.193	−0.288	−0.120	0.503
	(0.159)	(0.173)	(0.265)	(0.134)*	(0.220)	(0.238)	(0.304)	(0.585)
Social allowance	−0.064	−0.508	−0.348	0.330	−0.071	0.162	−0.244	−0.579
	(0.157)	(0.150)***	(0.226)	(0.105)***	(0.155)	(0.290)	(0.326)	(0.557)
Divorced	1.562	4.428	4.570	1.313	5.307	−3.090	1.734	−8.175
	(1.167)	(1.383)***	(1.931)**	(0.972)	(1.612)***	(2.264)	(2.751)	(4.248)*
Alcohol	0.189	−0.032	−0.049	−0.251	0.345	0.637	−0.533	0.675
	(0.172)	(0.196)	(0.318)	(0.178)	(0.215)	(0.295)**	(0.432)	(0.725)
Population density	3.393	3.202	7.439	1.170	3.939	2.191	2.139	−11.113
	(1.791)*	(2.181)	(3.761)**	(1.771)	(2.532)	(3.984)	(4.185)	(7.050)
Observations	251	251	251	251	251	251	251	251
R-squared	0.94	0.93	0.95	0.98	0.96	0.82	0.95	0.75

Notes: Robust standard errors in parentheses; *significant at 10%, **significant at 5%, ***significant at 1%. Fixed effects and year dummies are included in all regressions. The hypotheses that all fixed effects are equal to zero and that all time effects are equal to zero are rejected for all specifications.

Table A2. *Estimates including county-specific linear and quadratic time trends, property crime*

Variables (in logarithms)	Aggregate property crime	Burglary	Car theft	Bike theft	Pilfering motor vehicle	Pilfering shop	Robbery	Fraud
Unemployment	0.063	0.125	0.174	0.058	−0.015	−0.112	−0.003	0.167
	(0.046)	(0.069)*	(0.085)**	(0.033)*	(0.053)	(0.100)	(0.141)	(0.185)
Clear-up rate	−0.312	0.047	0.177	−0.049	−0.083	0.038	−0.258	−1.084
	(0.162)*	(0.073)	(0.102)*	(0.041)	(0.071)	(0.138)	(0.165)	(0.544)**
Mean income	1.952	−1.982	−4.234	−0.244	−0.590	0.795	5.401	9.315
	(1.970)	(1.528)	(2.276)*	(0.859)	(1.561)	(2.955)	(3.561)	(6.956)
Education	−0.213	−0.594	−0.259	−0.124	0.200	0.035	0.333	−0.090
	(0.151)	(0.162)***	(0.352)	(0.132)	(0.199)	(0.267)	(0.535)	(0.760)
Males 15–24	0.239	−1.820	−2.945	−1.270	−3.253	0.130	5.778	8.759
	(1.325)	(1.342)	(2.370)	(0.914)	(1.316)**	(3.488)	(3.272)*	(5.185)*
Foreign citizens	−0.042	−0.212	−0.384	−0.381	−0.018	−0.414	0.166	0.981
	(0.188)	(0.217)	(0.348)	(0.153)**	(0.242)	(0.363)	(0.437)	(0.797)
Social allowance	0.215	−0.309	−0.470	0.328	−0.042	−0.014	−0.307	0.269
	(0.283)	(0.194)	(0.310)	(0.135)**	(0.200)	(0.339)	(0.391)	(0.965)
Divorced	0.477	3.520	3.598	1.380	5.411	−1.613	2.991	−13.215
	(1.294)	(1.569)**	(2.402)	(0.985)	(1.906)***	(2.517)	(3.508)	(4.775)***
Alcohol	0.183	0.159	0.048	−0.068	0.291	0.773	−1.045	0.267
	(0.186)	(0.197)	(0.349)	(0.146)	(0.264)	(0.344)**	(0.441)**	(0.834)
Population density	6.737	11.108	9.048	8.987	11.627	18.292	15.013	−15.805
	(4.298)	(4.949)**	(7.777)	(3.349)***	(5.069)**	(10.289)*	(11.324)	(17.477)
Observations	251	251	251	251	251	251	251	251
R-squared	0.95	0.95	0.96	0.99	0.97	0.83	0.96	0.78

Notes: See Table A1.

References

Ahmed, E., Doyle, J. M. and Horn, R. N. (1999), The Effects of Labor Markets and Income Inequality on Crime: Evidence from Panel Data, *Southern Economic Journal 65*, 717–738.

Becker, G. S. (1968), Crime and Punishment: An Economic Approach, *Journal of Political Economy 78*, 526–536.

Ehrlich, I. (1973), Participation in Illegitimate Activities: A Theoretical and Empirical Investigation, *Journal of Political Economy 81*, 521–565.

Entorf, H. and Spengler, H. (2000), Socioeconomic and Economic Factors of Crime in Germany: Evidence from Panel Data of the German States, *International Review of Law and Economics 20*, 75–106.

Freeman, R. B. (1999), The Economics of Crime, *Handbook of Labor Economics 3*, 3529–3571.

Fritzell, J. (2001), *Inkomstfördelningens Trender under 1990-talet* (Trends in Income Distribution during the 1990s), SOU, Stockholm, 137–187.

Gould, E. D., Weinberg, B. A. and Mustard, D. (2002), Crime Rates and Local Labor Opportunities in the United States: 1979–1995, *Review of Economics and Statistics 84*, 45–61.

Levitt, S. D. (1996), The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation, *Quarterly Journal of Economics 111*, 319–352.

Lochner, L. (1999), Education, Work, and Crime: Theory and Evidence, Working Paper no. 465, University of Rochester.

Martens, P. L. (1992), *Familj, Uppväxt och Brott* (Family, Upbringing and Crime), National Council for Crime Prevention, Stockholm.

National Council for Crime Prevention (2001), *Brottsutvecklingen i Sverige: 1998–2000* (Trend Analysis of Crime in Sweden, 1998–2000), Stockholm.

Nilsson, A. and Agell, J. (2003), Crime, Unemployment and Labor Market Programs in Turbulent Times, Working Paper no. 14, Institute for Labor Market Policy Evaluation, Uppsala.

Papps, K. and Winkelmann, R. (2000), Unemployment and Crime: New Evidence for an Old Question, *New Zealand Economic Papers 34*, 53–72.

Raphael, S. and Winter-Ebmer, R. (2001), Identifying the Effect of Unemployment on Crime, *Journal of Law and Economics 44*, 259–283.

Rodríguez Andres, A. (2003), Los Determinantes Socio-económicos del Delito en España, *Revista Española de Investigación Criminológica*. www.criminologia.net/revista.

Schuller, B.-J. (1986), Ekonomi och Kriminalitet—En Empirisk Undersökning av Brottsligheten i Sverige (Economics and Criminality—An Empirical Study of Crime in Sweden), Ph.D. Thesis, Department of Economics, University of Gothenburg.

Scorcu, A. E. and Cellini, R. (1998), Economic Activity and Crime in the Long Run: An Empirical Investigation on Aggregate Data from Italy, 1951–1994, *International Review of Law and Economics 18*, 279–292.

Witte, A. D. and Tauchen, H. (1994), *Work and Crime: An Exploration Using Paneldata*, National Bureau of Economic Research, Cambridge, MA.

First version submitted June 2003;
final version received June 2004.