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LONG-TERM UNEMPLOYMENT,
VIOLENT CRIME AND VIOLENCE-RELATED BEHAVIOUR

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Abstract

This is a panel data study over 289 Swedish municipalities for the period of 2000-2018. The purpose of this study is to reinvestigate the relationship between long-term unemployment and violent crime, as well as alcohol-drugs-related behaviour. Fixed effects model with time and area fixed effects (with and without municipality-specific linear time trends added) was used to conduct this study. The results show a strong relationship between long-term unemployment and violent crime category: one percentage point increase in long-term unemployment increases violent crime rate by 2.8%, everything else held constant. This finding indicates that opposed to total registered unemployment, long-term unemployment measure might be a better identifier of individuals at the margin of engaging in criminal activity. It is also plausible, that as the duration of unemployment increases, so does the strain and frustration of being jobless, which in turn triggers violent, drug- and alcohol-related behaviour. Instrumental variables approach was used as a sensitivity test to confirm the relationship between unemployment and crime.

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1. Introduction

Loss of job leads to a decrease in income, lower wellbeing, happiness, and overall satisfaction with life. High unemployment rate is associated with increased expenses for unemployment benefits which are very costly for society, especially in a welfare state like Sweden. During the period of 2000-2018 national unemployment rate in Sweden showed a large variation with a minimum of 5.8% in 2001 and a maximum of 8.6% in 2010.[1] Economic theory of crime suggests that unemployment may cause an increase in crime as well, especially in property crime opposed to violent crime. Vast number of recent empirical studies support this claim.

Crime entails substantial costs for society in form of material loss and physical damage, along with psychological and emotional stress, which affects health and overall quality of life negatively (NCCP 2017, Report 2017:8). According to National Council for Crime Prevention (NCCP) many of international studies find that cost of violent crime is greater than cost of property crime. During the period of 2000-2018, property crime rates has shown a steady decrease, the opposite trend has been observed for violent crime.

The point of interest of this work is to reinvestigate the effect of long-term unemployment on violent crime in Sweden. The research work named "Long-term unemployment and violent crime" by M. Nordin and D. Almén (2017) is a unique study on the subject. It has been an inspiration and a guideline for the current paper. The researchers have found that long-term unemployment identifies a group at the margin of commuting crime and/or a specific mechanism that triggers violent behaviour better than total unemployment. The aim of this study is to investigate whether the findings of M. Nordin and D. Almén (2017) can be confirmed.

I replicated some of their steps in my analysis. Both studies were conducted on panel data sets for 289 Swedish municipalities and rely on two specifications of fixed effects model: 1) fixed effects model with area and time fixed effects; 2) fixed effects model with area and time fixed effects and municipality-specific linear time trends. Instrumental variables approach is used as a sensitivity test to confirm the relationship between unemployment and crime.

However, here are significant differences in data and time period between the two studies. For example, total unemployment rate from National Labour Market Board, used in the original study, was substituted with total registered unemployment rate from database STATIV at Statistics Sweden. Data on long-term unemployment rate were extracted from the same source (STATIV, Statistics Sweden). Violent crime category was expanded with alcohol-drugs-related

[1] Statistics Sweden (AKU database), for population aged 15-74.

crime. The list of explanatory variables was extended with marital status variables, more of age distribution variables were included. Time period is also different: 2000-2018 in this study and 1998-2010 in the original one. For comparison convenience, I gave the same names to corresponding variables.

2. Theoretical background and previous research

To defeat crime has been a challenge for human societies across the world through all times. Various measures have been developed by authorities to punish offenders and discourage criminal behaviour in the future. But which of these measures work best? It has become necessary to develop tools for policy evaluation.

Since 1920s, scholars attempted to clarify criminal behaviour in framework of sociology and psychology. Although, behavioural sciences produced explanations for crime through social structure and conditions, cultural aspects and norms, individual psychological traits, inadequacies and anomalies, they were of little use for policy-makers (Mastrobuoni 2014).

Becker (1968) pioneers with an economic model of crime and Ehrlich (1973) develops this model and extends it with a time constraint. According to Ehrlich (1973), individual decides whether to engage in illegal activity based on personal opportunities on labour market, perceived risks and consequences, rather than individual characteristics. A person compares the expected utilities of participation in legal or illegal labor markets and chooses where to allocate his or her time. One can choose an optimal combination of these two options. The model predicts that loss of job should increase marginal benefits of criminal activities and decrease relative time cost of participating in legal labour markets. Up until late 1990s academic research failed to produce strong evidence to confirm that bettered conditions of labor markets reduce crime. During the past 20 years research techniques and data quality has improved and new evidence of the effect of unemployment on crime has emerged (Mustard 2010).

Contemporary research commonly uses panel data at local level, area and time fixed effects model specification. Recent studies support the economic theory of crime, frequently found effect of unemployment on property crime is as follows: 1% point increase in unemployment rate increases property crime by 1-2% (Nilsson 2004, Linn 2008, Mustard 2010, Nordin and Almén 2017). The underlying factor for property crime is economic interest and monetary reward. Violent and alcohol-drugs-related crimes are rarely committed in pursue of economic gain, thus, it may look like that economic theory falls short to explain this category of crime. However, improved labour market conditions increase a possibility for legal earnings, therefore leaving less free time to spend on illegal activities, leading to a decrease in crime rates. Few studies, conducted on aggregated data found a relationship between unemployment and violent crime (Nordin and Almén 2017).

In theoretical framework for sociology and criminology, low self-control theory and strain theory may shed light upon association between unemployment and crime at individual level (Rege, Skardhamar, Telle, Votruba 2009). General theory of crime states that low self-control trait is associated with physical harm, criminal behaviour, removal from educational and work places, inability to build successful relationships with family, friends, colleagues. Low-self control is not a predisposition to commit crime, but rather an impulse to concentrate on short-term benefits without consideration for long-term consequences (Gottfredson and Hirschi 1990).

According to strain theory, loss of a job may induce mental stress, trigger anger and frustration, aggressive and violent behaviour, breaking rules and social norms (Agnew 1992).

The other important determinant of criminal behaviour is idleness. One needs an opportunity to commit a crime, not only a motivation. Being unemployed provides one with time for criminal activity and alcohol-drugs-related behaviour (Rege et al. 2009).

According to Mustard (2010) it is important to identify a marginal group of individuals who are likely to engage in criminal activity. In a panel data study over 95 French regions, Fougère (2009) identifies the effect of youth unemployment rate along with total unemployment rate on crime, but finds no connection between long-term unemployment and crime. Bell et al. (2018) in a panel data study over the US states and the UK standard regions found strong evidence that graduating from school and entering labour market in a recession period (when unemployment rate is 5 percentage points higher than usual) increases a probability of being arrested as well as becoming a career criminal. This finding indicates a significant and a long-lasting effect of youth unemployment on crime. On a contrary, Agell and Öster (2007) in a panel data study over 288 Swedish municipalities found no significant relationship between youth unemployment rate and crime. Some studies identify the effect of wages for low skilled workers on crime and find that it is bigger than the effect of unemployment (Machin and Meghir 2004, Krivo and Peterson 2004). Income inequality is also an important determinant of the effect on violent crime (Krivo and Peterson 2004, Nilsson 2004). Nordin and Almén (2017) found that one percentage point increase in long-term unemployment increases violent crime by 2.1 percent.

Theories which explain the economics of crime and violence-related behaviour are based on individual choice models, therefore studies conducted on microeconomic data set, containing information about individual's background and criminal record, are more precise and convincing than studies based on aggregated data.

A Norwegian study, using individual level data, found the effect of plant closure on violent crimes and violence-related behaviour, but no effect on property crime. Exposure to plant closure effected crime incidences during week days, but not weekends, proposing idleness as an important mechanism in such a relationship (Rege et al. 2009).

A Swedish study using individual level data on young people, unveiled the effect of unemployment on both property crime and violent crime. The duration of unemployment found to be an important determinant of young males' overrepresentation in committing crime. (Grönqvist 2011).

Idleness and strain increase with time, therefore total unemployment measure, which accounts mainly for short-term unemployment, fails to identify the group at the margin of committing violent crime. A unique Swedish study, using a panel data over 289 municipalities, analysed the impact of long-term unemployment on violent crime and found that this measure of unemployment is an important identifier of 1) a specific mechanism which is not captured by total unemployment measure, and/or 2) a group at the margin for committing violent crime (Nordin and Almén 2017).

3. Data and Methodology

In present study, a panel data set for 289 Swedish municipalities for the period from 2000 to 2018 is used to reinvestigate the relationship between long-term unemployment and violent crime. There are 290 municipalities in Sweden at present time, however, Knivsta municipality was established in the year 2003 and was excluded from the analysis. The large number of municipalities over the time period of 19 years provides with 5,443 observations. Some data on crime reports are missing[2]. One outlier has been removed from Handling Stolen Property data. For some types of crime the actual number of reports is zero. Zero values were changed to 0.00001 before logarithmic transformation. All the variables which were used in the analysis and their descriptive statistics are presented in Table 8.

3.1 Crime

Crime data are reported crimes per 100,000 residents, extracted from an open database at National Council for Crime Prevention (NCCP). Violent crime category consists of assault, sexual harassment, rape, robbery, drugs-related crime, driving under the influence of alcohol, driving under the influence of drugs. Crime types such as drugs-related crime, driving under the

[2] See Table 8 for details

influence of alcohol, driving under the influence of narcotics are violence-related and therefore are also included into this category. Property crime category includes theft, damage, burglary, auto theft and handling of stolen property. The proportions of crime types in each category are illustrated in Fig1 and Fig2.

Fig.1 Share of crimes in property crime category

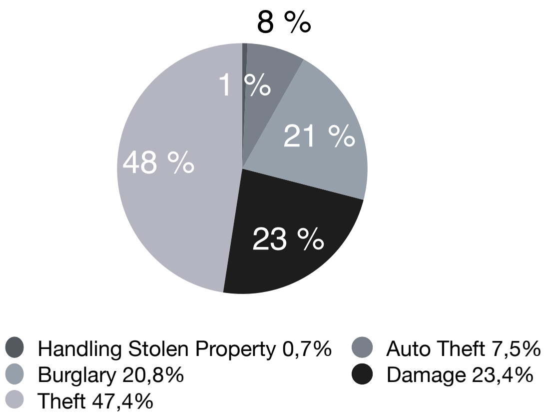
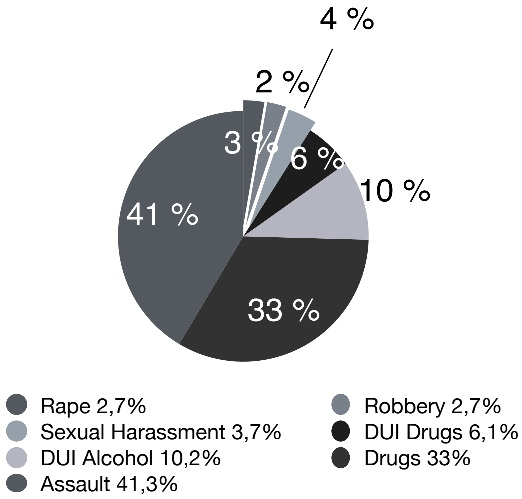
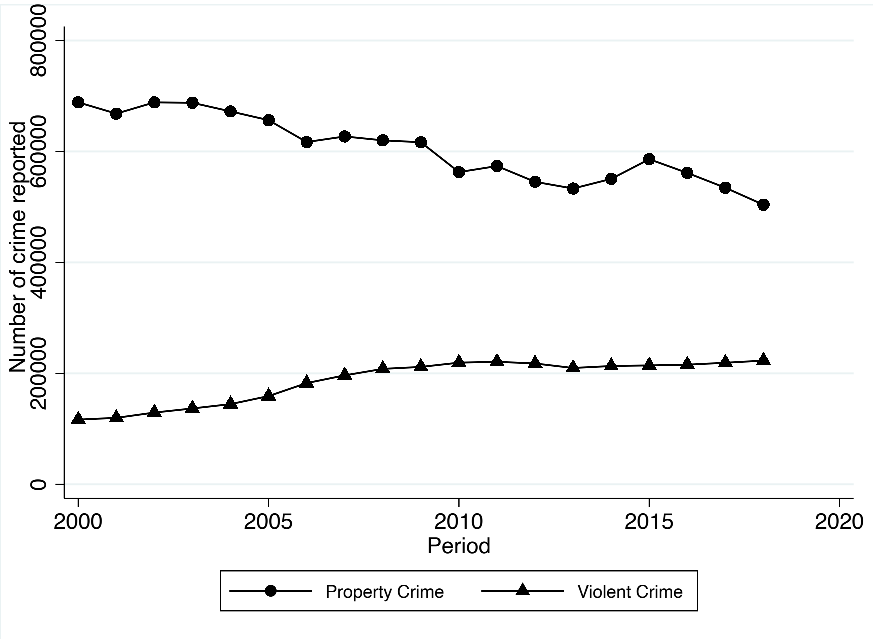


Fig.2 Share of crimes in violent crime category



According to NCCP, the total number of reported crime has increased by almost 28% during the time period of 2000-2018. There were reported 1,210,821 crimes in 2000, that number increased to 1,550,626 in 2018. Change in the number of reported crimes for the constructed categories of violent crime and property crime are shown in Fig.3. The amount of reported violent crime has nearly doubled: increasing by 91% from 116,771 reports in 2000 to 223,536 in 2018. Property crime exhibits an opposite trend, the number of reports has decreased by more than 26% from 688,764 in 2000 to 504,691 in 2018. Property crime is much more frequent than violent crime.

Fig. 3 Change in number of reports for violent crime and property crime in Sweden 2000 - 2018



Crime rates exhibit a broad variation across the municipalities during the study period. In general, municipalities with smaller size of population have the lowest crime rates. For example, the lowest total crime rate of 2,748 reports per 100,000 residents was in Ydre, a municipality with population of 3,612 residents, in 2012. There were 100 reports filed totally. The highest crime rates of 20,000 - 26,000 reports per 100,000 residents were common for Stockholm and Malmö. Surprisingly, Perstorp municipality with population of 7,479 inhabitants had the highest crime rate of 25,651 reports per 100,000 residents in the year 2018.

The lowest rates for property crime were reported in smaller populated municipalities. For example, Robertsfors, Pajala, Öckerö, Berg: municipalities with population under 15,000 residents, recorded the property crime rates under 1,500 reports per 100,000 residents. The highest rates were in Stockholm, Gothenburg, Malmö with magnitude between 10,000-14,000 reports per 100,000 residents. The mean mark over all municipalities is 4,860 reports. Violent crime rate varies from 97 (Ydre) to 11,775 (Perstorp) reports per 100,000 residents, with the mean over all municipalities of 1,574 reports.

Crime data are reported crimes and therefore, it is important to understand the relationship between reported crimes and crimes which were actually committed. Burglary, auto theft, damage and theft are often reported for insurance reasons: in order to claim a monetary compensation, crime must be reported to the police. Hence, it is unlikely that underreporting of property crime occurs. The propensity to report these types of crime does not change over time. In general, violent crimes like assault, rape, sexual harassment are reported at low rate. According to NCCP's Report 2017:5 (2017), crime is more likely to be reported if an offender and a victim are unfamiliar with each other, and if the severity of crime is high. Crime is not likely to be reported if an offender and a victim are connected by family ties. Drugs-related crimes, driving under the influence of alcohol, driving under the influence of narcotics are reported as a result of police controls. It is known that drug and alcohol consumption is positively correlated with violence. Hence, growing rates of these types of crime might indicate an increase of violence, especially domestic violence.

Growing rate of violent crime can be explained by a higher reporting rate. According to a survey research conducted by NCCP (2008), the reporting rate for violent crime has increased. For fixed effects estimate to be unbiased, the propensity to report crime should vary over municipalities and stay constant over time, or change over time in all municipalities in the same way. There is some evidence reported by NCCP, that the propensity to report crimes may vary across Swedish regions and has changed over time across Swedish municipalities differently, this may bias the estimates (NCCP 2008, Nordin and Almén 2017). However, Nilsson and Agell (2003) point out that there is no bias problem at the municipality level if the trends in unemployment and the trends in propensity to report crime are uncorrelated.

The relationship between reporting rate and unemployment might depend on social capital and norms within society: more crimes are reported when social capital increases (Buonanno et al. 2009, Nordin and Almén 2017). Unemployment and social capital are negatively related: the propensity to report crimes decreases, when unemployment increases, therefore the risk to overestimate the effect of unemployment on crime is small. However, inclusion of municipality-specific linear time trends in the model removes all linear trends in reporting crimes.

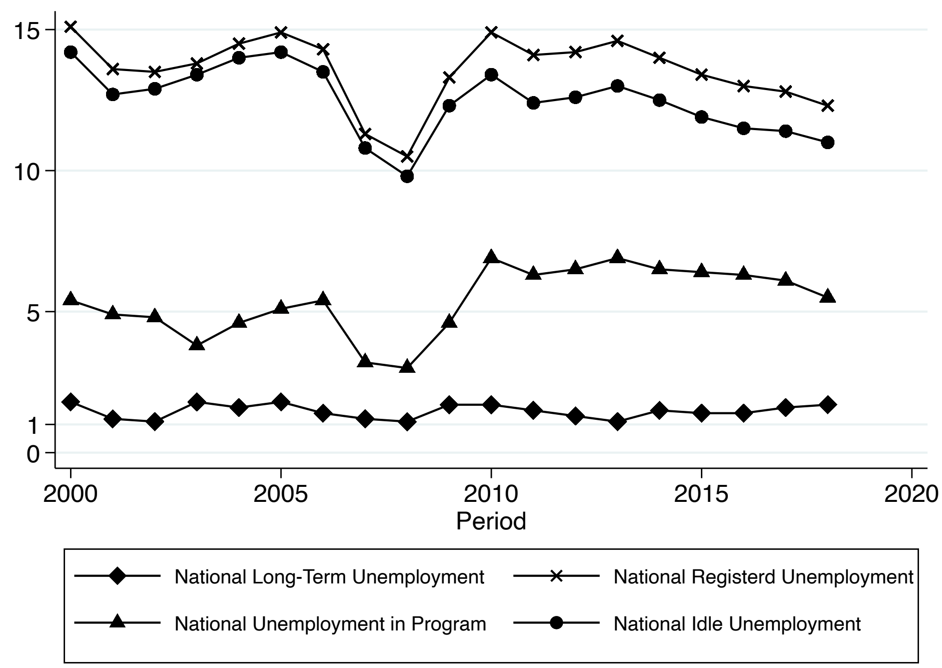
3.2 Unemployment

Unemployment data include two unemployment rates extracted from database STATIV at Statistics Sweden:

- municipal total registered unemployment rates for total population (aged 20-64)
- municipal long-term unemployment rates for total population (aged 20-64)

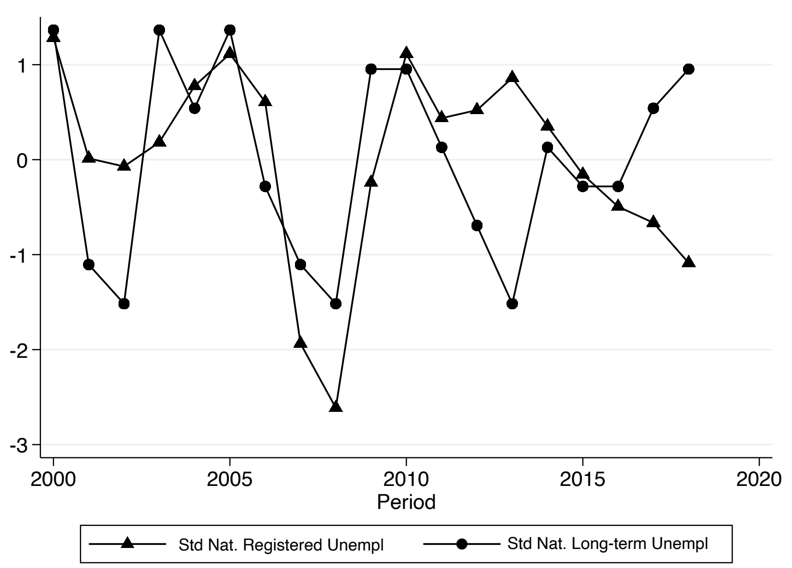
According to data descriptions at Statistics Sweden, total registered unemployment includes individuals who were listed as idle unemployed and/or unemployed participating in labor market programs at least once during a year. The majority of them are idle unemployed. Long-term unemployment is included in idle unemployment as a subgroup. Individuals aged under 25 years old are counted as long-term unemployed if they were listed as unemployed for more than 100 consecutive days. Individuals aged over 25 years old are registered as long-term unemployed if they have been listed as unemployed for a minimum of 6 consecutive months. All the unemployment rate measures are calculated as a proportion of total population in corresponding age, and not as a proportion of the labour force, variation of which may affect the unemployment rate (Fougère et al. 2009, Nordin and Almén 2017). Fig. 4 illustrates the unemployment rates in Sweden for the period of 2000-2018.

Fig. 4 Long-term unemployment rate, total registered unemployment rate, idle unemployment rate, unemployment rate for participating in labor market programs at national level in percent, Sweden 2000-2018



As shown on Fig. 4, total registered unemployment exhibits wider variation than long-term unemployment. Here I follow Nordin and Almén (2017) and compare standardised measures of national registered unemployment and national long-term unemployment. In order to obtain standardised measures of unemployment, I subtract the mean and divide by standard deviation. As shown on Fig. 5, these standardised unemployment measures exhibit similar variation.

Fig.5 Standardised measures of registered unemployment rate and long-term unemployment rate at national level in Sweden, 2000-2018



To make sure that variation in long-term unemployment at municipality level is sufficient for identifying the effects on crime, relative change measures for total registered unemployment and long-term unemployment have been computed (municipality *i* and year *t*):

$$(RegUnempl_{i,t} - RegUnempl_{i,t-1}) / mean\ (RegUnempl_i)$$
$$(LongUnempl_{i,t} - LongUnempl_{i,t-1}) / mean\ (LongUnempl_i)$$

Standard deviations of these relative changes provide with a tool for comparing variation in the unemployment rates, resulting in 0.109 for total registered unemployment and 0.363 for long-term unemployment. Hence, the relative variation in long-term unemployment shows 3.322 times larger variation than total registered unemployment, mainly between years than to the mean. Nordin and Almén (2017) have obtained relative variation measure equal to 1.65 based on National Labour Market Board's data for total registered unemployment and Statistics Sweden database STATIV's data on long-term unemployment for the time period 1998-2010.

Most of the Swedish studies rely on unemployment data presented by National Labour Market Board. I deliberately chose a different data source to see how it may affect the results.

The study period includes both boom and bust phases of economy, covers the period of the great recession (2007-2009). This yields a broad variation in unemployment rates over municipalities and years. The lowest rates for total registered unemployment are in between 4% and 5%, and are found in Danderyd, Ekerö, Täby, Lidingö – prosperous municipalities neighbouring Stockholm. The highest rates are in the range of 30-33% and are reported by Övertorneå, Pajala, Haparanda – smaller populated municipalities located in northern Sweden. The mean mark is 14.1%. The lowest long-term unemployment rates are below 1% and typically found in prosperous municipalities around Stockholm, the highest rates are in between 3-4.5%. The mean mark is 1.23%.

3.3. Empirical approach

To investigate the impact of unemployment on crime, fixed effects model is used.

$$\boldsymbol{Ln(crime_{i,t})} = \alpha_i + \delta_t + \beta\ \boldsymbol{Unemployment_{i,t}} + \rho \boldsymbol{X_{i,t}} + \boldsymbol{Y_{i,t}} + \varepsilon_{i,t}$$

($\boldsymbol{i}$ denotes municipality, $\boldsymbol{t}$ denotes year)

$\boldsymbol{Ln(crime_{i,t})}$ is a natural logarithm of number of reported crimes of certain category per 100,000 residents.

α_i is a municipality fixed effect. It captures and removes variation in crime rates, induced by unobserved factors which differ across municipalities and stay constant over time. For example, differences between urban and rural municipalities, climatic, geographical and cultural differences across municipalities.

δ_t is year fixed effect term, that eliminates aggregate trends. It captures and removes variation in crime rates, determined by unobserved factors which change over time in the same way in all municipalities. For example, police work gets more efficient due to technological innovation, methods of narcotics trade get more advanced. Due to this term, the within-municipality effect of unemployment on crime is not influenced by national trends.

$\boldsymbol{Unemployment_{i,t}}$ refers to total registered unemployment and long-term unemployment rates;

$\boldsymbol{X_{i,t}}$ is a vector of controls. To minimise the risk of bogus correlations and omitted-variable bias, wide range of demographic and socioeconomic explanatory variables is included into the model.

$\boldsymbol{Y_{i,t}}$ municipality-specific time trends. Including municipality-specific time trends in the model eliminates linear trends in reporting crimes.

$\varepsilon_{i,t}$ the error term.

For OLS estimation, which relies on variation in the averages between municipalities, omitted variables bias is a potential problem. Fixed effects estimation allows to control for all observable and unobservable differences across municipalities, restricting estimates to within-municipality variation. This restriction reduces the risk of omitted variable bias, as long as unobservable factors are constant over time and vary across municipalities or constant across municipalities but vary over time. For the estimates to be unbiased, the correlation between the error term and independent variables must equal zero, otherwise it is not possible to exclude the endogeneity bias and confirm the causal effect of unemployment on crime.

All data for crime explanatory regressors are at municipality level and collected at Statistics Sweden. Table 8 lists all the explanatory variables and provides with their descriptive statistics. According to National Council for Crime Prevention (2017, 2019), youth, males and immigrants are overrepresented in all crime categories. Individuals of different age groups, marital status, gender are victimised by different crime types. Furthermore, young and unexperienced have worse opportunities on legal labour market and are less attached to it. Therefore, variables for *age distribution* in total population (ages: 0-14, 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64), the *share of males* in total population and the *share of residents with foreign origin* in population aged 0-64 are included into the model (variables measured in percent).

According to Levitt and Lochner (2001) insecure family conditions have a strong impact on engagement of youth in criminal activities. Furthermore, single parent households are often low income ones. Becoming a divorcee or a widower brings big changes into one’s life, arises psychological and mental stress, which in turn might trigger anger and frustration, violent and alcohol-drugs-related behaviour. The proportions of *married*, *widowed* and *divorced* in population of each municipality, measured in percent, are therefore added to the model.

High income regions may experience either high or low crime rates. In a prosperous community crime is less tempting. People with higher incomes have fewer reasons to steel, and have more resources to protect their property. On the other hand, the returns to crime increase, due to the fact that wealthy people have more valuables to steal (Nordin and Almén 2017). According to Nordin and Almén (2017) income levels in municipalities are dynamic and in order to account for different effects of income on crime two income variable should be included in the model: *logarithm of income* and *first difference of logarithm of income*. Data on income are mean per capita gross income deflated with Consumer Price Index.

Crime levels per capita are higher in large cities, compared to small ones. *Logarithm of density of population* and *logarithm of size of population* are included for this reason.

Education plays a role in determining crime. Higher levels of education are associated with higher income and better labour market opportunities. The share of individuals who are *qualified for high school* and the share of individuals who are *qualified for university*, measured in percent are added to the analysis. This shares are calculated out of total number of students graduated in a given year, and identify scholarly performance among young adults, who are about to search for a job for the first time or continue with their studies.

In sensitivity analysis of their research, Nordin and Almén (2017) included variables *Conviction rate*$_{t-1}$ and *Logarithm of police force*$_{t-1}$ in order to control for risk of detection and punishment. I do not follow them here for two reasons. For the first, data on police force for the period of 2000-2014 is only available at county level (there are 21 counties in Sweden, each county consists of several municipalities) and for the period of 2015-2018 at police region level (there are 7 police regions in Sweden). Therefore, it is not possible to control for differences between the municipalities, which constitute one county or police region. For the second, criminals change their behaviour steadily over time, fixed effects should eliminate that change (at least a large part of it), therefore, if there is a risk of omitted variable bias, it is probably small (Nilsson & Agell 2003). Furthermore, a perpetrator might live in one municipality and choose to commit crime in the other (a criminal might come from a different country to commit crime in Sweden), causing crime rate to grow. These plausible events are not necessarily constant across municipalities and time invariant. I do not have any controls which account for this, therefore, there is a risk for omitted variable bias. To conclude, there is a risk of potential biases induced by omitted variables, measurement errors, simultaneity in the relationship between crime rates and unemployment rates, reversed causality. In fact, there is no such a model which can produce the exact estimates of causal relationship of unemployment on crime.

4. Results and Analysis

The results for property crime are presented in Table 1, the results for violent crime are presented in Table 2. Column 2 and column 3 in both tables show the results for municipality and year fixed effects model specification 1, columns 4 and 5 correspond to the results for municipality and year fixed effects with added municipality-specific linear time trends, model specification 2

$$Ln(crime_{i,t}) = \alpha_i + \delta_t + \beta\ Unemployment_{i,t} + \rho X_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$Ln(crime_{i,t}) = \alpha_i + \delta_t + \beta\ Unemployment_{i,t} + \rho X_{i,t} + Y_{i,t} + \varepsilon_{i,t} \quad (2)$$

Columns 2 and 4 correspond to total registered unemployment and columns 3 and 5 correspond to long-term unemployment. The results were obtained from separate regressions for each crime category and type of unemployment rate, clustered standard errors were applied to account for heteroskedasticity across the municipalities. All models were weighted with population size.

According to the obtained results, total registered unemployment has a small, but statistically significant impact (at 10% significance level) on property crime in model specification 1. One percentage point increase in total registered unemployment increases property crime by 0.7%, everything else held constant. This estimate is somewhat smaller than the effect of 1-2% found in previous Swedish and foreign research. For example, Nordin and Almén (2017) found the effect of 1.1%. The average annual number of property crime reports for the studied period nationwide is 604,957. If the point estimate is correct, one percentage point increase in total registered unemployment rate will lead to an increase of 4,356 property crime reports per year. Adding municipality-specific linear time trends (model specification 2) turns the estimate negative and non-significant.

Long-term unemployment exhibits an effect of a higher magnitude on property crime than total registered unemployment with a point estimate of 2.11, t=1.62, p-value = 0.10 in model specification 1. This result is only borderline significant at 10% significance level. One percentage point increase in long-term unemployment increases property crime by 2.1%, everything else held constant. If the point estimate is correct, this corresponds to 12,704 more property crime reports per year. This effect is economically significant and should not be disregarded. For comparison, Nordin and Almén (2017) found an effect of long-term unemployment on property crime with point estimate 1.81, significant at 10% level. Adding municipality-specific linear time trends (model specification 2) turns the estimate negative and non-significant. Interestingly, total registered unemployment has shown the same impact on violent crime as on property crime, point estimate 0.77, significant at 10% level of significance (model specification 1). Nordin and Almén (2017) did not find a significant relationship between total unemployment and violent crime, the same is true for many other Swedish and foreign studies. For illustration, the average number of violent crime reports during 2000-2018 at national level is 187,343. One percentage point increase in total registered unemployment rate will lead to 1,443 more of violent crime reports per year (everything else held constant), assuming the point estimate is correct. The impact of long-term unemployment on violent crime is greater than the effect of total registered unemployment with a point estimate 2.84, significant at 5% level. That is, one percentage point increase in long-term unemployment increases violent crime by 2,8%, everything else held constant. This means 5,246 more violent crime reports per year, if the point of estimate is correct. This result is of a higher magnitude compared to the findings of Nordin and Almén (2017): the point estimate is 2.13. Adding municipality-specific linear time trends (model specification 2) decreases the effect of long-term unemployment on violent crime and turns it non-significant.

Explanatory variables display both expected and surprising signs and magnitudes. In model specification 1, the share of population *aged 0-14* and the share of population *aged 15-19* show high and statistically significant positive impact (at 1% level of significance) on property crime rates (for both total registered unemployment and long-term unemployment). Adding municipality-specific linear time trends (model specification 2) turns these estimates non-significant for the proportion of individuals *aged 0-14* and reduces the effect and significance for the share of individuals *aged 15-19*. Both of these age distribution variables show negative and non-significant impact on violent crime in model specification 1, and positive non-significant effect in model 2. In their research Nordin and Almén (2017) find the opposite: the share of individuals *aged 15-19*, show strong positive correlation with violent crime, and negative correlation with property crime. Knowing that youth is highly overrepresented in crime, one would expect positive significant estimates of these age variables on property and violent crime.

The share of population *aged 25-29* shows large and significant effect on violent crime (model specification 1) with a point estimate of 8.29 for total registered unemployment and a point estimate of 8.49 for long-term unemployment. Adding municipality-specific linear time trends to the model turns the results negative and non-significant. The opposite effect is observed for property crime category. There is a strong negative correlation between the share of population *aged 25-29* and property crime with a point estimate of -5.94 for total registered unemployment and a point estimate of -5.79 for long-term unemployment. Due to the fact, that youth is overrepresented in crime, the negative estimates are surprising. The share of population *aged 45-49* show large negative and significant impact on property crime in both model specifications, while the share of population *aged 50-54* exhibit large positive effect on property crime in model specification 1, adding municipality-specific linear time trends turns the results negative and non-significant.

Interestingly, the *Share of Immigrants* in population show a negative impact on property crime in both models (specification 1 and 2). This is an unexpected result, due to the fact that persons with non-Swedish origin are overrepresented in crime. The *share of males* in population, as expected, show large and significant effect on violent crime (model specification 2), but no significant effect on property crime, which is a surprise, because male offenders and male victims are heavily overrepresented in crime. One percentage point increase in the *share of Males* in population increases violent crimes by 6%, everything else held constant in model specification 2, however in model specification 1 the estimates are lower and non-significant (for both total registered unemployment and long-term unemployment). The estimates for property crime in both models are positive, but not significant.

The *share of widowed* and *divorced* in population show large positive and significant impact on property crime, model specification 2. The magnitudes of these estimates are surprising, the share of widowed in population show an effect of over 9 % and the share of divorced – an effect of over 12% (for both total registered unemployment and long-term unemployment). This finding might indicate that distorted family circumstances do indeed matter and affect crime rates. To compare, Nilsson (2004) found that the proportion of divorced in population had a positive effect of nearly 20% on the overall crime rate. Surprisingly, the s*hare of married* in population show the effect of around 6% on property crime, significant at 1% level (model specification 1), adding municipality-specific linear time trends reduces the estimates and turns them non-significant. The *share of widowed* in population show a negative impact on violent crime in model specification 2, the results are significant for total registered unemployment only. The *share of divorced* in population show the effect of more than 8% on violent crime (everything else held constant) in model specification 2 (for both total registered unemployment and long-term unemployment).

The *density of population* show a negative impact on violent crime in model specification 1, adding municipality-specific linear time trends turns the estimates positive and non-significant. The *density of population* coefficients are negative and non-significant for property crime in both models. The *size of population* exhibits large positive and significant effect on property crime, model specification 2, while the results for model specification 1 are positive, but nonsignificant. All the coefficients of the *size of population* for violent crime are negative and nonsignificant in both models. The negative sign of these variables is surprising, since in general, crime rates are higher in large cities with denser population.

The explanatory variables for income are, as expected, negative both for property crime and violent crime with exception for long-term unemployment, model specification 2. But none of the income variables are statistically significant. The control variables on education are as expected, negative for all crime categories in both model specifications, but significant for violent crime only.

To conclude, it seems that results are sensitive to the specification of the model, adding municipality-specific linear time trends changes magnitude, sign and significance of the coefficient estimates of some variables.

Tables 3, 4, 5, 6 in the Appendix present the results on separate regression for each crime type, model specifications 1 and 2. The top rows represent results for total registered unemployment, the bottom rows correspond to long-term unemployment. Below I report statistically significant results. One percentage point increase in long-term unemployment increases *auto theft* by 5.3% , *assault* by 3%, *drugs-related crimes* by 6.5%, *driving under the influence of alcohol* by 5.6%, *driving under the influence of drugs* by 8.7% (everything else held constant) in model specification 1. In model specification 2, one percentage point increase in long-term unemployment increases *handling of stolen property* by 1.3 %, *assault* by 1.7 %, *driving under the influence of alcohol* by 3.8%, and decreases *damage* crime by 5%. One percentage point increase in total registered unemployment increases *assault* by 0.8%, *driving under the influence of alcohol* by 2.3 % (everything else held constant) in model specification 1, and decreases *sexual harassment* by 1.4% (everything else held constant) in model specification 2. For comparison, in their research Nordin and Almén (2017) found that one percentage point increase in long-term unemployment increased the assault rate by 1.6% in model specification 1, and by 2.4% in model specification 2. One percentage point increase in total unemployment increased theft by almost 1% and violation of women's integrity by 4.5% in model specification 2. Agell and Öster (2007) found that one percentage point decrease in unemployment decreased auto theft rate by 3.8% and burglary rate by 2.8%.

Table1 Effects of total registered unemployment, long-term unemployment on property crime in Sweden, years 2000-2018 Municipality and year fixed effects model (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5)

	Model 1. Municipality and year fixed effects without municipality-specific linear time trends		**Model 2.** Municipality and year fixed effects with municipality-specific linear time trends added	
	Property crime	Property crime	Property crime	Property crime
Registered unemployment	0.0072*	x	-0.0027	x
	(0.0043)	x	(0.0035)	x
Long-term unemployment	x	0.0211	x	-0.0113
	x	(0.0130)	x	(0.0099)
Share aged 0-14 years (%)	0.0549***	0.0540***	0.0062	0.0061
	(0 0189)	(0 .0186)	(0.0164)	(0.0165)
Share aged 15-19 years (%)	0.0678***	0.0670***	0.0392*	0.0384*
	(0.0210)	(0.0208)	(0.0219)	(0.0219)
Share aged 20-24 years (%)	0.0185	0.0179	0.0337	0.0328
	(0.0200)	(0 .0201)	(0.0237)	(0.0234)
Share aged 25-29 years (%)	-0.0594***	-0.0579***	0.0378	0.0379
	(0.0226)	(0.0220)	(0.0257)	(0.0252)
Share aged 30-34years (%)	-0.0534**	-0.0534**	0.0159	0.0161
	(0.0250)	(0.0256)	(0.0292)	(0.0289)
Share aged 35-39 years (%)	0.0183	0.0185	0.0165	0.0170
	(0.0180)	(0.0180)	(0.0304)	(0.0304)
Share aged 40-44 years (%)	-0.0037	-0.0013	0.0118	0.0125
	(0.01672)	(0.0167)	(0.0273)	(0.0273)
Share aged 45-49 years (%)	-0.0439**	-0.0379*	-0.0427*	-0.0429*
	(0.0209)	(0.0196)	(0.0244)	(0.0243)
Share aged 50-54 years (%)	0.0481***	0.0507***	-0.0093	-0.0088
	(0.0136)	(0.0134)	(0.0196)	(0.0196)
Share aged 55-59 years (%)	0.0003	0.0019	-0.0248	-0.0216
	(0.0133)	(0.0138)	(0.0159)	(0.0159)
Share aged 60–64 years (%)	0.0180	0.0191	-0.0047	-0.0040
	(0.0141)	(0.0145)	(0.0161)	(0.0161)
Share of males in population (%)	0.0394	0.0358	0.0140	0.0135
	(0.0245)	(0.0241)	(0.0244)	(0.0243)
Share of foreign origin (age 0-64) in population (%)	-0.0102*	-0.0086	-0.0153**	-0.0152**
	(0.0058)	(0.0053)	(0.0064)	(0.0064)
Share of married (%)	0.0608***	0.0593***	0.0249	0.0245
	(0.0186)	(0.0185)	(0.0183)	(0.0182)

Table1 Effects of total registered unemployment, long-term unemployment on property crime in Sweden, years 2000-2018 Municipality and year fixed effects model (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5)				
	Model 1. Municipality and year fixed effects without municipality-specific linear time trends		**Model 2.** Municipality and year fixed effects with municipality-specific linear time trends added	
	Property crime	Property crime	Property crime	Property crime
Share of widowed (%)	0.0001	-0.0049	0.0934**	0.0928**
	(0.0363)	(0.0374)	(0.0402)	(0.0400)
Share of divorced (%)	0.0081	0.0146	0.1266***	0.1255***
	(0.0246)	(0.0232)	(0.0289)	(0.0284)
Ln of density of population	-0.1511	-0.1122	-0.3203	-0.3201
	(0.2015)	(0.1958)	(0.2216)	(0.2199)
Ln of size of population	0.3488	0.3506	0.6173*	0.6090*
	(0.2640)	(0.2652)	(0.3220)	(0.3205)
First diff. of the ln of income	0.4447	0.5160	0.4362	0.3951
	(0.3981)	(0.4104)	(0.4131)	(0.4104)
Ln of income	-0.0792	-0.2624	-0.4162	-0.3848
	(0.4407)	(0.3887)	(0.6587)	(0.6185)
Share qualified for high school (%)	-0.0007	-.00007	-0.0004	-0.0004
	(0.0011)	(0.0011)	(0.0009)	(0.0008)
Share qualified for university (%)	-0.0007	-0.0007	-0.0004	-0.0004
	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Observations	5,443	5,443	5,443	5,443
R-squared	0.9249	0.9248	0.9474	0.9474

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Models are weighted with population size and include municipality and year fixed effects (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5). Robust clustered standard errors are in brackets,
*** $p < 0.01$ **$p < 0.05$ * $p < 0.1$

Table 2 Effects of total registered unemployment, long-term unemployment on violent crime in Sweden, years 2000-2018 Municipality and year fixed effects model (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5)				
	Model 1. Municipality and year fixed effects without municipality-specific linear time trends		**Model 2.** Municipality and year fixed effects with municipality-specific linear time trends added	
	Violent crime	Violent crime	Violent crime	Violent crime
Registered unemployment	0.0077*	x	-0.0062	x
	(0.0044)	x	(0.0042)	x
Long-term unemployment	x	0.0284**	x	0.0155
	x	(0.0121)	x	(0.0108)
Share aged 0-14 years (%)	-0.0330	-0.0334	0.0076	0.0109
	(0.0233)	(0.0121)	(0.0245)	(0.0243)
Share aged 15-19 years (%)	-0.0023	-0.0028	0.0105	0.0136
	(0.0202)	(0.0201)	(0.0211)	(0.0215)
Share aged 20-24 years (%)	-0.0022	-0.0022	-0.0231	-0.0165
	(0.0251)	(0.0249)	(0.0256)	(0.0261)
Share aged 25-29 years (%)	0.0829***	0.0849***	-0.0090	-0.0049
	(0.0300)	(0.0299)	(0.0301)	(0.0315)
Share aged 30-34years (%)	-0.0102	-0.0100	-0.0255	-0.0223
	(0.2196)	(0.0222)	(0.0282)	(0.0292)
Share aged 35-39 years (%)	-0.0464	-0.0459*	-0.0068	-0.0040
	(0.0237)	(0.0234)	(0.0328)	(0.0333)
Share aged 40-44 years (%)	0.0358	0.0382	0.0508*	0.0492
	(0.0234)	(0.0235)	(0.0307)	(0.0314)
Share aged 45-49 years (%)	-0.0207	-0.0140	-0.0072	-0.0070
	(0.0252)	(0.0252)	(0.0265)	(0.0271)
Share aged 50-54 years (%)	-0.0133	-0.0111	-0.0234	-0.0261
	(0.0234)	(0.0229)	(0.0356)	(0.0358)
Share aged 55-59 years (%)	-0.0222	-0.0203	-0.0226	-0.0237
	(0.0189)	(0.0187)	(0.0174)	(0.0176)
Share aged 60–64 years (%)	0.0173	0.0177	0.0137	0.0093
	(0.0175)	(0.0177)	(0.0269)	(0.0266)
Share of males in population (%)	0.0374	0.0326	0.0642*	0.0676**
	(0.0311)	(0.0307)	(0.0327)	(0.0328)
Share of foreign origin (age 0-64) in population (%)	0.0005	0.0019	0.0152	0.0137
	(0.0056)	(0.0056)	(0.0134)	(0.0135)
Share of married (%)	-0.0042	-0.0060	-0.0337	-0.0297
	(0.0164)	(0.0166)	(0.0221)	(0.0222)

Table 2 Effects of total registered unemployment, long-term unemployment on violent crime in Sweden, years 2000-2018 Municipality and year fixed effects model (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5)				
	Model 1. Municipality and year fixed effects without municipality-specific linear time trends		**Model 2.** Municipality and year fixed effects with municipality-specific linear time trends added	
	Violent crime	Violent crime	Violent crime	Violent crime
Share of widowed (%)	-0.0082	-0.0138	-0.1018*	-0.0965
	(0.0291)	(0.0290)	(0.0598)	(0.0607)
Share of divorced (%)	0.0168	0.0235	0.0823**	0.0864**
	(0.0298)	(0.0299)	(0.0418)	(0.0420)
Ln of density of population	-0.6579**	-0.6144*	0.0705	0.0007
	(0.3282)	(0.3374)	(0.4022)	(0.3919)
Ln of size of population	-0.0420	-0.0552	-0.6413	-0.6467
	(0.4049)	(0.4136)	(0.6265)	(0.6267)
First diff. of the ln of income	0.1672	0.2769	-0.1469	-0.0843
	(0.4957)	(0.4968)	(0.5958)	(5976)
Ln of income	-0.2046	-0.3635	-0.3871	0.0332
	(0.4353)	(0.3992)	(0.7361)	(0.7593)
Share qualified for high school (%)	-0.0017	-0.0018	-0.0026***	-0.0025***
	(0.0011)	(0.0011)	(0.0009)	(0.0009)
Share qualified for university (%)	-0.0019*	-0.0018*	-0.0007	-0.0007
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Observations	5,443	5,443	5,443	5,443
R-squared	0.8316	0.8316	0.8697	0.8697

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Models are weighted with population size and include municipality and year fixed effects (columns 2 and 3), municipality and year fixed effects with municipality-specific linear time trends added (columns 4 and 5). Robust clustered standard errors are in brackets,
*** $p < 0.01$ **$p < 0.05$ * $p < 0.1$

6. Instrumental variables approach

According to economic theory, businesses and low-wage employers might chose to relocate, when crime rates become high in the area, causing the unemployment rate to grow. It is also known that a person with a criminal background is less desirable as an employee and therefore is less likely to get a job. The cases of the reversed causality may bias the effects of unemployment on crime, overestimating them. If crime rates influence unemployment then the assumption of exogeneity of independent variable does not hold, and unemployment is correlated with an error term. To conduct a sensitivity test to support the causal relationship between unemployment and crime, the instrumental variable (IV) approach is used.

Instrumental variable must be partially correlated with unemployment and be exogenous to crime rate (must not be correlated with the error term in the regression equation). Such instrument has been developed and used in previous research (Agell and Öster 2007, Lin 2008, Fougère et al. 2009, Nordin and Almén 2017). In order to construct the IV, I follow the example of Nordin and Almén (2017) and also call it *Predicted employment*. It captures exogenous shocks imposed on employment at municipality level and therefore, is most likely exogenous to crime rates. Assume two similar municipalities, one with a large share of employees in IT-sector and the other with a large share of employees in manufacturing sector. An increase in national demand for employees in IT-sector will affect these two otherwise similar municipalities differently, benefiting the one with a large share of IT-sector employees.

The idea of *Predicted employment* instrument is to determine current employment at municipality level by using national changes in employment composition of different industrial and business sectors. Below I describe the construction of the IV.

Let the national industrial growth rate in industry j between time t and $t-1$ be

$$g_j = \frac{E_{j,t}}{E_{j,t-1}} - 1$$

where $E_{j,t}$ is the number of employees in industry j at time t in the country. The predicted employment in municipality i in industry j at time t is an interaction of aggregate industrial growth rate g_j and municipality-specific sectorial composition of employment lagged one period $E_{i,j,t-1}$

$$\textit{Predicted Employment}_{i,j,t} = \sum_{j=1}^{16} [(E_{i,j,t-1} \times gj) + E_{i,j,t-1}]$$

Employment data (day time employees) for 16 industry sectors in Sweden at municipality level for the period of 2000-2018 were obtained at Statistics Sweden. Lagging one period provides with an instrument for the years 2001-2018. The industry sectors include:

- agriculture, forestry and fishing
- manufacturing and production industries
- energy and environment
- building industry
- trade
- transport
- hotel and restaurant
- information and communication
- finance and insurance
- real estate
- corporate services
- civil authorities and defence
- education
- healthcare and public care
- personal and cultural services
- unknown.

To estimate the instrumental variable regression 2SLS two stage estimation method is used:

Second stage: $Ln\ (Crime\ rate)_{i,t} = \alpha_i + \delta_t + \beta_{\text{hat}}\ Unemployment_{i,t\ hat} + \rho X_{it} + \varepsilon_{it}$

First stage: $Unemployment_{i,t\ hat} = \alpha`_i + \delta`_t + \gamma\ Predicted\ Employment_{i,j,t} + \rho` X_{it} + \varepsilon`_{it}$

The first stage regression captures the effect of *Predicted Employment* on *Unemployment* in the municipalities. The second stage captures the effect of $Unemployment_{hat}$ on *Ln(Crime rate)*, where $Unemployment_{hat}$ is the exogenous variation in *Unemployment*, induced by *Predicted Employment.* Following Nordin and Almén (2017), I add *Squared Predicted Employment* to the model, due to a decreasing effect of *Predicted Employment* on unemployment.

The results were obtained from separate regressions for each crime category and type of unemployment rate, each unemployment rate was instrumented by *Predicted employment/1000* and *Squared predicted employment/1000*, clustered standard errors were applied to avoid heteroskedasticity problem across the municipalities. All models were weighted with population size. According to the obtained results, presented in Table 7, total registered unemployment has an effect of 13.10 on property crime and 4.06 on violent crime. Long-term unemployment has an effect of 37.11 on property crime and 16.69 on violent crime. Number of previous studies have reported high magnitudes of the IVs in 2SLS regressions. The high magnitude of the IV estimates might imply that *Predicted Unemployment* distinguishes a change in unemployment rate, that impacts crime, better than the average change in unemployment; it might also indicate a weak instrument, giving biased results and underestimated standard errors (Nordin and Almén 2017). However, both instruments are significant at first stage: $p < 0.01$, and show the right signs. Kleibergen-Paap Wald F-statistic for weak-IV test is below 10, which might indicate weakness of the instruments. However, according to Stock-Yogo weak ID test, the obtained F-statistic 7.42 for total registered unemployment and 8.49 for long-term unemployment lies above the critical value of 7.25 for 25% maximal instrumental variable size. Therefore, I can conclude that the instruments are strong at the excepted level of the maximal IV size. The instrumental variable approach confirms the effect of unemployment on crime and possibly uncovers that OLS regressions produce underestimated parameters. According to Nordin and Almén (2017) it should be seeing as a sensitivity test which confirms the effect of unemployment on crime and not a way to determine whether the parameters are biases or not.

Table 7 Instrumental variables results of the effect of unemployment on crime in Sweden, years 2001-2018

	Property crime	Violent crime	Property crime	Violent crime
Registered unemployment	0.1310**	0.0406*	x	x
	(0.0598)	(0.0216)	x	x
Long-term unemployment	x	x	0.3711*	0.1669**
	x	x	(0.2246)	(0.0806)
First stage results				
Predicted unemployment/1000	-0.0628***	-0.0628***	-0.0195***	-0.0195***
	(0.0168)	(0.0168)	(0.0048)	(0.0048)
Squared predicted unemployment/1000	0.00005***	0.00005***	0.00001***	0.00001***
	(0.00001)	(0.00001)	(4.12e-06)	(4.12e-06)
Weak-IV test	7.42	7.42	8.49	8.49
Observations	5,156	5,156	5,156	5,156

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Model is weighted with population size and includes municipality and year fixed effects and the vector of controls reported in Table 1 and Table 2. Robust clustered standard errors are in brackets. *** $p < 0.01$ **$p < 0.05$ * $p < 0.1$

6. Conclusion

The purpose of this study was to reinvestigate the relationship between long-term unemployment and violent crime. The strong effect of long-term unemployment on violent crime, found by Nordin and Almén (2017) in their unique research, is confirmed by the results of present study: one percentage point increase in long-term unemployment increases violent crime by 2.8% (everything else held constant). Moreover, long-term unemployment shows borderline significant effect on property crime with a point estimate of 2.1% (everything else held constant), confirming previous research on the subject and economic theory. The effect of total registered unemployment on both property and violent crime is significant, but small: one percentage point increase in total registered unemployment increases both property and violent crime by 0.7%, everything else held constant. Long-term unemployment shows statistically and economically significant impact on types of violent crime category such as assault, drugs-related crime, driving under the influence of alcohol, driving under the influence of drugs, and property crime category – auto theft. The results of instrumental variables method indicate that exogenous shocks to municipality employment have a large effect on both property and violent crime, suggesting that OLS regressions might have produced underestimated results. To summarise all of the above, the results of present study confirm the findings of Nordin and Almén (2017): the duration of unemployment does indeed matter: long-term unemployment, in contrast to total registered unemployment, is a better determinant of a specific mechanisms such as idleness, strain, low self-control, which may trigger violent behaviours and/or a different group of individuals at the margin of committing violent crime.

However, the result must be taken with a precaution, due to a risk of potential biases induced by omitted variables, measurement errors, simultaneity in the relationship between crime rates and unemployment rates, and reversed causality. Further research on the subject is necessary. In fact, the ongoing worldwide unemployment crisis caused by coronavirus pandemic is an excellent natural experiment for identifying the effect of unemployment on crime, and making steps closer towards discovering the true size of a burden which unemployment puts upon society.

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Appendix

Table 3 Model 1. Effects of total registered unemployment and long-term unemployment on types of property crime in Sweden, years 2000-2018. Municipality and year fixed effects model without municipality-specific linear time trends

	Theft	Damage	Burglary	Auto Theft	Handling stolen property
Registered unemployment	0.0006	0.0129	0.0085	-0.0036	0.0059
	(0.0033)	(0.0095)	(0.0054)	(0.0069)	(0.0193)
Observations	5,442	5,442	5,442	5,435	4,756
R-squared	0.9426	0.8472	0.7675	0.8646	0.3609
Long-term unemployment	0.0011	0.0228	0.0287	0.0535**	-0.0559
	(0.0104)	(0.0254)	(0.0184)	(0.0214)	(0.0630)
Observations	5,442	5,442	5,442	5,435	4,756
R-squared	0.9426	0.8468	0.7675	0.8652	0.3611

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Model is weighted with population size and includes municipality and year fixed effects, and the vector of controls reported in Table 1 and Table 2. Robust clustered standard errors are in brackets. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 4 Model 2. Effects of total registered unemployment, long-term unemployment on types of property crime in Sweden, years 2000-2018. Municipality and year fixed effects model with municipality-specific linear time trends

	Theft	Damage	Burglary	Auto Theft	Handling stolen property
Registered unemployment	-0.0046	-0.0020	-0.0055	-0.0018	-0.0069
	(0.0034)	(0.0086)	(0.0074)	(0.0073)	(0.0245)
Observations	5,442	5,442	5,442	5,435	4,756
R-squared	0.9569	0.8989	0.8187	0.8959	0.5133
Long-term unemployment	0.0014	-.0520**	0.0080	0.0218	0.1273**
	(0.0078)	(0.0205)	(0.0162)	(0.0184)	(0.0545)
Observations	5,442	5,442	5,442	5,435	4,756
R-squared	0.9569	0.8995	0.8187	0.8960	0.5140

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Model is weighted with population size and includes municipality and year fixed effects, and the vector of controls reported in Table 1 and Table 2. Robust clustered standard errors are in brackets. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 5 Model 1. Effects of total registered unemployment and long-term unemployment on types of violent crime in Sweden, years 2000-2018. Municipality and year fixed effects model without municipality-specific linear time trends							
	Assault	Drugs related	DUI Alcohol	DUI Drugs	Sexual harass.	Rape	Robbery
Registered unemployment	0.0088**	0.0030	0.0225***	0.0209	0.0024	0.0087	-0.0057
	(0.0037)	(0.0104)	(0.0058)	(0.0150)	(0.0075)	(0.0086)	(0.0136)
Observations	5,442	5,410	5,438	5,000	5,265	4,995	4,740
R-squared	0,8733	0.8035	0.6614	0.7522	0.4500	0.5579	0.5985
Long-term unemployment	0.0307***	0.0658**	0.0562***	0.0878*	0.0162	-0.0198	-0.0488
	(0.0084)	(0.0282)	(0.0184)	(0.0477)	(0.0222)	(0.0266)	(0.0389)
Observations	5,442	5,410	5,438	5,000	5,265	4,995	4,740
R-squared	0.8734	0.8042	0.6602	0.7526	0.4500	0.5778	0.5986

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Model is weighted with population size and includes municipality and year fixed effects, and the vector of controls reported in Table 1 and Table 2. Robust clustered standard errors are in brackets. *** p < 0.01 **p < 0.05 * p < 0.1

Table 6 Model 2. Effects of total registered unemployment, long-term unemployment on types of violent crime in Sweden, years 2000-2018. Municipality and year fixed effects model with municipality-specific linear time trends							
	Assault	Drugs related	DUI Alcohol	DUI Drugs	Sexual harass.	Rape	Robbery
Registered unemployment	0.0004	-.0134	0.0079	-0.0072	-0.0142*	0.0002	-0.0066
	(0.0033)	(0.0097)	(0.0054)	(0.0150)	(0.0082)	(0.0118)	(0.0150)
Observations	5,442	5,410	5,438	5000	5,265	4,995	4,740
R-squared	0.9019	0.8544	0.7314	0.8076	0.5247	0.6265	0.6889
Long-term unemployment	0.0168**	0.0141	0.0384**	0.0190	-0.0024	-0.0023	0.0620
	(0.0075)	(0.0244)	(0.0155)	(0.0475)	(0.0223)	(0.0286)	(0.0390)
Observations	5,442	5,410	5,438	5,000	5,265	4,995	4,740
R-squared	0.9020	0.8543	0.7318	0.8076	0.5244	0.6265	0.6891

Unemployment effect on logarithms of number of crime per 100,000 inhabitants is taken from separate regressions. Unemployment rates are in percent at municipal level. Model is weighted with population size and includes municipality and year fixed effects, and the vector of controls reported in Table 1 and Table 2. Robust clustered standard errors are in brackets.
*** p < 0.01 **p < 0.05 * p < 0.1

Table 8 Dependent and independent variables used in the models and their descriptive statistics, years 2000-2018, Sweden

Variables	Mean	Std. Err.	Between	Within	N/A	Zero	Sourse
Dependent Variables							
Property crime	4859.73	1847.81	1479.10	1112.67	0	0	The Nat.Council for Crime Prevention
Violent crime	1573.62	731.90	530.11	504.73	0	1	The Nat.Council for Crime Prevention
Auto theft	363.88	248.30	149.99	198.19	10	0	The Nat.Council for Crime Prevention
Burglary	1012.14	437.53	295.02	323.53	1	0	The Nat.Council for Crime Prevention
Damage	1136.82	592.15	475.56	353.82	1	0	The Nat.Council for Crime Prevention
Handling stolen property	34.40	133.88	33.56	129.49	718	83	The Nat.Council for Crime Prevention
Theft	2301.20	1024.91	827.69	606.27	1	0	The Nat.Council for Crime Prevention
Assault	658.35	257.3	197.77	165.01	2	0	The Nat.Council for Crime Prevention
Drugs related crimes	525.33	434.55	271.76	339.83	40	0	The Nat.Council for Crime Prevention
Rape	43.36	51.44	16.60	48.80	469	7	The Nat.Council for Crime Prevention
Robbery	43.73	41.69	35.81	18.52	730	77	The Nat.Council for Crime Prevention
Sexual harrasment	59.92	45.89	17.83	42.39	194	11	The Nat.Council for Crime Prevention
Driving under the influence of drugs	98.75	82.27	53.32	62.68	466	5	The Nat.Council for Crime Prevention
Driving under the influence of alcohol	163.97	81.32	55.95	59.14	7	0	The Nat.Council for Crime Prevention
Independent variables							
Municip. long-term unemployment total (%)	1.23	0.55	0.35	0.42	18	0	Statistics Sweden
Municip. registered unemployment total (%)	14.11	4.10	3.53	2.10	0	0	Statistics Sweden
Ln of income	6.67	0.14	0.11	0.09	0	0	Statistics Sweden
First diff. of the ln of income	0.02	0.01	0.002	0.01	0	0	Statistics Sweden
Share of males (%)	50.34	0.81	0.74	0.33	0	0	Statistics Sweden
Share of foreign origin (age 0-64) (%)	12.91	6.96	6.07	3.42	0	0	Statistics Sweden
Share of divorced (%)	35.73	3.04	2.94	0.79	0	0	Statistics Sweden
Share of widowed (%)	6.03	1.45	1.33	0.58	0	0	Statistics Sweden

Table 14 continued

Share of married (%)	8.94	1.25	1.13	0.53	0	0	Statistics Sweden
Share aged 0-14 years (%)	16.66	2.37	1.95	1.35	0	0	Statistics Sweden
Share aged 15-19 years (%)	6.40	0.84	0.42	0.73	0	0	Statistics Sweden
Share aged 20-24 years (%)	5.38	1.14	0.97	0.60	0	0	Statistics Sweden
Share aged 25-29 years (%)	5.06	1.28	1.15	0.58	0	0	Statistics Sweden
Share aged 30-34years (%)	5.44	1.07	0.92	0.55	0	0	Statistics Sweden
Share aged 35-39 years (%)	6.14	1.05	0.81	0.68	0	0	Statistics Sweden
Share aged 40-44 years (%)	6.55	0.81	0.62	0.52	0	0	Statistics Sweden
Share aged 45-49 years (%)	6.70	0.55	0.32	0.44	0	0	Statistics Sweden
Share aged 50-54 years (%)	6.77	0.55	0.32	0.46	0	0	Statistics Sweden
Share aged 55-59 years (%)	6.84	0.82	0.51	0.64	0	0	Statistics Sweden
Share aged 60–64 years (%)	6.62	1.05	0.72	0.77	0	0	Statistics Sweden
Ln of density of population	3.34	1.65	1.65	0.05	0	27	Statistics Sweden
Ln of size of population	9.83	0.94	0.94	0.04	0	0	Statistics Sweden
Share qualified for high school (%)	88.31	5.25	3.15	4.20	9	0	Statistics Sweden
Share qualified for university (%)	81.72	11.62	3.48	11.09	26	0	Statistics Sweden