

Sieger, Philip

Conference Paper

Job Losses and Criminal Gains: Analyzing the Effect of Unemployment on Criminal Activity

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung - Session: Regional Labor Markets, No. B18-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Sieger, Philip (2013) : Job Losses and Criminal Gains: Analyzing the Effect of Unemployment on Criminal Activity, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung - Session: Regional Labor Markets, No. B18-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/79929>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Job Losses and Criminal Gains: Analyzing the Effect of Unemployment on Criminal Activity

Philip Sieger†

January 2013

Abstract:

In this paper I analyze the relationship between unemployment and criminal activity. Using a unique panel data set on German counties covering the years 2003 to 2009, I estimate the effect of unemployment on crime rates for different kind of offenses. I extensively control for potential confounders as economic and demographic factors as well as time and county fixed effects. To circumvent the endogeneity of the unemployment rate in the structural equation of interest I interact two sources of variation which are exogenous to the change in crime within each county to construct an instrumental variable for unemployment. In addition to mean regression I also estimate quantile regressions in order to shed more light on the complex relationship between unemployment and criminal activity. The results based on mean regression show insignificant effects in the most general specification, while the results based on quantile regression are mixed.

Key Words: Unemployment; Crime; Quantile regression

JEL classification: C21, E24, C33

† Goethe University Frankfurt am Main, Faculty of Economics and Business Administration, Department of Applied Econometrics, Chair of Econometrics, Grueneburgplatz 1, RuW/PF 48, 60323 D-Frankfurt am Main, Germany, Tel: +49 69 798 34721, Email: sieger@wiwi.uni-frankfurt.de

1. Introduction

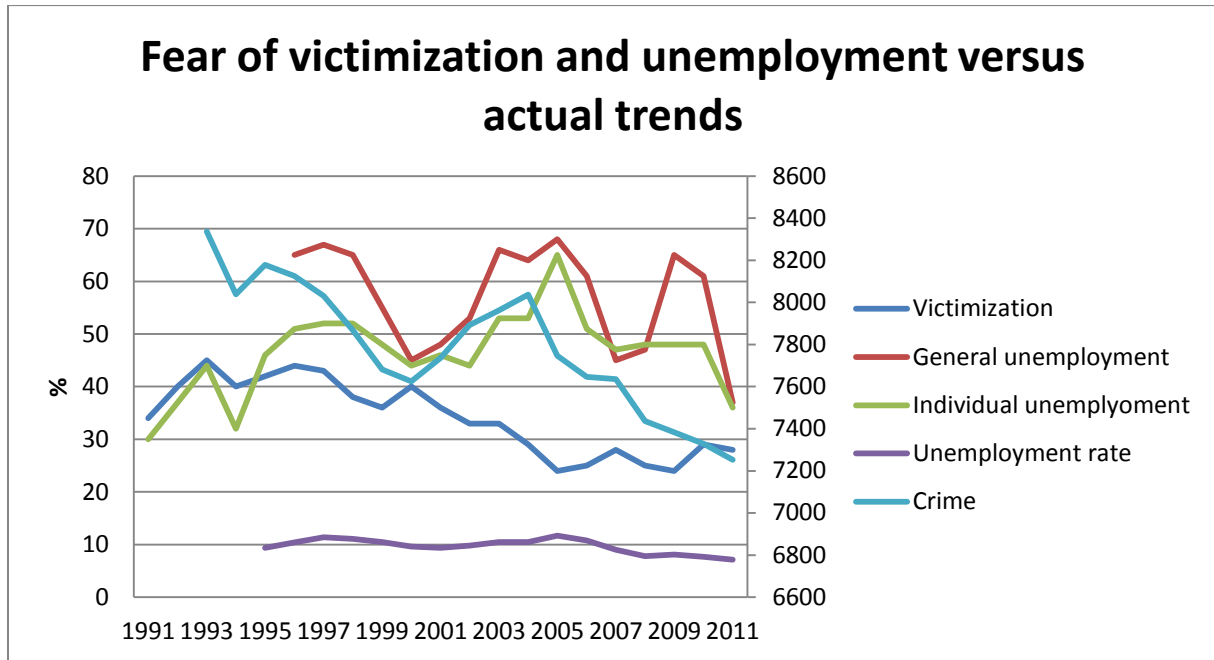
According to a yearly conducted survey by a German insurance company (R+V Versicherung) the fear to become a victim of a criminal offense regularly ranks in the top fifteen fears amongst Germans. In 2011, 28% of respondents stated that they are afraid of becoming a victim of a criminal offense. Although there is considerable variation across states in a given year (from 40% in Mecklenburg-West Pomerania to 25% in Saarland and Rhineland-Palatinate), there is remarkably little variation over time during the last ten years: in 2005 for example, an all time low was reached with 24%, while the highest value within the last ten years was 33% in 2002. This is in line with the fact that crime rates themselves in Germany have been stable (or rather declined slightly) between 2003 and 2010 (*Polizeiliche Kriminalstatistik/PKS* 2003, PKS 2010) but show considerable variation across states. In addition to being one of the major fears in Germany, criminal activity is associated with large costs. Miller, Cohen and Wieserna (1996) estimate the annual cost of crime in the United States to be about 450 billion dollars. Anderson (1999) even estimates cost associated with crime for the United States in the amount of 1.100 billion dollars¹. Given the large costs and the society's aversion towards crime it is obvious that fighting crime is of considerable policy interest: on the one hand, crime is something the electorate is afraid off, on the other hand crime is costly. From a politician's point of view, it is natural to ask how to fight criminal behavior in order to i) please their constituencies by reducing the (objective) risk of being victimized and ii) reduce the costs of crime and spend it for other purposes.

Another fear which usually even ranks in the top five is the fear of rising unemployment in Germany. This fear was expressed by roughly 50% of respondents in the early 2000s, increased to 68% in 2005 (when unemployment was particularly high in Germany with about 5 million registered unemployed), vanished from the top 7 fears in 2007 and 2008 but was again expressed by more than 60% in 2009 and 2010 (when the financial crises was expected to hit the German labor market). As with the fear of victimization, there is also large cross sectional variation in the fear of rising unemployment and in the unemployment rate itself. Reducing unemployment has ever since been the concern of policy makers for similar reasons as mentioned above for crime rates: rising unemployment is a major fear of people and

¹ Estimates for Germany can for example be found in Entorf (2010) and Spengler (2004).

unemployment is costly in various ways². The same rationale as the one for fighting crime rates should hence also operate when it comes to reducing unemployment.

Figure 1: Fear of victimization, general and individual unemployment versus actual trends



Note: “Crime” is measured as offenses reported to the police per 100,000 inhabitants. The corresponding scale is displayed on the right vertical axis. “Victimization”, “general unemployment” and “individual unemployment” show how many percent of the respondents articulate “great fear” of the respective situation. “Unemployment rate” is the official unemployment rate. The corresponding scale is the left vertical axis.

Figure 1 shows the development of the expressed fear of (general and individual) unemployment and victimization together with the actually observed trends in unemployment and crime. The fears of general and individual unemployment show a similar pattern and are highly correlated (correlation of 0.79). The correlation with the observed unemployment rate is also high with 0.71 for individual unemployment and 0.63 for general unemployment. The same also holds true for the relationship between observed crime and the fear of victimization. Both series decrease over time and show a high correlation of 0.73. The respondents hence seem to react to actual trends when asked about their fears.

In this paper I analyze whether there exists a causal link from unemployment to crime in Germany and if so, to what extent higher unemployment rates cause higher crime rates. The rationale why such a link might exist is the following: declining labor market opportunities (which are manifested by an increasing unemployment rate) worsen legal income

² The costs can be subdivided in direct costs of unemployment (such as unemployment benefits), opportunity costs of unemployment (such as foregone taxes) and indirect costs of unemployment (as worsening health conditions, see e.g. Dooley et al).

opportunities and therefore make crime more attractive. This rationale was first formulized by Becker (1968). Other studies focusing on the unemployment-crime relationship are (among many others) Cantor and Land (1985), Young (1993), Levitt (2001), Levitt (2004), Raphael and Winter-Ember (2001), Gould, Weinberg and Mustard (2002), Edmark (2005), Öster and Agnell (2007) and Lin (2008). These studies differ with respect to various aspects: the estimation method used, the time span and country under consideration and the conclusion drawn with respect to magnitude of the effect of unemployment on crime. Lin (2008, p. 414) summarizes the results in the following way: “In terms of empirical evidence, recent studies reach consensus that unemployment does have a positive, significant but only small effect on property crime, and no effect on violent crime.” Raphael and Winter-Ember (2001, p. 260f) postulate that the available evidence may understate the true effect of unemployment on crime due to the failure to control for variables that exert pro-cyclical pressure on crime rates in time-series analysis. On the other hand, reverse causation may upwardly bias OLS estimates of the causal effect of unemployment on crime: as criminal activity reduces the employability of offenders, criminal activity may contribute to observed unemployment. It is hence crucial to, on the one hand, control for as many potential determinates of crime as possible and, on the other hand, instrument the unemployment rate in order to mitigate the problem of reverse causation or other sources of endogeneity. The analysis conducted in this paper takes both problems into consideration. It is based on a unique and extensive panel data set covering the years 2003 to 2009 and all counties (*Kreise*) and urban municipalities (*kreisfreie Städte*) in Germany. The available variables ensure that omitted variables are not a mayor problem. Several estimation techniques are applied in order to answer the question whether a causal link exists. Starting with an ordinary least squares regression as a benchmark, I will allow county fixed effects in a second step in order to capture unobserved. In addition to that, I instrument the unemployment rate in order to circumvent the potential problem of endogeneity. When instrumenting the unemployment rate I utilize the ideas of Blanchard et al (1992), Gould, Weinberg and Mustard (2002) and Öster and Agnell (2007). In a second step I deviate from existing studies in the sense that I examine whether the effect of unemployment on crime depends on the level of crime by applying quantile regression methods. Making use of the results of Koenker (2004), Chernozhukov and Hansen (2008) and Harding and Lamarche (2008) I am able to estimate the corresponding models described above for quantile regressions models. The results of this study are of interest to policy makers since, given a causal link can be established, it would be possible to fight crime by reducing unemployment. Policy makers could therefore kill two birds with one stone by reducing unemployment.

The remainder of this paper is organized as follows: chapter 2 gives an overview over the determinants of crime and their theoretical background. The underlying dataset is described in detail in chapter 3. Summary statistics for the most important variables are provided. Chapter 4 discusses the applied econometric methodology. In chapter 5 the results of the estimation are presented and discussed in detail. Potential caveats are described and possible solutions will be discussed. Chapter 6 finally concludes.

2. Theoretical background of the determinates of Crime

In this paragraph I will present the theoretical background of the determinants of crime. I will elaborate on the seminal paper of Becker (1968) and the model developed therein, followed by a discussion of further determinants of crime not embodied in the Becker model.

2.1.Deterrence as a determinant of criminal behavior- The Becker model

The distinguished philosopher and jurist Jeremy Bentham writes in his 1843 published book “The Principles of Penal Law”: “The profit of the crime is the force which urges man to delinquency: the pain of punishment is the force employed to restrain him from it. If the first of these forces be the greater, the crime will be committed; if the second, the crime will not be committed” (Bentham 1843, p.399, Eide 1999). This point of view is congruent with the modern economist’s point of view that criminals are rational agents acting under uncertainty, as popularized by the seminal paper “Crime and Punishment” by Becker (1968). Opposed to sociologists, psychologists and criminologists, who rather stress concepts like deviance, depravity, deprivation, insanity and abnormality as explanations why people commit crimes, Becker (1968) presents a model of rational agents who decide to offend for economic reasons.

Becker’s model neglects, however, some important features of the criminal’s decision problem as, for example, the cost of arrest, detentions or the problem of time and/or wealth allocation. Several authors have enriched the basic model in order to capture these additional factors. Examples are (among others) Allingham and Sandmo (1972) who focus on income tax evasion, Heineke (1975) who explicitly focuses on modeling the criminal’s choice problem, Grogger (1998) where individuals allocate their time (and not their wealth or income) to legal or illegal activities, respectively, and Ehrlich (1973) and Block and Heineke (1975), who also focus on the problem of time allocation between legal and illegal activities.

The problem of time allocation and how it influences the decision of becoming a criminal or not and its relation to unemployment is discussed at the end of section 2.3.

2.2. Demographics as a determinant of criminal behavior

Several other determinates of crime have been discussed in the literature besides the just discussed deterrence variables (as the probability of conviction or the severity of fines). One of these determinants is the age structure of society³. As outlined by Farrington (1986) who focuses on the United Kingdom and the United States the age-crime curve has a peak usually at teenage years and declines afterwards, meaning that individuals are most crime-prone at young ages and less so when growing older. Grogger (1998, p. 756) also provides evidence for this phenomenon: “Thirty five percent of all Philadelphia males born in 1945 were arrested before the age of 18, and one-third of all Californian men born in 1956 were arrested between the ages of 18 and 30. The 1990 census counted 1.1 million persons in jail, the vast majority of whom were men in their twenties and thirties.” Similar patters can be observed for Germany. While the crime suspects (*Tatverdächtige*) aged six to 20 make up 28.4% of all crime suspects in 2003, the respective age group only makes up 15% of the population. In comparison, while the crime suspects aged 40 and above constitute 28.7% of all alleged criminals, the respective age group constitutes 52.5% of the population (PKS 2003). A similar picture arises from the 2009 data: crime suspects aged six to 20 make up 26.1% of all crime suspects but only 13.7% of the population. The crime suspects aged 40 and above make up 32.4% of all crime suspects but 56.9% of the population (PKS 2009). As Farrington (1986, p. 190) correctly points out, the meaning of that peak at teenage years is not completely clear: “Does the peak in the teenage years reflect a peak in the number of different offenders, in the number of different types of offenses committed by each offender, or in the number of offenses of each type committed by each offender (or in some combination of these)?”. In addition, different offenses peak at different ages. An extreme example is investment fraud (*Kapitalanlagebetrug*). In 2003, less than 1% of crime suspects come from the age group six to 20, while 55.7% of crime suspects come from the age group 40 and older. The opposite picture emerges when looking at damage to property (*Sachbeschädigung*): 53.6% of crime suspects come from the age group six to 20, while only 16.3% come from the age group 40

³ A current research project conducted by the *Kriminologisches Forschungsinstitut Niedersachsen* (Criminological Research Institut of Lower Saxony) deals explicitly with the influence of the demographic change on the development of crime.

and older. Given the descriptive evidence from the PKS and the mostly⁴ accepted empirical evidence from other studies (as, e.g. Freeman 1996) it seems imperative to include the age structure as a further control variable when it comes to explaining crime. One would in general expect a positive influence of the share of crime-prone aged people in the population on criminal activity. Besides the fact that people in their young ages tend to commit more crimes, they also seem to be victimized more often (PKS 2009, Table 91): in about one third of all offenses the victim was less than 21 years old. A large share of young people might therefore foster criminal activities in two ways: it increases the supply of criminals as well as the supply of victims.

Another group that is exceptionally crime-prone in Germany is the group of non-German crime suspects (*nichtdeutsche Tatverdächtige*), a variable also included by Entorf and Spengler (2000) in their econometric specification. As the data from the PKS for the year 2003 show, non-German crime suspects make up 23.5% of all crime suspects, although contributing only 8.9% to total population. The same picture holds true for the year 2009, where the numbers are 21.1% versus 8.7%⁵. Possible reasons for this huge overrepresentation are discussed in Albrecht (1997). He mentions, among other things, deprivation and control theories, which focus on problems of social integration and reduced opportunities to develop ties to conventional society. The reasons for the apparent overrepresentation of foreigners in criminal activity shall not be discussed here in detail, but the mere numbers give rise to the need to control for the composition of a region with respect to foreign population when explaining crime.

Overrepresentation of crime suspects can be observed for yet another demographic group: men. Freeman (1996) asks the question: “Why do so many young men commit crimes (...)?” Freeman (1996, p. 25) argues “that participation in crime and involvement with the criminal justice system has reached such levels as to become part of normal economic life for many young men.“ In addition, he presents evidence that “labor market incentives influence the level of crime”, and he argues “that the depressed labor market for less skilled men in the 1980s and 1990s has contributed to the rise in criminal activity by less skilled men.” Whether these reasons also hold for the case of Germany shall not be discussed here. But inspection of

⁴ Levitt (1999) and Levitt (2004) argue that the age structure alone does only have a limiting influence on the evolution of crime rates. Given that the age structure is as important as usually assumed, there should not have been a decline in crime rates from 1995 to 2004 in the United States. Since this decline was observed despite a larger share of crime-prone aged people, he argues that the effect of age structure on crime is rather limited.

⁵ Even after excluding those offenses which can only be committed by non-Germans (such as offenses against asylum law and alike), the numbers only go down to 19% (2003) and 19.4% (2009) respectively (PKS 2009, p.105).

the raw numbers tells the following story: in 2003 (2009), out of the 2.355 (2.187) Million crime suspects, 1.8 Million (1.64) were male. That equals a share of 76% (75%) in 2003 (2009). Depending on the offense under consideration, these shares even go up to more than 90%. This is for example the case for auto theft (between 93% and 95% in the time span 2003 to 2009) or street crime (90.1% in 2005). Only very few and specific offenses are committed equally frequent by women as by men. Examples are divestment of minors (*Entziehung Minderjähriger*) with 943 versus 909 offenses, child trafficking (*Kinderhandel*) with eight versus eight offenses, credit and bank card abuse (*Missbrauch von Scheck-Kreditkarten*) with 1,534 versus 1,233 offenses or, to a lesser extent, shop lifting (*Ladendiebstahl*) with 182,731 versus 122,745 offenses. Controlling for the gender composition of the respective county hence seems to be as important as controlling for the already discussed demographic variables. One would expect a higher share of males in a given region to increase the number of offenses *ceteris paribus*.

The last determinant which shall be discussed in this section is population density. It is defined as “number of people living in a given area/area in square kilometers”. In Germany, population density varies considerably from 37.59 in the county *Mecklenburg-Kreilitz* to 4,282.21 in Munich. So the most densely populated county (or urban municipality) is more than 110 times as densely populated compared to the least densely populated county. There exist several theories why population density might be an important determinant of crime. On the one hand, densely populated areas (which are usually large cities) feature a weaker net of social control (Glaeser and Sacerdote 1999). The anonymity of the city makes it easier for individuals to commit crimes, since the potential stigma given being caught is less severe. In addition, similar to the argument applied above to the age composition, a large population density makes a “match” between a criminal and a victim more likely. Criminals may also have greater access to the wealthy in urban areas. This effect is even accelerated by the potential of spillover effects in crime rates, as discussed by Glaeser, Sacerdote and Scheikmann (1999). Glaeser and Sacerdote (1999, p. 227) also mention the possibility that criminals may face a lower probability of detection and arrest in urban areas and that urban areas themselves attract (or create) crime-prone individuals. These theoretical considerations are confirmed for the data set which is used in this analysis. The bivariate correlation between overall crime rates and population density is remarkably high with 0.63. One would therefore again expect a positive impact of population density on crime rates.

2.3. Economic factors as determinants of criminal behavior

Another important determinant of crime is disposable income. Speaking within the framework of Becker (1968), higher legal income should decrease criminal activity (given legal income is lost once an individual commits a crime and is convicted⁶). This is true for the following reason: legal income in this situation displays part of the opportunity costs of conviction. Higher legal income prevents a potential offender from committing a crime because he fears losing the legal income. Everything else equal (probability of detection and conviction and illegal income opportunities) higher legal income decreases criminal activity. There is, however, another channel through which legal income affects crime if one switches from a micro to a macro perspective. If average legal income in a certain region (as a German county) increases, the potential offender is on the one hand more likely to have a higher legal income himself on average, and hence he is less likely to commit crime. On the other hand, a higher average legal income might also increase his illegal income opportunities, since now there is more income or wealth he can steal from. At least for property crime, a higher legal income on average could therefore also increase criminal activity: the potential offender can expect larger loot since people around him are richer. This would, everything else equal, increase the utility of committing a crime. The effect of disposable income is therefore ambiguous, since it influences the decision to commit a crime or not through different channels. The picture gets even more complicated once the detection probability is treated as endogenous. In this case, a higher legal income could be used to increase the detection probability (through more police spending for example). This would mitigate the loot effect of higher average legal income within a region.

The discussion of determinants of crime now turns to the unemployment rate as a determinant of crime, which is the main focus of this analysis. The potential channel through which unemployment affects the crime rate was already briefly mentioned in the introductory chapter: declining labor market opportunities (which are manifested by an increasing unemployment rate) worsen legal income opportunities and therefore make crime more attractive. In their influential paper, Raphael and Winter-Ebmer (2001,p.262) express this idea the following way: “Conceptualizing criminal activity as a form of employment that requires time and generates income, a “rational offender” should compare returns to time use in legal and illegal activities and make decisions accordingly. Holding all else equal, the decrease in income and potential earnings associated with involuntary unemployment increases the

⁶ As would be the case if the criminals loses his or her job subsequently.

relative returns to illegal activity.” The idea of time allocation between legal and illegal activities and its influence on the decision whether or not to participate in criminal activities was formalized in a theoretical framework by Grogger (1998). Beginning with a consumer who has preferences only over consumption and leisure, where leisure is defined as time neither spent at work nor spent committing crime, the consumer maximizes utility by choosing time spent at market work and time committing crime. He takes the market wage, returns to crime and the total time available as given⁷. Denoting the utility function by U , leisure by L , consumption by c , the market wage by w , the time spent at market work or criminal work, respectively, by h_m and h_c , the return to crime function by $r(h_c)$ ⁸, total time available by T and nonlabor income by A , the decision problem of the consumer reads as

$$\max U(c, L)$$

subject to the constraints

$$c = wh_m + r(h_c) + A$$

$$L = T - h_m - h_c$$

In words: consumers maximize utility, which only depends on the amount of consumption and the amount of leisure. Consumption consists of market income wh_m (the wage times the amount of time worked in the market), illegal or criminal income $r(h_c)$ (where the amount of time committing crime is transformed in consumption via the returns to crime function $r(\cdot)$) and nonlabor income A . Leisure is simply the time left after having spent h_m hours working in the market and h_c hours committing crime. Note that the consumer in this setting is amoral as O. W. Holmes (1897/1997) “bad man” in the sense that he does not care whether he dedicates an additional hour to work or committing crime. As Grogger (1998, p. 760) points out, this model is formally very similar to the model of consumers’ allocation of time between leisure, market work and home production as developed by Gronau (1977), where crime takes the place of home production in the model presented here. Hence the consumer’s problem has a recursive structure: he or she first decides how much time to spend on criminal activity and then decides how much time he or she spends working on the market. As Grogger (1998, p.

⁷ Grogger (1998, p. 760) refrains from taking uncertainty into account as “the data do not contain measures of the uncertainty of criminal income or of consumers’ attitudes towards risk.”

⁸ The return to crime function is assumed to be increasing and concave in the amount of time spent on committing crime.

761, footnote 5) points out, the separation is rather logical than temporal, meaning that the crime and labor supply decisions are both made in the same (single) time period.

The model has the following implications⁹: there exists a reservations wage w^* . A necessary condition for individuals to work in the market is $w > w^*$. A necessary condition for committing crime is $r'(0) > w^*$. In words: the returns to the first hour of crime must exceed the reservation wage. A necessary condition for a consumer to work in the market and to commit crime is given by $r'(0) > w$. In words: only those for whom the first hour of crime exceeds the market wage also engage in criminal activity. A consumer who works in the market and commits crime equates his marginal returns of crime, $r(h_c)$, to the marginal return of market work, the wage w . The optimal crime choice hence only involves these two entities, his or her productivity in crime and in the labor market. On the other hand, workers for whom $r'(0) \leq w$ commit no crime and choose their hours of working in the labor market in order to equate the marginal rate of substitution between consumption and leisure to the market wage.

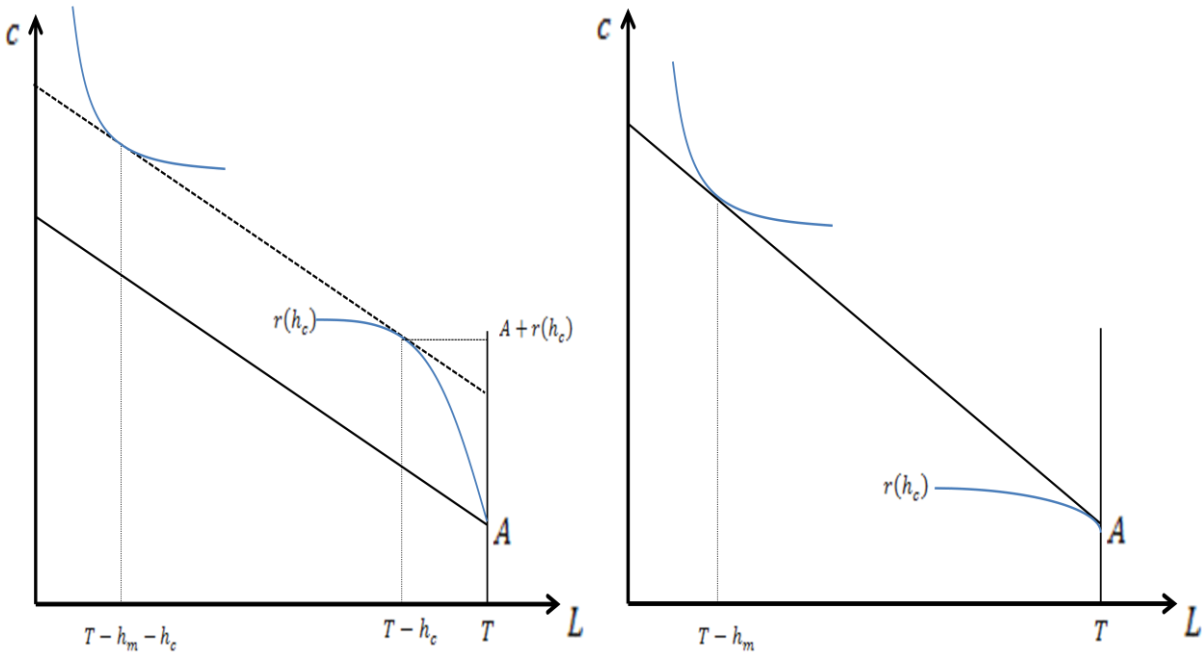
Figure 2 illustrates the implications described above graphically for two consumers who both work in the market. Both have the same nonlabor income A , face the same wage w but differ with respect to their returns to crime function $r(h_c)$. The consumer depicted in the left part of Figure 2 (called consumer C_1) is a more able criminal (or faces a more favorable environment), since his returns from the first hour of crime are larger than for the consumer depicted in the right part of figure 1 (called consumer C_2). It is apparent from Figure 2 that for C_1 , it is lucrative to commit crime, since his returns to the first hour of crime are larger than his wage (which is given by minus the slope of the budget constraint). He chooses the amount of time to spend on crime in order to equate his marginal returns to crime to his wage, where his effective nonlabor income is $A + r(h_c)$ and his effective time budget equals $T - h_c$. He subsequently decides on how many hours to work on the market by equating his wage to the marginal rate of substitution taking into consideration his previous choice of h_c . Consumer C_2 does not commit any crime, since the returns from his first hour of crime are less than his wage. He therefore sets $h_c = 0$ (which leaves him with T hours time available) and chooses his market hours h_m to equate his marginal rate of substitution with his wage, taking his decision on h_c into account.

As Raphael and Winter-Ebmer (2001, p. 264-265) lay out, the model can be used to predict how unemployment affects criminal activity. “For persons that engage in criminal activity

⁹ For details see Grogger (1998, p. 761-762).

while working, the model predicts that unemployment increases time allocated to crime.” For individuals who already do not work in the market but only commit crime (or who do neither of both and simply consume their leisure time), an unemployment spell does not affect the time allocated to crime. For workers not committing crime, the effect of an unemployment spell depends on whether the return to the first hour of criminal activity exceeds his reservation wage. Consumers whose reservation wage is rather high are unlikely to be pushed into crime by an unemployment spell. Consumers with comparably low reservation wages are more likely to be influenced by unemployment and might try to offset lost income by engaging in criminal activity.

Figure 2: Criminal participation and choice of criminal hours



Consumer works on the market and commits crime (left); consumer only works on the market (right)

Raphael and Winter-Ebmer (2001, p. 264) conclude the discussion of the model by noting that “the theoretical model yields four possible types of individuals roughly defined by potential earnings in the labor market relative to the returns to criminal activity and preferences over income and nonmarket time. The theory predicts that for two of these four categories, an unemployment spell will increase time allocated to criminal activity (and thus increase the crime rate), while for the remaining two categories, there is no response to an unemployment spell.” This rather simplistic model hence justifies the use of the unemployment rate as a determinant of crime.

2.4. At the heart of Economics - Education

Another determinant of criminal behavior which fits in neither of the two discussed categories is education. A model-based justification for this claim can, e.g., be found in Lochner (2004). The author develops a model in which agents undertake investment in human capital which in turn increases the opportunity costs of incarceration¹⁰. Empirical evidence is rather limited, with notable exceptions being Lochner and Moretti (2004) and Machin, Marie and Vujic (2011). Both articles show that higher educational attainment is associated with less engagement in criminal activity. They take the endogeneity of the schooling decision into account by using changes in compulsory schooling laws in the United States and the United Kingdom.

Unfortunately, there does not exist comprehensive data on educational attainment of the German population at the county level. The only variable that covers education at the county level is the share of workers subject to social security contribution who have not completed a vocational training (*sozialversicherungspflichtig Beschäftigte ohne abgeschlossene Berufsausbildung*). This variable only covers the education of a certain group of people, namely those who are subject to social security contribution. Phrased differently, this variable only captures educational attainment of a part of the work force in a given county, and not of the whole population in a given county. The predicted influence of this variable on crime is therefore hard to determine: on the one hand, less educated people are expected to commit more crime. One could therefore expect a positive influence of this variable on crime. On the other hand, a high share of workers subject to social security contribution who have not completed a vocational training means that there are good labor market opportunities even for rather unskilled workers. Under this interpretation, a higher share of such workers would have a negative effect on crime. Empirical evidence for this can e.g. be found in Gould et. al. (2002).

3. Data Description

The analysis is based on a unique dataset covering the years 2003 to 2009 and all counties and urban municipalities¹¹ in Germany. It includes variables which cover all determinants of

¹⁰ This idea can also be incorporated in the model discussed in section 2.3., assuming that more educated agents face a higher market wage and are therefore less likely to engage in criminal activity.

¹¹ From now on referred to only as “the counties”

criminal behavior described in section 2 as deterrence variables, demographic variables and economic variables. This section describes the variables used in the analysis in detail. Extensive summary statistics will be presented together with a graphical representation of regional distribution of the most important variables.

3.1. The dependent variables

The dependent variables used in this study are the crime rates in each county¹². Before defining the term “crime rates” I will describe which kinds of offenses are analyzed. These are burglary (*Wohnungseinbruchsdiebstahl*), street crime (*Straßenkriminalität*), drug related crime (*Drogenkriminalität*), auto theft (*Diebstahl in/aus Kraftfahrzeugen*), assault (*Körperverletzung*) and damage to property (*Sachbeschädigung*). The exact definition of each offense is given in the following paragraph. These definitions are translated by the author from the German “*Strafgesetzbuch*” (StGB), i.e. the penal code¹³ and the “*Betäubungsmittelgesetz*” (BtMG), i.e. narcotics law.

Burglary (*Wohnungseinbruchsdiebstahl*), criminal offense according to §244 Abs. 1 Nr. 3 StGB: Committing a larceny, for which the burglar breaks into a flat, enters with a counterfeit key or hides within the flat.

Street crime (*Straßenkriminalität*): 23 different offenses are collected under the label “street crime”. In a nutshell, it covers every offense which, based on its criminological appearance, can be expected to be predominantly committed in the street or in public places. These are for example pickpocketing (*Taschendiebstahl*), indecent behavior (*Erregung öffentlichen Ärgernisses*), theft from convenience stores (*Diebstahl in /aus Kiosken*), certain types of robbery (*Zechanschlußraub, Handtaschenraub, räuberischer Angriff auf Kraftfahrer*), damage to automobiles (*Sachbeschädigung an Kraftfahrzeugen*) and alike.

Drug related crime (*Drogenkriminalität*), criminal offense according to §29-30 BtMG: Cultivation, production and trade, import, export, alienation and other forms of supply of narcotic substances for private or commercial use.

As is pointed out in the PKS (2009, p. 24), when recording drug related crimes with several drugs involved, only the offense related to the most dangerous/harmful drug is recorded. In

¹² These data have been extracted from the yearly published PKS (2003-2009)

¹³ The author would like to point out that the translation covers the most important points of the respective paragraphs, but does not constitute a word-by-word translation. German speaking readers are referred to the original source.

exceptional cases it is possible to record the other offense related to the less dangerous drug¹⁴. The same holds true for several offenses related to the same drug (only the most severe offense is recorded).

Auto theft (*Diebstahl in/aus Kraftfahrzeugen*), criminal offense according to §242 StGB: Taking away an alien and movable object from another person with the intention to illegally acquiring it¹⁵.

Assault (*Körperverletzung*), criminal offense according to §223-227, 229, 231 StGB: Physically abusing another person or damaging another persons' health (§223); assault using a weapon, especially a knife or other dangerous tools, or using a deceitful attack, or a group, or method to endanger the life of someone (§224); assault resulting in: the loss of a limb, the sight of one or both eyes, hearing, speech, or the ability to procreate; or, the long-term distortion of such; or, state of sickness, paralysis, or mental illness (§226); assault resulting in death (§227); negligent assault (§229); the participation in a fight or an attack by several perpetrators that resulted in the death of a person or in serious bodily harm (§231)¹⁶.

Damage to property (*Sachbeschädigung*), criminal offense according to §303-305a StGB: the illegal damage to or destruction of someone else's property (§303); the illegal erasure, suppression, change, or making unusable of data (§303a); the disruption of data processing that is of considerable significance to someone else's firm, business, or office through illegal erasure, suppression, change, or making unusable of data (§303b); the illegal damage to or destruction of: items in tribute to a state-recognized church or items used in religious services; or grave markers, public monuments, natural monuments; or artistic, scientific, or trade works that are part of public collections or public exhibits; or items meant to serve the public good or the beautification of public paths, places, or parks (§304); the illegal complete or partial destruction of a building, bridge, dam, paved road, railway, or other structure that is someone else's property (§305)¹⁷; the illegal complete or partial destruction of a technical work equipment of considerable value that is of essential importance in order to either construct,

¹⁴ If being caught with 1 gram of cocaine and 1 gram of cannabis, only the offense related to cocaine abuse is recorded. If being caught with 8 gram of cocaine and 2.3 kilogram of cannabis, the cannabis related offense can be recorded.

¹⁵ This is the general definition of the offense theft (*Diebstahl*). The variable auto theft only covers those cases where either a car was stolen or something was stolen out of the car. Other kinds of theft that fall within this definition are not included in the variable auto theft.

¹⁶ Translation taken from Entorf and Spengler (2000, p. 103).

¹⁷ Translation taken from Entorf and Spengler (2000, p. 103).

maintain or dispose a certain facility or company; the illegal complete or partial destruction of a motor vehicle owned by the police or the *Bundeswehr* (§305a).

These offenses are chosen because they constitute the only offenses for which the PKS provides information at the county level.

Having presented the offenses which will be analyzed in this study, I proceed by defining the term “crime rates”. The crime rates usually used when analyzing the connection between criminal activity and certain explanatory variables is the so called frequency ratio (*Häufigkeitszahl*). It is defined as the number of cases (for a given offense) reported to the police per 100,000 inhabitants. This standardization is necessary in order to compare the crime intensity across areas with a different number of inhabitants. As is pointed out by the PKS (e.g. PKS 2003, p. 14), the explanatory power of the frequency ratio is limited by the fact that only part of committed crimes are reported to the police and by the fact that illegal aliens, tourists and transients might also commit crimes but are not counted as inhabitants of Germany¹⁸. The second problem is, however, negligible: in 2009 out of the 2,187,217 crime suspects only 46,132 (or 2.11%) were illegal aliens and 6,739 (0.31%) were tourists and transients, adding up to only 2.42% of all crime suspects. A slightly broader perspective which in addition includes asylum seekers (22,137 or 1.01%) and stationed armed forces (*Stationierungstreitkräfte*) and their family members (2,249 or 0.1%) produces a share of 3.53% of all crime suspects.

Table 1 presents descriptive statistics for the frequency ratio for overall crime, burglary and street crime.

Table 1: Descriptive statistics of frequency ratios for various offenses

Percentiles	Frequency ratio overall crime	Frequency ratio burglary	Frequency ratio street crime
5%	3417.5	22	612
25%	4759	47	928
50%	6301	84	1472
75%	8368.5	138.5	2114.5
95%	12775	275	3395
Minimum	2367	3	350
Maximum	19195	605	5813
Mean	6912.12	105.05	1634.22
Standard Deviation	2867.28	79.19	886.60

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

¹⁸ The first problem (known as the dark figure problem) can be mitigated by the inclusion of fixed effects, assuming that the dark figure does not change over time in a given county.

It is apparent from Table 1 that there is a huge variation in the respective crime rates. For overall crime, the frequency ratio varies from a minimum of 2367 offenses per 100,000 inhabitants (recorded in the county Straubing-Bogen (Bavaria) in the year 2006) to a maximum of 19,195 offenses per 100,000 inhabitants (recorded in the urban municipality Frankfurt a. d. Oder (Brandenburg) in the year 2003). As can be seen from Figure A1, the distribution of frequency ratios for overall crime during the years 2003 to 2009 is right-skewed and has a unique peak at about 6000 offenses per 100,000 inhabitants. The regional distribution of frequency ratios for overall crime in the year 2009 is visualized in Figure A2. Crime rates in 2009 are obviously higher in the north and east compared to the south and west. In addition, the urban municipalities clearly stand out with higher crime rates. The spatial dependence seems rather limited from an eyeball inspection.

Similar patterns hold true for the frequency ratio for burglary. Both are heavily right-skewed and show an enormous variation. The minimum frequency ratio for burglary is only 3 (recorded in Hildburghausen (Thuringia) in 2008), with the 5% percentile being as low as 22. In contrast, the maximum frequency ratio of 605 (recorded for Cologne (North Rhine-Westphalia) in 2003) is about 200 times higher than the minimum. The distribution over the whole time period under consideration and the graphical visualization of the distribution in the year 2009 are displayed in Figure A3 and Figure A4 respectively. Noteworthy is the clustered appearance of burglaries in the north and the west, while the south-west does not exhibit high frequency ratios even in the urban municipalities.

Frequency ratios for street crime do not vary as much as those for burglary. A minimum of 350 (recorded in the county Bayreuth (Bavaria) in 2006) is accompanied by a maximum of 5813 (recorded in Bremen in 2007). The distribution over the years 2003 to 2009 is again right-skewed, as can be seen in Figure A5. The geographical distribution (Figure A6) again shows a higher incidence of crimes in the north compared to the south. The urban municipalities again stand out due to their higher crime rates. This effect is particularly pronounced in Bavaria, where only urban municipalities have frequency ratios in the highest category (more than 1891 in the respective figure).

Table 2 shows descriptive statistics for the frequency ratio for drug related crime, auto theft and assault. For drug related crime, the minimum of 30 offenses per 100,000 inhabitants was recorded for the county Saalkreis (Saxony-Anhalt) in 2006, while the maximum was recorded for the county Viersen (North Rhine-Westphalia) in 2007. The distribution over all years is again heavily right-skewed with a peak at 200 as can be seen from Figure A7. The

geographical distribution in the year 2009 (Figure A8) does not show the clear distinction between south and north. Although urban municipalities again stand out there seem to be some areas particularly affected by drug related crime. These are in the south-west of Germany (Rhineland-Palatine) and in northern areas like the region around the city Hannover. Interestingly, the capital Berlin is not among the most affected areas when it comes to drug related crime.

Table 2: Descriptive statistics of frequency ratios for various offenses

Percentiles	Frequency ratio drug related crime	Frequency ratio auto theft	Frequency ratio assault
5%	110.5	66.5	325
25%	174	138.5	421
50%	244	246	538.5
75%	366	413	704
95%	639	878.5	1094.5
Minimum	30	20	202
Maximum	1566	2437	2108
Mean	293.90	325.68	597.06
Standard Deviation	175.40	274.18	242.45

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

The overall distribution of the frequency ratio for auto theft is display in Figure A9. In this figure it is nicely visualized what can also be inferred from percentiles in Table 2: Although the maximum frequency ratio for auto theft is 2437 (recorded in Bremen in 2007), the 95% percentile is only 878.5, with a median of only 246. The minimum is even as small as 20, which was recorded in the county Forchheim (Bavaria) in 2008. Hence the distribution is even more heavily skewed than the others inspected so far. The regional or geographical distribution (Figure A10), however, again shows the by now familiar north-south pattern with higher frequency ratios in the north. Urban municipalities, at least those in the south (Bavaria and Baden-Württemberg), do not stand out particularly from an eyeball inspection of the Figure A10.

Assault, with a minimum frequency ratio of 202 (recorded in the county Enzkreis (Baden-Württemberg) in 2003) and a maximum of 2108 (recorded in the urban municipality of Neumünster (Schleswig-Holstein) in 2007), does not show as much variation as did the other offenses analyzed so far. The ratio of minimum to maximum is rather low with a ratio of 10 (compared to, e.g., a ratio of 100 for auto theft or even 200 for burglary). In addition, the distribution over all years is rather symmetric compared to the other distributions (see Figure A11). Urban municipalities are among the most affected counties related to assault. They

clearly stand out in the geographical distribution of the year 2009 (see Figure A12). Besides the urban municipalities, the city states Berlin, Bremen and Hamburg as well as the region around the city of Hannover and the Rhine-Ruhr metropolitan region show rather large frequency ratios. The contrast between the south and the north is less pronounced than it is for auto theft or street crime.

The last dependent variable to be discussed is the frequency ratio for damage to property. The descriptive statistics can be found in Table 3 (together with information on other variables to be discussed in the next section). The minimal frequency ratios for the offense damage to property was recorded in the county Nienburg (Lower Saxony) in the year 2009 with a frequency ratio of 220, while the maximum, recorded in Brandenburg an der Havel¹⁹ (Brandenburg) in 2008, was 4040. The distribution is, similar to the offense assault, comparably symmetric (see Figure A13), with a peak at about 800, which is also the median (and close to the mean) of the distribution. Figure A14 shows that urban municipalities, the eastern states and the Rhine-Ruhr metropolitan areas are particularly affected by the offense damage to property.

Table 3: Descriptive statistics of frequency ratios and clear-up rates for various offenses

Percentiles	Frequency ratio damage to property	Clear-up rate overall crime	Clear-up rate burglary
5%	443	48.95	8.7
25%	614	53.95	15.6
50%	802	59.2	23.2
75%	1034	64.6	33.9
95%	1584	70.6	51.9
Minimum	220	34.8	0
Maximum	4040	84.3	118
Mean	875.36	59.01	25.98
Standard Deviation	372.64	7.44	13.86

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

3.2. The explanatory variables

In this section descriptive statistics are presented for the explanatory variables discussed in section 2. These variables are exactly those that will be used in the empirical analysis to explain the just discussed crimes rates. These are deterrence variables, demographic variables, economic variables (including education) and the instrument.

¹⁹ Also known as Brandenburg City.

3.2.1. The explanatory variables- Deterrence

As already pointed out in section 2.1, deterrence plays a crucial role in determining crime rates. Based on the Becker model, criminals compare their expected utility from committing crime to the expected utility of exclusively engaging in legal activities. The severity of the expected fine as well as the probability of being caught are examples for deterrence measures that influence the agent's decision. Other measures frequently used in empirical analysis in order to capture these deterrence effects are the size of the police force (e.g. Lin 2008, Levitt 1997), the incarceration rate (Raphael and Winter-Ebmer (2001), Phillips and Land (2012)) or the clear-up rate (Entorf and Spengler 2000). Although theory suggests that it is imperative to include a variable that measures some form of deterrence, some studies fall short of including them (e.g. Yearwood and Koinis (2009) or Öster and Agell (2007)).

Based on data availability, I follow Entorf and Spengler and use the clear-up rate as a measure of deterrence. The clear-up rate is defined (according to PKS 2009, p. 14) as the ratio of solved cases times 100 to cases known to the police²⁰. If cases reported in the previous year are mostly solved in the current year, this might result in a clear-up rate larger than 100 (which indeed has happened in the period under consideration).

The overall clear-up rate (with descriptive statistics shown in Table 3) in the years 2003 to 2009 varies from a minimum of 34.8 (reported in Cologne (North Rhine-Westphalia) in 2004) to a maximum of 84.3 (reported in the county Freyung-Grafenau (Bavaria) in 2004).

A quite different picture arises when looking at the clear-up rate for burglary (Table 3): the average clear-up rate for burglary during the period under consideration is only 25.98% compared to an average overall clear-up rate of 59%. For burglary, 95% of observed units show a clear-up rate less than 52%. In several counties the clear-up rate for burglary comes close to 100%, in some counties even exceeding it²¹ (the maximum clear-up rate was reported in the county Altenburger Land (Thuringia) in 2007). In contrast to these extreme high values, there are several counties where the clear-up rate for burglary was 0. These counties, however, suffered from only a small number of cases (between 5 and 24 cases per 100,000 inhabitants).

²⁰ The data have been extracted from the yearly published PKS (2003-2009)

²¹ This can happen if cases that were reported in the previous year are mostly solved in the current year together with cases reported to the police in the current year.

Table 4 displays the clear-up rates for street crime, drug related crime and auto theft. The clear-up rates for street crime are comparably low. 95% of all districts in the period under consideration have clear-up rates for street crime lower than 32.8%. This is not surprising taking into account which kind of offenses are subsumed in the definition of street crime, many of which are difficult to prosecute (as pickpocketing or damage to automobiles). The lowest clear-up rate for this offense was reported in the county Wittmund in 2008, while the highest clear-up rate was reported in Hamelin-Prymont in 2009 (maybe the Pied Piper of Hamelin made all criminals follow him to the police).

Table 4: Descriptive statistics clear-up rates for various offenses

Percentiles	Clear-up rate street crime	Clear-up rate drug related crime	Clear-up rate auto theft
5%	11.85	89.1	4.2
25%	16.5	94.2	8.1
50%	20.6	96.5	12.8
75%	24.8	98.1	20
95%	32.8	99.6	35.25
Minimum	4.3	31.9	0
Maximum	63.8	106.7	115.9
Mean	21.14	95.64	15.39
Standard Deviation	6.38	4.03	10.42

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

The clear-up rates for drug related crime are in general very large. Only 5% of districts during the period under consideration have less a clear-up rate of less than 89.1%. There are some exceptions, however. The minimal clear-up rate is only 31.9% (recorded in Oldenburg in 2009). The maximum of 106.7% was recorded in Bonn in 2004. As can be seen from the percentiles in Table 4, the distribution of clear-up rates is very leptokurtic. The reason for these extremely high clear-up rates may lie in the nature of the crime: it is arguably unlikely that those directly involved in the criminal act (as the drug seller and the drug addict) report it to the police (in contrast to the offense of auto theft or assault for example). Those cases which are reported to the police are probably cases that are detected by the police itself, delivering potential suspects right away and thereby leading to these high clear-up rates. The dark figure problem in turn might be particularly severe for this offense, although empirical evidence on that issue does not, to the best of the author’s knowledge, exist so far.

The clear-up rates for the offense auto theft are again very low with a minimum of 0% (recorded in the county Saale-Holzland in 2009); 95% of all counties during the period under

consideration have clear-up rates lower than 36%. On the other hand, the highest clear-up rate again exceeds 100% (recorded in Chemnitz 2007) with only very few exceeding 50%

Table 5 presents descriptive statistics on the clear-up rate on assault and damage to property. The clear-up rates for assault are very high with a minimum of 75.5% (recorded in Bonn in 2009) and with only 5% of counties having rates lower than 84.3%. The highest clear-up rate of 99.7% was recorded in the county Lahn-Dill in 2009. The explanation for these high rates may again lie in the nature of the crime: as a victim of assault, one usually has, at least, seen the offender. In some cases victims may even know the name of the offender or at least have an idea where the offender operates. These features clearly distinguish assault from other offenses as damage to property, to which I turn next.

The clear-up rate for damage to property is much lower than the one for assault. The maximal clear-up rate for damage to property (90.8%, recorded the county Nienburg (Weser) in 2009) is about the same as the median for assault (91.2%) and the value of the 95% percentile for damage to property (40.4%) is even lower than the minimum rate for assault (75.5%).

Table 5: Descriptive statistics of frequency ratios and clear-up rates for various offenses

Percentiles	Clear-up rate assault	Clear-up rate damage to property
5%	84.3	18.1
25%	88.8	22.7
50%	91.2	26.7
75%	92.9	31.7
95%	95.2	40.4
Minimum	75.5	10.4
Maximum	99.7	90.8
Mean	90.66	27.68
Standard Deviation	3.28	6.96

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

3.2.2. The independent variables- Demographics

As described in section 2.2, demographics play a key role in explaining criminal behavior. This section provides descriptive statistics for the demographic variables used in the empirical analysis. Table 6 displays information on certain cells of the age structure of the German counties and urban municipalities.

The share of the population that is younger than 15 years old (referred to as the young population) is the first cell to be analyzed. The first column of Table 6 shows considerable

variation across counties. The smallest share was recorded in the urban municipality of Suhl (Thuringia) in 2006 with only 8.19% of the population being younger than 15 years old. The maximum, in contrast, is more than twice as high with 20.95% of the population being younger than 15 years old. This figure was recorded in the county Cloppenburg (Lower Saxony) in 2003, which also used to have the highest fertility rate in Germany (a for German measure astonishing 1.97 children per woman in 2000, compared to an average fertility rate in Germany of 1.37 in 2008²²).

Table 6: Descriptive statistics of demographic variables

Percentiles	Share of population younger than 15	Share of population aged 15 to 24	Share of population aged 25 to 54
5%	0.0981	0.1013	0.3992
25%	0.1160	0.1109	0.4153
50%	0.1416	0.1173	0.4249
75%	0.1551	0.1236	0.4358
95%	0.1711	0.1387	0.4580
Minimum	0.0819	0.0892	0.3739
Maximum	0.2095	0.1770	0.4929
Mean	0.1371	0.1180	0.4262
Standard Deviation	0.0236	0.0113	0.0174

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

The second column of Table 6 shows descriptive statistics for the share of the population aged 15 to 24 (from here on referred to as the youth population). From the percentiles one sees that the distribution of shares of the youth population is less dispersed than the distribution of shares of the young population. The county with the smallest share of youth population, 8.92%, is the county Greiz (Thuringia, recorded in 2009), while the county with the largest share of youth population is urban municipality Greifswald (Mecklenburg-Western Pomerania, recorded in 2005).

Turning to the share of the population aged 25 to 54 (referred to as the adult population) one can see that the difference between the 95% percentile and the maximum (49.29%, recorded in Heidelberg (Baden Württemberg) in 2003) is larger than the difference between the 5% percentile and the minimum (37.39%, recorded in the county Lüchow-Dannenberg (Lower Saxony) in 2009) indicating a close-to-normal distribution with a slightly more pronounced right tail.

Information regarding the share of the male and foreign population as well as population density is provided in Table 7. The county with the lowest share of males is Baden-Baden

²² Source: „Die demographische Lage der Nation“, Berlin-Institute für Bevölkerung und Entwicklung.

(Baden Württemberg) with a share of 45.99% (recorded in 2004) while the county with the highest share is Aachen (North Rhine-Westphalia) with 51.48% (recorded in 2009). 95% of all counties during the period under consideration have male shares less than 50%, so in almost all counties there are more women than men.

The share of the foreign population varies considerable across German counties (see Table 7). The lowest share of foreigners was recorded in Sömmerda (Thuringia) in the year 2007 with only 0.68% foreigners in the population, while the highest share of foreigners was recorded in Offenbach am Main (Hesse) in 2003 with more than 26% of the population being foreign. A look at the percentiles shows that there are many counties with rather low shares of foreigners (50% have rates lower than 5.78%), while there are few counties with rather high shares of foreigners (5% of the counties in the period under consideration have shares of foreigners in the population higher than 15%).

Population density shows an interesting pattern as well: while 50% of all counties have population densities smaller than 197.31, 5% of counties are more than ten times as densely populated (with a population density larger than 2800) as the median county. The mean value of population density (512.34) hence does not convey much information about the “typical” county: more than 70% of all counties have a smaller population density than this mean, which is inflated by a small number of extremely densely populated areas. The most densely populated county is Munich; the least densely populated county is Mecklenburg-Strelitz (Mecklenburg-Western Pomerania). These two counties differ by a factor larger than 100 in terms of population density.

Table 7: Descriptive statistics of demographic variables

Percentiles	Share of male population	Share of foreign population	Population density
5%	0.4771	0.0135	68.93
25%	0.4864	0.0323	115.85
50%	0.4909	0.0578	197.31
75%	0.4949	0.0943	658.88
95%	0.4996	0.1556	2815.56
Minimum	0.4599	0.0068	37.59
Maximum	0.5148	0.2628	4282.21
Mean	0.4901	0.0679	512.34
Standard Deviation	0.0069	0.0463	662.08

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

3.2.3. The explanatory variables- Economics

Table 8 entails descriptive statistics of economic variables. These are the unemployment rate, net income of private households and gross domestic product (GDP) per capita. Before discussing the various statistics it is imperative to clearly define the unemployment rate and how it is measured, since there are various ways how to measure unemployment and, based on the number of unemployed, the unemployment rate. A naïve definition is to divide the number of unemployed persons by the total work force. This raises the question who is counted as an unemployed person and which persons are considered to be in the work force. According to the *Sozialgesetzbuch 3* (SGB 3), i.e. the Social Security Code, §16 Abs. 2 a person is to be considered unemployed if

- he or she is temporarily not in an employment relationship or works less than 15 hours per week.
- he or she is looking for an employment subject to social security contributions.
- he or she is at the disposal of the job employment agency's placement effort.
- he or she has registered as unemployed at the job employment agency.

Having defined the number of unemployed one has to define which persons are considered to be in the work force. In Germany there are two different ways the work force is defined. The first one is based on all persons in a dependent civilian employment (*abhängige zivile Erwerbspersonen*). These are persons within an employment subject to social security contribution (including apprentices), public servants (without soldiers) and persons in employment incentive programs (like "*1-Euro-Jobs*"). The second definition is based on persons within any kind of civilian employment (*alle zivilen Erwerbspersonen*). This broader measure includes all persons in a dependent civilian employment and in addition all self-employed persons and helping family members. The unemployment rate as displayed in Table 8 refers to the second definition of the work force and is hence based on the number of persons within any kind of civilian employment. After having clarified the issue of how unemployment is measured in Germany the discussion of the respective descriptive statistics can be conducted.

The unemployment rate varies considerably across German counties. The county with the lowest unemployment rate during the period under consideration is the county Eichstätt (Bavaria) with a rate of 1.6% (recorded in 2008). The county with the highest rate is the county Uecker-Randow (Mecklenburg-Western Pomerania) with a rate of 29.3% (recorded in

2004). Figure A15 shows the distribution of unemployment rates during the period under consideration. It is right-skewed with a unique peak at about 8%. A considerable fraction of districts (more than 5%) experienced unemployment rates higher than 20%. Taking a look at the regional distribution of unemployment rates across German counties in the year 2009 (Figure A16) shows that even 19 years after Reunification, the new German states still lack behind in terms of labor market success. Except for some urban municipalities (especially in the Rhine-Ruhr metropolitan area) the counties with unemployment rates higher than 10% are almost exclusively in East Germany. In addition, only very few county in East Germany have an unemployment rate smaller than 7%. The vast majority of counties with rates below 5% are all found in the south (states of Bavaria and Baden-Württemberg), while in the rest of Germany rates vary from 5% to 10%.

Table 8: Descriptive statistics of economic variables

Percentiles	Unemployment rate	Net income of private households	GDP per capita
5%	0.039	29907	15520
25%	0.061	34747	19592
50%	0.087	39650	23694
75%	0.130	43527	29355
95%	0.202	49845	47047
Minimum	0.016	24545	11755
Maximum	0.293	69030	86078
Mean	0.100	39520	26338
Standard Deviation	0.051	6289	10358

Note: Statistics based on the years 2003 to 2009 and all German counties and urban municipalities.

The variation in net income of private households is less pronounced than the variation in unemployment rates using the coefficient of variation as a measure of dispersion. The lowest net income was reported in Leipzig (Saxony) in 2003 with 24,545€, while the highest net income was reported in the county Starnberg (which is located in the periphery of Munich, Bavaria) in 2006. 50% of households have a net income between 35,000€ and 44,000€ at their disposal. Only 5% have less than 30,000€ and only 5% have more than 50,000€. As already mentioned, only in very few counties privat households have more than 50,000€ net income at their disposal.

Column 3 of Table 8 entails descriptive statistics for GDP per capita. Although this variable was not explicitly mentioned as a determinant of crime (and will not be used in the subsequent empirical analysis) a brief discussion seems worth the effort, since it gives an additional impression of the economic strength of a county. GDP per capita varies from a low

of 11,755€ (recorded in the county Südwestpfalz (Rhineland-Palatinate) in 2003) to a high of 86,078€ (recorded in Munich Bavaria) in 2007). 50% of counties during the period under consideration have a GDP per capita between roughly 20,000€ and 30,000€.

Although discussed in a separate paragraph in section 2.4, the share of workers subject to social security contribution without completed vocational training (from here on referred to as the share of unskilled workers in the work force²³) will be discussed in the section about economic variables. As described above, it is not entirely clear whether this variable truly captures education or rather job opportunities for unskilled workers. In order to answer this question one has to take a deeper look at the level of educational attainment. As already mentioned above, the information on educational attainment in the entire population is not available at the county level. It is, however, available at the state level based on census data (Statistisches Bundesamt). By looking at the regional distribution of the shares of unskilled workers in the workforce in the year 2009 (Figure A17) one can see that the share of unskilled workers in the work force is low in the new federal states while high in the south-west and rather mixed in the rest of Germany. If this variable were truly to capture educational attainment in the population (as opposed to the work force), one would expect to see the same pattern on the state level, namely high rates of unskilled workers in the population in the south-west, low rates in the east and mixed rates in the rest of Germany. This is, however, not the case: In the new German states, the share of unskilled workers in the population is indeed much lower than the respective shares in Bavaria and Baden-Württemberg (18.5% versus 28.2% and 30.4% respectively). This finding would support the interpretation that the share of unskilled workers in the workforce would proxy educational attainment: since their share in the population is lower their share in the work force is also lower. It should be noted, however, that most of the old German states have shares of unskilled workers in the population in the range of 30% (the average is 30.4%), while none of them has equally high shares of unskilled workers in the work force. If the share of unskilled workers in the workforce was to proxy the share of unskilled workers in the population (and hence educational attainment) one would expect to see a similar pattern as in Figure A48 for all states that have similar rates of unskilled workers in the population. This is clearly not the case: Lower Saxony, e.g., has a share of unskilled workers in the population of 29.7%, which is very close to the respective rates for Bavaria and Baden-Württemberg. But one can see in

²³ This abbreviation is slightly misleading, since the variable captures only those workers subject to social security contribution. As described above, there are more people in the work force than those subject to social security contributions.

Figure A17 that the share of unskilled workers in the workforce is clearly very different in Lower Saxony compared to Bavaria and Baden-Württemberg. Putting the pieces together one could conclude that the share of unskilled workers in the workforce rather captures labor market opportunities for unskilled workers than educational attainment²⁴. The differences in the shares of unskilled workers in the workforce are partly explained by the differences in the shares of unskilled workers in the population but, as just argued, not entirely. In Baden-Württemberg, e.g., a lot of medium sized and small businesses are located, especially in the manufacturing trade. These businesses seem to offer jobs also to unskilled workers, whereas the economic situation in the new German states is generally less beneficial.

Table 9: Descriptive statistics of demographic, educational and regional variables

Percentiles	Share of workers without completed vocational training	Population	Area
5%	0.0882	53798	66.95
25%	0.1140	100933	280.41
50%	0.1562	137259	786.99
75%	0.1824	226252	1255.74
95%	0.2187	483632	2092.26
Minimum	0.0725	34109	35.63
Maximum	0.3064	3442675	3058.28
Mean	0.1522	193900	853.24
Standard Deviation	0.0421	219297	626.11

Statistics on the years 2003 to 2009 and all German counties and urban municipalities.

The descriptive statistics are displayed in Table 9. The lowest share of unskilled workers (7.25%) was reported in 2009 in the county Greiz (Thuringia), the highest share (30.64%) was reported in 2009 in the county Tuttlingen (Baden-Württemberg). Although the maximum is 30.64%, the 95% percentile is only 21.87%, indicating a pronounced right tail.

3.2.4. The instrument

Since the unemployment rate is likely to be endogenous in any crime regression due to reasons discussed above, it is imperative to instrument the unemployment rate at some point in the empirical analysis. An instrumental variable has to fulfill two assumptions in order to circumvent the problem of endogeneity: it has to be relevant and exogenous. Relevance of the instrument means that the instrumental variable (IV from here on) helps explaining the potentially endogenous variable. More formally, the respective coefficient has to be non zero in the linear projection of the IV and all exogenous variables on the endogenous variable.

²⁴ In addition, the share of people in the population with tertiary education or with a completed vocational training is very similar in the new and old German states.

Phrased differently, the IV must be partially correlated with the endogenous variable. The second assumption, instrument exogeneity, means that the IV must not be correlated with the error term in the respective regression equation. This in turn implies that the IV must not be correlated with any time varying omitted variables determining crime rates²⁵. In order to construct such a variable, I follow the ideas of Blanchard et al (1992), which were slightly adjusted by Gould, Weinberg and Mustard (2002) and Öster and Agnell (2007). The idea behind the instrument is to find some measure for labor demand (which in turn influences the unemployment rate) that is uncorrelated with crime rates. Their approach interacts two sources of variation which are exogenous to the county's crime rate: the industrial composition within in each county and the national industrial composition trends in employment in each industry. A small example with two industries and two counties might clarify the intuition: the urban municipality of Frankfurt am Main has a rather large share of workers working in the financial service sector, whereas the urban municipality of Stuttgart has a large share of workers working in the manufacturing sector. A national increase in demand for workers in the financial service sector will affect these two urban municipalities in a very different way (it will benefit Frankfurt more than Stuttgart) while a national increase in demand for workers in the manufacturing sector has the opposite effect.

Following the notation of Gould et. al. (2002), the instrument is constructed the following way: Let $f_{i|ct}$ denote industry i 's share of employment in county c at time t and let $f_{i|t}$ denote the industry's share of employment at time t for the nation. The growth in industry i 's employment nationally between time $t-1$ and time t is hence given by

$$grow_i = \frac{f_{i|t}}{f_{i|t-1}} - 1.$$

The instrument for the change in labor demand in county c at time t is then

$$instrument1_{c,t} = \sum_i f_{i|c,t-1} grow_i$$

As Gould et. al. (2002, p. 60) phrase it, “we estimate the growth in labor demand in city c by taking the weighted average of the national industry growth rates. The weights for each city correspond to the initial industry employment shares in the city.”

²⁵ The time invariant omitted variables will be absorbed in the individual fixed effects.

Following Öster and Agnell (2007, p. 773), I construct another instrument with the respective employment shares lagged two periods

$$instrument2_{c,t} = \sum_i f_{i|c,t-2} grow_i$$

The first assumption the IV has to fulfill (relevance) can (and will) be tested via statistical methods. The second assumption (validity) cannot be tested directly²⁶ (since it entails the unobservable error term in the regression equation). It has to be argued by logical reasoning that the IV is indeed uncorrelated with the error term. This is likely to be the case: neither the industrial composition in a county nor the national trends in employment have an obvious impact on crime rates in a given county.

Based on data availability, I differentiate between the following six industries:

- 1) agriculture, forestry and fishery (*Land- und Forstwirtschaft, Fischerei*)
- 2) processing trade (*verarbeitendes Gewerbe*)
- 3) building and construction (*Baugewerbe*)
- 4) commerce, hotel and restaurant industry and transportation (*Handel, Gastgewerbe und Verkehr*)
- 5) financing, leasing and corporate services (*Finanzierung, Vermietung, Unternehmensdienstleistungen*)
- 6) public and private supply of services (*öffentliche und private Dienstleister*)

4. Methodology

As already mentioned in the introduction, I will apply two estimation techniques: mean regression and quantile regression. While mean regression delivers a single parameter estimate for the effect of unemployment on crime (which is in itself an interesting object), quantile regression allows different impacts of unemployment on crime depending on the level of criminal activity. This is useful for the following reason: one might get an insignificant effect of unemployment on crime in mean regressions, while there is indeed a negative (and significant) effect of unemployment on crime for low-crime areas while a positive (and significant) effect for high-crime areas. In mean regression these two effects

²⁶ There is, however, a way to test the validity of subsets of instruments. This test of over identifying restrictions will be performed in the empirical analysis.

would simply cancel out, leaving the researcher with the conclusion that unemployment does not affect crime, while there might be in fact a highly non-trivial relationship between the two. Quantile regression can therefore be seen as a tool of deeper inspection of the results of the mean regression, a path that has not been pursued in the context of analyzing the relationship between crime and unemployment so far.

4.1. Methodology- Mean regression

As mentioned in section 1, I will proceed in a stepwise fashion in the empirical analysis. Starting with an ordinary least squares regression which serves as a benchmark model in a first step, I will introduce fixed effects in the estimation in order to circumvent problems of unobserved heterogeneity; finally I will use instrumental variables estimation in order to get mitigate the problem of endogeneity.

4.1.1. Ordinary Least Squares Regression

The starting point for the empirical analysis is the following model specification for the dependence of crime on unemployment

$$(1) \text{Crime}_{i,t} = \beta \text{Unemployment}_{i,t} + \gamma' X_{i,t} + \tau_t + \varepsilon_{i,t}$$

The coefficient of interest is β which captures the effect of unemployment in year t in county i on crime in year t in county i . The vector of parameters γ captures the influence of other explanatory variables as demographic, economic or deterrence variables. The τ 's are time fixed effects and capture the influence of shocks on the crime rate which affect all counties in the same way. $\varepsilon_{i,t}$ denotes the error term.

This model specification suffers from at least two methodological deficiencies. First and foremost this specification does not utilize the panel structure of the data. Panel data are superior compared to a pooled cross section in that the former allows the researcher to include so called unobserved effects (or individual fixed effects). These unobserved effects are able to capture all time invariant factors which influence the crime rate and are specific to a certain county. Rural areas for example might be very different from urban areas in many respects which do not change over time (especially not over a rather short time period as analyzed here). These unobserved factors, which are specific to a county but do not change over time can all be lumped together in the unobserved fixed effect. Their inclusion can therefore help to mitigate the problem of omitted variables (Wooldridge 2002, p. 247).

The second deficiency stems from the fact that the unemployment rate is most likely not an exogenous variable in equation (1) due to two issues. The first is the correlation of unemployment with unobserved factors: the failure to control for variables that exert cyclical pressure on crime rates may bias estimates of the unemployment-crime effect (Raphael and Winter-Ebmer 2001, p. 2). The second is reverse causation: as criminal activity reduces the employability of offenders, criminal activity may contribute to observed unemployment (Raphael and Winter-Ebmer 2001, p. 3).

4.1.2. Fixed Effect Regression

As described in the previous paragraph, by neglecting the panel structure of the data one might unnecessarily run into the problem of omitted variable bias and the resulting inconsistent parameter estimates. By including these fixed effects, the problem of omitted variables is mitigated and the resulting regression equation reads as

$$(2) \text{Crime}_{i,t} = \alpha_i + \beta \text{Unemployment}_{i,t} + \gamma' X_{i,t} + \tau_t + u_{i,t}$$

where α_i denotes the fixed effect for county i and $u_{i,t}$ is the new error term. Although the α_i 's are unobservable it is still possible to estimate the parameters of interest in equation (2) by subtracting the (over time) mean of each individual from the respective observation. Denoting mean values by upper bars, the regression equation reads as

$$(3) \text{Crime}_{i,t} - \overline{\text{Crime}}_i = \beta (\text{Unemployment}_{i,t} - \overline{\text{Unemployment}}_i) + \gamma' (X_{i,t} - \bar{X}_i) + \tau_t + u_{i,t} - \bar{u}_i$$

Note that the unobserved effect α_i does not appear in equation (3) anymore, but the parameters are the same as in equation (2). It is hence possible to estimate the parameters of interest β by applying OLS to equation (3).

This specification still suffers from the problem that unemployment might not be an exogenous variable in equation (3). To circumvent this problem it is necessary to instrument the unemployment rate by a suitable variable. This procedure will be discussed in the next section.

4.1.3. Fixed Effect Instrumental Variable Regression

In presenting the method of fixed effect instrumental variable estimation, I will abstract from the panel dimension of my dataset and present the method for a general linear system of

equations. I will follow the notation of Wooldridge (2002, chapter 8) and consider a model of the form

$$(4) \quad y_i = X_i\beta + u_i$$

where y_i is a $G \times 1$ vector, X_i is a $G \times K$ matrix and u_i is a $G \times 1$ vector of errors²⁷. In addition, I will assume that a $G \times L$ matrix Z_i of instruments is available (where the matrix of instruments includes all exogenous explanatory variables plus the “true” instruments excluded from equation (4)).

In the case where the number of true instruments equals the number of endogenous variables (exact identification), the method of moments estimator chooses $\hat{\beta}$ to solve the following set of moment conditions:

$$(5) \quad N^{-1} \sum_{i=1}^N Z_i'(y_i - X_i\hat{\beta}) = 0$$

In the case over identification, where we have more true instruments than explanatory variables ($L > K$), equation (5) will in general not have a unique solution. One way to deal with this is to minimize the Euclidian distance of the $L \times 1$ vector in equation (5). Based on this rationale, one chooses $\hat{\beta}$ which makes the following expression as small as possible:

$$(6) \quad \left[\sum_{i=1}^N Z_i'(y_i - X_i\hat{\beta}) \right]' \left[\sum_{i=1}^N Z_i'(y_i - X_i\hat{\beta}) \right]$$

A more general class of estimators can be constructed by including a weighting matrix in the quadratic form in equation (6). For this purpose I denote by \widehat{W} a symmetric, positive semidefinite $L \times L$ matrix, where the hat stresses the fact that the matrix has to be estimated in general. A generalized method of moments (GMM) estimator of β is a vector $\hat{\beta}$ which solves the following problem:

$$(7) \quad \min_{\hat{\beta}} \left[\sum_{i=1}^N Z_i'(y_i - X_i\hat{\beta}) \right]' \widehat{W} \left[\sum_{i=1}^N Z_i'(y_i - X_i\hat{\beta}) \right]$$

The problem (7) has a closed form solution as it is a quadratic function of $\hat{\beta}$.

A specific choice of \widehat{W} produces the GMM estimator with the smallest variance. This choice of \widehat{W} is given by the following expression (for details why this is true see Wooldridge, p. 191):

²⁷ In the case of panel data, we would have $G=T$, where T is the number of time periods in the panel.

$$(8) \widehat{W} = (N^{-1} \sum_{i=1}^N Z_i' \tilde{u}_i \tilde{u}_i Z_i)^{-1}$$

Where \tilde{u}_i are residuals based on an initial consistent estimator of β .

To summarize the procedure of GMM with optimal weighting matrix²⁸, one has to conduct the following steps:

- i) Let $\tilde{\beta}$ be an initial consistent estimator of β ²⁹.
- ii) Obtain a residual vector

$$\tilde{u}_i = y_i - X_i \tilde{\beta}$$
- iii) Choose \widehat{W} as described in (8)
- iv) Use this matrix to obtain the GMM estimator with optimal weighting matrix according to (7).

4.2. Methodology- Quantile Regression

Mean regression deals with estimating the conditional mean function. This function describes how the mean of the dependent variable changes with the vector of explanatory variables. The underlying assumption is that the error term in the regression equation has the same distribution independent of the values of the explanatory variable. Given this assumption holds true, knowing the mean function tells everything the researcher needs to know. However, there exists the possibility that the explanatory variables influence the conditional distribution of the dependent variable in many other ways: stretching one tail of the distribution, inducing multimodality or expanding its dispersion (Koenker 2001, p. 1). Investigating these other possibilities might offer a more detailed view on the relationship between the dependent and the explanatory variables. In particular, it might shed light on the question whether the effect of unemployment on crime depends on the level of crime.

There are (at least) two alternative crime-unemployment profiles that are imaginable from a theoretical point of view:

- i) A declining crime-unemployment profile, where the effect of unemployment on crime is high in low-crime areas and low in high-crime areas.
- ii) An increasing crime-unemployment profile, where the effect of unemployment on crime is low in low-crime areas and high in high-crime areas.

²⁸ This estimation method is sometimes also called two-step feasible GMM.

²⁹ This will be the pooled 2SLS estimator in my analysis.

These two different crime-unemployment profiles correspond to two different interpretations on how criminals react to the level of criminal activity. If one was to observe i), a declining crime-unemployment profile, this would give rise to what I call the opportunity-based behavior. Given criminal activity is low an increase in unemployment has a large impact on crime, because the supply for crime is highly elastic if there are attractive targets and only a few competitors. If there are only a few drug dealers in the street, becoming a drug dealer is more profitable than if there are already many drug dealers around. If there are only a few burglars around, trying to break into a house is more profitable (maybe because people do not invest so much in crime-preventing equipment as alarm and warning devices). If crime is already high, that means the supply side of the “crime-market” is already rather competitive, engaging in criminal activities after becoming unemployed is not as attractive anymore. Hence the supply becomes inelastic and the effect of unemployment on crime would be lower.

If one was to observe ii) instead, an increasing crime-unemployment profile, this would give rise to what I call the stigma-based behavior. Given criminal activity is low, getting unmasked as a criminal in case of detection places a high stigma on the person, since there are only a few criminals, and he or she is one of them. A higher unemployment rate would hence not necessarily push someone into criminal activity, since the fear of the stigma prevents him or her from doing so. If there is already a lot of criminal activity, becoming a criminal does not bother him or her too much, since even after being detected he or she will not be seen as the “black sheep”. A rise in unemployment would hence more easily push the person into criminal activity³⁰.

4.2.1. Ordinary Quantile Regression

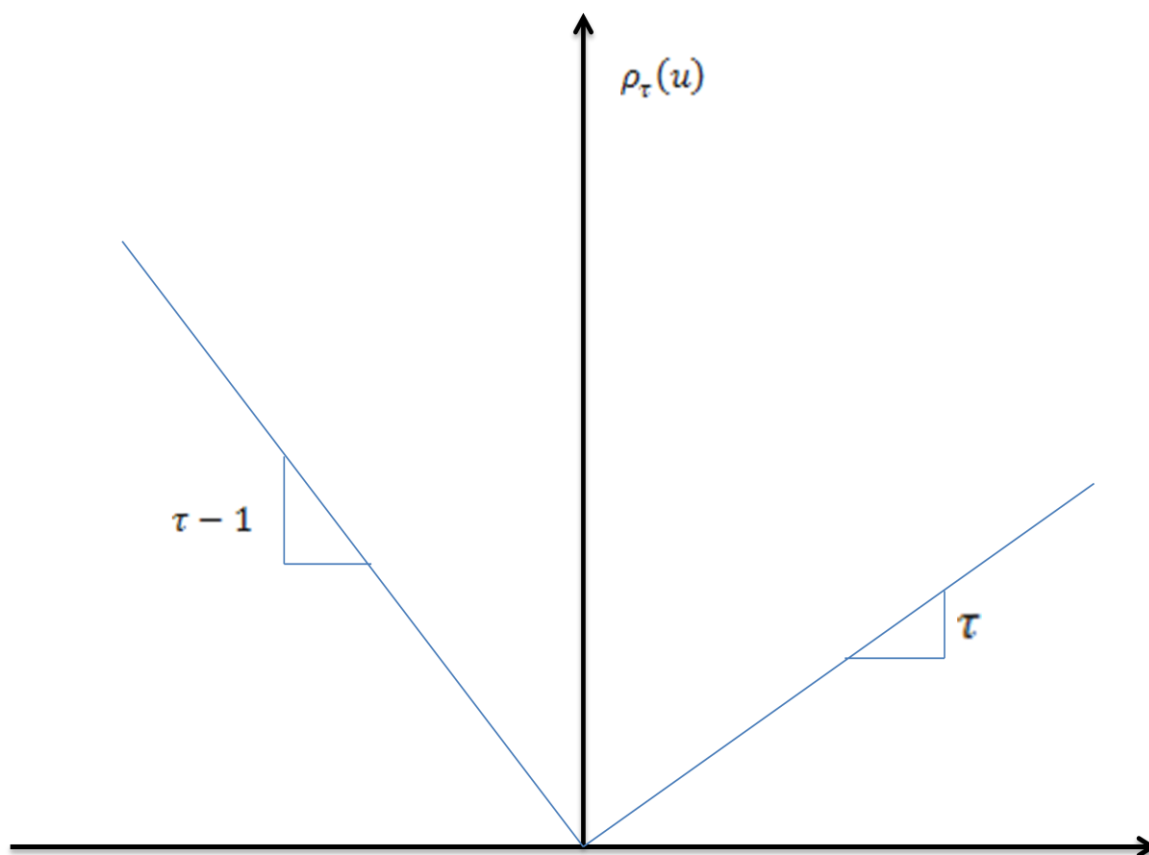
It might come as a mild surprise that quantiles, although seeming to be inseparately linked to the operations of ordering and sorting, can also be defined via a simple optimization problem (Koenker 2001, p.2). Similarly to OLS, where estimation is based on minimizing a sum of squared residuals, quantile estimation is based on minimizing a sum of weighted absolute residuals. More precisely, estimating the conditional quantile function for quantile τ is achieved by solving the following minimization problem

$$(9) \min_{\beta} \sum \rho_{\tau}(y_{i,t} - \xi(x_{i,t}, \beta))$$

³⁰ These two different explanations could in principle be incorporated in the model of Grogger if one would allow the return to crime function to depend on the level of criminal activity.

where β is the parameter of interest, $\rho_\tau(u) = [\tau I\{u \geq 0\} + (1 - \tau)I\{u < 0\}]|u| = u(\tau - I\{u < 0\})$ is the quantile loss function (visualized in Figure 2) and $\xi(x_{i,t}, \beta)$ is some parametric function³¹. In a first step, the parametric function will be a linear function of the explanatory variables and the parameters to be estimated, as the right hand side of regression equation (1). This approach suffers from the same deficiencies as described above (neglecting the panel structure and not taking into account the possible endogeneity of the unemployment rate). These deficiencies will be dealt with in the next sections.

Figure 3: Quantile loss function



4.2.2. Quantile regression with fixed effects

Following Koenker (2004) I will consider the following model for the conditional quantile functions of the dependent variable of individual i at time t :

$$(10) \quad Q_{y_{i,t}}(\tau|x_{i,t}) = \alpha_i + x'_{i,t}\beta(\tau)$$

³¹ I denotes the indicator function taking the value 1 if the expression in the cambered brackets is true and 0 otherwise.

where the α_i again denote the individual fixed effect, $x_{i,t}$ is a vector of explanatory variables and the τ -dependent vector β is the vector of parameters to be estimated. In order to estimate model (5) for several quantiles simultaneously, Koenker (2004) proposes solving the following:

$$(11) \quad \min_{(\alpha, \beta)} \sum_{k=1}^q \sum_{t=1}^T \sum_{i=1}^n \omega_k \rho_{\tau_k} (y_{i,t} - \alpha_i - x'_{i,t} \beta(\tau_k))$$

or, if the number of individuals is large relative to the number of time periods, a penalized version of (6), which reads as

$$(12) \quad \min_{(\alpha, \beta)} \sum_{k=1}^q \sum_{t=1}^T \sum_{i=1}^n \omega_k \rho_{\tau_k} (y_{i,t} - \alpha_i - x'_{i,t} \beta(\tau_k)) + \lambda \sum_{i=1}^n |\alpha_i|$$

where the ω_k 's are weights which control the relative influence of the q quantiles $\{\tau_1, \dots, \tau_q\}$ on the estimation of the α_i parameters (Koenker 2004, p. 77), $\rho_{\tau}(\cdot)$ is again the quantile loss function and λ is a shrinkage parameter. For $\lambda \rightarrow 0$, one would obtain the fixed effect estimator based on optimizing (6), while for $\lambda \rightarrow \infty$ one would obtain an estimate of the model purged of the fixed effects (Koenker 2004, p. 78)³². A routine that implements this estimator (and variants of it) has been provided by Roger Koenker and Stefan Bache and is available for R.

4.2.3. Quantile regression with fixed effects and instrumental variables

Although the estimation method described in the previous paragraph fixes the problem of unobserved heterogeneity, it still suffers from the fact that the variable of interest (the unemployment rate) might not be an exogenous variable. The approach outlined in Harding and Lamarche (2009) tries to overcome this problem by developing an estimation technique which is able to control for unobserved heterogeneity on the one hand, but is also able to incorporate the idea of instrumental variables. The model reads as follows:

$$(13) \quad y_{i,t} = d'_{i,t} \delta + x'_{i,t} \beta + \alpha_i + u_{i,t}$$

$$(14) \quad d_{i,t} = h(x_{i,t}, w_{i,t}, v_{i,t})$$

$$(15) \quad \alpha_i = g(x_{i,1}, \dots, x_{i,T}, d_{i,1}, \dots, d_{i,T}, \varepsilon_i)$$

The first equation represents the usual panel data model. The vector d is a vector of endogenous variables, x is a vector of exogenous variables and u is the error term. The

³² If the shrinkage parameter goes to infinity, the estimated fixed effects have to go zero in order to find a minimum of equation (7).

endogenous variable(s) d is assumed to depend on a vector of instruments w , which are assumed to be independent of u , and a variable v which is allowed to be dependent on u . Equation (15) describes the typical situation that the individual effect might be correlated with the explanatory variables, where ε_i is assumed to be independent of both v and u . The parameter of interest in this case is δ , the effect of the endogenous variable on the dependent variable. The estimation technique developed by Harding and Lamarche (2009) extends the work of Chernozhukov and Hansen (2008) on instrumental variables by allowing for fixed effects as discussed above and works in the following way: the objective function for the conditional instrumental quantile relationship

$$(16) \quad R(\tau, \delta, \beta, \gamma, \alpha) = \sum_{t=1}^T \sum_{i=1}^n \rho_{\tau}(y_{i,t} - d'_{i,t}\delta - x'_{i,t}\beta - z'_{i,t}\alpha - \hat{w}'_{i,t}\gamma)$$

is first minimized for β , γ and α as functions of τ and δ . ρ_{τ} again denotes the quantile loss function, z is an indicator variable for the individual effect α_i and \hat{w} is the least squares projection of the endogenous variable d on the instruments w , the exogenous variables x and the vector of individual effects z . Formally:

$$(17) \quad \{\hat{\beta}(\tau, \delta), \hat{\gamma}(\tau, \delta), \hat{\alpha}(\tau, \delta)\} = \arg \min_{\beta, \gamma, \alpha} R(\tau, \delta, \beta, \gamma, \alpha)$$

In as second step, Harding and Lamarche (2009) estimate the coefficient of interest by finding the value of δ which minimizes a weighted distance function defined on γ :

$$(18) \quad \hat{\delta}(\tau) = \arg \min_{\delta} \hat{\gamma}(\tau, \delta)' A \hat{\gamma}(\tau, \delta)$$

for a given positive definite matrix A .

A routine that implements this estimator has been provided by Matthew Harding and Steven Lamarche and is available for R.

5. Estimation results

The results of the different estimation techniques will be presented in this section. I will first present the results from the mean regression and discuss the resulting implications. In a second step I will turn to the results from the quantile regression.

5.1. Estimation results- Mean regression

Table 10 shows the results for the three mean regression applied in this study. The dependent variable is the logarithm of the frequency ratio of the respective offense. All regression include, besides the unemployment rate, the logarithm of clear-up rate for the respective offense lagged by one period³³, the logarithm of disposable income, the share of foreigners, the share of the young population (aged younger than 15), the share of the youth population (aged 15 to 24), the share of the adult population (aged 25 to 55), the share of unskilled workers and time dummies. Population density is included in the OLS regression, while in the fixed effect regression and the fixed effect instrumental variable regression this variable is replaced by the logarithm of the overall population³⁴. The fixed effect regression and the fixed effect instrumental variable regression include individual fixed effects in addition.

The analysis covers the years from 2005 to 2009, although data are available from 2003 onwards. The reason for this is a labor market reform (the so called “Hartz-Reform) which was implemented in 2005. This reform had a major impact on the number of unemployed persons: people who were receiving social welfare benefits (Sozialhilfe) before 2005 were counted as unemployed after 2005. In order for the results not to be affected by this institutional change the time period used for estimation was restricted to the years 2005 to 2009.

Table 10 displays the results of the three mean regressions. The estimated parameters are to be interpreted as semi elasticities: an increase of the unemployment rate by one unit (which is one percentage point in this case) increases criminal activity by $\beta\%$. Based on the naïve OLS regression, unemployment has a positive and significant effect on crime for the following offenses: burglary (9.6%), auto theft (10.3%), damage to property (2.1%) and street crime (5.2%). Negative effects are observed for assault (-0.4%) and drug related crime (-3.4%), while only the effect for drug related crime is significant. These results are in line with previous findings: the unemployment rate has a large effect for property crimes (burglary and auto theft) while only small or insignificant effects for violent crime (assault, damage to property). The results for street crime are hard to interpret in this respect, because all kind of different offenses are subsumed in this variable.

³³ Lagging the clear-up rate by one period is done in order to avoid problem of simultaneity: if crime rates are high this might induce more effort by the police or more police spending which in turn will have an influence on the crime rate itself. By lagging the clear-up rate by one period this problem is at least mitigated.

³⁴ This is done because population density does hardly vary over time (exceptions are small redistrictions that happened in some counties in the new federal states). Including population density together with fixed effects would therefore cause problems of multicollinearity.

The OLS specification does not take the panel structure into account. The fixed effect regression (column FE in Table 10) does include county fixed effects and is therefore able to control for unobserved heterogeneity across counties. This does change the estimated effects of unemployment on crime enormously. There are only three offenses that are significantly influenced by the unemployment rate (burglary, drug related crime and street crime), and only one offense is positively affected by an increase in the unemployment rate (street crime). Auto theft and damage to property have positive but insignificant coefficients for the unemployment rate, while assault has negative and insignificant coefficients. In addition, the positive and significant coefficient on street crime is only about one fifth of what is has been in the OLS regression.

Table 10: Results from the mean regression for the effect of unemployment on crime

Offense	OLS	FE	FEIV
Assault	-0.3644984 (0.2890236)	-0.1099368 (0.4189148)	-2.482087 (3.951465)
Burglary	9.63391*** (0.9090215)	-2.035835* (1.348)	-5.564844 (9.279668)
Auto theft	10.31895*** (0.9105708)	1.0896 (1.033302)	-9.902562 (7.270021)
Damage to property	2.089316*** (0.2966023)	0.0956616 (0.4238148)	-0.6587526 (3.137964)
Drug related crime	-3.363926*** (0.6354227)	-2.092266** (0.8314305)	-2.21474 (6.004155)
Streetcrime	5.182263*** (0.5284713)	1.072879** (0.4385171)	-3.859871 (3.294916)
Number of observations	1947	1947	1947
F test of excluded instruments³⁵	-	-	F>10 in all cases
Underidentification test³⁶	-	-	H_0 rejected in all cases
Overidentification test (Hansen J statistic)³⁷	-	-	H_0 not rejected in all cases

Note: Cluster-robust standard errors in parenthesis. Dependent variable: log(frequency ratio). All regression include log(clear-up rate) for the respective offense lagged by one period, log(disposable income), share of foreigners, share of the young population, share of the youth population, share of the adult population, share of unskilled workers and time dummies. All regressions have been weighted by the county specific population. *, ** and *** denote significance at the 10%-, 5% and 1%-level respectively.

Estimating the third specification which controls, on the one hand, for unobserved heterogeneity by the inclusion of county fixed effects and, on the other hand, for the

³⁵ The rule of thumb of Bound et al (1995) states that an F statistic larger than 10 indicates a strong instrument.

³⁶ The null hypothesis for this test is that the model is underidentified. A rejection of the null hypothesis hence implies an identified model.

³⁷ The null hypothesis for this test is that the overidentifying restrictions are valid. If this hypothesis is not rejected it gives rise to the validity of the instrument.

endogeneity of the unemployment rate does again change the picture. All offenses are not significantly influenced by an increase in the unemployment rate. Although this result seems surprising, the model does not seem to be miss specified based on the various specification tests employed after the estimation. The F statistic of excluded instruments is between ten and twelve for the various offenses and exceeds the rule of thumb value of 10 introduced by Staiger and Stock (1997) and popularized by Stock and Yogo (2005). Together with the underidentification test one can unambiguously draw the conclusion that the instruments used in the analysis are sufficiently partially correlated with the endogenous variable. The over identification test, whose rejection would cast doubt on the validity of the instruments, cannot be rejected at any customary level of significance for all offenses³⁸. In addition, a lot of potentially confounding factors have been controlled for such that it is unlikely that the results suffer from an omitted variable bias. A possible explanation why the coefficients in the FEIV regression are much smaller is that the OLS and FE regression are heavily plagued by the issue of reverse causation mentioned in the introduction: as criminal activity reduces the employability of offenders, criminal activity may contribute to observed unemployment and thereby biasing the coefficient on unemployment upwards. This seems to be the case here. One explanation for the insignificance of the effects are the extremely high standard errors in the FEIV regression compared to the OLS and FE regression, something typically found when applying the instrumental variable approach. Another explanation might be that some people commit crimes although being active in the labor market (Grogger 1995) as also outlined in the theoretical justification in section 2.3. In order to deal with this problem, which cannot be addressed with the data set at hand, one would need individual data on the criminal record, something that is hardly available for Germany.

5.2. Estimation results- Quantile regression

The estimation of quantile regressions serves the purpose to analyze whether the effect of unemployment on crime depends on the level of crime and, if this should be the case, how agents react to different levels of crime. If the effect of unemployment on crime is increasing in the level of crime, this would give rise to the interpretation of stigma based behavior of agents. If, on the other hand, the effect of unemployment on crime is decreasing with the level of crime, this would give rise to the opportunity based behavior of agents.

³⁸ The only exception is the offense street crime, where the null hypothesis can be rejected at the 5% significance level.

5.2.1. Ordinary quantile regression

Table 11 gives an overview of the results for the ordinary quantile regression. The results for the offense damage to property are in line with the results from the OLS regression. While with OLS I estimate an effect of 2.1% increase in crime if the unemployment rate increases by one percentage point, the estimates from the quantile regressions vary from a 1.8% increase (for the 95% quantile) to 2.5% (for the 75% quantile). The crime-unemployment profile is rather flat, as can also be seen from Figure A18. A similar conclusion can be drawn for the offense damage to property, drug related crime and street crime, where the crime-unemployment profile is flat (Figure A19, A20 and A21) and the respective estimates have a similar magnitude as the one obtained from the OLS regression.

Table 11: Results from the ordinary quantile regression for the effect of unemployment on crime

Offense	Quantile regression				
	0.05	0.25	0.5	0.75	0.95
Assault	1.126409* (0.6809122)	0.9468126*** (0.3068544)	0.4180014 (0.3328466)	0.411756 (0.3918754)	-0.714608 (0.976763)
Burglary	15.18543*** (1.21154)	9.718282*** (0.8854864)	7.490865*** (0.671189)	7.037665*** (0.960069)	5.924248*** (1.051466)
Auto theft	12.78875*** (1.619261)	9.834917*** (0.7416253)	8.828921*** (0.688995)	8.579097*** (0.8891756)	7.921626*** (1.630655)
Damage to property	1.948386*** (0.6671565)	1.972584*** (0.240282)	2.342387*** (0.3780384)	2.5315*** (0.3551846)	1.825829** (0.7992698)
Drug related crime	-1.627576* (0.8497524)	-2.960089*** (0.7581106)	-2.688531*** (0.779388)	-3.617629*** (1.008148)	-3.6018*** (0.7246929)
Streetcrime	3.494546*** (1.002983)	5.249943*** (0.5284244)	4.354522*** (0.4412872)	5.625728*** (0.4978109)	3.649925*** (0.71235)

Note: Bootstrapped standard errors in parenthesis. Dependent variable: log(frequency ratio). All regression include log(clear-up rate) for the respective offense lagged by one period, log(disposable income), share of foreigners, share of the young population, share of the youth population, share of the adult population, share of unskilled workers and time dummies. *, ** and *** denote significance at the 10%-, 5% and 1%-level respectively.

A more sophisticated picture emerges from the offenses assault, burglary and auto theft. While the estimated effect of an increase in the unemployment rate on crime rates for assault is insignificant in the OLS regression, it is positive and significant in the ordinary quantile regression at least for low levels of crime (for the 5% and 25% quantile). In addition, the crime-unemployment profile is slightly decreasing (Figure A22). This is even more pronounced for the offenses burglary and auto theft (Figure A23 and A24). A clearly decreasing crime-unemployment profile can be observed, giving rise to the interpretation that agents take the opportunity of committing crime as a response to unemployment if the “supply” of crime is rather low. In addition, the OLS estimate are in the middle of the respective quantile regressions (9.6% for burglary in the OLS regression versus 15.2% to

5.90% in the quantile regression; 10.3% for auto theft in the OLS regression versus 12.8% to 7.9% in the quantile regression), supporting the apprehension that in the OLS regression the effects at different quantiles are simply averaged and do not reveal the full picture of the crime-unemployment relationship.

5.2.2. Estimation results- Quantile regression with fixed effects

Table 12 displays the results from quantile regression with fixed effects. The results are in general very similar to those obtained from ordinary quantile regression. The effect of an increase in the unemployment rate on street crime varies from 2.8% (95% quantile) to 5.3% (75% quantile), the effect on drug related crime varies from -2.1% (5% quantile) to -3.6% (95% quantile). The effect of unemployment on assault is insignificant over the whole range of quantiles (while it was significant in the ordinary quantile regression at least for low levels of crime). The effect on burglary and auto theft is still significant for all quantiles, although the effect is a little bit smaller at low quantiles compared to the results from ordinary quantile regression. The crime-unemployment profile is decreasing for the offenses burglary, auto theft, drug related crime and assault³⁹. For the offense street crime one can observe a drop at least for the 95% quantile, where the effect is much smaller than for the other quantiles (2.9% versus 4% to 5.3%). A rather flat crime-unemployment profile can be observed damage to property (0.96% to 2.02%).

Table 12: Results from quantile regression with fixed effects for the effect of unemployment on crime

Offense	Quantile regression with fixed effects				
	0.05	0.25	0.5	0.75	0.95
Assault	-0.01116 (0.72934)	0.07667 (0.50502)	-0.1579 (0.44828)	-0.52201 (0.54669)	-1.41595 (0.89027)
Burglary	10.86242*** (1.30179)	9.14274*** (1.1066)	8.33945*** (1.08481)	6.72702*** (1.24689)	6.13967*** (1.53928)
Auto theft	9.37268*** (1.2033)	9.09249*** (0.89253)	9.00066*** (1.00994)	8.4001*** (1.04269)	6.74223*** (1.89177)
Damage to property	1.41547** (0.58763)	0.96538* (0.4989)	1.808*** (0.5432)	2.02377*** (0.60034)	1.52354 (1.07072)
Drug related crime	-2.08741 (1.54518)	-3.31008*** (0.845)	-2.74978*** (0.92646)	-3.45782*** (1.02422)	-3.67223*** (1.42829)
Streetcrime	4.53995*** (0.9316)	4.02472*** (0.8293)	5.03624*** (0.69592)	5.29937*** (0.6757)	2.8704*** (0.77632)

Note: Bootstrapped standard errors in parenthesis. Dependent variable: log(frequency ratio). All regression include log(clear-up rate) for the respective offense lagged by one period, log(disposable income), share of foreigners, share of the young population, share of the youth population, share of the adult population, share of unskilled workers and a linear time trend. *, ** and *** denote significance at the 10%-, 5% and 1%-level respectively.

³⁹ The effect of rising unemployment on assault is, however, not significant.

Concerning the offenses burglary, auto theft and drug related crime agents seem to act according to opportunity based behavior: an increase in the unemployment rate has a larger effect on criminal activity in areas when crime rates are low and the “market” for crime is not very competitive.

5.2.3. Estimation results- Quantile regression with fixed effects

In the last specification, I take the endogeneity of the unemployment rate into account by incorporating the idea of instrumental variables in the quantile regression with fixed effects. The results of this estimation are displayed in Table 13.

Table 13: Results from quantile instrumental variable regression with fixed effects for the effect of unemployment on crime

Offense	Quantile instrumental variable regression with fixed effects				
	0.05	0.25	0.5	0.75	0.95
Assault	-3.064537*** (0.32438)	-2.809542*** (0.502877)	-1.80696*** (0.499957)	-0.477463 (0.562265)	-0.420565 (0.312232)
Burglary	-4.9877*** (0.268062)	-5.430827*** (0.961786)	-2.441955 (1.968584)	1.380547 (1.978904)	2.174373* (1.288444)
Auto theft	-4.967983*** (1.276564)	-3.898914*** (1.602242)	-1.032806 (1.352414)	0.762045 (1.27440)	1.500648** (0.701544)
Damage to property	-7.234947*** (0.258382)	-6.601222*** (0.653109)	-5.292126*** (0.69844)	-3.559735*** (0.607245)	-2.976577*** (0.370385)
Drug related crime	0.485864*** (0.219389)	1.598142 (1.546294)	4.58735*** (1.294186)	6.835037*** (1.383201)	7.502487*** (0.539488)
Streetcrime	-2.34224*** (0.465398)	-1.969574*** (0.499739)	-0.972629 (0.558619)	-0.016129 (0.385697)	0.214483** (0.091975)

Note: Standard errors in parenthesis. Dependent variable: log(frequency ratio). All regression include log(clear-up rate) for the respective offense lagged by one period, log(disposable income), share of foreigners, share of the young population, share of the youth population, share of the adult population, share of unskilled workers and a linear time trend. *, ** and *** denote significance at the 10%-, 5% and 1%-level respectively.

While the results based on ordinary quantile regression (Table 11) and quantile regression with fixed effects (Table 12) are very similar, this does not hold for the quantile instrumental variable regression. First and foremost, all offenses show an increasing crime-unemployment relationship across quantiles, while before one could observe a decreasing crime-unemployment relationship for some offenses. This means that the impact of a rising unemployment rate on crime is higher in high crime areas compared to low crime areas. Agents do not seem to care about the competitiveness of the supply side of the crime “market”. The observed pattern rather points to the stigma based behavior, where agents are less and less deterred to commit a crime in response to increasing unemployment as the potential social stigma is less and less severe. It is surprising to see the crime-unemployment relationship totally reversed once the unemployment rate has been instrumented.

Another rather surprising result is that the effects of unemployment on crime is mostly negative, which is, however, in line with the results based on the FEIV mean regression (Table 10, column 3). The only offense for which a rise in unemployment influences the crime rate positively across all quantiles is drug related crime. For burglary and auto theft, I estimate positive coefficients only at higher quantiles (75% and above), while I estimate large and negative effects at lower quantiles. For damage to property I estimate large negative effects across all quantiles (-7.23% for the 5% quantile to -2.98% for the 95% quantile).

A possible explanation for the fact that I find mostly positive effects of unemployment on crime when abstaining from using instrumental variable estimation is the problem of reverse causation. As already mentioned in the context of mean regression, the positive coefficients in the OLS and FE regression might be misleading because higher crime rates might themselves have an influence on unemployment. Ignoring this reverse causation biases the coefficients upwards. The same holds true, of course, for the quantile regressions.

Turning to the interpretation of the estimated parameters the first thing to note is that the standard errors of the quantile instrumental variable regression with fixed effects are to be taken with caution, since these are not clustered at the county level and are therefore likely too large. In addition, the estimation of standard errors in this specification involves a bandwidth to which choice the standard errors are rather sensitive. Having said that the mostly negative coefficient estimates still need to be interpreted. In case of the offense damage to property, where the effect of unemployment on crime varies from -7.23% (5% quantile) to -2.98% (95% quantile), an explanation for the negative estimates could be the following: as the unemployment rate increases, more and more people stay at home instead of going to work. These people are therefore more able to keep an eye on their property as well as their neighbor's property, deterring potential offenders (which are men younger than 25 in more than 50% of the cases). The same argument would hold for auto theft and, in particular, burglary: if a person is unemployed and spends most of his or her time at home, it becomes difficult if not impossible for the burglar to break into the flat. Since most burglars are assumed to be active in the late morning (ten to twelve) or late afternoon (14 to 20), an increasing unemployment rate makes it more difficult for the burglar to find an unwatched object to break into.

In the case of assault, where the effect of unemployment on crime varies from -3.06% (5% quantile) to -0.42% (95% quantile) there is a similar channel through which a higher unemployment rate impacts crime rates. As already mentioned in section 2.2, in order for an

assault to be committed there must be a match between offender and victim. This match becomes more unlikely as more people stay at home in response to an unemployment spell.

The effect of an increase in the unemployment rate on street crime is negative and significant at small quantiles (-2.34% at the 5% quantile to -1.97% at the 25% quantile for street crime). Since the standard errors are likely to be a too small, I would see these results rather as evidence for no, or at most a very weak, relationship between unemployment and crime.

The results for drug related crime are interesting for at least two reasons. Firstly it is the only offense for which I estimate a positive relationship between unemployment and crime at all quantiles. Secondly, the estimated coefficients for drug related crime are negative for all other specifications presented here except for the quantile instrumental variable regression with fixed effects. Although this specification (and the FEIV specification in the mean regression) is to be the most reliable one, it seems surprising that this specification clearly contradicts the results from all other specifications. The intuition for these findings might be the following: an increasing unemployment might induce certain hopelessness among people, to which they react with drug abuse; they might also respond with drug selling activities due to worsened legal income opportunities. Both these explanations would support the positive relationship between an increase in unemployment and increasing crime rates.

6. Conclusion

This paper uses data from 2003 to 2009 on approximately 400 German counties to study the effect of unemployment on crime. After controlling for various potentially confounding factors, taking the endogeneity of unemployment into account and applying several different estimation techniques, the primary conclusion of this study is that the effect of unemployment on crime is everything but clear-cut. The results obtained in the analysis heavily depend on the applied estimation method. While simple OLS regression produces large, positive and significant effects for property crimes as auto theft and burglary, the most general specification (including fixed effects and instrumenting the unemployment rate) shows insignificant and mostly negative effects. The same conclusion can be drawn from the quantile regression results: While simple quantile estimation produces positive effects for property crimes over the whole range of quantiles with a decreasing crime-unemployment profile, allowing for fixed effects and taking the endogeneity of unemployment into account produces negative effects with an increasing crime-unemployment profile. These mixed

results indicate the need to further investigate the relationship between unemployment and crime. Although this study goes beyond many existing studies in using data at a relatively low level of aggregation (counties), using individual level data might be able to shed more light on the causal relationship.

Appendix

Figure A1: Distribution of frequency ratio overall crime for the years 2003 to 2009

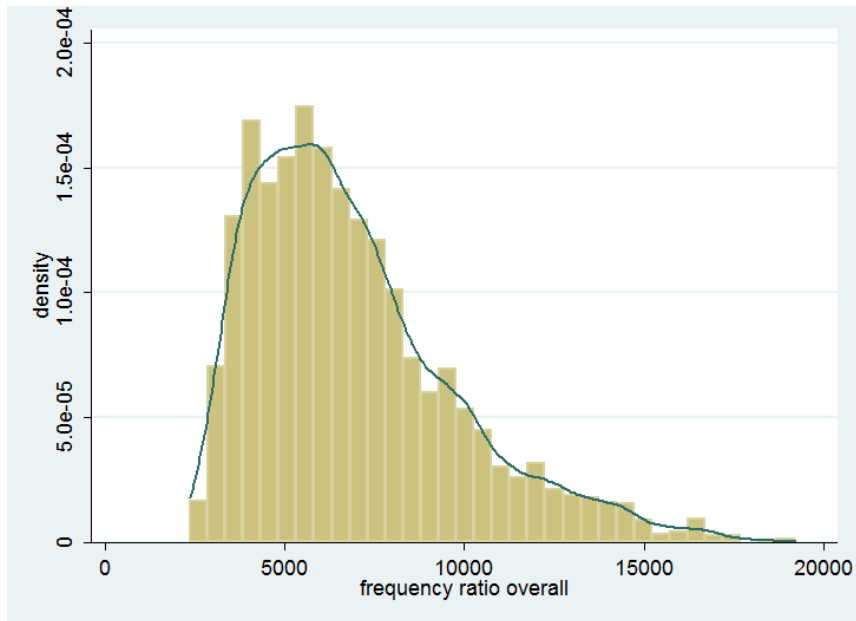


Figure A2: Regional distribution of frequency ratio overall crime in the year 2009

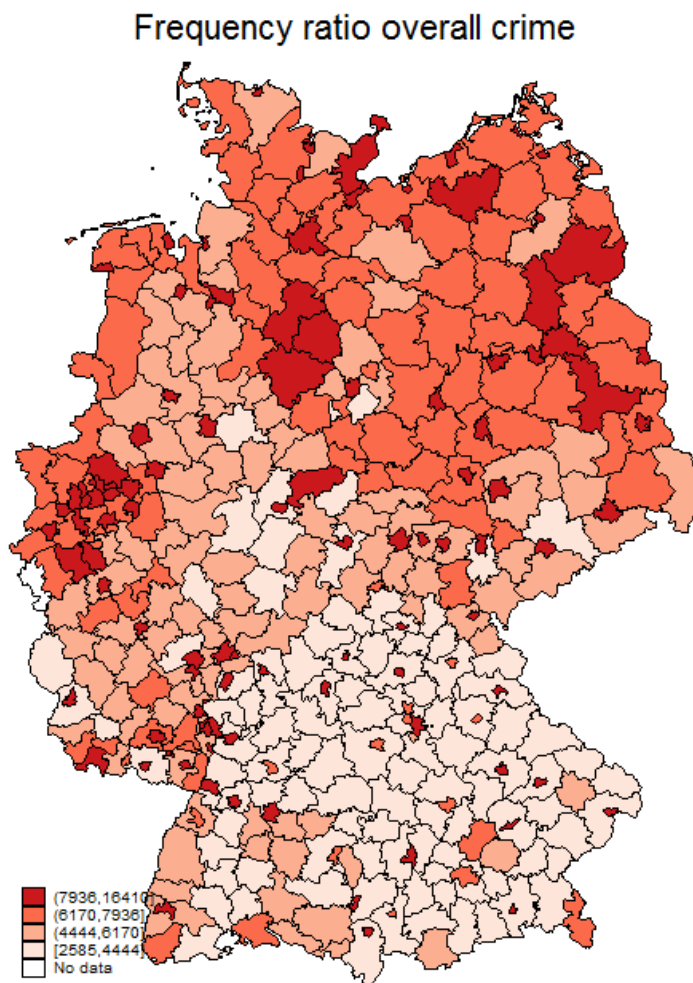


Figure A3: Distribution of frequency ratio burglary for the years 2003 to 2009

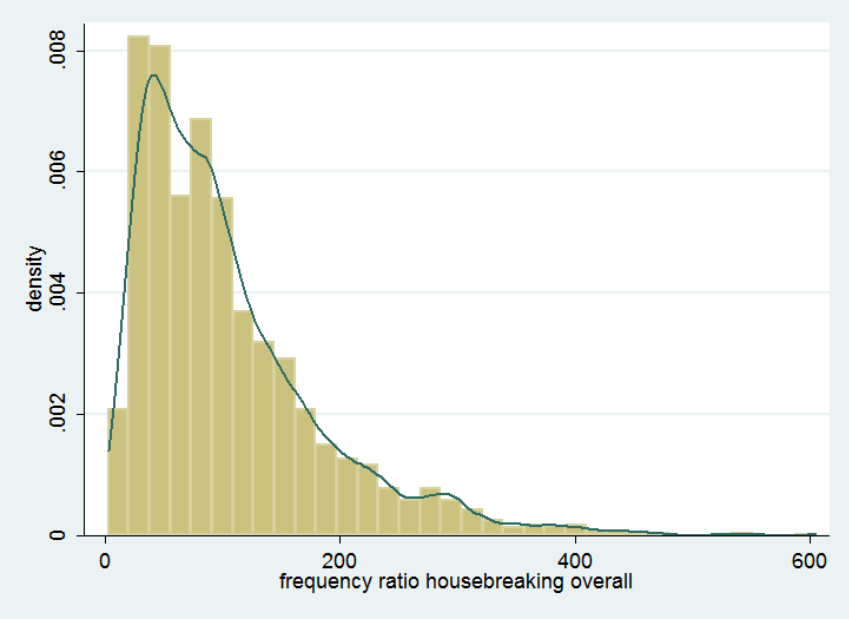


Figure A4: Regional distribution of frequency ratio burglary in the year 2009

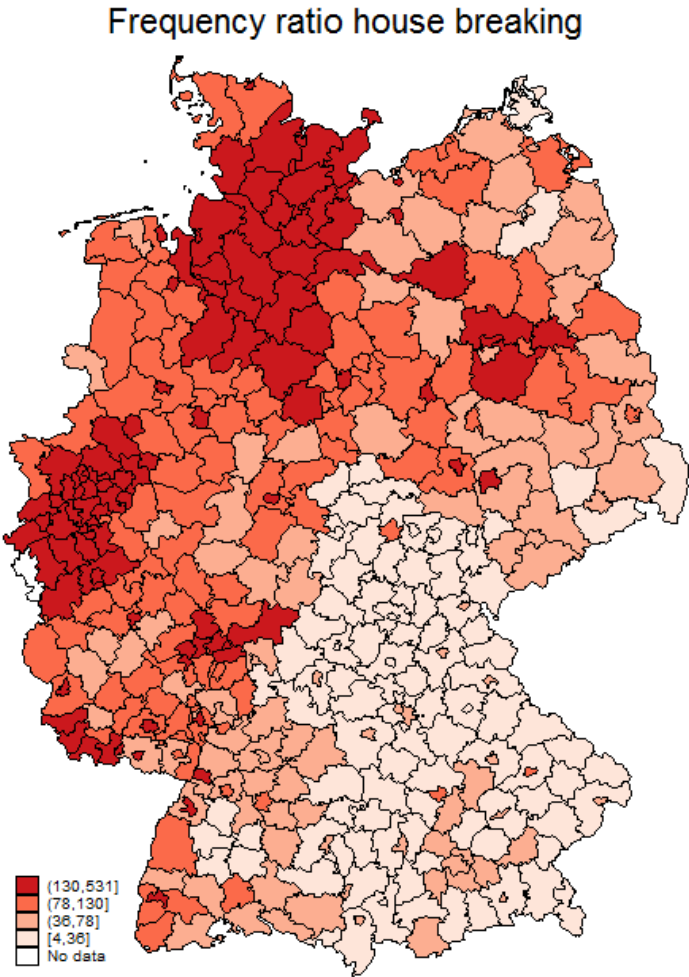


Figure A5: Distribution of frequency ratio street crime for the years 2003 to 2009

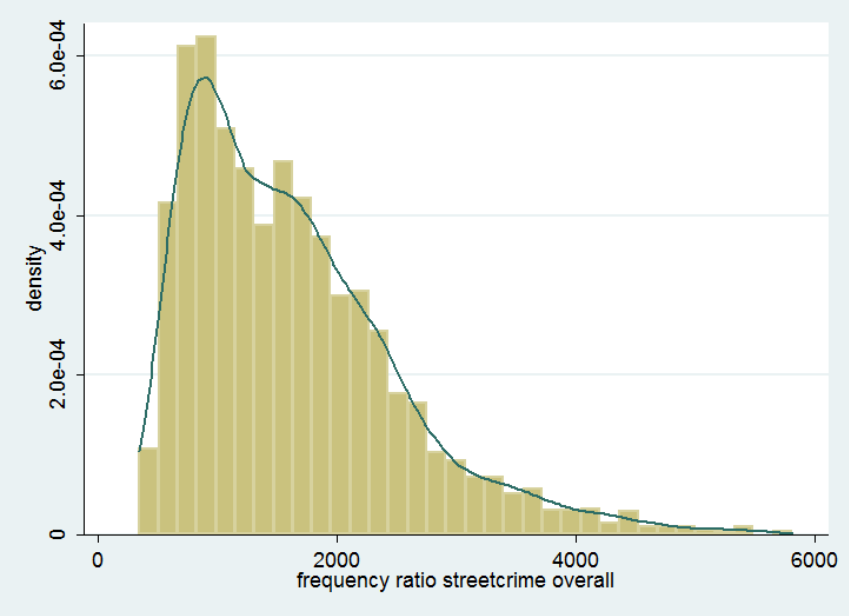


Figure A6: Regional distribution of frequency ratio street in the year 2009

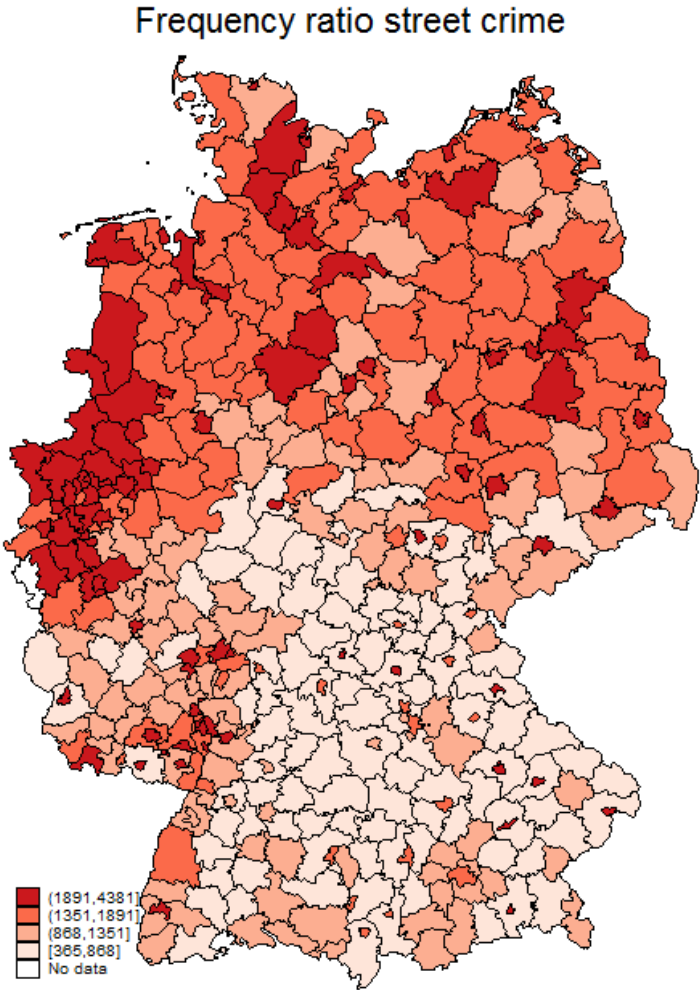


Figure A7: Distribution of frequency ratio drug related crime for the years 2003 to 2009

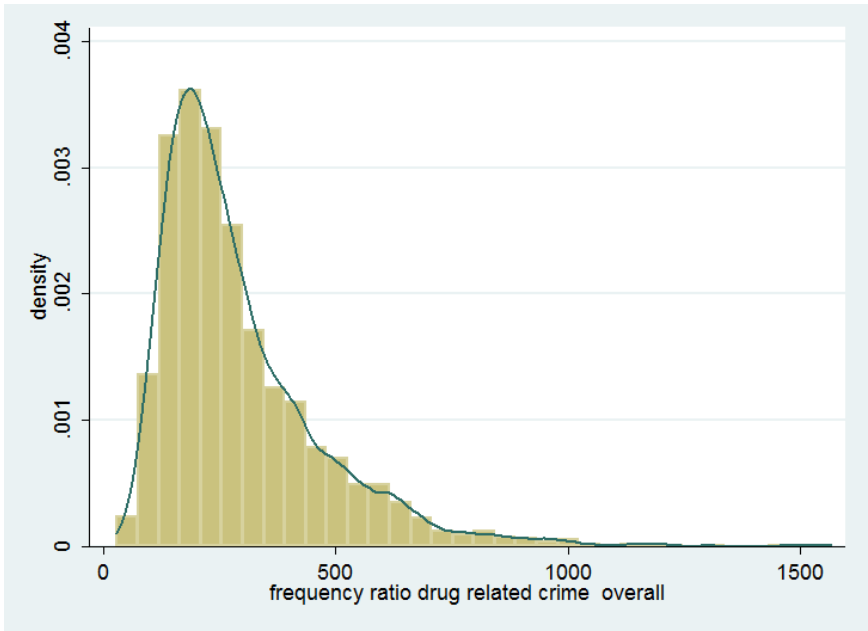


Figure A8: Regional distribution of frequency ratio drug related crime in the year 2009

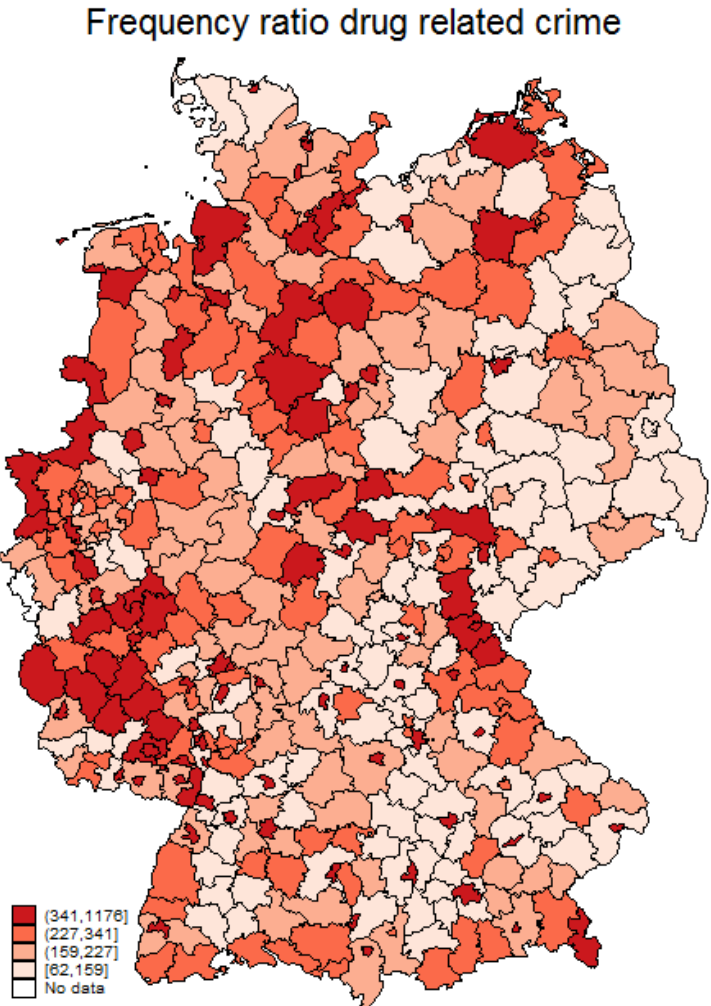


Figure A9: Distribution of frequency ratio auto theft for the years 2003 to 2009

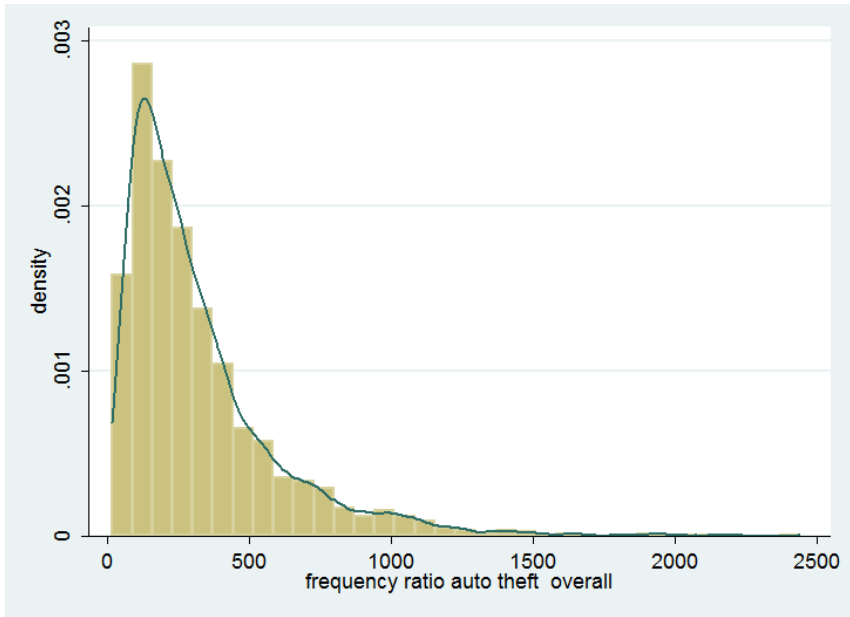


Figure A40: Regional distribution of frequency ratio auto theft in the year 2009

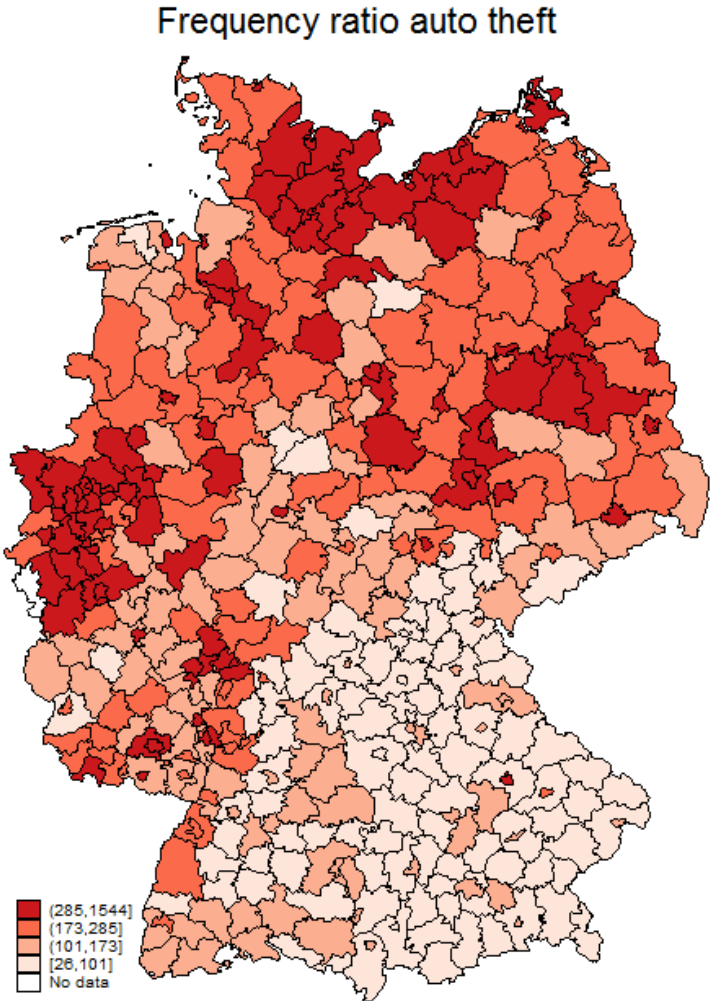


Figure A51: Distribution of frequency ratio assault for the years 2003 to 2009

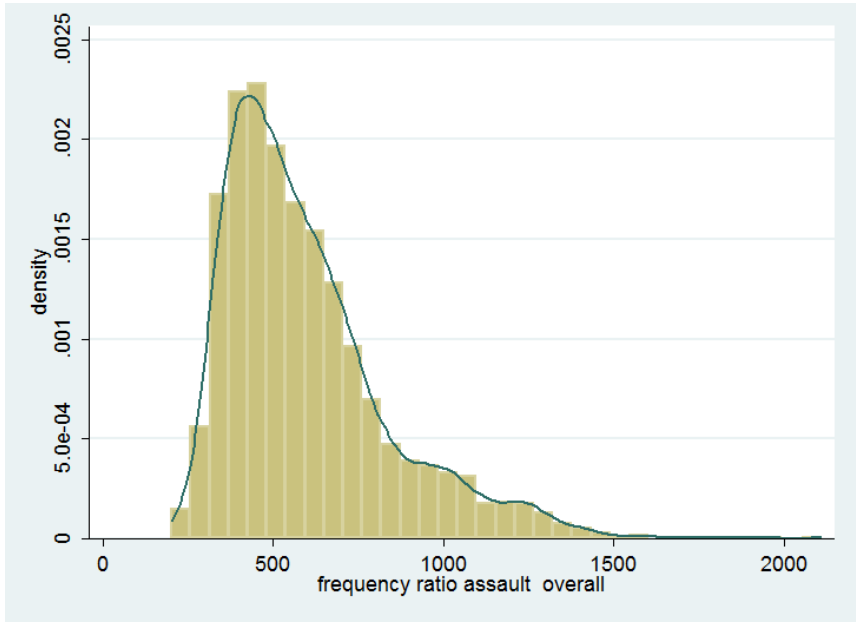


Figure A62: Regional distribution of frequency ratio assault in the year 2009

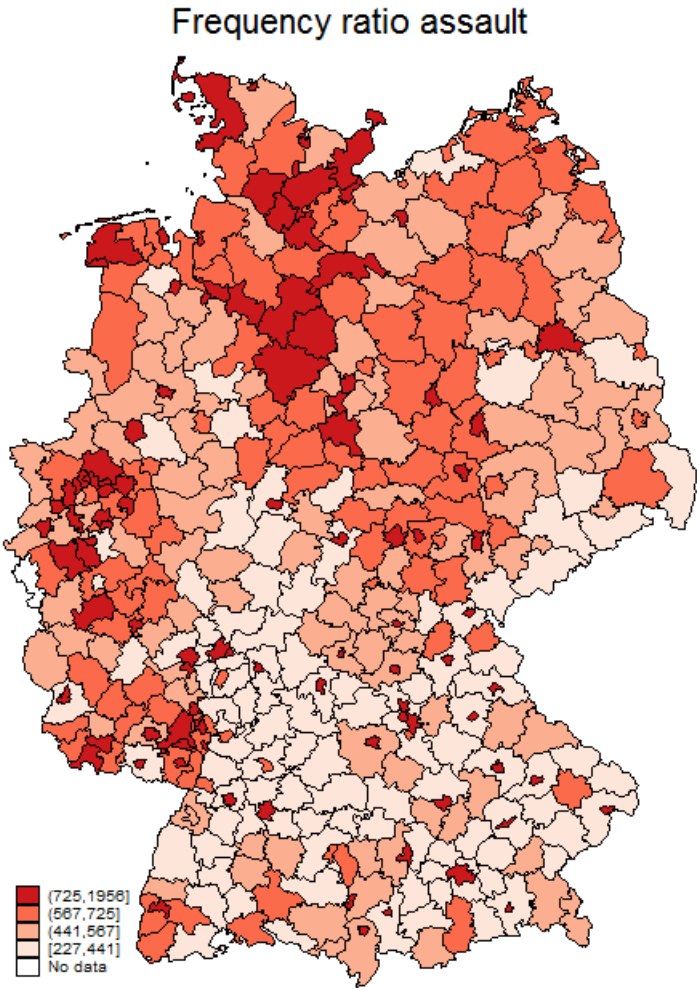


Figure 73: Distribution of frequency ratio damage to property for the years 2003 to 2009

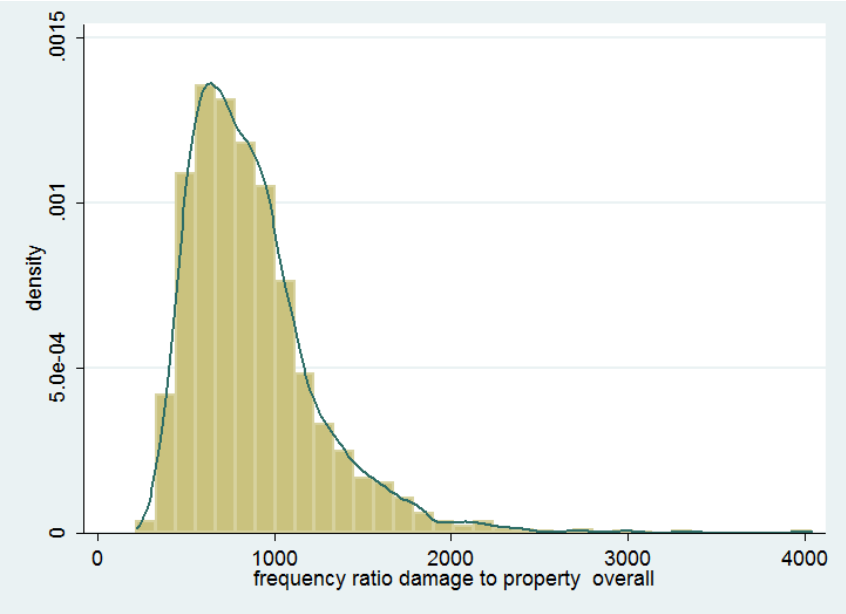


Figure 84: Regional distribution of frequency ratio damage to property in the year 2009

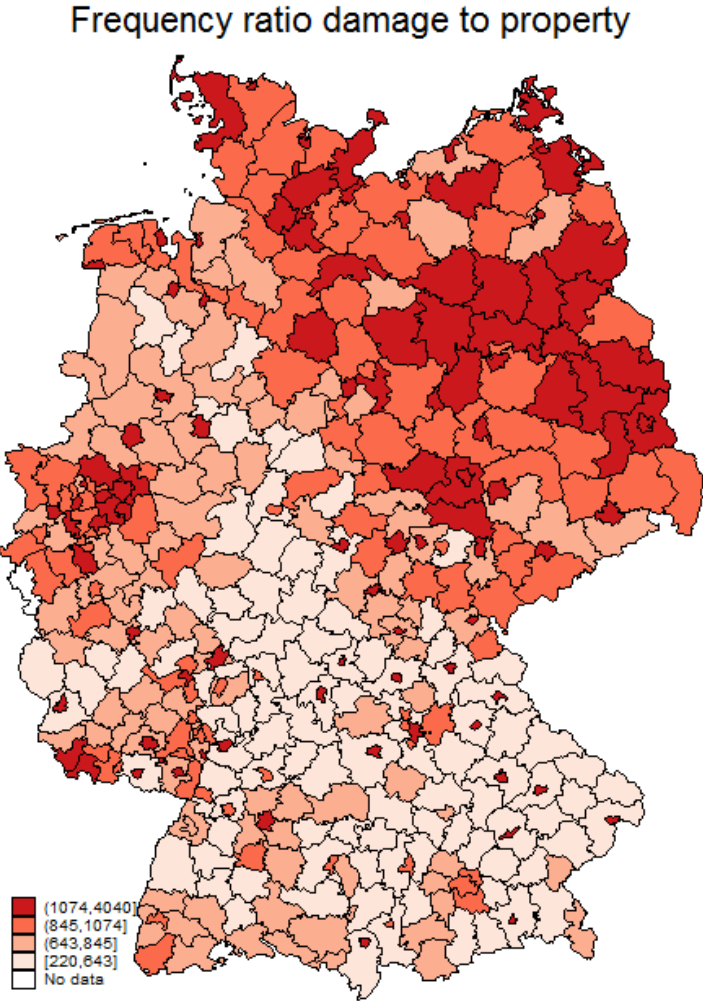


Figure 15: Distribution of unemployment rate for the years 2003 to 2009

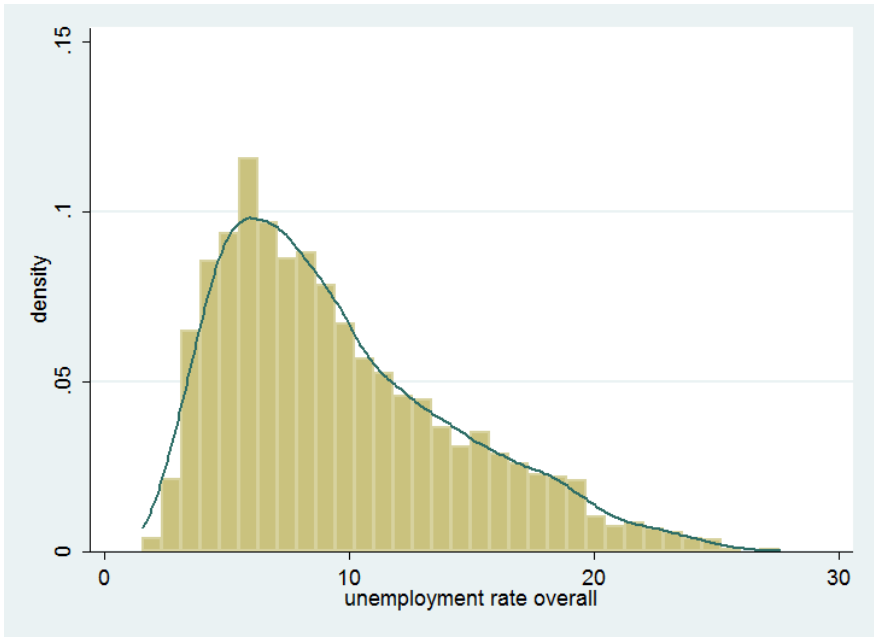


Figure 16: Regional distribution of unemployment rate in the year 2009

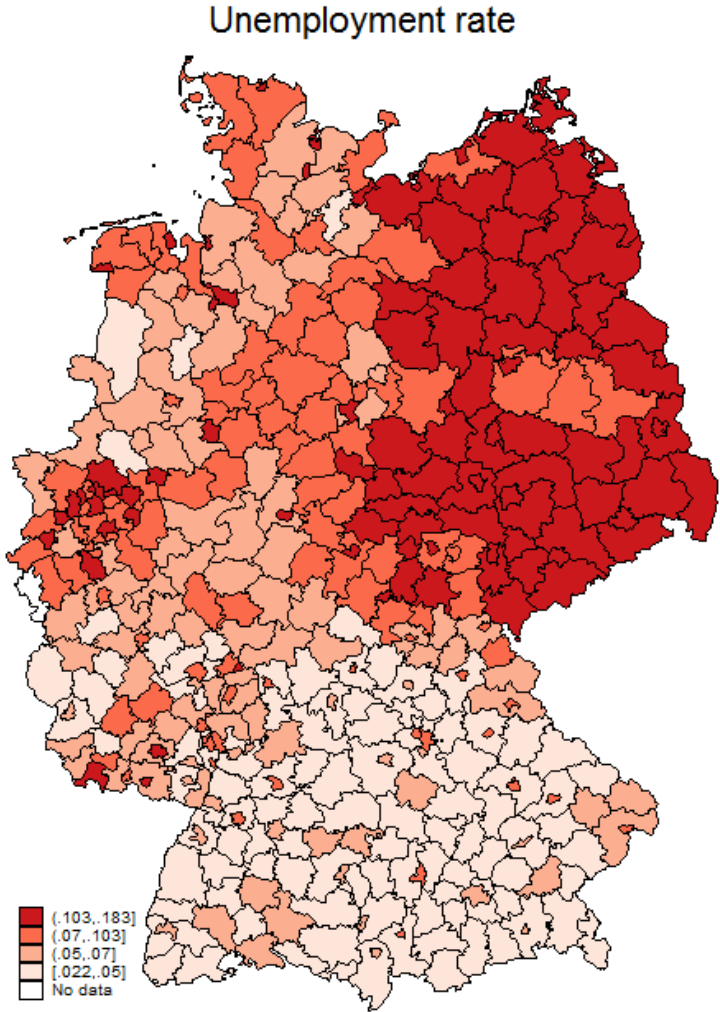


Figure A97: Regional distribution of share of unskilled workers in the year 2009

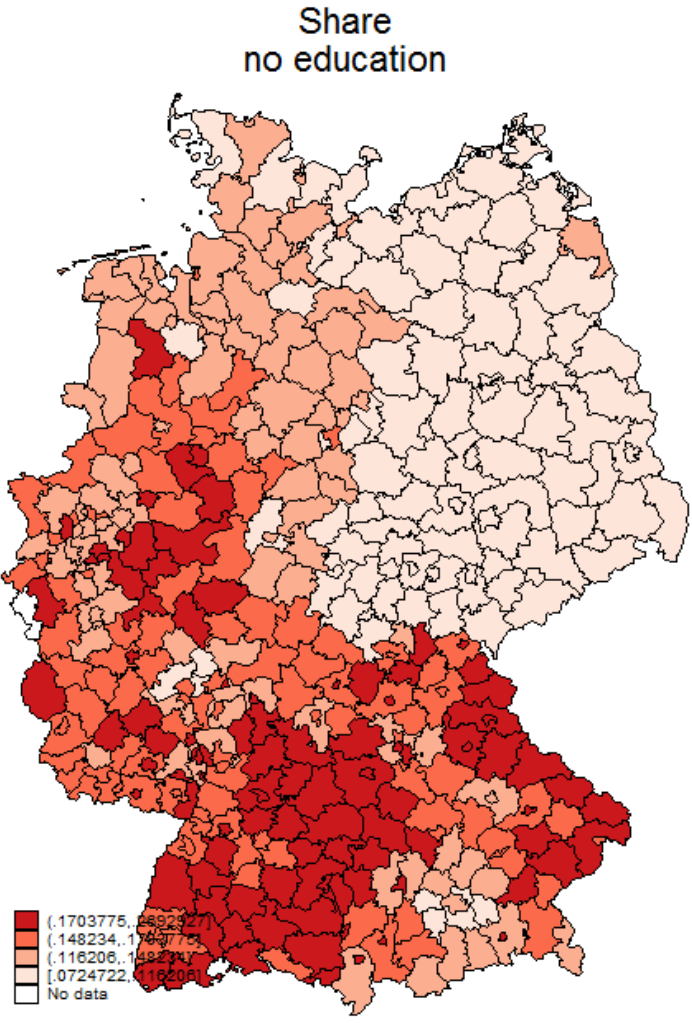


Figure A18: Effect of an increase in unemployment on overall crime at different quantiles

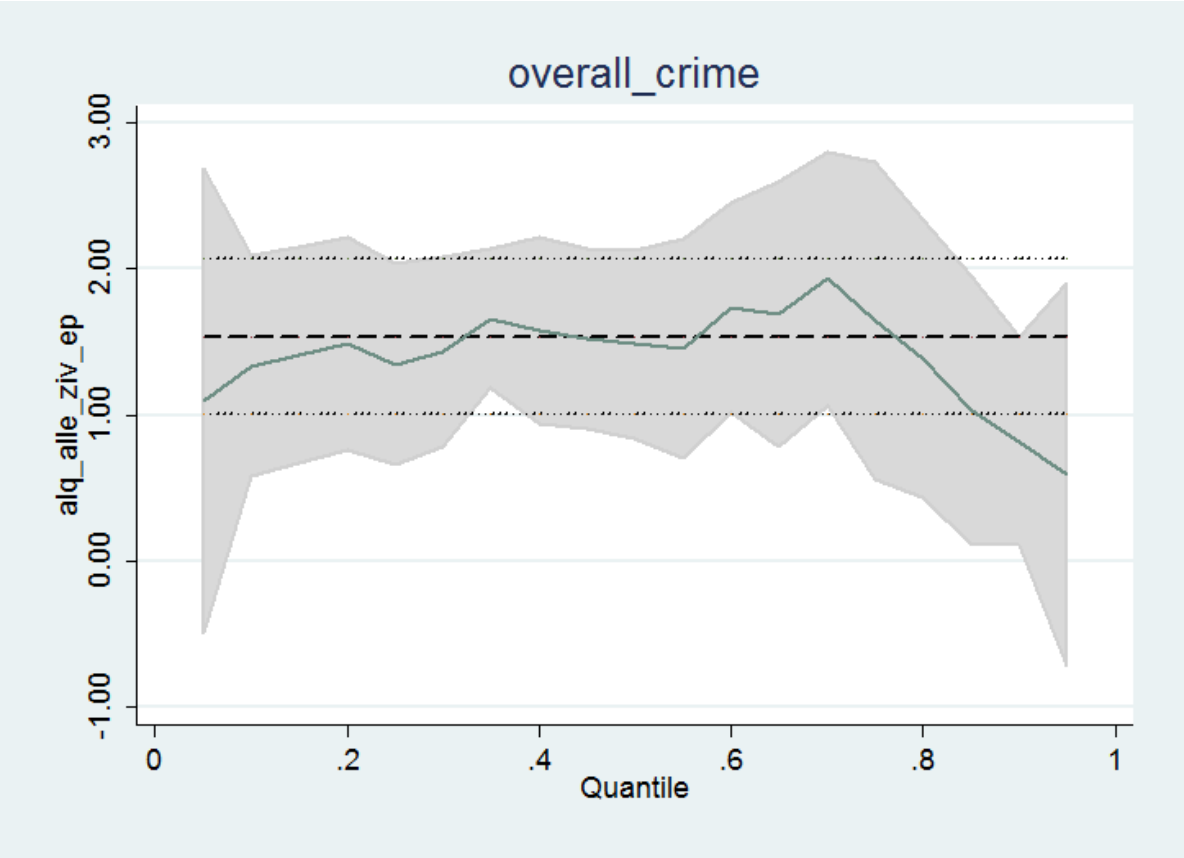


Figure A19: Effect of an increase in unemployment on damage to property at different quantiles

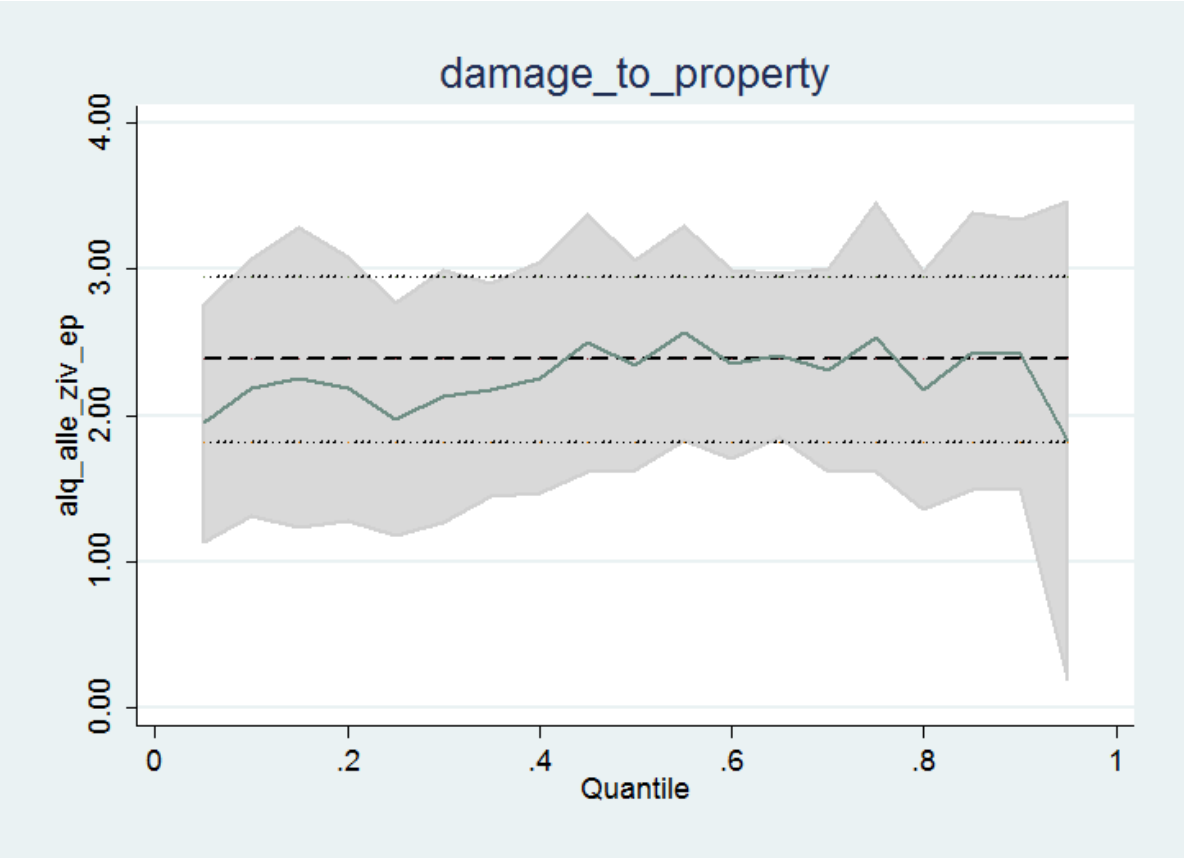


Figure A100: Effect of an increase in unemployment on drug related crime at different quantiles

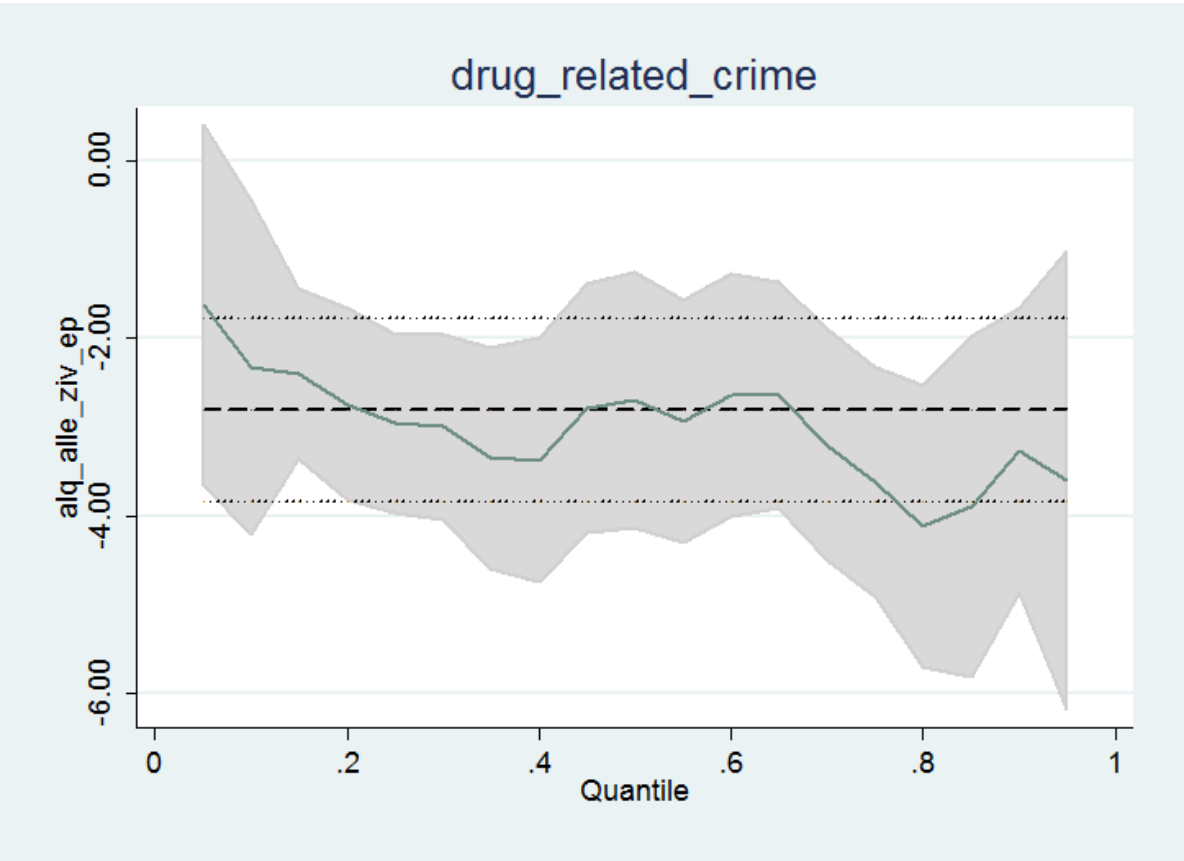


Figure A111: Effect of an increase in unemployment on street crime at different quantiles

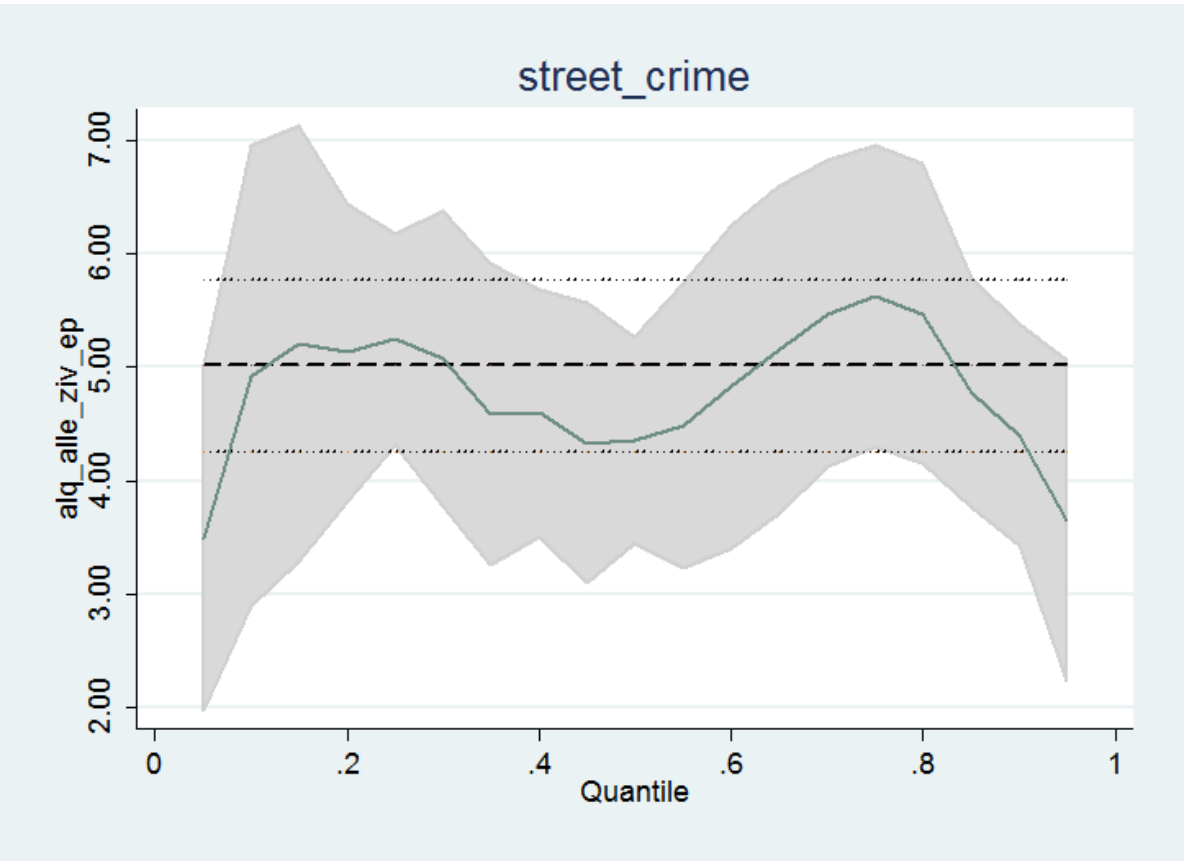


Figure A122: Effect of an increase in unemployment on assault at different quantiles

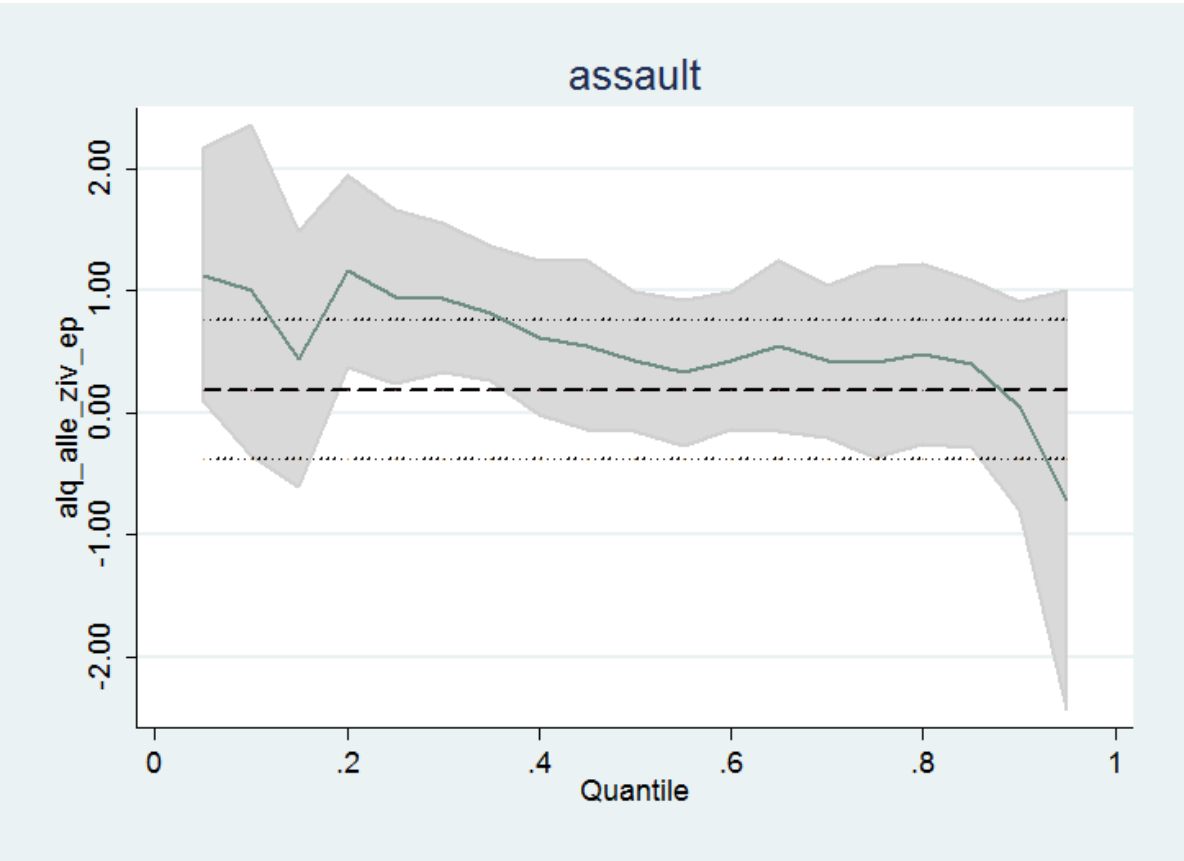


Figure A133: Effect of an increase in unemployment on burglary at different quantiles

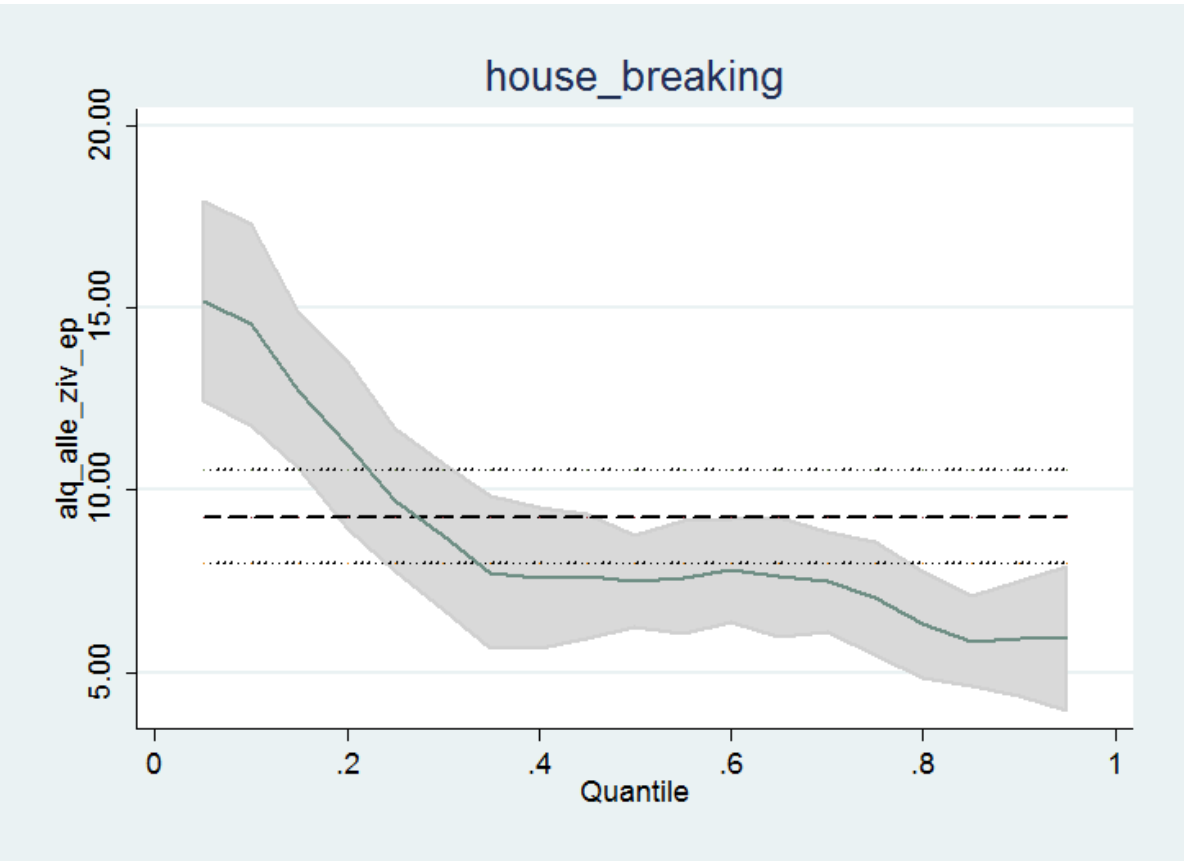
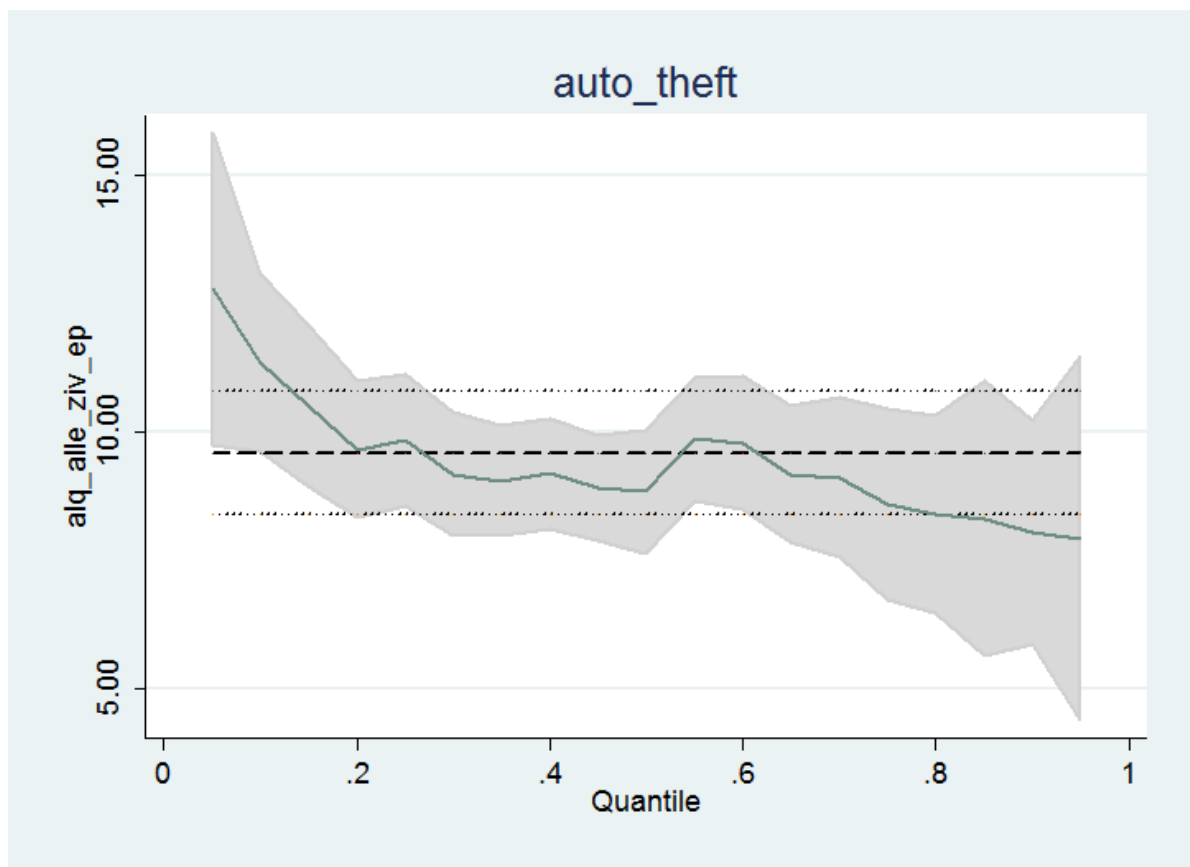


Figure A144: Effect of an increase in unemployment on auto theft at different quantiles



References:

- Allingham, Michael G., and Agnar Sandmo. 1972. "Income Tax Evasion: A Theoretical Analysis." *Journal of Public Economics* 1: 323-338.
- Anderson, David. 1999. "The Aggregate Burden of Crime". *Journal of Law and Economics* 42(2): 611-642.
- Bound, John, David A. Jaeger and Regina M. Baker. 1995. "Problems with Instrumental Variables Estimation When the Correlation Between the Instrument and the Endogenous Explanatory Variable is Weak." *Journal of the American Statistical Association* 90(430): 443-450.
- Becker, Gary. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76(2): 169-217.
- Bentham, Jeremy. 1843. "Principles of Penal Law." *Works* 1, 399 ff.
- Blanchard, Olivier Jean, Lawrence F. Katz, and Robert E. Hall. 1992. "Regional Evolutions." *Brookings Papers on Economic Activity* 1992(1): 1-75.
- Block, Michael K. and John Heineke. 1975. "A Labor Theoretic Analysis of the Criminal Choice." *The American Economic Review* 65(3): 312-325.
- Bundeskriminalamt (Ed.): Polizeiliche Kriminalstatistik (various issues, 2003-2009). Wiesbaden, Germany. Website: http://www.bka.de/DE/Publikationen/PolizeilicheKriminalstatistik/pks_node.html.

- Cantor, David, and Kenneth C. Land. 1985. "Unemployment and Crime Rates in the Post-World War II United States: A Theoretical and Empirical Analysis." *American Sociological Review* 50(3): 317-332.
- Chernozhukov, Victor, and Christian Hansen. 2008. "Instrumental variable quantile regression: A robust inference approach." *Journal of Econometrics* 142(1): 379-398.
- Dooley, David, Jonathan Fielding, and Lennart Levi. 1996. "Health and Unemployment." *Annual Review of Public Health* 17: 449-465.
- Edmark, Karin. 2005. "Unemployment and Crime: Is there a Connection?" *Scandinavian Journal of Economics* 107(2): 353-373.
- Ehrlich, Isaac. 1973. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." *Journal of Political Economy* 81(3): 521-565.
- Eide, Ehrling. 2000. "Economics of Criminal Behavior." In *Encyclopedia of Law and Economics: 345-389*, ed. Boudwijn Bouckaert, and Gerrit De Geest. Cheltenham, United Kingdom: Edward Elgar Publishing Limited.
- Entorf, Horst, and Hannes Spengler. 2000. "Socioeconomic and Demographic Factors of Crime in Germany: Evidence from Panel Data of the German States." *International Review of Law and Economics* 20(1): 75-106.
- Entorf, Horst. 2010. "Strafvollzug oder Haftvermeidung-was rechnet sich?" *Aus Politik und Zeitgeschichte* 7: 15-21.
- Freeman, Richard B. 1996. "Why Do So Many Young American Men Commit Crimes and What Can We Do About It?" *The Journal of Economic Perspectives* 10(1): 25-42.
- Farrington, David P. 1986. "Age and Crime." *Crime and Justice* 7: 189-250.
- Glaeser, Edward L., Bruce Sacerdote, and Jose A. Scheinkman. 1996. "Crime and Social Interactions." *The Quarterly Journal of Economics* 111(2): 507-548.
- Glaeser, Edward L., and Bruce Sacerdote. 1999. "Why Is There More Crime in Cities?" *Journal of Political Economy* 107(6): 225-258.
- Grogger, Jeff. 1995. "The Effect of Arrest on the Employment and Earnings of Young Men." *The Quarterly Journal of Economics* 110(1): 51-71.
- Grogger, Jeff. 1998. "Market Wages and Youth Crime." *Journal of Labor Economics* 16(4): 756-791.
- Gronau, Reuben. 1977. "Leisure, Home Production, and Work: The Theory of the Allocation of Time Revisited." *Journal of Political Economy* 85(6): 679-694.
- Gould, Eric, Bruce Weinberg, and David Mustard. 2002. "Crime Rate and Local Labor Market Opportunities in the U.S.: 1979-1997." *Review of Economics and Statistics* 84(1): 45-61.
- Harding, Matthew, and Carlos Lamarche. 2009. "A quantile regression approach for estimating panel data models using instrumental variables." *Economics Letters* 104(3): 133-135.
- Heineke, John M. 1975. "A Note on Modeling the Criminal Choice Problem." *Journal of Economic Theory* 10(1): 113-116.
- Holmes, Oliver Wendell. 1997. "The Path of Law." *Harvard Law Review* 100(5): 991-1009.
- Koenker, Roger. 2004. "Quantile regression for longitudinal data." *Journal of Multivariate Analysis* 91(1): 74-89.

- Levitt, Steven D. 1997. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *The American Economic Review* 87(3): 270-290.
- Levitt, Steven D. 1999. "The Limited Role of Changing Age Structure in Explaining Aggregate Crime Rates." *Criminology* 37(3): 581-597.
- Levitt, Steven D. 2001. "Alternative Strategies for Identifying the Link Between Unemployment and Crime." *Journal of Quantitative Criminology* 17(4): 377-390.
- Levitt, Steven D. 2004. "Understanding Why Crime Fell in the 1990s: Four Factors That Explain the Decline and Six That Do Not." *The Journal of Economic Perspectives* 18(1): 163-190.
- Lin, Ming-Jen. 2008. "Does Unemployment Increase Crime?" *The Journal of Human Resources* 43(2): 413-436.
- Lochner, Lance. 2004. "Education, Work, and Crime: A Human Capital Approach." *International Economic Review* 45(3): 811-843.
- Lochner, Lance, and Enrica Moretti. 2004. "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self Reports." *American Economic Review* 94(1): 155-189.
- Machin, Stephen, Olivier Marie, and Sunicica Vujic. 2011. "The Crime Reducing Effect of Education." *The Economic Journal* 121(May): 463-484.
- Miller, Ted, Mark Cohen, and Brian Wiesema. 1996. "Victim Costs and Consequences: A New Look." National Institute of Justice Research Report, NCJ-155282. Website: <http://www.ncrjs.org/pdffiles/victcosts.pdf>.
- Öster, Anna, and Jonas Agell. 2007. "Crime and Unemployment in Turbulent Times." *Journal of the European Economic Association* 5(4): 752-775.
- R+V Versicherung-Infocenter. Website: http://www.ruv.de/de/presse/r_v_infocenter/studien/aengstender-deutschen.jsp.
- Raphael, Steven, and Rudolf Winter-Ebmer. 2001. "Identifying the Effect of Unemployment on Crime." *Journal of Law and Economics* 44(1): 259-283.
- Phillips, Julie, and Kenneth C. Land. 2012. "The Link Between Unemployment and Crime Rate Fluctuations: An Analysis at the County, State and National Level." *Social Science Research* 41(3): 681-694.
- Spengler, Hannes. 2004. "Ursachen und Kosten der Kriminalität in Deutschland-drei empirische Untersuchungen." Dissertation, Faculty of Law and Economics, Technische Universität Darmstadt. Website: http://tuprints.ulb.tu-darmstadt.de/epda/000531/spenlger_hannes_diss.pdf.
- Staiger, Douglas and James H. Stock. 1997. "Instrumental Variables Regression With Weak Instruments." *Econometrica* 65(3): 557-586.
- Statistisches Bundesamt (Ed.). 2009. "Bildungsstand der Bevölkerung." Website: https://www.destatis.de/DE/Publikationen/Thematisch/BildungForschungKultur/Bildungsstand/BildungsstandBevoelkerung5210002097004.pdf?__blob=publicationFile.
- Stock, James H. and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." *Identification and Inference in Econometric Models: A Festschrift in Honor of Thomas Rothenberg*. Donald W.K. Andrews and James H. Stock (Ed.). Cambridge University Press: 80-108.

- Yearwood, Douglas L. and Gerry Koinis. 2009. "Revisiting Property Crime and Economic Conditions: An Exploratory Study to Identify Predictive Indicators beyond Unemployment Rates." *MPRA Paper* No. 16834.
- Young, Thomas J. 1993. "Unemployment and Property Crime: Not a Simple Relationship." *American Journal of Economics and Sociology* 52(4): 413-416.