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Horst Entorf, Department of Applied Econometrics and International Economic Policy, Goethe University, Frankfurt am Main, Germany
Philip Sieger, Department of Applied Econometrics and International Economic Policy, Goethe University, Frankfurt am Main, Germany

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Two alternative hypotheses – referred to as opportunity- and stigma-based behavior – suggest that the magnitude of the link between unemployment and crime also depends on preexisting local crime levels. In order to analyze conjectured nonlinearities between both variables, we use quantile regressions applied to German district panel data. While both conventional OLS and quantile regressions confirm the positive link between unemployment and crime for property crimes, results for assault differ with respect to the method of estimation. Whereas conventional mean regressions do not show any significant effect (which would confirm the usual result found for violent crimes in the literature), quantile regression reveals that size and importance of the relationship are conditional on the crime rate. The partial effect is significantly positive for moderately low and median quantiles of local assault rates.

Introduction

According to an annual survey on the fears of German citizens (Ängste der Deutschen, conducted by insurer *R+V Versicherung*) the fear of becoming a victim of a criminal offense regularly ranks high on the list. In 2014, 26 percent of respondents stated that they were afraid of becoming a victim of a criminal offense. Although there was considerable variation across states in that year (from 38 percent in Schleswig-Holstein and Hamburg to 21 percent in Rheinland-Pfalz and Saarland), there is remarkably little variation in the national figure over the years of this century: in 2013 an all-time low was reached with 24 percent, while the highest value was 33 percent in 2002. This is in line with the observation that in Germany crime rates themselves were stable (or rather declined slightly) between 2003 and 2013 (Polizeiliche Kriminalstatistik [PKS] 2003, 2013) but show considerable variation across states. In addition to being one of the major fears, criminal activity is associated with large costs. According to Entorf and Spengler (2002), estimates of costs of crime range between 4 and 7 percent of GDP in most industrialized countries. Another fear which generally ranks among the top five is rising unemployment. This fear was expressed by roughly 50 percent of respondents in the early 2000s, increased to 68 percent in 2005 (when unemployment was particularly high in Germany with about five million registered unemployed), vanished from the top seven fears in 2007 and 2008 but was again expressed by more than 60 percent in 2009 and 2010 (when the financial crisis 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.

In this paper we reconsider the complex link between unemployment and crime using Germany district panel data. The economic rationale why such a link might exist is the following: Declining labor market opportunities (manifested in an increasing unemployment rate) worsen legal income opportunities and therefore make crime more attractive. This idea was first formulized by Becker (1968). The many other studies focusing on the unemployment-crime relationship include Cantor and Land (1985), Young (1993), Levitt (2001, 2004), Raphael and Winter-Ebmer (2001), Gould et al. (2002), Edmark (2005), Öster and Agnell (2007), Lin (2008), Phillips and Land (2012), Lastauskas and Tatsi (2013), and Sieger (2014). These studies differ with respect to various aspects: estimation methods used, period and country under consideration, and conclusions drawn with respect to the magnitude of the effect of unemployment on crime. Lin (2008, 414) summarizes the results: “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.”

We depart from existing studies by applying quantile regression methods, which allow the identification of nonlinear crime-unemployment relationships (for example, a high impact of unemployment on crime for low-crime regions and a low impact for high-crime regions). That particular pattern would be consistent with a hypothesis of opportunity-based behavior: Those who become unemployed in a low-crime area have higher incentives to commit a crime than those in high-crime regions, because they would face less effective prevention by potential victims and lower competition from other criminals. However, there could also be an opposite nonlinear pattern, which we call the stigma-based hypothesis. This predicts low marginal effects from increasing unemployment rates in low-crime areas, because here any potential detection bears a higher risk of stigma than in regions where criminal behavior is more common. These examples show that there are good reasons to take a closer look at the unemployment-crime relationship using quantile regressions. Surprisingly, there is little research based on this technique in the criminological literature. To the best knowledge of the authors, the only contribution is Bandyopadhyay et al. (2015). Based on time-series evidence from six crime categories and forty-three police force areas, they confirm not only that unemployment does increase crime but that it does so more in high-crime areas. Moreover, they find that the crime-reducing effect of higher detection rates is stronger in low-crime areas.

The quantile analysis conducted in this paper is based on a panel data set covering about four hundred German *Landkreise* (districts) and urban municipalities (*kreisfreie Städte*) for the years 2005 to 2009 in Germany. The same source (German districts and urban municipalities) has recently also been used by Messner et al. (2013) and Lastauskas and Tatsi (2013).

1. Factors of Crime

1.1. Economic Factors

Legal income opportunities represent an important factor of crime. Following Becker (1968), higher legal income should decrease criminal activity, because legal income represents part of the opportunity costs of conviction. Higher legal income prevents a potential offender from committing a crime because they fear losing it. All other things being equal (probability of detection and conviction and illegal income opportunities) higher legal income is expected to decrease criminal activity. However, if one switches from a micro to a macro perspective, there is another channel through which legal income affects crime. If average legal income in a certain region (as a German district) increases, the potential offender is on the one hand more likely to have a higher legal income, and hence less likely to commit a crime. On the other hand, a higher average legal income might also increase illegal income opportunities, since now there is more income or wealth to steal from. At least for property crime, a higher legal average income could therefore also increase criminal activity. Mobile criminals from other regions might also be attracted. This would increase the utility of committing a crime and, in turn, also the likelihood of rising local crime rates (note that crime rates are registered in the city or district where the crime is committed). The effect of disposable income is therefore ambiguous, since it influences the decision to commit a crime (or not) through different channels.

The potential channel through which unemployment affects the crime rate has already been briefly mentioned above: Declining labor market opportunities (manifested in an increasing unemployment rate) worsen legal income opportunities and therefore make crime more attractive. In their influential paper, Raphael and Winter-Ebmer (2001, 262) express this idea as follows: “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 relative returns to illegal activity.” The idea of time allocation between legal and illegal activities and its influence on the decision to participate in criminal activities was formalized in a theoretical framework by Grogger (1998). As Raphael and Winter-Ebmer (2001) lay out, Grogger's model implies four different employment-crime situations which can be used to predict how unemployment affects criminal activity. For individuals who engage in both criminal activity and job market activity, the model predicts that unemployment increases time allocated to crime. For individuals who do not work in the regular job market but only commit crimes, an unemployment spell cannot affect the time allocated to criminal activity. For workers not committing crimes, the effect of unemployment depends on whether the return to the first hour of criminal activity exceeds the reservation wage. Individuals whose reservation wage is high are unlikely to be pushed into crime by an unemployment spell. Individuals 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. Thus, Grogger's model predicts that for two out of four situations an unemployment spell will increase time allocated to criminal activity (and thus increase the crime rate), while for the remaining two cases, there is no response to an unemployment spell. Applying the model to regional data, theory would predict that responses to changing unemployment rates should be smaller in regions with already high crime rates than in regions where crime rates are low (given that reservation wages are not prohibitively high).

1.2. Demographics, Education, and Urbanity

Becker's (1968) seminal economic model of crime abstracts from some important features of the criminal's decision problem. Several other determinants of crime have been discussed in the literature besides deterrence variables (probability of conviction or severity of punishment). One of these is the age structure of society. As outlined by Farrington (1986), who focuses on the United Kingdom and the United States, the age-crime curve usually peaks in teenage years and declines afterwards. Grogger 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." (1998, 756). Similar patters can be observed for Germany. Those aged 6 to 20 make up 26.1 percent of all crime suspects but only 13.7 percent of the population, while those aged 40 and above make up 32.4 percent of all crime suspects but 56.9 percent of the population (PKS 2009). Given the descriptive evidence and the mostly accepted empirical evidence from other studies (for example Freeman 1996),[1] it seems imperative to include age structure as a further control variable when it comes to explaining crime. One would expect the proportion of people of crime-prone age in the population to have a positive influence on criminal activity. Younger people are also victimized more often (PKS 2009, table 91), so a larger proportion of young people might therefore foster criminal activities in two ways: it increases both the supply of criminals and the supply of victims.

Data from the German police statistics (PKS) show that non-German crime suspects make up 21.1 percent of all crime suspects, although contributing only 8.7 percent of the total population (PKS 2009).[2] 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 mainstream society. The reasons for the apparent overrepresentation of foreigners in criminal activity will not be discussed in detail here, but the numbers indicate the need to control for the composition of the regional population.

Overrepresentation of crime suspects can be observed in yet another demographic group: men. Inspection of the

1 Levitt (1999, 2004) argues that the age structure alone has only a limited influence on the evolution of crime rates, because the decline in crime rates during the time period from 1995 to 2004 in the United States was at odds with a rising share of the most crime-prone demographic age group of young males.

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

raw numbers tells the following story: in 2009, out of the 2.19 million crime suspects, 1.64 million were male (75 percent). Controlling for the gender composition of the respective district hence seems to be as important as controlling for the demographic variables discussed above.

Another determinant of criminal behavior is education. Unfortunately, there is no comprehensive data on educational attainment of the German population at the district level. The only variable that covers education at the district level is the proportion of workers subject to social security contributions who have not completed vocational training *(sozialversicherungspflichtig Beschäftigte ohne abgeschlossene Berufsausbildung)*. This variable only covers the education of a certain group, namely those who are subject to social security contributions. 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 crimes. One could therefore expect a positive influence of this variable on crime. On the other hand, a high proportion of workers subject to social security contribution not having completed vocational training means that there are good labor market opportunities even for unskilled workers. Under this interpretation, a higher proportion of such workers would have a negative effect on crime. Empirical evidence for this can be found in Gould et al. (2002).

The last determinant discussed in this section is population density. There are several theories why population density might be an important determinant of crime. On the one hand, densely populated areas (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 involved in being caught is less. In addition, similar to the argument applied above to age composition, a high population density makes a "match" between criminal and victim more likely. Criminals may also have greater access to the wealthy in urban areas. Glaeser and Sacerdote (1999, 227) also mention the possibilities that criminals 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 used in this analysis. The bivariate correlation between overall crime rates and population density is remarkably high, with 0.63. One would therefore expect a positive impact of population density on crime rates.

2. Data Used

The empirical analysis is based on data covering districts *(Landkreise)* and urban municipalities *(kreisfreie Städte)* in Germany. *Landkreise* usually include one or more moderate-sized towns, as well as villages and rural areas, whereas municipalities are organized as stand-alone communities *(kreisfreie Stadt)*. In the following, both urban municipalities and rural counties will be referred to as "the districts."[3] This section introduces the variables included and presents detailed summary statistics. Crime data (number of offenses and clearance rates) are collected by regional state offices of the German Federal Criminal Police Office *(Bundeskriminalamt)* and are published in *Polizeiliche Kriminalstatistik* (PKS, police criminal statistics). Covariates come from two sources: unemployment and employment data are gathered by the German Federal Employment Agency *(Bundesagentur für Arbeit)*, whereas demographics and income data are obtained from the Federal Statistical Office *(Statistisches Bundesamt)*.

2.1. The Dependent Variables

The dependent variables used in this study are the crime rates in each district. Before defining the term "crime rates" we describe which offenses are included. These are burglary, auto theft, and assault. The offenses are defined as follows in the German penal code (*Strafgesetzbuch*, StGB).[4]

3 Messner et al. (2013) prefer to use the German word " Kreise," because they differ from counties or districts in the United States. For example, large city such as Houston may be within a district with other large cities; however, in Germany Houston would be a stand-alone community *kreisfreie Stadt*, i.e. counted as "Kreis".

4 The translation covers the most important points. German speaking readers are referred to the original source.

- Burglary (*Wohnungseinbruchsdiebstahl*, §244 Abs. 1 Nr. 3 StGB): entering a home by force or deception with the intention of stealing property.
- Auto theft (*Diebstahl in/aus Kraftfahrzeugen*, §242 StGB): Stealing a car or stealing property from a car.
- Assault (*Körperverletzung*, §223–227, 229, 231 StGB): Bodily injury, dangerous bodily injury, maltreatment of wards, serious bodily injury, bodily injury resulting in deaths, negligent bodily injury, participation in a brawl (see the official translation of the German Criminal Code: http://www.iuscomp.org/gla/statutes/StGB.htm#223)

“Crime rates” are defined as the frequency ratio *(Häufigkeitszahl)* from the German police statistics. This is the number of cases (of a given offense) reported to the police per 100,000 inhabitants in the district where the crime was committed. As is pointed out in the PKS (for example PKS 2003,14), the explanatory power of the frequency ratio is limited by the fact that only part of the committed crimes are reported to the police and by the fact that illegal aliens, foreign tourists and transients might also commit crimes but are not counted as inhabitants of Germany. However, the latter restriction is negligible: in 2009 out of the 2,187,217 crime suspects only 46,132 (or 2.11 percent) were illegal aliens and 6,739 (0.31 percent) were foreign tourists and transients, adding up to only 2.42 percent of all crime suspects. A slightly broader perspective, which also includes asylum seekers (22,137 or 1.01 percent) and stationed armed forces, including their family members (2,249 or 0.1 percent), produces a share of 3.53 percent of all crime suspects. The second problem of unreported crimes is more severe, though it can be mitigated by using fixed-effect models (see below).

Table 1 presents descriptive statistics for the frequency ratio for burglary, auto theft, and assault. It is apparent that there is huge variation in the respective crime rates. The overall distribution of the frequency ratio for auto theft is displayed in Figure 1, which nicely visualizes what can also be inferred from percentiles in Table 1. Although the maximum frequency ratio for auto theft is 2,437 (recorded in Bremen in 2007), the 95 percent percentile is only 878.5, with a median of only 246. The minimum is as small as 20, recorded in the district Forchheim (Bavaria) in 2008. Hence the distribution is heavily skewed. Moreover, the geographical distribution (Figure 2) shows a north-south pattern with higher frequency ratios in the north. Urban municipalities, at least in the south (Bavaria and Baden-Württemberg), do not stand out particularly on visual inspection of Figure 2.

Table 1: Frequency ratios for burglary, auto theft, and assault (descriptive statistics)

Percentile	Burglary	Auto theft	Assault
5%	22	66.5	325
25%	47	138.5	421
50%	84	246	538.5
75%	138.5	413	704
96%	275	878.5	1094.5
Minimum	3	20	202
Maximum	605	2437	2108
Mean	105.05	325.68	597.06
Standard deviation	79.19	274.18	242.45

Note: Statistics based on 3,020 pooled annual district and urban municipality data points for 2003 to 2009. Due to administrative reforms, the number of districts fell from 438 in 2003 to 412 in 2009. Frequency ratio is the number of reported offenses per 100,000 inhabitants.

Figure 1: Distribution of frequency ratio auto theft, 2003 to 2009

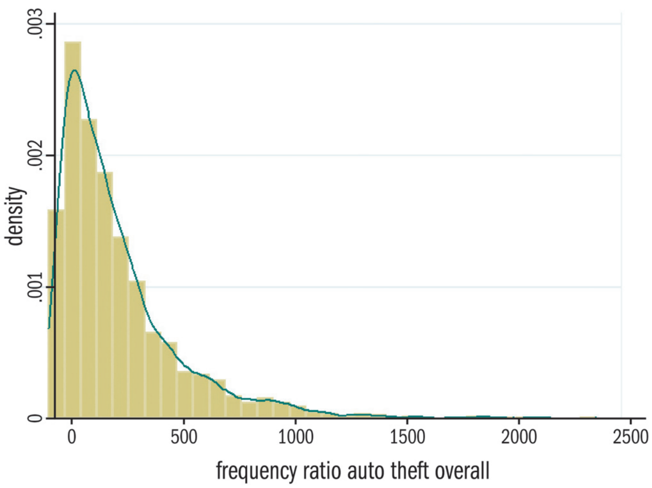
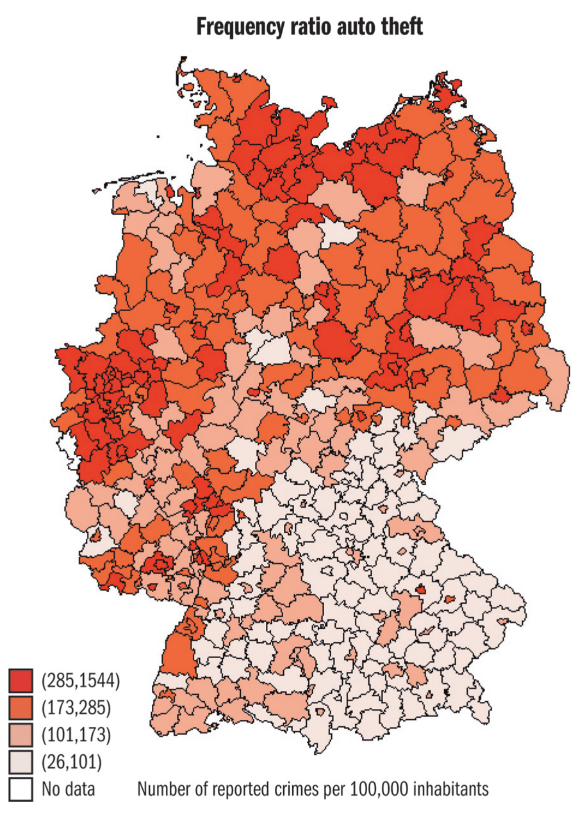
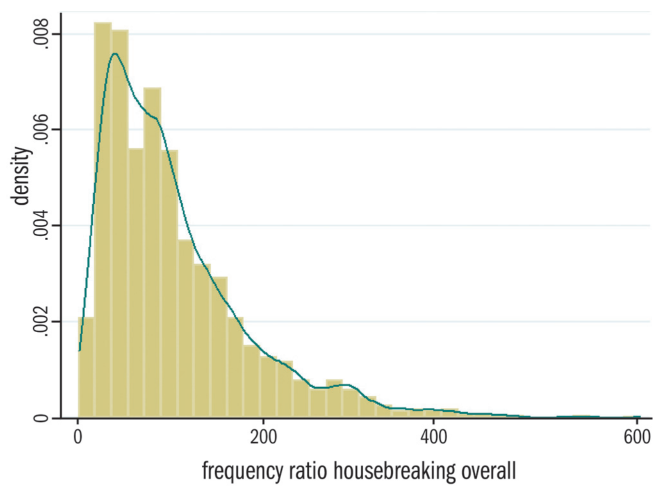


Figure 2: Regional distribution of frequency ratio auto theft, 2009



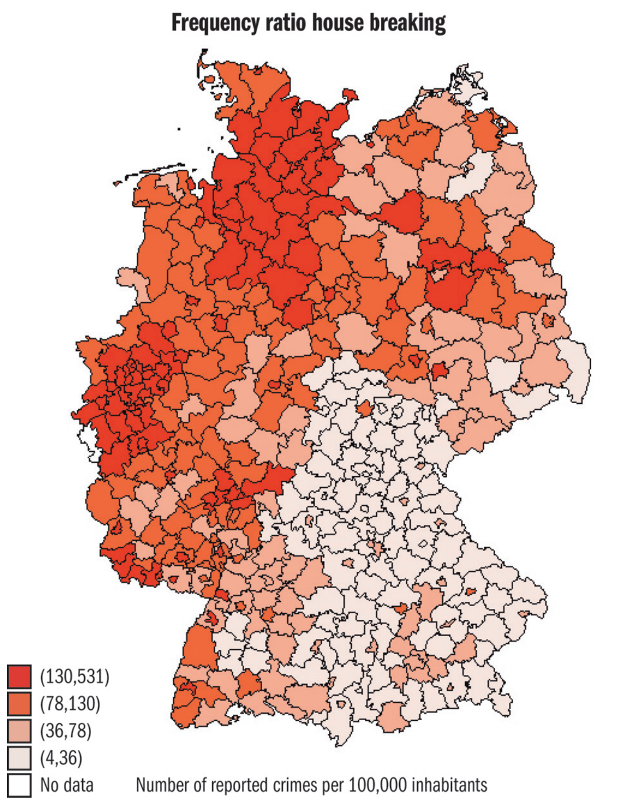
Similar patterns hold true for the frequency ratio for burglary. Here, too, we observe a heavily right-skewed distribution and enormous variation. The minimum frequency ratio for burglary is only 3 (Hildburghausen, Thuringia, 2008), with the 5 percent percentile as low as 22. In contrast, the maximum frequency ratio of 605 (Cologne, North Rhine-Westphalia, 2003) is about two hundred times the minimum. The distribution over the whole time period under consideration and the graphical visualization of the distribution in 2009 are displayed in Figure 3 and Figure 4, respectively. Noteworthy is the clustered appearance of burglaries in the north and west, while the south-west does not exhibit high frequency ratios even in the urban municipalities.

Figure 3: Distribution of frequency ratio burglary, 2003 to 2009



Assault, with a minimum frequency ratio of 202 (Enzkreis, Baden-Württemberg, 2003) and a maximum of 2,108 (Neumünster, Schleswig-Holstein, 2007), does not show as much variation as the other offenses. The ratio of minimum to maximum is lower (ten compared to one hundred for auto theft and two hundred for burglary). In addition, the distribution is more symmetrical than to the other distributions (Figure 5). Urban municipalities are among the most heavily affected districts for assault. They clearly stand out in the geographical distribution for 2009 (Figure 6). Besides the urban municipalities, the city states Berlin, Bremen, and Hamburg, the region around the city of Hannover, and the Rhine-Ruhr metropolitan region all show elevated frequency ratios. The contrast between the south and the north is less pronounced than it is for auto theft or burglary.

Figure 4: Regional distribution of frequency ratio burglary, 2009



One possible objection to using crime rates at district level is that criminals do not necessarily live in the district where they commit the crime. For the offenses under consideration, however, about 75 percent of criminals live in the district where they committed the crime (PKS 2009).

Figure 5: Distribution of frequency ratio assault, 2003 to 2009

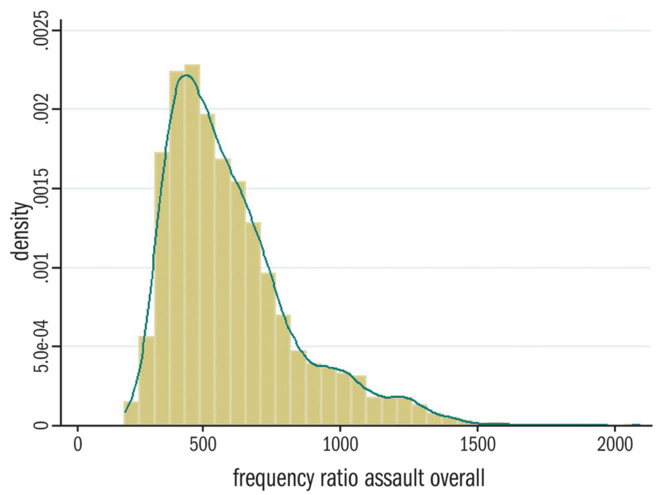
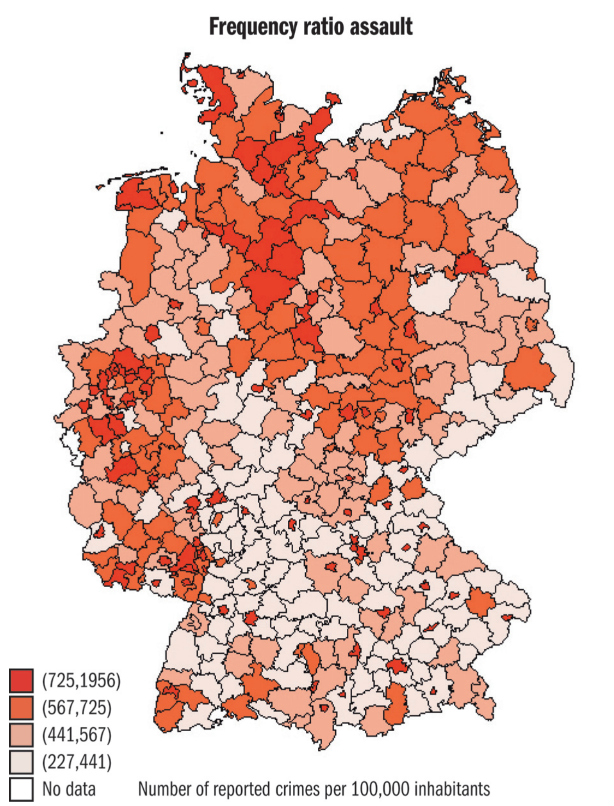


Figure 6: Regional distribution of frequency ratio assault, 2009



2.2. Economic Explanatory Variables

Table 2 shows descriptive statistics for the explanatory economic variables: unemployment rate and net household income. As unemployment is the major variable of interest, it is important to know its exact definition. The unemployment rate is defined as the number of unemployed persons divided by the total workforce. This raises the question who is counted as an unemployed person and which persons are considered to be in the workforce. According to the German Social Security Code (*Sozialgesetzbuch 3* [SGB 3], §16 Abs. 2), a person is to be considered unemployed if he or she

1. is temporarily not in an employment relationship or works less than 15 hours per week,
2. is looking for employment subject to social security contributions,
3. at the disposal of the employment agency,
4. has registered as unemployed at the employment agency.

The workforce consists of all persons in dependent civilian employment plus all self-employed persons and helping family members.

The unemployment rate varies considerably across German districts. The district with the lowest unemployment rate during the period under consideration is Eichstätt (Bavaria) (1.6 percent, 2008). The district with the highest rate is Uecker-Randow (Mecklenburg-Western Pomerania) (29.3 percent, 2004). Figure 7 shows the distribution of unemployment rates during the period under consideration. It is right-skewed with a peak at about 8 percent. A considerable number of districts (more than 5 percent) experienced unemployment rates exceeding 20 percent. The geographical distribution of unemployment rates in (Figure 8) shows that even nineteen years after Reunification, the new German states still lag behind in terms of labor market success. Districts with unemployment rates higher than 10 percent are almost exclusively located in eastern Germany (along with a few urban municipalities in the west, especially in the Rhine-Ruhr metropolitan area), where very few districts have a rate smaller than 7 percent. The vast majority of districts with rates below 5 percent are found in the south (Bavaria and Baden-Württemberg), while in the rest of Germany rates range between 5 and 10 percent.

Table 2: Descriptive statistics for economic variables

Percentile	Unemployment rate	Net household income (euros)
5%	0.039	29,907
25%	0.061	34,747
50%	0.087	39,650
75%	0.130	43,527
95%	0.202	49,845
Minimum	0.016	24,545
Maximum	0.293	69,030
Mean	0.100	39,520
Standard deviation	0.051	6,289

Note: Statistics based on 3,020 pooled annual district and urban municipality data points from 2003 to 2009. Due to administrative reforms of geographical boundaries, the number of districts changed from 438 in 2003 to 412 in 2009.

Figure 7: Distribution of unemployment rate, 2003 to 2009

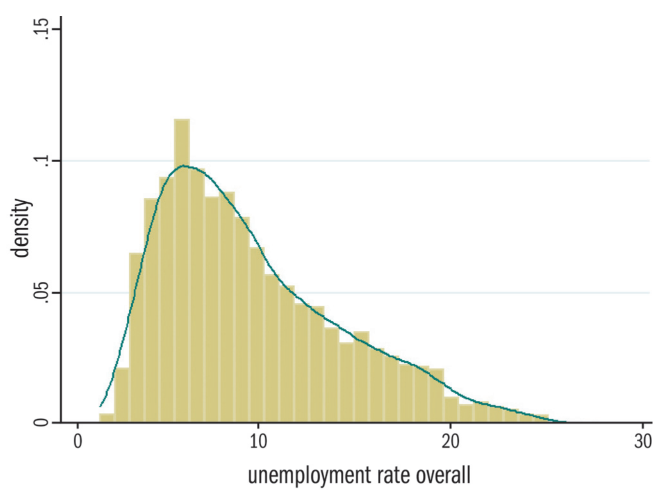
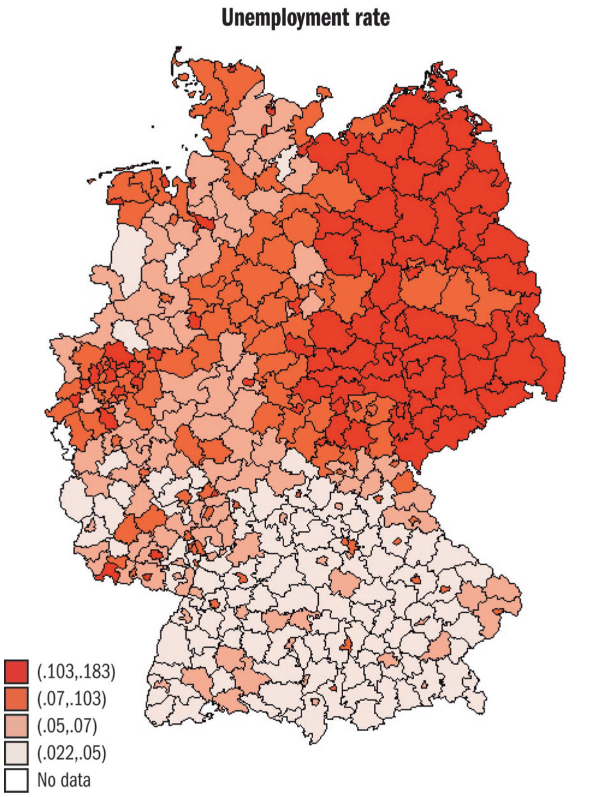


Figure 8: Regional distribution of unemployment rate, 2009



The variation in net household income is less pronounced than the variation in unemployment rates using the coefficient of variation as a measure of dispersion. The lowest average net income was reported in Leipzig (Saxony) in 2003 with 24,545, while the highest one was reported in Starnberg (on the periphery of Munich, Bavaria) in 2006. 50 percent of districts have an average net household income between 35,000 and 44,000. Only 5 percent have less than 30,000 and only 5 percent have more than 50,000. As already mentioned, only in very few districts is average household income above 50,000.

2.3. Other Explanatory Variables

The share of workers subject to social security contributions without completed vocational training (median = 15.6 percent, mean = 15.2 percent; from here on referred to as the share of unskilled workers in the workforce) has been introduced as factor representing the prevailing level of education. However, as described above, it is not entirely clear whether this variable truly captures education or rather job opportunities for unskilled workers. The share of unskilled workers in the workforce is low in the new federal states, high in the south-west, and rather mixed in the rest of Germany, suggesting that the share of unskilled workers in the workforce captures labor market opportunities for unskilled workers rather than educational attainment. For example, the small and medium-sized and manufacturing businesses concentrated in Baden-Württemberg seem to offer jobs to unskilled workers, whereas the economic situation in the new German states is generally less beneficial. The lowest share of unskilled workers in 2009 (7.3 percent) was reported in Greiz (Thuringia), the highest share (30.6 percent) in Tuttlingen (Baden-Württemberg).

Deterrence plays a crucial role in economic models of crime. The severity of the expected punishment and the probability of arrest are deterrence measures that influence the likelihood of committing a crime. The size of the police force (Levitt 1997, Lin 2008), the incarceration rate (Raphael and Winter-Ebmer 2001, Phillips and Land 2012), and the clearance rate (Entorf and Spengler 2000) are frequently used in empirical analyses. Although theory suggests that it is imperative to include a variable that measures some form of deterrence, some studies fail to do so (Öster and Agell 2007, or Yearwood and Koinis 2009). Based on data availability, we follow Entorf and Spengler and use the clearance rate as a measure of deterrence. The clearance rate is defined as the number of "solved" cases in a given year as a percentage of the total number of crimes recorded by the police in the same period (PKS 2009, 14). A case is considered to be "solved" when a suspect is identified and a charge is laid, regardless of whether the accused is convicted. As some cases reported in the previous year are solved in the current year, this might result in a clearance rate greater than 100 (which indeed happened in the period under consideration). Clearance rates significantly differ by type of crime. Whereas average clearance rates are rather low for burglary (26.0 percent, median 23.2 percent) and car theft (15.4 percent, median 12.8 percent), the rate for assault is 90.7 percent (median 91.2 percent).

The demographic structure plays a key role in explaining criminal behavior. The share of the population aged 15 to 24 (mean = 11.8 percent, median 11.7 percent; referred to as the youth population) ranges from 8.9 percent in Greiz (Thuringia, 2009) to 17.7 percent in the urban municipality of Greifswald (Mecklenburg-Western Pomerania, 2005) with. Turning to the share of the population aged 25 to 54 (referred to as the "active population"; mean 42.6 percent, median 42.4 percent) one can observe a close-to-normal distribution with a slightly more pronounced right tail (maximum 49.3 percent, in Heidelberg, minimum 37.4 percent, in Lüchow-Dannenberg (Lower Saxony).

Population density, the share of males, and the share foreigners complete the list of explanatory variables. In Germany, population density varies considerably from 38 per square kilometer in Mecklenburg-Kreilitz to 4,282 in Munich. The mean population density (512 inhabitants per square kilometer) does not convey much information about the "typical" district: more than 70 percent of all districts have a smaller population density than this mean, which is inflated by a small number of extremely densely populated areas (the median is 197). The district with the lowest share of males is Baden-Baden (Baden-Württemberg) with a share of 46.0 percent (recorded in 2004) while the district with the highest share is Aachen (North Rhine-Westphalia) with 51.5 percent (recorded in 2009). 95 percent of all districts have male shares less than 50 percent during the period under consideration, so in almost all districts there are more women than men (mean 49.0 percent, median 49.1 percent). However, it turned out that the variation of males across districts and over time is rather low and highly collinear with other factors of the population structure such that we had to omit it from the econometric analysis. The share of foreigners varies considerably across German districts. The lowest share of foreigners was recorded in Sömmerda (Thuringia) in 2007 with only 0.7 percent, while the highest share was recorded in Offenbach am Main (Hesse) in 2003 with more than 26 percent. A look at the percentiles shows that there are many districts with rather low shares of foreigners (50 percent have rates lower than 5.8 percent; mean 6.8 percent), while there are few districts with high shares of foreigners (5 percent of the districts have shares of foreigners higher than 15 percent).

3. Methodology

Ordinary least squares regressions determine the conditional mean of a response (dependent, endogenous) variable given values of explanatory (exogenous) variables. In this section we go beyond this standard method and also analyze the relationship between unemployment and crime using quantile regression (for example Koenker 2005). This technique has been proposed to discover relationships in cases with unequal impacts of explanatory variables for different ranges of the dependent variable. Hence, quantile regression allows identification of relationships even when there is no relationship or only a weak relationship between the *means* of such variables, but perhaps one at the median or in lower or upper parts of the distribution. Therefore, application of quantile regression seems to be promising in regional data sets with uneven distributions of the response variable, which is certainly the case for the heavily skewed distribution of crime rates across regions.

3.1. Mean Regression

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

$$(1)\quad Crime_{i,t} = \beta\ Unemployment_{i,t} + \gamma' X_{i,t} + \theta_t + \varepsilon_{i,t}$$

The coefficient of interest is β which captures the effect of unemployment in year t in district i on crime in year t in district i. The vector of parameters γ captures the influence of other explanatory variables as demographic, economic, or deterrence variables. The θs are time-fixed effects and capture the influence of shocks on the crime rate which affect all districts in the same way. $\varepsilon_{i,t}$ denotes the error term.

This model specification suffers from unobserved heterogeneity (for example due to region-specific shares of unreported crimes) which would lead to inconsistent and biased OLS estimates. The problem can be tackled by utilizing the panel structure of the data. Panel data are superior to a pooled cross-section in that the former allows the researcher to consider unobserved effects (or individual fixed effects). They are able to capture time-invariant (or slowly changing) factors that influence the crime rate and are specific to a certain district (rural areas, for example, are fundamentally different from urban areas). These factors can all be lumped together in the fixed effects. Their inclusion can therefore help to mitigate the problem of omitted variables (Wooldridge 2002, 247). Note that the use of random-effects (RE) modelling does not provide a reasonable alternative to the fixed-effects approach used in this study. Consistency of RE panel data modelling requires that unobserved factors of unobserved heterogeneity (the α_is, see below) are uncorrelated with included regressors. This presumption seems rather unrealistic as observed factors such as local unemployment, income, or clearance rates are most likely related to unobserved factors such as the share of unreported crime in the region. Nevertheless, it should also be noted that including fixed effects is no cure-all against omitted variable biases, because factors such as the share of unreported crimes may change over time. They are only useful when included observed factors change much faster than excluded unobserved factors. We assume that this is plausible for the data under comparison.

By including these fixed effects, the resulting regression equation reads:

$$(2)\quad Crime_{i,t} = \alpha_i + \beta\, Unemployment_{i,t} + \gamma' X_{i,t} + \theta_t + u_{i,t},$$

where α_i denotes the fixed effect for district i and $u_{i,t}$ is the new error term. Although the α_is are unobservable it is still possible to estimate the parameters of interest in equation (2) by subtracting the (over time) mean of each district from the respective observation (or, equivalently, by including district dummy variables). Denoting mean values by overlining, the regression equation reads:

$$(3)\quad Crime_{i,t} - \overline{Crime}_i = \beta(Unemp_{i,t} - \overline{Unemp}_i) + \gamma'(X_{i,t} - \overline{X}_i) + \theta_t + u_{i,t} - \bar{u}_i$$

Note that the unobserved effect no longer appears in equation (3), but the parameters are the same as in equation (2). It is hence possible to estimate the parameters of interest by applying OLS to equation (3).

This specification might still suffer from the potential problem that unemployment is not an exogenous variable in equation (3). Econometric endogeneity problems (inconsistency and biasedness of parameter estimates) arise when regressors are correlated with residuals of the statistical model. The major reason for endogeneity of unemployment can be suspected in a potential correlation between unemployment and unobserved factors in the error term, such as the degree of regional social disruption and social control. This shortcoming relates to the omitted variable bias discussed above. A further potential reason for endogeneity is simultaneity, which might for instance occur when high local crime rates have a reversal effect on corresponding labor markets. The potential endogeneity of unemployment in crime equations is beyond the scope of this article, but has been addressed at length elsewhere (Raphael and Winter-Ebmer [2001] and Lin [2008]; Lastauskas and Tatsi [2013] and Sieger [2014] consider German district data). Experience from previous research has shown that the likelihood of potentially biased parameters on unemployment is much smaller when panel data are used and time as well as district effects are included.

3.2. Quantile Regression

While mean regression delivers a single parameter estimate for the *average* partial effect of unemployment on crime, quantile regression allows different impacts of unemployment on crime depending on the level of criminal activity. This is useful for several reasons. For instance, one might find an insignificant effect of unemployment on crime in mean regressions, while there is in fact a negative (and significant) effect of unemployment on crime for low-crime areas and a positive (and significant) effect for high-crime areas. In mean regressions both effects would simply cancel out, leaving the researcher with the false conclusion that unemployment does not affect crime. Moreover, as suggested by the Grogger (1998) model, it makes a difference whether a certain percentage change Δu^* of the unemployment rate hits a region with few criminals, or a region with a comparatively large proportion of full-time criminals. Quantile regression can therefore be seen as a tool for deeper inspection of the results of the mean regression, a path that does not seem to have yet been pursued in the context of analyzing the relationship between crime and unemployment (with the notable exception of Bandyopadhyay et al. 2015).

Mean regression estimates the conditional mean function, given values of explanatory variables. That 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. Instead of predicting the mean of the endogenous variable, quantile regressions aim at predicting the quantiles of the regession, i.e., the median (50 percent median), 25 percent, 75 percent etc. However, there is a 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 and Hallock 2001, 143). Investigating these other possibilities might offer a more detailed view on the relationship between the dependent and explanatory variables. In particular, it might shed light on the question whether the effect of unemployment on crime differs between different levels of crime.

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

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

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

These two different crime-unemployment relationships correspond to two different interpretations of how criminals react to the level of criminal activity. A declining crime-unemployment relation would give rise to what we call opportunity-based behavior. It would also be in line with the Grogger (1998) model. When criminal activity is low, the supply of crime is highly elastic (that is, criminals show strong responsiveness to changing incentives). Hence, in such situations an increase in unemployment has a relatively large impact on crime: There are attractive and unprotected victims and only 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 also because people do not invest so much in crime-preventing equipment such as alarm and warning devices). If crime is already high, that means the "crime market" is already rather saturated, and engaging in criminal activities after becoming unemployed is not as attractive anymore. Then the supply becomes inelastic and the effect of unemployment on crime would be lower or insignificant. At a first glance, the reasoning seems plausible for property crimes, but less so for violent crimes such as assault. However, it also makes a difference for violent crimes whether the marginal crime effect of a certain change of the unemployment rate Δu^* hits a neighborhood of less protected citizens in low-crime areas or a region of already high crime rates where further increases become unlikely, in particular because more and more people have taken precautions and avoid risky places.

An increasing crime-unemployment link, on the other hand, would follow from what we call stigma-based behavior. If criminal activity is low, being unmasked as a criminal creates a strong stigma, since the person concerned is one of only a few criminals. Funk (2004) describes stigma of potential detection as a crime deterrent. Higher unemployment rates would not necessarily push a person into criminal activity, since the fear of the stigma prevents the potential offender from doing so. However, if there is already a lot of criminal activity, there is less impediment to becoming a criminal, since even detection would not make the person a "black sheep." A rise in unemployment would hence more easily push the person into criminal activity.

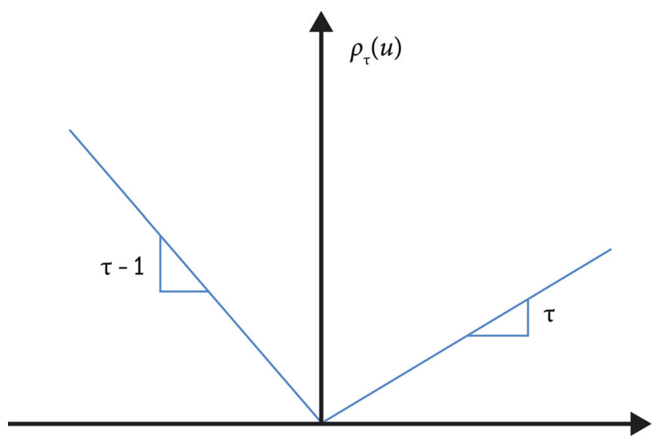
3.2.1. Ordinary Quantile Regression

It might come as a mild surprise that quantiles, although linked to the operations of ordering and sorting, can also be defined via a simple optimization problem (Koenker and Hallock 2001, 145). Similarly to OLS, where estimation is based on minimizing a sum of squared residuals u_{it}, quantile estimation is based on minimizing a sum of weighted absolute residuals $\rho_\tau(u_{it})$. More precisely, estimating the conditional quantile function for quantile τ is achieved by solving the following minimization problem

$$(4)\quad min_\beta \sum \rho_\tau (y_{i,t} - \xi(x_{i,t}, \beta))$$

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 asymmetric quantile loss function (visualized in Figure 9),[5] respectively weighting function of residuals u_{it}, and $\xi(x_{i,t}, \beta)$ is some parametric function of explanatory covariates, which may include controls for time effects (these are included in performed regressions but omitted here for notational convenience). 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), i.e. $\xi(x'_{i,t}, \beta) = x_{i,t}\beta$ (in vector notation). This approach suffers from the same deficiencies described above, in particular that it is not fully exploiting the panel structure by using fixed effects and taking unobserved heterogeneity into account. This feature will be added in the next subsection. The interpretation of quantile regression coefficients follows the interpretation of ordinary regression coefficients, with the important difference that reported parameter estimates only affect the quantile in question (instead of the mean). Thus, in the median regression the constant is the median of the sample while in the .75 quantile regression the constant is the 75th percentile for the sample, etc.

Figure 9: Quantile loss function



Note: See Koenker and Hallock (2001) for a similar illustration.

3.2.2. Quantile Regression with Fixed Effects

The approach presented above might suffer from the problem of unobserved heterogeneity. Following Koenker (2004) we consider the following model for the conditional quantile functions of the dependent variable of individual i at time t:

$$(5)\quad Q_{y_{i,t}}(\tau | x_{i,t}) = \alpha_i + x'_{i,t}\,\beta(\tau)$$

Where the a_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 such models the fixed effects a_i imply a pure location shift on the conditional quantiles of the response. Thus, the effects of the covariates are permitted to depend on the quantile, τ, whereas the effects a_i do not, but they are still useful to control for unobserved heterogeneity and can be interpreted in the way discussed above. In order to estimate model (5) for several quantiles simultaneously, Koenker (2004) proposes solving the following:

$$(6)\quad \min_{(\alpha,\beta)} \sum_{k=1}^{q} \sum_{t=1}^{T} \sum_{i=1}^{n} \omega_k \rho_{\tau_k} \left(y_{i,t} - \alpha_i - x'_{i,t}\,\beta(\tau_k)\right)$$

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

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

$$(7)\quad \min_{(\alpha,\beta)} \sum_{k=1}^{q}\sum_{t=1}^{T}\sum_{i=1}^{n} \omega_k \rho_{\tau_k}\left(y_{i,t}-\alpha_i-x'_{i,t}\beta(\tau_k)\right)+\lambda\sum_{i=1}^{n}|\alpha_i|$$

where the ω_ks 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, 77), $\rho_\tau(\cdot)$ is again the quantile loss function and λ is a shrinkage parameter. For $\lambda \to 0$, one would obtain the fixed effect estimator based on optimizing (6), while for $\lambda \to \infty$ one would obtain an estimate of the model purged of the fixed effects (Koenker 2004, 78).[6] A routine that implements this estimator (and variants of it) has been provided by Roger Koenker and Stefan Bache and is available for the statistical software package *R*. More recent work on fixed effects quantile regressions also deals with potential endogeneity of explanatory variables. The approach outlined in Harding and Lamarche (2009) tries to overcome this problem by extending the work of Chernozhukov and Hansen (2008) and 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.

4. Estimation Results

4.1. Mean Regressions

Table 3 shows the results for the two mean regressions applied in this study. The dependent variable is the logarithm of the frequency ratio of the respective offense. Besides the unemployment rate, OLS regressions also include the logarithm of the clearance rate for the respective offense lagged by one period,[7] the logarithm of disposable income, the logarithm of population density, 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 "active population" (aged 25 to 55), the share of unskilled workers, and time dummies. The analysis covers the years from 2005 to 2009, although data are available from 2003 onwards. The reason for the choice of this time span is a major labor market reform (the so called "Hartz-Reform") implemented in 2005. This reform had led to a redefinition of unemployment: Most people who were receiving social welfare benefits *(Sozialhilfe)* before 2005 have been counted as "employable" thereafter and therefore unemployed after 2005 (instead of being out-of-the-labor force before). To avoid potentially biased results stemming from the changing definition of the unemployment rate, we restricted the time window to the years 2005 to 2009.

Table 3 displays the results of OLS and fixed effects mean regressions.[8] The estimated parameters are to be interpreted as semi-elasticities: an increase of the unemployment rate by one unit (one percentage point in this case) increases criminal activity by percent. Based on the standard OLS regression, unemployment has a positive and significant effect on crime for burglary (9.6 percent) and auto theft (10.3 percent), and a negative but insignificant effect on assault (-0.4 percent). These results are in line with previous findings from the literature: the unemployment rate usually has a significant positive effect on property crimes (here burglary and auto theft) while only small or insignificant effects on violent crime, here measured in terms of assault. This is consistent with the vast majority of cross-section findings in the literature, and

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

7 Lagging the clearance rate by one period mitigates the problem of simultaneity.

8 Note that the maximal number of 398 districts used in the subsequent multivariate analysis differs from the one in Messner et al. (2013), who report results based on 413 districts. The difference might be explained by the way data are employed. As violent offenses can be rare events in less populated districts (contrary to large cities and the more urbanized areas), Messner et al. decided to use the average annual robbery and assault rates per 100,000 population for the three-year period 2005, 2006, and 2007. By contrast, our paper fully exploits the panel data structure of the five years period from 2005 to 2009, i.e. data are collected over time and over the same districts and then regressions (in form of panel econometric methods and quantile techniques) are run over these two dimensions. In turn, some district observations are lost due to redefinitions of geographical district boundaries which took place during 2007 and 2009 in the East German states Sachsen-Anhalt and Sachsen (see Wikipedia 2015, for details of boundary reforms in Germany). Further observations are lost due to missing data of explanatory variables. Lastauskas and Tatsi (2013), who estimate cross-sectional spatial models based on data from 2008 and 2009, report the use of 402 districts. In 2007 the total number of districts was still 439. This number fell (with time-variant boundaries) to 412 in 2009. As of 2015 there are 402 districts (295 *Landkreise* and 107 *kreisfreie Städte*).

even with findings on the influence of the contemporaneous unemployment rate on the assault rate in time series studies (Phillips and Land 2012). However, the OLS specification does not consider the panel structure, so regional peculiarities such as locally high or low shares of unreported crimes or unobserved factors of urbanity are not taken into account. The fixed effect regression (column FE in Table 3) does include district fixed effects and is therefore able to control for unobserved heterogeneity across districts.[9] Applying it does not change the insignificance of unemployment on assault, but parameters of the FE estimation on car theft and burglary differ substantially from the ones of OLS estimation. The effect on auto theft becomes insignificant, and the estimated parameter on the link between burglary and unemployment is been reduced to 4.4 (recall that the median district unemployment rate is about 9 percent, so a one percentage point fall would be equivalent to a -11.1 percent change experienced by a median district).[10]

Reported inference is based on cluster-robust standard errors. The employed Stata command is based on the work of White (1980, 1984) and Huber (1964, 1967), and allows the assumption of independently distributed residuals to be relaxed. The routine produces consistent standard errors if the residuals are correlated within, but uncorrelated between clusters (districts). In spatial models it may be rather optimistic to assume that the residuals are correlated within but uncorrelated between clustered regions. Beck and Katz (1995) suggested the application of panel-corrected standard errors (PCSEs) which correct for contemporaneous correlation between the clusters. However, their approach is based on large T-asymptotics (a large time-series dimension), while our approach is based on a large cross-sectional dimension N, with N » T. Hoechle (2007) points out that the PCSE estimate will be rather imprecise if the ratio T/N is small. Thus, we stick with White-Huber robust standard errors, which seems to be justified as we only consider five years of data and also correct for time and district fixed effects.

Table 3: Results from the mean regression for the effect of unemployment on crime

Offense	OLS	FE
Assault	–0.364 (0.289)	0.175 (0.382)
Burglary	9.634*** (0.909)	4.432*** (1.493)
Auto theft	0.319*** (0.911)	–1.053 (0.851)
Number of observations	1,947	1,947

Note: Cluster-robust standard errors in parentheses. Dependent variable: log (frequency ratio). OLS regressions include log(clearance rate) for the respective offense lagged by one period, log(disposable income), log of population density, share of foreigners, share of the young population, share of the youth population, share of the active population, share of unskilled workers and time dummies. FE regressions include log (clearance rate) for the respective offense lagged by one period, log (disposable income) and time dummies. All regressions are weighted using the size of the district population. Note that due to regional reorganizations some districts had to be excluded from the data set. Further note that panel data analysis requires at least two subsequent periods with identical regional boundaries and without missing data. This was the case for 383 districts with five-year time spans, one additional district for the four-year time span between 2006 and 2009, and an additional fourteen districts for the time span 2008/09, resulting in 1,947 observations. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

9 However, this comes at some costs. On inclusion of fixed effects all slowly varying or quasi time-invariant variables became highly collinear and completely insignificant. For this reason share of foreigners, share of unskilled workers, and all other variables representing the population structure have been omitted from the fixed-effect specification.

10 Sieger (2014) confirms significance (respectively insignificance) and sign of presented FE results using an IV approach.

4.2. Quantile Regressions

Table 4 gives an overview of the results for the ordinary quantile regression. Some interesting insights emerge from comparing the methods under consideration. While the estimated effect of an increase in the unemployment rate on the rate of assault was insignificant in the OLS regression (see Table 3), it is positive and significant in the ordinary quantile regression at least for low levels of crime (the 5 percent and 25 percent quantiles). In addition, the strength of the crime-unemployment link is slightly decreasing (Figure 10). The downward slope is even more pronounced for burglary and auto theft (Figures 11 and 12), giving rise to the interpretation that agents are committing crime when the "supply" of crime is rather low, and "tolerance" towards crime is still high (see also Ehrlich 1996, who argues that tolerance towards crime represents the demand side of a market of offenses). Moreover, OLS estimates are within the middle of the respective quantile regressions, 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 (but note that mean and median results differ due to the skewed crime distribution).

Table 4: Results from the ordinary quantile regression for the effect of unemployment on crime

Offense	Quantiles				
	0.05	0.25	0.5	0.75	0.95
Assault	1.126* (0.681)	0.947*** (0.307)	0.418 (0.333)	0.412 (0.392)	–0.715 (0.977)
Burglary	15.185*** (1.212)	9.718*** (0.885)	7.491*** (0.671)	7.038*** (0.960)	5.924*** (1.051)
Auto theft	12.789*** (1.619)	9.835*** (0.741)	8.829*** (0.689)	8.579*** (0.889)	7.921*** (1.631)

Note: Bootstrapped standard errors in parentheses. Dependent variable: log (frequency ratio). All regressions are based on 1,947 observations and include log(clearance rate) for the respective offense lagged by one period, log (disposable income), log (population density) 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 are weighted using the size of the district population. See Table 3 for details on data. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

Figure 10: Effect of an increase in unemployment on assault at different quantileshere

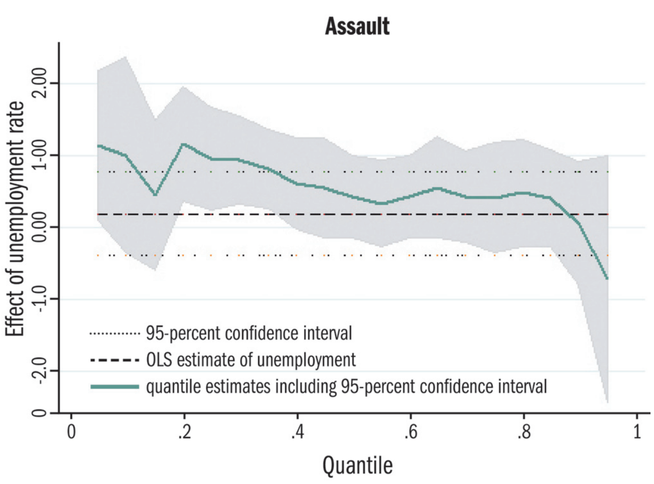


Figure 11: Effect of an increase in unemployment on burglary at different quantiles

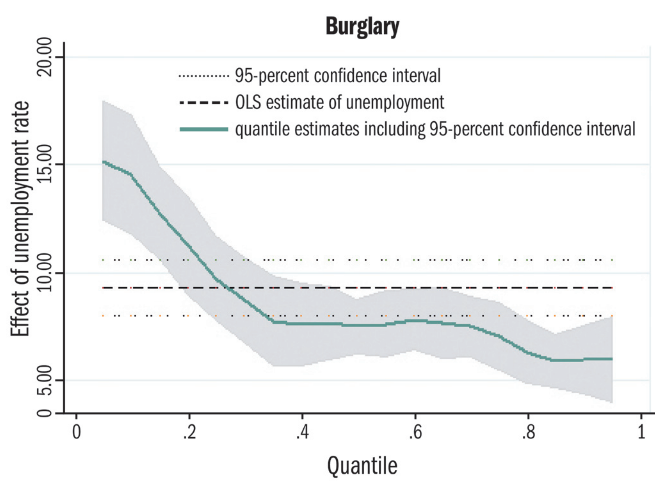


Figure 12: Effect of an increase in unemployment on auto theft at different quantiles

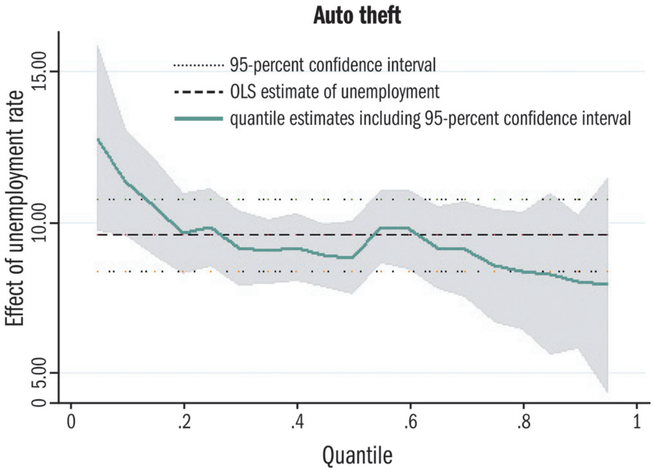


Table 5 displays the results from quantile regression with fixed effects. Note that the usual inclusion of time-fixed effects has caused indications for serious multicollinearity problems such that we deviate from previous specifications by including a linear time trend instead of time dummies. We consider quantile regressions with fixed effects as the most reliable and preferred, as they control for potential district-specific unobserved heterogeneity. The significance of parameter estimates is in line with the one obtained from ordinary quantile regression, but the pattern of the unemployment-crime link has changed, in particular for property crimes. The effect on burglary and auto theft is still significant for all quantiles, but results do not confirm the decreasing pattern in Table 4 (where estimates below the 50 percent quantile of the regional crime distribution are particularly high). Instead, quantile parameters exhibit a rather flat crime-unemployment profile, which is not indicative for or against stigma or opportunity-based behavior. The effect of unemployment on assault is significant for rather low-crime (25 percent-quantile) and median-crime regions (50 percent quantile) and insignificance is confirmed for quantiles above 50 percent. This lack of significance for high-crime areas is in line with opportunity-based criminal behavior, but the FE approach does not confirm the strictly downward effect found with ordinary quantile regressions.[11]

Table 5: Results from quantile regression with fixed effects for the effect of unemployment on crime

Offense	Quantiles				
	0.05	0.25	0.5	0.75	0.95
Assault	0.908 (0.570)	0.896** (0.378)	1.344*** (0.432)	0.980 (0.856)	0.388 (1.610)
Burglary	11.910*** (1.297)	10.990*** (1.383)	11.270*** (1.363)	11.318*** (1.596)	11.888*** (1.418)
Auto theft	12.416*** (1.505)	11.005*** (1.330)	11.706*** (1.079)	12.628*** (1.560)	14.434*** (1.943)

Note: Bootstrapped standard errors in parentheses. Dependent variable: log (frequency ratio). All regressions are based on 1,947 observations and include log (clearance rate) for the respective offense lagged by one period, log (disposable income) and a linear time trend. All regressions are weighted using the size of the district population. See Table 3 for details on data. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

11 Sieger (2014) also presents some preliminary quantile FE IV estimates. However, the results lack robustness and seem to be highly sensitive to the choice of specification such that we do not comment on them further in this paper.

4.3. Further Results

Tables 6 and 7 show results for the effects of other factors of the economics of crime model: clearance rate and net income. In line with theoretical expectations, the log of the lagged clearance rate is negative and significant for all but one model specification. The only exception is the fixed effects mean regression of assault. The effect of the clearance rate for property crimes ranges between -0.15 and -0.30. The much larger effect of a 1 percent change in the clearance rate for assault can be explained by its relatively high median clearance rate of 91 percent (compared to only 13 percent for auto theft, and 23 percent for burglary) and its low variation across districts. The quartiles at 25 percent and 75 percent are 89 percent and 93 percent, respectively, such that a change by 1 percent (for instance, from a 90-percentile down to the 89.1-percentile) already represents a substantial change, in particular given that assault rates – in contrast to auto theft and burglary – do not show strong variation across districts (see above).[12] So when interpreting and comparing parameter estimates it needs to be taken into account that increasing the clearance rate for assault by 1 percent would be more difficult, less likely, and perhaps also much more costly than increasing the clearance rate for property crimes by the same amount.

As regards the structure of the quantile regression estimates, Bandyopadhyay et al. (2015) report that the crime-reducing effect of higher detection rates is stronger in low-crime areas. This can be confirmed for assault and using ordinary quantile regressions (as also applied by Bandyopadhyay et al.) in Table 6, whereas for fixed-effects and property crimes there is no obvious quartile-specific pattern.

Table 6: Results from pooled OLS and ordinary quantile regression

Log(clearance rate), lag(-1)		Quantiles		
	POLS	0.25	0.5	0.75
Assault	2.762*** (0.275)	–2.305*** (0.367)	–1.685*** (0.342)	–1.590*** (0.465)
Burglary	–0.313*** (0.035)	–0.274*** (0.053)	–0.309*** (0.034)	–0.299*** (0.028)
Auto theft	–0.201*** (0.027)	–0.156*** (0.026)	–0.184*** (0.027)	–0.164*** (0.031)

Net income		Quantiles		
	POLS	0.25	0.5	0.75
Assault	–1.265 *** (0.079)	–1.137*** (0.089)	–1.187*** (0.113)	–1.118*** (0.099)
Burglary	–0.010 (0.212)	–0.729*** (0.239)	–0.613*** (0.212)	–0.269 (0.226)
Auto theft	–0.007 (0.233)	–0.830*** (0.256)	–0.717*** (0.271)	–0.289 (0.254)

Note: Cluster-robust (POLS) and bootstrapped standard errors in parentheses.
Dependent variable: log (frequency ratio). See Tables 4 and 5 for further details. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

12 The 25% quartiles of auto theft and burglary are 8.1% and 20%, respectively. The corresponding 75% quartiles are 15.6% and 33.9% (Sieger 2014).

Table 7: Results from fixed effects means and quantile FE regressions

Log(clearance rate), lag(-1)		Quantiles		
	FE	0.25	0.5	0.75
Assault	0.214 (0.182)	–3.919*** (0.393)	–4.158*** (0.376)	–4.437*** (0.586)
Burglary	–0.091*** (0.025)	–0.299*** (0.053)	–0.395*** (0.052)	–0.376*** (0.039)
Auto theft	–0.040*** (0.011)	–0.252*** (0.047)	–0.245*** (0.038)	–0.278*** (0.041)

Net income		Quantiles		
	FE	0.25	0.5	0.75
Assault	–0.430** (0.197)	–0.899*** (0.106)	–0.777*** (0.112)	–0.844*** (0.170)
Burglary	–0.810 (0.770)	0.593 (0.391)	0.220 (0.403)	0.141 (0.412)
Auto theft	0.219 (0.431)	0.423 (0.360)	0.315 (0.299)	0.261 (0.382)

Note: Cluster-robust (FE) and bootstrapped standard errors in parentheses.
Dependent variable: log (frequency ratio). See Tables 4 and 5 for further details. *, **, and *** denote significance at the 10%, 5% and 1% level respectively.

Results for net income (Table 7) are more heterogeneous. The clearest empirical evidence can be observed for assault, where all estimates confirm the hypothesis that better legal earning opportunities are associated with lower crime rates. The same effect occurs for the 25 percent and 50 percent percentiles (but not for the 75 percent percentile) of ordinary quantile regressions for auto theft and burglary. However, quantile fixed effects, pooled OLS, as well as standard mean FE modelling do not confirm this result so that we cannot reach a unanimous conclusion with respect to the effect on property crimes.

5. Summary and Conclusions

This paper uses regional panel data from about four hundred German districts and quantile regressions to study the effect of unemployment on crime. The main contribution is to test the hypothesis that size and significance of the effect of unemployment on crime may depend on the relative position of the prevailing regional crime level within the overall distribution of crime rates, i.e. whether the local crime rate is relatively low or large. We present two conjectures about the non-linear pattern of the relationship between unemployment and crime. First, there could be a downward sloping crime-unemployment link with a high marginal impact of unemployment on crime for low-crime regions. This pattern might arise when job losses imply high incentives and relatively large opportunities to become criminals. Likewise, potential criminals would face less crime prevention and precautions from potential victims than those in regions where crime is already more elevated. The opposite pattern might follow from the alternative stigma effect: If there are only a few criminals around, there are strong moral obstacles to becoming a criminal, since any detection would make the person a “black sheep.” This contrasts to a situation with many criminals in the neighborhood where acting illegally becomes more likely as many others or even peers already have criminal experience. Empirical results show that conventional mean regressions might indeed produce misleading results. For instance, while simple OLS and FE regressions depict insignificant results for *assault* (which would confirm the usual result for violent crime found in the literature), the preferred fixed quantile regressions reveal positive and significant effects for the districts representing the 50 percent and 25 percent percentiles of the crime distribution, i.e. for median- and low-crime regions, respectively. The analysis of *property crimes* illustrates that results based on quantile fixed effect modeling might substantially differ from those of ordinary quantile regressions. The latter seem to indicate behavior in line with the opportunity-based approach (the effect of unemployment on crime in regions with relatively low crime rates is stronger than in regions with relatively high crime rates), but this result cannot be confirmed when including fixed effects. As this technique has the advantage that it corrects for unobserved heterogeneity and is therefore a favored estimation strategy, we may conclude that the positive and significant effect on considered property crime categories is rather constant across quantiles. This indicates a conventional linear relationship between property crime and unemployment and corroborates standard theoretical explanations based on expected values of distributions and usual mean regressions. However, future work should also use individual data to identify and better understand the complexity of incentives and activities of potential criminals in high- and low-crime regions.

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Horst Entorf
entorf@wiwi.uni-frankfurt.de

Philip Sieger
sieger@wiwi.uni-frankfurt.de