Socioeconomic Determinants for Regional Variation of Crime in Germany

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Master thesis submitted

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Abstract

This work explores which spatial patterns of crime exist in Germany and what their socio-economic determinants are. This is done using the PKS crime statistic for six types of crime on the county level for the years 2003-2014. To the authors knowledge, this is the first time crime in Germany has been studied with such granular data on such a broad scale. Due to the granularity of the data set, spatial dependencies of crime and its covariates became very apparent, which made it necessary to use a random effects spatial durbin model (SDM) to model regional variation of crime. With this, I was able to show that the factors explaining crime in one county also spill-over and affect crime in a neighboring one. To my knowledge, this hasn't been done before either for Germany. Also, I was able to confirm earlier findings that the Becker-Ehrlich model works well explaining property crime in Germany and the social disorganization theory explaining violent and drug crime, with the routine activity mostly working in both cases. Also as a first for Germany, there is some evidence that the broken-window theory applies and that disorder can drive crime to an extend.

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List of Abbreviations

2SLS	Two-step least squares
AIC	Akaike information criterion
AR(k)	Autoregressive process of order k
BBSR	Federal Institute for Research on Building, Urban Affairs and Spatial Development (Bundesinstitut für Bau- Stadt- und Raumwesen)
BIC	Bayesian information criterion
BKA	Federal criminal police (Bundeskriminalamt)
BKG	Federal office for cartography and geodesy (Bundesamt für Kartographie und Geodäsie)
BLU	Best linear unbiased
CLT	Central limit theorem
CPI	Consumer price index
DHI	Disposable household income
FE	Fixed effects
FGLS	Feasible generalized least squares
GDP	Gross domestic product
H_0, H_1	Null and alternative hypothesis
i.i.d.	Independently and identically distributed
LM	Lagrange multiplier
LR	Likelihood ratio
MAUP	Modifiable area unit problem
MLE	Maximum likelihood estimation
NUTS3	Regional unit of level 3 by EU-classification (Nomenclature des unités territoriales statistiques 3)
OLS	Ordinary least squares
OVB	Omitted variable bias
p.c.	per capita
PKS	Crime statistics recorded by the BKA (Polizeiliche Kriminalstatistik)
RE	Random effects
SAR	Spatial autogregressive model
SEM	Spatial error model
SDM	Spatial Durbin model

1 Introduction

It is the consensus among most economists that physical safety and the safety of one's property are necessary conditions for a prospering society. Therefore, studying how crime can be prevented and fought in an effective manner is also a question of economics. However, crime is simultaneously also the result of economic processes. As will be shown, many types of crime are causally linked to economic variables such as unemployment, household income or the human capital stock. Since this is the case, a study like this obviously benefits from granular data with as little aggregation as possible, so that these relationships do not get "averaged away". Unfortunately, due to lacking data availability, crime in Germany was until now mostly studied on the level of its 16 states, most importantly by Entorf and Spengler (2000) and (2002). Recently, there have been some exceptions, like the work by Messner, Teske, et al. (2013), that do look at crime on the county level, but only for a few types of crime, covering a short time-span, and sometimes only in a specific part of Germany. Since better data is available now, I will instead study crime on the level of all 402 counties (as of 2014, equivalent to NUTS3 by EU-classification) and over 11 years, which to the best of my knowledge hasn't been done before for Germany. This, however, comes with the necessity to account for spatial dependencies, i.e. one county influencing the development in another.

That crime exhibits spatial dependencies on this granular a scale is not very surprising. As the often cited first law of geography by Tobler (1970, p. 236) states, *"everything is related to everything else, but near things are more related than distant things"*. It is also long understood that the location of a crime is not arbitrary, but rather causally linked to victim, perpetrator and motive. For example, the best known sociological theories of crime explicitly look at the ecological context a crime takes place in, see Cohen and Felson (1979) or Shaw and McKay (1942) for example. At the same time, studies of crime which take the space-dimension into account are all fairly recent.

This is also partially due to the fact that much of spatial econometrics wasn't developed until the eighties, see Cliff and Ord (1981) and Anselin (1988) for some of the early work. But today, not accounting for spatial dependencies is not acceptable when studying crime and using data with even some degree of granularity. As will be shown, this will give rise to biased, inefficient and difficult to interpret parameter estimators, see also LeSage and Pace (2009). Yet, even some of the current economic research often chooses to ignore this source of endogeneity, while usually making big efforts to account for temporal autocorrelation. Besides simply controlling for these spatial interactions, using spatial techniques also comes with a great chance to study what kind of spill-over effects exist with crime and what kind of clustering they result in. This is especially relevant from a policy perspective. For one, seemingly effective crime-fighting strategies might not actually stop crime but just change where it takes place (Weisburd et al. 2006). And, as with all externalities, these types of spatial spill-overs can give rise to inefficiencies in the crime fighting policies, as a county will likely choose its policy in a way that benefits them without regard to what the effect on its neighbors might be. To my knowledge, until now no study has looked at these spillover and clustering effects for Germany.

The outline of this thesis is as follows. After this introduction, I will give a brief overview over the relevant theories regarding crime on a societal level and previous research results, resulting in a set of hypothesis to be tested and verified in the remainder of this thesis. Next, I will introduce the methods used to test these hypothesis and discuss possible problems and pitfalls that come with them. In the fourth chapter, I will give an overview of the data I intend to use for testing these hypothesis and shortly discuss how the data-set was assembled. In the fifth chapter, I will present the results. The sixth and last chapter discusses the policy implications of these findings, their limitations and finally draws a conclusion.

2 Theoretical Background

Throughout the more than 200-year long history of research on crime on a societal level, two main lines of inquiry emerged. These can be categorized into those which looked at crime in a descriptive manner and those which are interested in cause and effect. While descriptive studies were always concerned with the geography and clustering of crime, and therefore especially done by geographers, these was for the longest time ignored by researches interested in causes of crime, i.e. economists and sociologists. For example, the relatively recent meta-studies by Weatherburn and Schnepel (2015) or Pratt and Cullen (2005) barely mention spatial effects of crime and include no paper which looks at these in a systematic manner. Only recently these two lines of inquiry have merged, resulting in the research outlined at the end of this section. First, however, I will give an overview over the non-spatial empirical and theoretical work relevant for the development of my hypothesis. Much of this work stems from the eighties and nineties, likely because the record crime numbers in most western countries made this field especially interesting during these years, with interest waning as crime numbers fell.

2.1 The Becker-Ehrlich Deterrence Model

The best known and most used economic model of crime is the deterrence model first proposed by Becker (1968) and refined and extended by Ehrlich (1973). Here, a rational agent maximizes his or her expected utility when deciding whether to commit a certain crime. This results in an aggregate "supply-function" of this specific type of crime, similar to a Cobb-Douglas production function. In the econometric specification by Ehrlich (1973,

p. 537), the model takes the following form:

$$\begin{aligned} &Q = P^{\alpha} F^{\beta} Y^{\gamma_1} Y_l^{\gamma_2} U_l^{\delta} V^{\rho} Z \cdot exp\{\mu\}, \\ \Leftrightarrow\ &q = \alpha p + \beta f + \gamma_1 y + \gamma_2 y_l + \delta u_l + \rho v + z + \mu. \end{aligned} \tag{2.1.1}$$

Here Q denotes the crime rate per inhabitant, P the perceived probability of getting caught, F the monetary value of the punishment given when caught, Y the income from the crime and Y_l the income from legal activities. U_l denotes the unemployment rate, or, within the rationale of this model, the average probability of being unemployed in the current period. V is a vector containing other explanatory variables not part of the theoretical model, Z is a constant which sums up individual psychological effects and μ is a white-noise error term. The lower-case letters denote the natural logarithm of the upper-case denoted variables.

The interpretation of this model is quite straightforward and intuitive. Since the individual has the choice between legal work or criminal activity, it compares the utility of the expected income generated by both activities. Since committing crimes comes with the chance of being caught, their expected income from crime is $Y - PF$. At the same time, legal employment comes with the chance of becoming unemployed, so here the expected income is $(1 - U_l)Y_l$. The individual then makes a utility maximizing choice whether to commit a crime or pursue legal employment. Therefore, we would expect γ_1 and δ to have positive signs and α, β and γ_2 to have negative signs, i.e. we would expect higher unemployment and better illegal income opportunities to increase crime, while we would expect higher wages, a higher chance of getting caught and more severe punishments to decrease crime. These last two elements are the reason why this model is called the "deterrence model", as the clear policy implication is that reducing crime can be achieved by more police, an efficient justice system and more severe punishments.

This has largely been confirmed by empirical research, for example by Ehrlich (1973), Wolpin (1978) and for Germany by Entorf and Spengler (2000). Therefore, this model serves as a good baseline for the questions I am trying to answer. However, empirical research often struggled with finding a good proxy for illegal income opportunities, and disentangling these from legal ones. Entorf and Spengler (2000) used median household income and unemployment as a proxy for legal income opportunities and per capita GDP for illegal ones, arguing that a high GDP per capita represents a target rich environment for criminals, especially regarding property crimes. Draca et al. (2015) show that order statistics of wages tend to perform better than the unemployment rates as a proxy for legal income opportunities. Therefore, they use median wages as a proxy for legal income opportunities, and various price indices as a proxy for illegal income opportunities arguing that the prices for different metals or for electronics motivates theft and burglaries of these items. However, Fougère et al. (2009) and Grönqvist (2013)) also found (youth)-unemployment to have explanatory power.

Another issue encountered by researchers using this model is that the (subjective) probability of getting caught is impossible to measure. To remedy this, they have used various proxies such as clearance-rate (i.e. the proportions of crimes solved), imprisonment-rate, or number of policemen per capita. All these variables, but especially the last one, come with the potential problem of simultaneity. Wilson and Boland (1978) for example found only low and sometimes negative correlations between police and crime, which is likely due to police being deployed in high crime areas, thereby creating simultaneity. To deal with this problem, Levitt (1995) uses a dummy for whether it is a local election year as an instrument for deterrence. He argues that in election years the number of police deployed and the number of arrests increase for political reasons, and therefore for reasons independent of crime rates. Doing so, he indeed found that in gubernatorial and mayoral election years the number of policemen increases and crime drops, thereby confirming his intuition.

With regards to other possible explanatory variables exogenous to the model, i.e. those incorporated in the vector V, I will give an tabular overview at the end of this chapter (Table 1). One obvious candidate however is education, or the human capital stock if you will. Machin et al. (2011) for instance found that one more year of compulsory eduction drastically lowers crime rates, a finding generally confirmed by Åslund et al. (2015). In the end it should also be mentioned that there exist various extensions of the Becker model, where the Ehrlich model is only the most widely used version. One such extension of note is the dynamic version of the Becker-Ehrlich model first proposed by Sah (1991). He argues that, since we are dealing with expectations, the individual has to makes his or her decision whether to commit a crime based on the facts known from the previous period. This simple assumption, and the fact that law enforcement in turn reacts to changes in crime rates, gives rise to a complex dynamic system with several possible equilibria. Therefore it is of some interest, whether these assumptions hold true in Germany.

2.2 Social Disorganization Theory

While the Becker model and its extension is the most popular in economic studies of crime, there are several sociological theories which are also of interest. First, let us consider the so-called "social disorganization theory", first formulated by Shaw and McKay (1942). They propose that crime is largely the result of a society with little "organization", or, as an economist might call it, institutions. As causes for this they suggest a lack of social cohesion, i.e. weak friendship networks, low participation rates in clubs and weak supervision of teenagers. The core idea of this theory is that it is not just a lack of legal income opportunities, but rather, a failure of local societies "to realize the common values of its residents and maintain effective social controls", as Sampson and Groves (1989, p. 780) put it. How well the community works together to exercise social control of course correlates with access to resources, but goes further than that. Sampson and Groves argue that this also includes the disruption of families, ethnic diversity and the turn-over of residents, i.e. how long they stay in a region. The authors used survey-data to test this theory, and found that especially urbanization, family disruption and organizational participation had much explanatory power regarding crime, while ethnic heterogeneity, strength of the friendship network and residential mobility did not for most types of crime and only a little for the others. This was confirmed by Lowenkamp et al. (2003) and Miethe et al. (1991), who also showed that the number of people living in a single room had a positive impact on crime, even when income was controlled for. See also Glaeser and Sacerdote (1999) for the effect of urbanization on crime. That access to resources also plays an important role in this theory is emphasized by Zhang (1997), who showed that various welfare programs, like housing or cash dispersion, can significantly lower crime. The same was shown more recently by Mesters et al. (2016). The effect of marital status on crime has also been confirmed (Kposowa et al. 1994, Sampson, Raudenbush, et al. 1997). Barnes et al. (2014) however found that there exists some simultaneity in this relationship, i.e. that criminal offenders are also a lot less likely to get married, so that the real effect marriage has is much lower than previously estimated. In theory, marital status also matters, as two people can share the responsibility of looking after children and earning a living, leading not only to higher household incomes, but also more social control of children. This is why many authors like Kposowa et al. (1994), Miethe et al. (1991) or Sampson and Groves (1989) also include female labor-force participation rates as an exogenous variable in their estimations, since the tasks of looking after the children traditionally falls on women. In this context, the controversial article by Donohue and Levitt (2001) should also be mentioned. They argue that the falling crime numbers in the US during the late nineties are largely due to the legalization of abortions two decades earlier; an hypothesis that unfortunately can't be tested with the data-set at hand due to its time-frame.

As the social disorganization theory is well-studied and usually has a lot of explanatory power, it seems like a natural extension of the basic Becker-Ehrlich model presented before, especially as I see no reason why these two theories should be mutually exclusive. The obvious problem of using social organizational theory in empirical research is that it relies entirely on latent variables, for which proxies have to be found. This is the reason why most of the work presented up to now relied on survey data. However, Entorf and Spengler (2002) used administrative data to test this theory for various European countries, and found it largely confirmed. They didn't explicitly control for variables of "social cohesion", i.e. strength of social networks and participation in clubs etc., arguing that this was in turn determined by the socio-economic and demographic variables they did control for. More recently, Birkel (2015) used a similar set-up and found similar results for Germany. One interesting difference between these European studies and those using US data is that in the US, authors tend to use racial heterogeneity as a proxy for ethnic diversity, while in Europe most authors use the share of foreign nationals living in the area. This is likely due to data availability, but possibly also because of the different histories of migration in the two regions. The effect of migration on crime in Germany was also recently studied by Piopiunik and Ruhose (2017), whose results would suggest that migration does indeed causes an increase in crime. They found this by exploiting the natural experiment of the migration of Germanic Russians ("Russlanddeutsche") in the 1990's. However , similar studies by Bianchi et al. (2012) for Italy or Bell, Fasani, et al. (2013) for the U.K. found no or only weak effects on crime caused by migration.

Closely related to this theory is the concept of "social capital" affecting crime, an idea introduced by Knack and Keefer (1997). Here, social capital means civic norms, general trust and social networks, and it is easy to see how these might lower crime. This is especially well studied for violent crime (Rosenfeld et al. 2001, Fajnzylber et al. 2002 etc.), where social capital is measured by various proxies such as charitable giving or participation. Buonanno et al. (2009) obtained good results using among others voter-turn-out during referenda as a proxy for this when fitting their spatial model.

2.3 Routine Activity Theory

Another well-known sociological theory of crime in places is the so-called "routine activity theory", first laid-out by Cohen and Felson (1979). It is based on the simple premise that, for a crime to take place, three components need to come together at the same place and time: First, a person willing to commit a crime for some reason, second, a victim this crime can be successfully committed against, and thirdly a lack of oversight from third parties, like the police or the community. With regards to the last component, there is obviously some overlap with the "social disorganization theory" mentioned above. Cohen and Felson argue that the co-occurrence of these conditions would depend largely on the daily routines of the people in that area. To test this, Messner and Blau (1987) used the amount of time people spent watching TV in an area as a proxy for how much of their leisure time was spent at home. The idea is that people were less likely to become victims to various crimes that depend on the victim not being at home, like theft, robbery, burglary etc. Other variables they use for measuring how much of people's leisure-time is spent outside are attendance at cinemas, sport-events, church and clubs. This poses an obvious problem when trying to incorporate both this and the social disorganization theory into a single model, as both use attendance at clubs etc. as proxies, but want to measure different things and expecting opposite signs of the coefficient. Therefore, other authors have used different variables to measure the crime opportunities, such as bar attendance (Liu and Zhu 2017) or tourist activity (Tarling and Dennis 2016 among many others).

For the other components of this model, i.e. willingness to commit a crime and supervision by "guardians", Messner and Blau, and many authors after them, use the socio-economic variables we have seen before, like unemployment, GDP, racial heterogeneity, age-structure of the area etc. Within this context, Cantor and Land (1985) argue that unemployment has a two-fold effect. For one, since people in a high-unemployment neighborhood are poorer, there are less viable victims of property crimes, and since they are usually home more, there is also more supervision. On the other hand, unemployed people also have more incentives and time to commit a crime themselves. Cantor and Land further argue, that these two effects differ in the time they take place to manifest, i.e. that the increased supervision happens instantly, while the higher motivation to commit a crime is delayed. Therefore, by the inclusion of a lag term, the two effects could be differentiated. This theory was recently tested by Ha and Andresen (2017) and largely confirmed, which could also explain, why many other studies have found only insignificant relationships between crime and unemployment (see Entorf 2008 for example).

As we could see, the real practical difference stemming from this model is that it also looks at the victim of a crime and the variables that led to this victimization. Other than the issue regarding club-attendance etc., the routine activity and social disorganization theories are surprisingly compatible. Therefore, I don't see a problem in incorporating them both into my model. Especially, as both have been empirically tested many times. Recently, the seminal study by Messner and Blau on routine activity was replicated by Miller (2013) and their findings where largely confirmed. Miethe et al. (1991) however found that the social disorganization theory performed better in their data-set of crime in US-cities.

Closely related to the routine activity theory is the so-called "broken window" theory of crime. This theory is interesting, as it is not as well studied by academics and yet very influential in law enforcement, especially in the US. The name goes back to a news magazine article by Wilson and Kelling (1982), where they argue, that on a community level "crime and disorder are usually inextricably linked"(p.2). The idea is that small misdemeanors, like smashing in a window, create an environment which breeds more serious crime. This article was largely ignored by academia, but not by New York law enforcement, who implemented a strategy based on this theory for their subway system. They focused on restoring "order" in the subway, i.e. on removing graffiti, litter and dirt. The resulting drop in crimes like theft, robbery and even murder (Kelling and Coles 1997) got noticed by many police departments in the US, who as a result often implemented their own "broken window"-strategies. See also Kelling (2015) for a short history of this idea. In the meantime, Keizer et al. (2008) conducted a series of controlled experiments in a now famous study, where they showed graffiti, litter and other signs of disorder to have a significant effect on rule-violating and criminal behavior, ranging from not returning a shopping cart to theft. So while there is a lot of quite robust evidence for this theory on a small scale, this is often ignored on larger-scale studies. One exception is the paper by Liu and Zhu (2017), who used the endogenous variables of vehicle theft and burglary, and found them to be causally linked, even while not explicitly citing the broken window theory.

2.4 Spatial Patterns of Crime

That spatial interaction effects in fact exist with crime was shown many times for different units of observation and different geographic areas. One early example is the paper by Morenoff and Sampson (1997), who looked at crime rates in Chicago spanning two decades and found spatial autocorrelation for homicide rates and poverty, resulting in clusters of poor, crime-ridden neighborhoods, especially at the edges of the city. A little later, Messner, Anselin, et al. (1999) also found spatial autocorrelation of homicide-rates in cities by using exploratory pattern detection techniques. While these works showed convincingly that there exist spatial effects regarding crime, it is important to note here, that this happens in a purely descriptive manner, i.e that these works only showed that crime rates in one area have an effect on the crime rates in neighboring ones.

Most research trying to explain these patterns relied on one or more of the theories mentioned above, either implicitly or explicitly. An early example is Morenoff, Sampson, and Raudenbush (2001), who try to predict murders in Chicago neighborhoods. They draw on the social disorganization theory, but argue that it is not enough to look at social cohesion inside arbitrary borders but that neighborhood are interdependent instead. To model this, they include a spatial lag of the dependent variable (SAR-model), and use Bayesian techniques to estimate it. As expected, they found the coefficient corresponding to the spatial-lag term to be highly significant. In this vein, quite a lot of researchers looked at crime in a specific city or even city-district to get very granular data while losing some generality. Andresen (2006) examined various types of crime in Vancouver with a spatial error model (SEM), combining the social disorganization and routine activity theories. Here, the spatial dependence of the endogenous variable is just controlled for and not explicitly modeled, but their findings are overall as expected and confirm previous research on the matter. One surprising result, however, is a negative relationship between ethnic heterogeneity and both car thefts and violent crime. The authors explain this with the specifics of immigrant settlement patterns in Vancouver and don't expect it to be generally true. Other examples for such studies, which mostly found very similar results, are Kershaw and Tseloni (2005), Breetzke (2008), Liu and Zhu (2017), Andresen and Malleson (2013) and many others. In this context I should also mention the study by Weisburd et al. (2006), who looked at crime in Jersey City (USA) to see whether a policing strategy focusing on hot-spots actually lowered crime overall or simply displaced it into another part of the city. If this were the case, we would expect a negative spatial autocorrelation of crime, i.e. a decrease of crime in one area leading to an increase in a neighboring one. However, Weisburd et.al. found no evidence for this.

A lot rarer are studies, which cover an entire country. This is largely due to a lack of available data. Given that any data is available, usually this data is less granular. To the authors knowledge, county level is the smallest unit of observation used by such studies.

One early example is the work by Baller et al. (2001), who studied homicides in the US over a long time-frame (1960-90). Not only did they discover significant spatial dependence in the data, they also found the model to be instable in both the time and the spatial dimension. For example, they found different signs for coefficients when looking at different subsets of the data, for example the South compared to the northern parts of the US, or different decades. For Europe, noteworthy studies include the one by Cracolici and Uberti (2009), who studied crime in Italy and the paper by Hooghe et al. (2010), studying crime in Belgium. Both of which used a SAR-model and draw on the social disorganization theory to explain regional variation of property and violent crimes. One interesting result by Hooghe et.al. is the significant negative relationship between inequality and both violent and property crimes. In a similar fashion, Tarling and Dennis (2016) look at crime in Great Britain. However, they use a non-spatial multilevel-model for this, arguing that this is enough to account for spatial auto-regression, an assumption I find questionable for the reasons discussed in Chapter 3. Interestingly, they found that areas with a high degree of transients, i.e. people working in an area in which they do not live, has a positive effect on both violent as well as property crimes. Torres-Preciado et al. (2015) use county-level data from Mexico to explore the relationship between GDP and crime, which, as many researchers before have found, is bi-directional (see Arvanites and Defina 2006 and for Germany Entorf and Spengler 2002). For this they use a spatial durbin model (SDM).

For Germany, I know of only three attempts of using spatial techniques to study crime. One is the study by Oberwittler and Gerstner (2011), who look at crime in the state of Baden-Württemberg from 2003-2007 in a mostly descriptive manner. They apply various measures of spatial autocorrelation and cluster analysis to describe crime patterns and patterns of its covariates. They also use regression analysis, but for some unexplained reason use weighted OLS, which, given the spatial patterns they found, is sure to give biased and inefficient results, as will be shown in the next section. The second is the study by Ceccato and Oberwittler (2008), who used robbery data for the city of Cologne to compare it to Tallinn in Estonia, where they find little structural difference, which supports the possibility of a "generalizable" spatial theory. However, since they found significant spatial dependence only in Tallinn and not in Cologne, they use a non-spatial OLS approach for this city. However, these findings might also be explained by their usage of a different kind of spatial weight matrix for each city. Non-the-less, this lack of spatial dependency in Cologne goes contrary to those found by most researchers in other cities. Lastly, the study by Messner, Teske, et al. (2013) comes closest to my own attempt to study spatial patterns of crime. They also use county level panel-data and employ spatial regression techniques to fit a model based on a combination of routine activity theory. However, they look at just two types of crime, robbery and assault, and over a relatively small time-frame, 2005-2007. Their approach also differs from mine, as they use a SEM for their regressions. Here they control for spatial correlation in the error term, but fails to actually explain it. As we will see, by using a SDM, we gain a lot more insight into the actual workings of spatial transmissions. Also, while having controlled for variables related to social disorganization and routine activity theories, the authors do not incorporate the rational choice theory by Becker-Ehrlich nor do they control for autocorrelation within crime according to the broken window theory. Yet, while I would not call their results definitive for these reason, they can serve as a comparison against the results of my own study. Their study is also interesting, as it is one of the few I know of that includes interaction effects in their regressions.

2.5 Hypothesis

Variable	Latent Variable	Theory	Source
GDP per capita	Illegal income opportunities	Becker-Ehrlich	Entorf and Spengler (2000) etc.
CPI, other price indices	Illegal income opportunities	Becker-Ehrlich	Draca et al. (2015)
Unemployment rate	Legal income opportunities	Becker-Ehrlich	Entorf and Spengler (2000) etc.
Youth unemployment	Legal income opportunities	Becker-Ehrlich	Grönqvist (2013) etc.
Median Wage	Legal income opportunities	Becker-Ehrlich	Entorf and Spengler (2000) etc.
Gini-coefficient	Legal income opportunities	Becker-Ehrlich	Fajnzylber et al. (2002) etc.
Bankruptcies per capita	Legal income opportunities	Becker-Ehrlich	Birkel (2015)
Clearance rates	Probability of getting caught	Becker-Ehrlich	Draca et al. (2015)etc.
Number of police	Probability of getting caught	Becker-Ehrlich	Wilson and Boland (1978) etc.
Electoral cycles	Probability of getting caught	Becker-Ehrlich	Levitt (1995)
Conviction rates	Probability of getting caught	Becker-Ehrlich	Entorf and Spengler (2000) etc.
Average Sentence	Cost of getting caught (F)	Becker-Ehrlich	Wolpin (1978) etc.
Prison Population	Cost of getting caught (F)	Becker-Ehrlich	Han et al. (2013)
Lag of deterrence vars.	Cost of getting caught (F)	Becker-Ehrlich	Sah (1991)
Population density	Urbanization	Social Disorganization	Hooghe et al. (2010) etc.
Share of foreigners	Ethnic diversity	Social Disorganization	Hooghe et al. (2010) etc.
Index for racial heterogeneity	Ethnic diversity	Social Disorganization	Morenoff and Sampson (1997)
Welfare spending	Access to resources	Social Disorganization	Birkel (2015) etc.
Divorce rates	Family disruption	Social Disorganization	Kposowa et al. (1994) etc.
Female labor force participation	Lack of parental control	Social Disorganization	Kposowa et al. (1994)
People per room	Family disruption	Social Disorganization	Miethe et al. (1991)
Voter turn-out	Social capital	Social Disorganization	Buonanno et al. (2009) etc.
Unemployment	Guardianship	Routine activity	Andresen (2006) etc.
Number of police	Guardianship	Routine activity	Andresen (2006) etc.
Tourist activity	Criminal Opportunity	Routine activity	Tarling and Dennis (2016) etc.
TV ratings & watch time	Criminal Opportunity	Routine activity	Miller (2013) etc.
Bar attendance	Criminal Opportunity	Routine activity	Liu and Zhu (2017) etc.
Lag of unemployment	Motive	Routine activity	Ha and Andresen (2017)
Graffiti & Litter	Disorder	Broken Window Theory	Keizer et al. (2008) etc.
Years of schooling	-	-	Åslund et al. (2015) etc.
Share of young people	-	-	Hooghe et al. (2010) etc.
Share of male inhabitants	-	-	Piopiunik and Ruhose (2017) etc.
Dummies for south and east Germany	-	-	Messner, Teske, et al. (2013)
Dummies for border region	-	-	Oberwittler and Gerstner (2011)

Table 1: Exogenous variables used in various studies, by theoretical background

Before formulating my hypothesis, I will give a short overview of what explanatory variables I could use for my model, based on the research mentioned above (Table 1). This list is not exhaustive, and will for example exclude those based on survey-data. In order to save space, I also include only one source per variable, even though many are used by several authors, a fact I indicate with "etc." It would be naive to just include all proposed variables into a model, as this would likely lead to multi-collinearity, since many are measuring the same thing. Therefore, a selection has to be made. Based on this previous research and the data available for Germany (see Chapter 4), I would expect the following hypotheses to hold true.

- **H1:** Following Becker (1968) and Entorf and Spengler (2000), I would expect the clearance rates and efficiency of the judiciary to negatively impact crime rates while unemployment and per capita GDP should have a positive impact. Inequality or median wages should also have a positive impact. Also, these relationships should be weak or non-existent for non-for-profit crimes like assault, as they are almost always irrational. If Sah (1991) is right, including a time lag of the deterrence variables should increase the explanatory power of the model.

- **H2:** According to the social disorganization theory, I would expect population density, share of non-citizens and divorce rates to have a positive impact on crime rates. Also, assuming that these variables don't entirely account for social cohesion, I will use voter turn-out as a proxy for how close the ties to the community are. I would expect this to negatively impact crime.

- **H3:** Due to the research on the routine activity theory, I would expect unemployment to have a negative effect on crime and lagged unemployment rates to have a positive one. This is obviously not compatible with H1, so we will have to see which performs better. Also, I would expect tourist activity to have a positive impact on crime, while a proxy for the number police deployed should have a negative one.

- **H4:**From the broken-window theory, I would expect minor crimes, like damage to property or drug offenses, to cause more major crimes.

- **H5:**Lastly, I expect there to be spatial dependence of both the ex- as well as the endogenous variables. Specifically, I expect there to be spatial autocorrelation for all types of crime, as these are well known to exhibit such behavior. I would also expect spatial dependencies among explanatory variables like unemployment, which should be modeled explicitly. Since we can't expect spatial dependency to stop at the national border, but our data-set is only for Germany, I've included border-dummies as explanatory variables. This would also be in line with much anecdotal evidence, which states that crime is higher in regions at the border, especially at the border to eastern European countries. If this is the case, we would expect this effect to trickle down through the counties, which is why I've also included a spatial lag of these dummies.

These hypotheses lead to a model of the form:

$$Y_t = \rho W Y_t + \beta X_t + \gamma W Z_t + \theta A_{t-1} + \zeta W B_{t-1} + u_t. \tag{2.5.1}$$

Here, Y_t denotes the vector of crime rates in the 402 counties at time t. W is a row-standardized spatial weight matrix with a zero diagonal, which, if multiplied with a vector or matrix of variables creates a spatial lag of these. X_t includes all explanatory variables at point t, Z_t those where I want to include a spatial lag, but not a temporal one. A_{t-1} includes the temporally lagged variables, and B_{t-1} those where I want both a temporal and a spatial lag. This model is a variant of the spatial durbin model (SDM), the properties of which I will examine in the next chapter. Since the Becker-Ehrlich model requires it and to somewhat account for other non-linear behavior I will use logs of all variables except for the dummies.

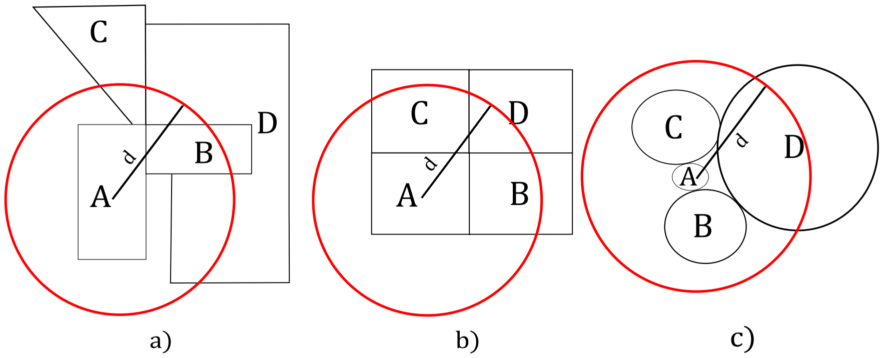
3 Methodology

Before a detailed discussion of the specification and estimation of the SDM, I will give a short overview of the exploratory spatial and non-spatial techniques I used to discover patterns and to validate my model choice. I will also mention when I have used user-written commands for STATA 13, the software utilized to obtain all of my results. The complete code can also be found on the CD accompanying this thesis.

3.1 Spatial Weight Specification

At the core of all spatial techniques must lie a definition of neighborhood. This determines how the spatial weight matrix W is formed, and, more importantly, what question exactly is answered by our model. In general, there are two different approaches to define neighborhood, either over some measure of distance or over political borders, i.e. contiguity. For an example of the differences, see Figure 1 and for a more complete overview see Anselin (2002). Here, I will only focus on the most commonly used specifications, *first-order contiguity*, *binary distance* and *inverse distance* based weights.

The easiest way to define neighborhood, and therefore the often used default, is the first-order contiguity definition. This simply sets $w_{ij} = 1$ if i and j share a common border and zero otherwise, i.e. also if $i = j$. The advantage of this definition is clearly it's simplicity, but also that it doesn't create "islands", i.e. regions not neighboring any other region, unless they are literal islands or exclaves. Another advantage is that it defines neighborhood in a clear and unambiguous way, even though some variants like "rook" and "queen" contiguity exist (see Figure 10 in the Appendix A). The disadvantage is that it relies only on arbitrary and for the normal person mostly meaningless political borders, which might not describe the reality accurately. Also, it might not be a good fit when looking at the policy implications of crime, as for example police districts often span over



After Getis (2009), own representation

Figure 1: Difference between contiguity and distance based spatial weights

several counties. Another drawback is that it does not work well with geographic units of very different sizes and shapes, as can be seen in Figure 1.
In this example, a contiguity-based weighting matrix would look exactly the same in all three instances, while a distance based weight matrix would look different in each case, as can be seen for instance below. This problem, also called "topological invariance" (Getis 2009, p. 405), makes contiguity based matrices a bad choice for regions of varying shape or size.

$$\begin{array}{cc} & \begin{matrix} A & B & C & D \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \end{matrix} & \begin{bmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \end{array} \quad \begin{array}{cc} & \begin{matrix} A & B & C & D \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \end{matrix} & \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \end{array} \quad \begin{array}{cc} & \begin{matrix} A & B & C & D \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \end{matrix} & \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Contiguity weights, all cases *Binary distance weights, case a)* *Binary distance weights, case c)*

(3.1.1)

It would therefore be reasonable to assume, that distance based weights are strictly better suited for my study. The most common specification is setting $w_{ij} = 1$ if $d_{ij} < r, i \neq j$ and zero otherwise, which results in binary distance-cut-off based weights. This comes with new challenges, however. For one, it has to be decided how the distance d is defined exactly. A logical starting point is to measure the euclidian distance from the geographical center of each region. But as we can see in case a) from the example above, finding this center of arbitrarily shaped region is not as simple as just taking the average of the x- and y-coordinates of the border. Doing so could easily result in a point which is not part of the region itself, which would for example be the case for region D in case a). Instead, one could measure this distance from the center of mass or centroid of a region, i.e. the average of *all* points of the plane. For this, I use the `gencentroid` option of the `shp2dta` STATA-command by Crow (2015). The other drawback of binary distance based weights is that they require a cut-off point r. Choosing too short a distance for this would result in many "islands", i.e. regions neighboring no-one else, while too long a distance would dilute the definition of neighborhood, so that inference would be more difficult. One popular solution is to set the cut-off point by finding first the minimum distance from each region j to all other regions, and out of these the maximum, i.e:

$$r = \max_i\{ \min_j\{d_{12}, ...d_{1j}, ...d_{1n}\}, ... ,\min_j\{d_{i1}, ...d_{ij}, ...d_{in}\}, ...\}, i \neq j. \tag{3.1.2}$$

Defining r in such a way ensures that each region has at least one neighbor without the cut-off distance being too large in most cases, unless areas vary widely in size. But even this can't remedy the problem of arbitrariness completely. An alternative would be to use the inverse distance function as weights, i.e. set $w_{ij} = \frac{1}{d_{ij}^2}$, similar to a gravity model in trade economics. This would not require a cut-off point, as the weights approach zero as the distance grows larger, but due to its exponential nature, this specification is sensitive to the unit of measurement. And since here W would contain $(N-1)$x$(N-1)$ non-zero weights, it is computationally more intensive and can lead to problems regarding identification, as it will likely result in models containing more than N parameters to be estimated (Anselin 2002).

There is little formal guidance on how to choose "correct" spatial weights, as Anselin (2002) points out. There are some cross-validation and goodness-of-fit approaches (e.g. Wang et al. 2013, Samper and Neuman 1989), and some that use data-driven techniques to build a spatial weight matrix (e.g. Bhattacharjee and Jensen-Butler 2013, Getis and Aldstadt 2010). However, since the specifications discussed above are only a fraction of those proposed in literature, these procedures can also not be much more than a crutch. LeSage and Pace (2014) argue, that as long as two weight matrices are similar enough, they will lead to very similar result, something that has been validated in simulation studies, for example by Stakhovych and Bijmolt (2009) or Wang et al. (2013). Theoretically, a wrong specification can lead to bias and inefficiency when estimating a model containing spatial lags (but not when estimating a SEM). But LeSage and Pace find both theoretically and in simulations, that even grossly miss-specifying W changes the resulting estimates very little. They therefore call model sensitivity to W a "myth", and attribute those findings that would suggest otherwise to mis-interpretation of parameters instead. This of course assumes that W and the true weights are at least somewhat similar. To check this, they use the Bravais-Pearson correlation of the spatial lag of some randomly generated variable, i.e. $corr(uW_a, uW_b)$, where u is a randomly generated 1xN vector. I will follow this approach trying the three most commonly used and simplest weight matrix specification, queen contiguity, distance cut-off and inverse distance squared as described above. If I indeed find the resulting matrices to be similar, I will use queen contiguity weights for my estimations, as they are the simplest of them all. For comparability, and ease of interpretation, I will in use the row-standardized versions in all three cases. Here, each weight w_{ij} is divided by the row-sum of all weights, $\sum_{j=1}^{n} w_{ij}$, so the weights associated with each region i will add up to one.

3.2 Measures of Spatial Autocorrelation

Having discussed a definition of neighborhood, and before proceeding with any estimations, I should first see whether spatial dependency actually exists in my data. From the econometric perspective, spatial dependency is a kind of autocorrelation, as it describes a situation where the value of some variable for region i correlates with that of it's neighbor j in a systematic manner. From the economic perspective, this is an externality, as decisions made in region i also effect region j and the other way around. In some ways, this resembles an autoregressive (AR) process in time-series econometrics, but with the crucial difference, that it is bi-directional. With time-series, y_{t-1} can affect y_t, but for logical reasons not the other way around. In the spatial context, we have to assume that the relationship goes both ways, which in turn leads to feedback loops, as some event in region i impacts region j which then in turn affects region i again. And, assuming j is a neighbor of region k, while i isn't, we also have higher order effects, as some change in i affects j which then impacts both i and k which in turn again affect j etc. For a visulization of these feedback loops see Figure 12 in Appendix A. I will go into further detail about how to estimate marginal effects in the presence of these feedback loops later in this chapter, for now I will focus on how this kind of autocorrelation can be detected.

Since I am using a SDM, I have to test for the presence oft spatial dependency of both the endogenous as well as the spatially lagged explanatory variables. To do so, I will employ three methods. First, I will visually check a map of the the quartiles for these variables, to see what pattern emerges. If the patterns emerging from this are anything but completely random, we can assume that some form of spatial dependence of either the variable itself or some covariate exists, as the assumption of $Cov(u_i, u_j) = 0$ seems to be violated for the case where i and j are neighbors and $u_i = y_i - E(y_i|x_i)$. Secondly, I will use two formal tests for spatial dependence, global and local Moran's I.

Moran's I, first proposed by Moran (1950), is an indicator for the existence of global spatial autocorrelation and is in fact quite similar to the conventional Bravais-Pearson correlation measure. In the denotation by Getis (2010), it looks like this:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(y_i - \bar{y})(y_i - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad , \quad i \neq j. \tag{3.2.1}$$

This is of course simply the (spatially) weighted Covariance of y_i, y_j, scaled by

$$\frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}}[\frac{1}{Var(y_i)}]. \tag{3.2.2}$$

to make it comparable. As shown by Moran, the expected value of this expression, given the H_0 of spatial randomness, is $E(I) = -1/(N-1)$. Given this, and since the Lindeberg-Levy CLT applies, due to I relying purely on the first and second moments of $y_{i/j}$ and their linear transformations, we can easily derive a test of spatial auto-correlation from this. Formally:

$$\frac{I - E(I)}{[Var(I)]^{\frac{1}{2}}} \overset{as.}{\sim} N(0,1). \tag{3.2.3}$$

And while this is quite straight-forward, finding the standard deviation of I is less simple. The STATA-command I use for calculating Moran's I, `spatgsa` by Pisati (2001), calculates the standard deviation under the "total randomization assumption", for details see Cliff and Ord (1981) or Sokal et al. (1998). The resulting statistic not only tells us whether we have spatial autocorrelation, but also whether the correlation coefficient is positive or negative. This matters, since this determines the pattern resulting from spatial autocorrelation. As can bee seen in from the stylized representation of Figure 11 in Appendix A, positive spatial autocorrelation leads to large geographic clusters of high- or low values (associated with $I - E(I) > 0$) whereas negative spatial dependency leads to a kind of chess-board pattern with high value areas right next to low value ones. In the case of positive autocorrelation however, Moran's I doesn't say anything about what kind of clusters exist, i.e. whether they are high or low value clusters, or both.

It is necessary for the estimation of a SDM that the sign of the correlation coefficient is the same for all regions. If it is not, our estimation will fail. Since I have panel data, I therefore either look at these statistics for each year or use averages over all periods, as appropriate. To check for stability of the spatial dependency and for outliers, I use a Moran scatterplot and box-plots of the local Moran's I as proposed by Anselin (1995). The main difference between the local Moran's I and the global variant is that here we look at single observations and it's neighbors. As a result, we deal with rather small N, therefore the asymptotics used for the test above don't work as well. To correct for this and the multiple testing problem, I use Bonferroni-bounds when assessing significance, as proposed by Aldstadt (2010). Other than this, the two measures are identical in interpretation, as can also be seen from the fact, that the global statistic is simply the average of all local Moran's Is, since it is given by:

$$I_i = \frac{y_i - \bar{y}}{\frac{1}{N}\sum_{i=1}^{N}(y_i - \bar{y})^2} \sum_{j=1}^{N} W_{ij}(y_i - y_j). \tag{3.2.4}$$

3.3 Spatial Patterns and Clusters

As mentioned before, Moran's I does not tell us whether we have high or low value clusters. For this, I use a second statistic, the local Getis-Ord G, first proposed by Getis and Ord (1992). This statistic does not tell us whether we have positive spatial autocorrelation, but rather where we have it. In other words, Getis-Ord G is able to find clusters of high and low values, also called hot- and cold-spots. It does so by comparing the average of some variable within a neighborhood to the over-all average (or theirs sums, as $\frac{1}{N-1}$ obviously cancels out):

$$G_i = \frac{\frac{1}{N-1}\sum_{j=1}^{N} w_{ij}y_j}{\frac{1}{N-1}\sum_{j=1}^{N} y_j} \quad , \quad i \neq j. \tag{3.3.1}$$

As $E(G_i) = \frac{1}{N-1}\sum_{j=1}^{N} w_{ij}$, and with the same reasoning as before, we can again build a test statistic, although with a different set of hypotheses. While with Moran's I we had a H_0 of spatial randomness, here, we have a null-hypothesis of spatial randomness *or* negative spatial dependencies. H_1 is positive spatial autocorrelation with either high or with low clusters, depending on the sign of the test-statistic, which is constructed like this:

$$\frac{G_i - E(G_i)}{[Var(G_i)]^{\frac{1}{2}}} \overset{as.}{\sim} N(0,1). \tag{3.3.2}$$

Since w_{ij} is the ij-element of the spatial weight matrix W, it is only not equal to zero if i and j are neighbors. In the normal version, w_{ij} is also zero if $i = j$, like in any normal spatial weight matrix. Getis and Ord (1992) however also include a second measure they call G^*, where $w_{ij} = 1$ if $i = j$. The reasoning for this is that it would better detect clusters, as it now includes the pivotal region i for which neighborhood is defined. Since I'm interested in this statistic only for cluster detection, this is the version I will use. As this is a local statistic, it comes with the same issues as the local Moran's I, which is why I will also use Bonferroni-bounds when making inferences (see Sokal et al. (1998)). However, Getis-Ord G requires unstandardized weights, so I can't use the same W here I use for the rest of my calculations.

Since Getis-Ord G allows me to find crime hot- and cold-spots associated with positive spatial autocorrelation, it would further be interesting to explore whether there exists a relationship between crime hot-spots and clustering structurally similar counties. To find such clusters, I use non-spatial hierarchical cluster analysis using the non-deterrence related explanatory variables, following Oberwittler and Gerstner (2011). I will then use choropleth maps to compare the resulting pattern with the results from Getis-Ord's G.

As is likely understood by the reader, hierarchical cluster analysis is a way to find, in an exploratory manner, groups of observations that are in some way similar to each other and dissimilar to those in other groups. It does so by means of an algorithm, where at each step the two closest clusters are merged and then the distances re-calculated. The difference of various algorithms is how the distance of two clusters is calculated. There exist various approaches (see Rencher 2003), but I will focus on two methods, *average linkage* and *Ward*. The Ward method is generally thought to be the most robust overall, but is "space contracting", meaning that individual observations tend to join already existing clusters rather than forming a new one. This is also called "chaining" and can lead to big clusters with quite dissimilar members. Therefore, I will compare those with the results from a average-linkage procedure, which is also quite robust but "space-dilating". Following the advice of Rencher (2003), I will accept the results if they are mostly similar.

The difficulty with all clustering techniques is defining a stop rule, i.e. a rule where the algorithm stops and presents the clusters found at that point. Otherwise, hierarchical clustering algorithms will always end up with one cluster containing all observations, which is obviously useless. There are many possibilities how to define such a rule, but again, I will rely on two. For one I will use a dendrogram, which plots the measure dissimilarity for each step of the algorithm. A natural stopping point is a large jump in dissimilarity. I will compare the results of this graphical approach with the more formal one by Caliński and Harabasz (1974). They calculate a so-called "pseudo F"-index which seeks to minimize within-cluster sum of distance square while maximizing the between-cluster one. This is done for each step of the algorithm. And since there is obviously a trade-off between these two goals, the behavior of this pseudo-F is, in contrast to the measure of dissimilarity used in the dendrogram, no longer monotonic with a decreasing number of clusters. This let's us pick a good solution, which is associated with the lowest pseudo-F. But as this technique is exploratory, and too large a number of clusters makes it impossible to interpret the results, much of the decision where to stop is op to the researcher, with no clear "best" solution.

3.4 Regression Modeling

3.4.1 Panel SDM

As noted before, the equation 2.5.1 derived from my hypotheses is a spatial durbin model, depicted cross-sectionally. The data-generating process associated with it can be found by solving for y_t (see Anselin 1988, who also coined the term "spatial durbin model"):

$$y_t = \rho W y_t + \beta X_t + \theta W Z_t + \epsilon_t, \quad \epsilon_t \overset{i.i.d.}{\sim} (0, \sigma^2 I_N), \tag{3.4.1}$$

$$\Leftrightarrow y_t = (I_N - \rho W)^{-1}\beta X_t + (I_N - \rho W)^{-1}\theta W Z_t + (I_N - \rho W)^{-1}\epsilon_t. \tag{3.4.2}$$

For ease of notation, here the matrices X_t and Z_t already include the temporally lagged variables and X_t also a vector of ones for the constant terms. The distribution of the error term is of course just an assumption, which will need to be tested (see Section 3.4.2). It should also be obvious that, assuming equation 3.4.2 describes the true data-generating process, estimating a naive model like $y_t = X_t\beta + \epsilon_t$ would necessarily lead to omitted variable bias, since $Cov(X_t, WZ_t) \neq 0$ is very likely. Also, when re-defining the error term as $u_t = (I_N - \rho W)^{-1}\epsilon_t$, it is apparent, that the OLS-assumption of $Cov(u_{it}, u_{jt}) = 0$ is violated, as $u_{it} = f(\epsilon_{it}, \epsilon_{jt})$. OLS, given a SDM represents the true data generating process, would therefore also lead to inconsistent estimates, as it implies $E(X_t'\epsilon_t) \neq 0$, which would also mean that the estimate of the standard errors would be biased (Wooldridge 2010 and

Anselin 1988). Therefore using a spatial model in the presence of spatial dependencies is not a matter of choice, but rather of necessity.

But of course a SDM isn't the only possible choice when trying to control for these dependencies. Another often used model is the spatial error model (SEM). It is specified like so (LeSage and Pace 2009):

$$y_t = X_t\beta + u_t, \tag{3.4.3}$$

$$u_t = \lambda W u_t + \epsilon_t, \quad \epsilon_t \overset{i.i.d.}{\sim} (0, \sigma^2 I_N), \tag{3.4.4}$$

$$\Leftrightarrow y_t = X_t\beta + (I_N - \lambda W)^{-1}\epsilon_t. \tag{3.4.5}$$

As we can see, the SDM actually incorporates the SEM, but also models spatial dependency explicitly. The SEM has the great advantage that it does not need any assumptions on what the spatial autocorrelation process looks like, while coming with the disadvantage that it also doesn't tell us anything about it. However, as LeSage and Pace (2009) point out, even if the true data-generating process is the one of a SAR or SEM, estimating a SDM will result in inefficient, but unbiased and consistent estimators. Furthermore, since I have a fairly large number of observations, efficiency is less of a concern, as asymptotic behavior sets in.

Until now, I've only been concerned with *spatial* autocorrelation and heteroskedasticity. However, since I'm using panel data, I also have to deal with the temporal dimension. Because the cross-sectional dimension is more than an order of magnitude larger than the time dimension, possible miss-specifications are less critical here, but should obviously still be avoided. Since my model contains some time-invariant variables like dummies indicating border regions, a fixed effects (FE) approach is not feasible, as the FE-term would soak-up all time-invariant, region-specific effects. Also, since the time dimension T is relatively small, I could not rely on asymptotics when estimating these effects (see Elhorst 2010). Instead I will use a random effects (RE) approach. Here, a random region-specific variable c_i is introduced and a distribution assumed, usually $c_i \overset{i.i.d.}{\sim} N(0, \sigma_c^2)$. The model now looks like this (Bell and Jones 2015):

$$y_{it} = \beta_0 + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \sum_{k=1}^{K} \beta_k, x_{kit} + \sum_{j=1}^{N} w_{ij} \sum_{q=1}^{Q} \theta_q x_{qjt} + c_i + \epsilon_{it}. \tag{3.4.6}$$

Here $k \in K$ are all explanatory variables (including those lagged in time) and $q \in Q$ are those were we want to include a spatial lag, $Q \subseteq K$. This however comes with it's own set of problematic assumptions. For one, I have to assume that $Cov(x_{it}, c_i) = 0 \quad \forall t \in T$ (see Wooldridge 2010). This is quite a restrictive assumption, and is hard to justify only from theory. Instead, I will use the well-known test proposed by Hausman and Taylor (1981) to check whether this assumption is justified. As mentioned before, including time-invariant variables in an FE-estimation would result in multi-collinearity, therefore I will only use time-variate variables when comparing FE and RE. As will be shown, the test strongly rejects the H_0, suggesting an RE approach would lead to omitted variable bias (OVB). However, as discussed before, FE is not a valid alternative in my case. Therefore, I will use an approach proposed by Debarsy (2012) and Bell and Jones (2015) to deal with the issue of OVB. Here, the averages over time of each time-variant variable, calculated for each region, are added as explanatory variables to soak up any bias. This goes back to an idea of Mundlak (1978), who uses this for an auxiliary regression in a testing procedure. To explain why this controls for the OVB arising from using a pure RE model, consider a simplified version of my SDM with only one explanatory variable:

$$y_i = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 x_{it} + \beta_2 \bar{x}_i + \theta_1 \sum_{j=1}^{N} w_{ij} x_{jt} + \theta_2 \sum_{j=1}^{N} w_{ij} \bar{x}_j + c_i + \epsilon_{it}. \tag{3.4.7}$$

By defining $\beta_2 \equiv \beta_3 - \beta_1$, $\theta_2 \equiv \theta_3 - \theta_1$, where β_3, θ_3 are some new coefficients, and after some rearrangement, we get:

$$\begin{aligned} y_i = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_1 (x_{it} - \bar{x}_i) + \beta_3 \bar{x}_i + \theta_1 \sum_{j=1}^{N} w_{ij} (x_{jt} - \bar{x}_j) \\ + \theta_3 \sum_{j=1}^{N} w_{ij} \bar{x}_j + c_i + \epsilon_{it}. \end{aligned} \tag{3.4.8}$$

In a sense, we have now divided the effects of our variable into a *between* and a *within* effect. Here, the effect variation of x within a region and its neighbors over time has, is measured by β_1, θ_1 and the between-effect by β_3, θ_3. A FE-model would only take the within-variation into account, while all between-effects would be soaked up by the FE-term. With the same reasoning, this ensures that this model produces BLU estimations under the same assumptions needed for the FE-model, as all between variation is controlled for, leading to $Cov(x_{it}, c_i) = 0 \quad \forall t \in T$. This also makes intuitive sense, as the only thing that might correlate with the region-specific, but time-invariant term c_i are the region-specific, but time-invariant parts of x_{it}, that we have now controlled for explicitly. For a formal proof see Mundlak (1978). That the procedure deals with this problem effectively has also been confirmed via simulations by Bell and Jones (2015). However, it does not exclude all forms of OVB, as $Cov(x_{it}, \epsilon_{it}) \neq 0$ is still possible if important explanatory variables are excluded, but the same is true for a FE-model. An alternative to this approach would be using a FE model and then decomposing the FE-term as proposed by Plümper and Troeger (2007). But this has the disadvantage that it is much more computationally intensive and less easy to interpret. So, the model I will set forth to estimate looks like this:

$$\begin{aligned} y_{it} = \beta_0 + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \sum_{k=1}^{K} \beta_{1k}(x_{kit} - \bar{x}_{ki}) + \sum_{k=1}^{K} \beta_{2k}\bar{x}_{ki} \\ + \sum_{j=1}^{N} w_{ij} \sum_{q=1}^{Q} \theta_{1q}(x_{qjt} - \bar{x}_{qj}) + \sum_{j=1}^{N} w_{ij} \sum_{q=1}^{Q} \theta_{2q}\bar{x}_{qj} + c_i + \epsilon_{it}. \end{aligned} \tag{3.4.9}$$

Another complication that comes with using RE is the region-specific effect c_i must be assumed to be randomly distributed. This requires that the set of regions $i \in N$ can be treated as a random sample, the size of which could theoretically approach infinity (Elhorst 2010). Of course, my observations do not necessarily have to stop at the German border, it would be possible to include regions in other European countries, or in the whole world for that matter. In that case, $N \to \infty$ might be a reasonable approximation. But it would still be questionable, whether my sample is representative of the entire population. Unfortunately, there is not much one can do about this, but refer to the famous quote by Box and Draper (1987, p. 74): "all models are wrong; the practical question is how wrong do they have to be to not be useful". As we will see, my results are largely in line with what other authors have found for other countries, so I would argue that treating my selection of observations as a random sample is not too wrong to be useful. Another question is, whether assuming a normal distribution of the RE-term is justified, which I will discuss in the next section.

3.4.2 ML-Estimation

It should be obvious to the reader that the model in equation 3.4.9 can not be estimated using a least squares technique like OLS or FGLS. This is the case for several reasons. To mention just one, simply the inclusion $\rho W y_t$ causes OLS-estimates to be biased. To show this, consider a simple model that only includes this spatial lag, i.e:

$$y = \rho W y + \epsilon. \tag{3.4.10}$$

The OLS-estimator would then be $\hat{\rho}_{OLS} = ([Wy]'Wy)^{-1}[Wy]'y$. By solving equation 3.4.10 for y we get (Anselin 1988):

$$\begin{aligned} \hat{\rho}_{ols} &= ([Wy]'[Wy])^{-1}[Wy]'(\rho W y + \epsilon), \\ \Leftrightarrow \hat{\rho}_{ols} &= \rho + ([Wy]'[Wy])^{-1}[Wy]'\epsilon, \\ \text{with } & E[([Wy]'[Wy])^{-1}[Wy]'\epsilon] \neq 0, \\ \text{since } & E([Wy]'\epsilon) = E([W(I - \rho W)^{-1}\epsilon]'\epsilon) \neq 0. \end{aligned} \tag{3.4.11}$$

As the last term is not equal to zero unless $\rho = 0$, the estimator is biased. In contrast to the AR(1) model in time series econometrics, $\hat{\rho}_{ols}$ is also not consistent, since $plim \frac{1}{N}[Wy]'\epsilon \neq 0$ (see Anselin (1988)). The same is true for FGLS, as the first step, finding an estimator for the variance-covariance matrix Ω, would require an unbiased and consistent estimator for ρ, which isn't possible via OLS, as just shown. A 2SLS approach is also not an option, as it would require finding an instrument for y_t that doesn't exhibit spatial dependencies, and I can't think of such an instrument in my case. Instead, as is usually done in spatial econometrics, I will use a maximum-likelihood estimation for my estimations.

Of course, the ML approach requires us to define a conditional likelihood function of y_{it}. Let us assume $\epsilon_{it} \overset{i.i.d.}{\sim} N(0, \sigma_\epsilon^2)$. With this, and since we have assumed $c_i \overset{i.i.d.}{\sim} N(0, \sigma_c^2)$, we can redefine the error term as $\epsilon_{it} + c_i = u_{it}$, which will also be normally distributed with mean zero. And, since we assume independence of the error terms, we know that y_{it} is conditionally normal distributed as well. From that we can construct a conditional log-likelihood function as a joint normal distribution like below, see Elhorst (2003) for a formal derivation :

$$\begin{aligned} \ln L = -\frac{NT}{2}\ln(\pi\sigma_\epsilon^2) + \frac{N}{2}\ln\theta^2 + T\sum_{i=1}^{N}\ln(1-\rho\sum_{j=1}^{N}w_{ij}) - \frac{1}{2\sigma_\epsilon^2}\sum_{t=1}^{T}e_t'e_t, \\ \text{with } e_t = (I_{NT} - pWI_T)y_t - Z_t\delta, \quad \text{and } \theta^2 = \frac{\sigma_\epsilon^2}{T\sigma_c^2 + \sigma_\epsilon^2}. \end{aligned} \tag{3.4.12}$$

Here Z_t includes all exogenous variables (including spatial lags etc.) at point t and the vector δ all corresponding coefficients. For a detailed discussion on the properties of this log-likelihood function see Lee and Yu (2016) or Bekti and Rahayu (2013). Of course this assumes that the error term and the RE term are actually normally distributed. There is no theoretical reason to believe this is the case, making my estimator technically a quasi-maximum-likelihood estimator (see Wooldridge 2010). To check whether the assumption of normality is not "too wrong to be useful", I will plot the residuals e and use kernel density estimation (KDE) with an Epanechnikov kernel to see whether they are roughly normally distributed. See Li and Racine (2007) for a detailed discussion of KDE and the Epanechnikov kernel.

It is well understood that maximizing a conditional log-likelihood of this form must be done numerically. The `xsmle`-command by Belotti et al. (2017) uses the built-in `maximize`-function of STATA to do so. This utilizes by default a modified Newton-Raphson algorithm, see Gould et al. (2010) for details. This kind of algorithm can easily get stuck in non-concave areas. To prevent this, I also use the `difficult`-option of `maximize`. This changes the size of deviation in each iteration, in the hope this will make it less likely to get stuck. `maximize` also comes with its own procedure to find starting values. However, this approach did not work well in my case and tended to produce initial log-likelihoods to small for STATA to handle. I therefore developed my own two-step algorithm to find initial values. First, I set all coefficients to zero and the error- and RE-variances to 1. With this, I estimate my model for only two years. I then use the results from this preliminary estimation as initial values for the real estimation, which I found to work quite reliably. I should also note here that the `xsmle`-command requires a perfectly balanced panel, which is why I had to use some imputations, as will be discussed in the next chapter.

3.5 Direct, Indirect & Total Effects

Having estimated the model, I would now turn to the interpretation of the results. This is a bit tricky with SDMs however, as, since contrary to conventional linear models, $\beta_k = \frac{\delta y_{it}}{\delta x_{kit}}$ is no longer true. Therefore, the estimation results cannot be interpreted as the marginal effects anymore. The reason for this is the feedback mechanism I alluded to before. Since I assume spillovers from one region to another which are bi-directional, a change in region 1 has an effect on region 2 which in turn effects both region 1 and 3 and so on. These feedback-loops are infinite in theory, although the size of the effect decreases exponentially with each iteration. For a visualization see Figure 12 in the Appendix A. As a result, the marginal effect of some variable is no longer a scalar, but a matrix. Here, each row denotes all the different effects a marginal change of that variable has across all N regions. Formally, this matrix is derived as follows, starting with the SDM model in matrix form and neglecting the time-dimension for notational ease (LeSage and Pace 2009):

$$\begin{aligned} (I_N - \rho W)y &= X\beta + WZ\theta + \overrightarrow{1}_N\beta_0 + u, \\ \Leftrightarrow y &= V\sum_{k=1}^{K} I_N\beta_k x_k + V\sum_{q=1}^{Q} I_N\theta_q z_q + V\overrightarrow{1}_N\beta_0 + Vu. \end{aligned} \tag{3.5.1}$$

Here $V \equiv (I_N - \rho W)^{-1}$ and $\overrightarrow{1}_N$ represents a Nx1 vector of ones. By then defining $S_k(W) = V(I_N\beta_k I_N x_k + W\theta_k), \quad \theta_k = 0$ if $k \notin Q$, we can rewrite the model as:

$$y = \sum_{k=1}^{K} \begin{bmatrix} S_k(W)_{11} & S_k(W)_{12} & \dots & S_k(W)_{1N} \\ | & S_k(W)_{22} & \dots & S_k(W)_{2N} \\ | & & .. & | \\ - & - & - & S_k(W)_{NN} \end{bmatrix} \begin{pmatrix} x_{1k} \\ x_{2k} \\ . \\ . \\ x_{nk} \end{pmatrix} + V\overrightarrow{1}_N\beta_0 + Vu. \tag{3.5.2}$$

And while I have neglected the time-dimension in the notation above, these results do not change, as stacking the model above over all $t \in T$ does not change the essential structure of the model (see LeSage and Pace 2009, Elhorst 2003). Now we can easily see, that $\delta y_{it}/\delta x_{kit} = S_k(W)_{ii}$. This is the so-called direct effect and now includes the effect from the feedback loop. But, other than in a normal linear model, $\delta y_{it}/\delta x_{kjt} = S_k(W)_{ij} \neq 0$. This is the so-called indirect effect, i.e. the impact a change in region j has on i. This effect is non-zero even if i and j aren't neighbors due to the impact "trickling own" through the regions. Note that these effects include all higher order effects (see Figure 12 in the Appendix for a visualization of this process). As interpreting a NxN matrix is not very pleasant or useful, the effects are usually divided into direct effects (the main diagonal of

$S_k(W)$) and the indirect effects (the off-diagonal elements). By then averaging these effects across all regions, we get a good idea on what spatial spillovers exist. LeSage and Pace (2009) point out, that the indirect effects can be interpreted as the indirect impact *from* or *to* a region, since the $S_k(W)$ matrix is symmetric. Formally (LeSage and Pace 2009):

$$\bar{M}_{direct} = n^{-1}\text{trace}(S_k(W)), \tag{3.5.3}$$

$$\bar{M}_{total} = n^{-1}\overrightarrow{1}'_N S_k(W)\overrightarrow{1}_N, \tag{3.5.4}$$

$$\bar{M}_{indirect} = \bar{M}_{total} - \bar{M}_{direct}. \tag{3.5.5}$$

Of course, calculating direct and indirect effects in such a manner is not very practical and computationally hard, as it would require finding KxN! solutions. Instead, the `effects`-option of `xsmle` by Belotti et al. (2017) uses the Monte-Carlo approach laid out by LeSage and Pace (2009). This solves the main problem of calculating trace($S_k(W)$ and, as LeSage and Pace show, results in very little loss compared to the analytical solution laid out above. For details see also Barry and Pace (1999).

3.6 Further Specification Issues

Having thus found a technique resulting in interpretable estimates, I will shortly discuss further specification issues before turning to a description of the data set.
One of the problems that any kind of spatial technique comes with is the "modifiable area unit problem" (MAUP), also called "ecological fallacy". As mentioned before, the geographic scale of my observations is essentially arbitrary and dictated by the data available. I use county-level data, but there is no theoretical reason for not using street-level data instead for example. Hence, the level of aggregation is not theoretically determined and "modifiable" instead. As Openshaw and Taylor (1979), who also coined the term MAUP, show, different levels of aggregation of the same data can vastly change correlation efficients, as it can average away existing (co-)variance to different degrees. This obviously presents a problem, as it means that using a different level of aggregation can change the estimation results, i.e. introduce an "aggregation bias" (Haining 2010, p. 214).

Unfortunately, there is not much one can do about this as long as there is no individual data available and while still using regressions or other techniques relying on covariances. King (1997) proposed a method on how to dis-aggregate data to solve this problem. Unfortunately, this method is not applicable in my case, as it would require at least some lower-level data. Besides this, it is also controversial whether this method actually deals with MAUP effectively (Wong 2009). But not only is there no real solution to this problem, there is also no way of knowing whether this problem actually exists within my data and how serious it is. As a defense for proceeding anyway, despite this unsatisfying conclusion, I should note that the previous spatial studies on crime also had no solution for MAUP and mostly didn't even mention it.

Another source of miss-specification is non-stationarity. Stationarity means that the joint distribution of any subset of observations is identical, i.e that the data is homogenous (Anselin 1988). To test for stationarity, I use the well-known unit-root test by Breitung and Das (2005). This is a panel-data variant of the famous Dickey-Fuller test used in pure time-series. It tests the null-hypothesis of all panels containing a unit-root versus the H_1 of stationarity. For this, it essentially estimates the following equation and checks whether γ is significantly smaller than 1 (one-sided test):

$$y_{it} = \alpha_{it} + \gamma y_{it-1} + \epsilon_{it}. \tag{3.6.1}$$

As this is done using robust standard errors, this test also works under serial correlation of the error terms. Note that under H_0, all y_{it} have the same dependence on y_{it-1} across all regions, i.e. $\gamma_i = \gamma_j \geq 1 \quad \forall i \neq j$. There are other tests, like the one by Im et al. (2003), that don't need this assumption, i.e. allow for different dependencies in different regions. This however requires a larger time-frame than I have available. The test by Breitung is executed via the `xtunitroot breitung`-command built into STATA. As this test will show, non-stationarity in time is not a concern with my data, likely due to the relatively short time-frame.

Lastly, different kinds of endogeneity may lead to biased or inefficient estimates. One such source of endogeneity might be auto-correlation in the error-term. As I have explicitly modeled spatial autocorrelation, the only source of this could be serial correlation in the time dimension. As is likely understood by the reader, serial correlation of the error-term does not bias the results, but can make them inefficient. To test for this, I use a procedure proposed by Wooldridge (2010). Here, a regression of the first-differenced endogenous variables is estimated and it's residuals examined. As Wooldridge shows, in the absence of serial correlation $Cov(\Delta\epsilon_{it}, \Delta\epsilon_{it-1}) = -.5$ This can be tested via a simple t-test with the H_0 of no serial correlation. Note that clustered standard errors are used in these auxiliary regressions, so that autocorrelation in the space-dimension is controlled for. This test will be executed via the `xtserial` command by Drukker (2003). As we will see, we indeed have to assume autocorrelation. To deal with this, I use the robust standard errors by Cameron et al. (2011). They are a generalization of the well-known White standard errors and robust to heteroskedasticity in both the time- and the space-dimension. This is implemented via the `vce(robust)` option of `xsmle`.

Other possible sources of endogeneity include omitted variable bias (OVB) and simultaneity. By specifiying the SDM the way I did, I already dealt with one source of OVB, omitted time-invariate variables. And since I include most variables proposed by previous studies in my model, I find it unlikely that other forms of OVB will arise. Also, as LeSage and Pace

(2009) point out, a SDM is quite robust to OVB compared to other spatial models due to the inclusion of spatial lags of the explanatory variables. Simultaneity is another matter however. As could be seen in Chapter 2 of this study, there are several possible sources of simultaneity, for example in the police-crime relationship. Therefore, it is essential that the variables included in my model are picked in such a way that simultaneity is prevented, more on this in the next chapter.

4 Data

My data-set contains observations for all 402 German counties and spans over 12 years (2003-14). I should note here that when I speak of counties, I mean those regions with their own NUTS3-classification, i.e. both "Kreise" and "kreisfreie Städte" by the German classification. Also, when mentioning "states", I mean the 16 "Bundesländer". During these twelve years, there have been several reforms of county structure, especially in the East. Specifically, these are the reforms in Saxony-Anhalt 2007, Saxony 2008, Mecklenburg-West Pomerania 2011 and the combination of the city and the county of Aachen in 2009. All these reforms have lowered the number of counties, from 439 in 2003 to 402 in 2014. For details on these reforms, I refer the reader to the website of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR)[1]. This matters especially from a data-handling perspective, as it necessitates a homogenization of the data. In most cases, this is quite straightforward, as usually two or more smaller counties were combined into a larger one. In these cases, the numbers for the new county were retrospectively calculated by simply adding those of the smaller counties together. Since all my raw data also included absolute numbers, even in cases where I wanted to use rates or other relative measures, I was simply able to calculate these after the aggregation, with only few minor shortcuts described later. The exception to this is the area-reform of Saxony-Anhalt in 2007. Here, some counties where cut up and re-assembled in a somewhat arbitrary fashion, making it harder to homogenize observations before and after the reform. As in most cases no lower-level data was available, I instead combined these counties as best I could, i.e. merging a county with another if most inhabitants of these two counties ended up the new one. This is of course a source of aggregation error, to control for which I have included a dummy for these years and counties. But since we are only talking about 7 counties over 3-4 years (2003-07, depending on whether the data of 2007 was reported for the old or the new counties), I am satisfied that this is only a minor source of measurement-error. This is supported by the fact that in none of my regressions this dummy-term ("lk-ref") is significant. Lastly, as `xsmle` requires a perfectly balanced panel, some imputation had to be done where there was data missing. Overall, imputations were only necessary for four variables, and at most 2.6% of the observations had to be imputed, in the other cases far less. For an overview of what data had to be imputed and how

[1] http://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Raumabgrenzungen /Kreise_Kreisregionen/Kreisreformen/xneueTypen.html.

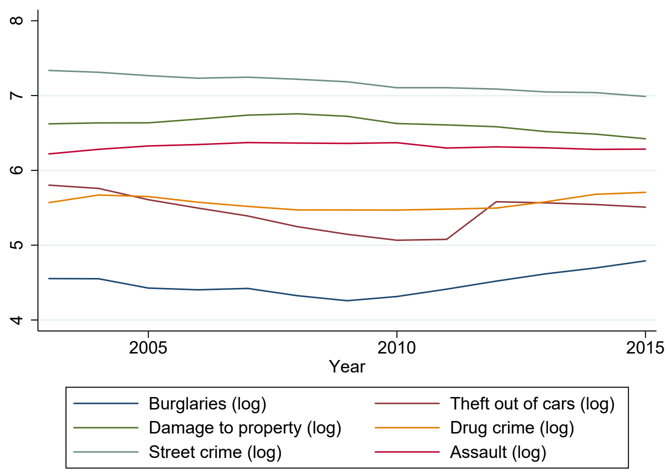
imputations where performed, see Table 21 in the Appendix B. I will now describe the data used and it's sources in more detail, an overview of all data-sources can also be found in the Appendix B.

4.1 Crime in Germany, 2003-14

The most important source of crime data in Germany is the PKS, the crime-statistic recorded by the Federal Criminal Police (BKA). Here, statistics on a wide range of offenses are reported, both regarding the crime, the suspects and the victims. Unfortunately, this data is only available on the county-level since 2013. And since much of my other data is only available up to 2014, this is not a satisfying time-frame. Therefore, I'm very grateful to the department IZ 33 of the BKA for granting me access to data for internal use that goes back to 2003. The drawback of using this data is that it includes far less characteristics of an observation. For one, it includes no information on suspect or victim. For another, it only includes six types of crimes and the total crime number. However, as using this data adds ten years to the time-frame and therefore 4020 observations to the data-set, I feel justified in using it.

The six types of crime included in the data are burglary, theft out of cars, assault (both light and aggrevated), damage to property, drug offenses and "street crime". This last type is a bit of a catch-all, as it includes all crimes taking place in a public space, which is why there is obviously some overlap with the other types of crime. For an exact definition of these types of crime, see the PKS documentation by the Bundeskriminalamt (2017). In further examinations I won't use the total number of crimes, which is also reported. The reason for this is that the total number of crimes consists to a large degree of offenses that, while against the law, wouldn't be usually called crimes, like using public transport without a ticket or passing the border without permission. The latter for example is the reason why Passau in 2014 had by far the highest crime rate per capita, almost doubling that of Berlin, when many refugees crossed the border there. Besides these minor offenses, the total crime number largely consists of theft and fraud, which are then given the same weight as a murder for instance (see also Entorf and Spengler (2002)). This makes the total crime number "almost useless", as Entorf and Spengler put it (p.7.), which is why I will not use it in my study. Also, as in this data-set crimes are reported in absolute numbers, I calculated the number of crimes commited per 100,000 inhabitants (from now on: "crime rate"). The population data for this comes from the "Statistische Ämter der Länder und des Bundes".

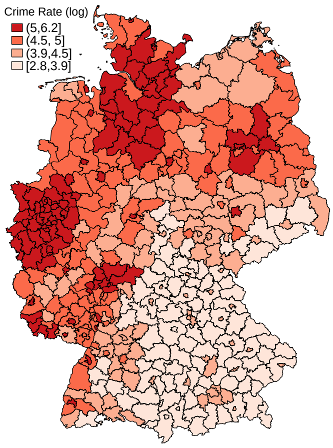
Besides the raw numbers of crimes recorded, this data also includes numbers on how many of these cases were solved, which makes it easy to calculate a clearance rate for each type of crime for the Becker-Ehrlich model. The resulting numbers are of differing quality, however. This is due to a well-known problem when it comes to police recorded crime numbers, as they naturally only record crimes the police became aware of. With some kinds of crime, this is not a big problem. It is for example reasonable to assume that almost all burglaries are reported to the police, as insurance policies usually require a police report in order to pay out and there is also little reason not to report it. The situation is very different when it comes to drug offenses for example. These are almost never reported, as in most cases both parties willingly commit the crime together, in a drug deal for instance. Therefore, the vast majority of drug offenses in this data are instances of the police catching an individual with drugs on their person or vehicle, for instance during traffic stops or border controls (see Commandeur et al. (2014)). As a result, with my data, the average clearance rate of drug crimes is 95.6%, which clearly in no way reflects the actual clearance rate, nor the probability of getting caught. I therefore use the clearance rate of street crimes as a proxy for the overall clearance rate, as it is reasonable to assume that when it comes to pickpocketing, robbery or assault, the vast majority of incidents are reported. The issue of underreporting of course does not only applies to clearance rates, but also to the crime rates themselves. Of course, this only represents a problem if the underreporting of crime is not homogeneous over space and time, e.g. if in some county or during a certain year people where less likely to report a robbery for instance. But as Tarling and Morris (2010) show, there is some reason to believe this is the case, as there survey data shows that people in areas with lower GDP and higher unemployment are less likely to report crimes. It is also possible that this underreporting introduces some amount of simultaneity to the data, as it might be that better staffed and equipped police forces uncover more crimes, thereby causing a higher reported crime rate. However, as this is the only source for crime numbers on the county level, there is not much I can do about this but point out that the vast majority of studies on crime use this type of data, with the notable exceptions being those relying on survey-data (e.g. Entorf (2015)).



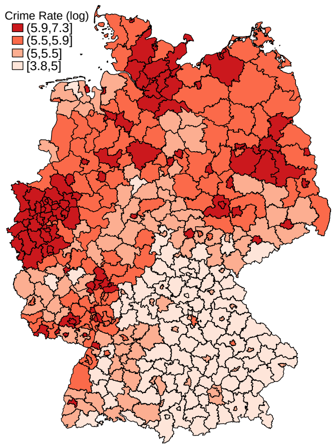
Source: BKA, own calculations

Figure 2: Crimes per 100,00 inhabitants (log), average over counties, 2003-14

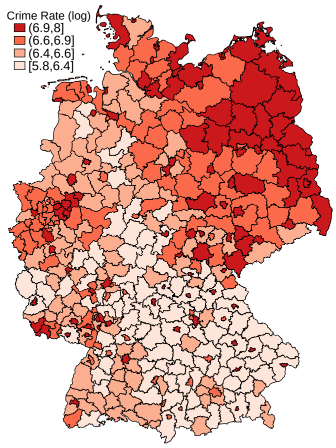
Looking at the time-dimension depicted in Figure 2, we see very little change of the crime numbers between 2003 and 2014, with only burglaries exhibiting a small upward trend from 2010 onwards. This stands in stark contrast to the time-series reported by Entorf and Spengler (2000) for the years 1975-96, that show a very strong upward trend for almost all types of crime. From an econometric perspective, this supports the assumption of stationarity, which will be confirmed by the tests described before. But it also means that there is very little variance in the time-dimension, which suggests that the estimation results will have little explanatory power within a region. However, when looking at the spatial distributions of crime in Figure 3, we see a lot of variance. The base map material comes by courtesy of the "Bundesamt für Kartographie und Geodäsie" (BKG).



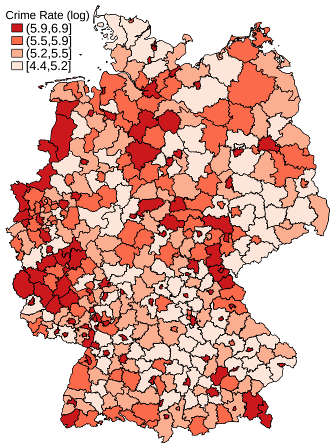
(a) Burglaries (log)



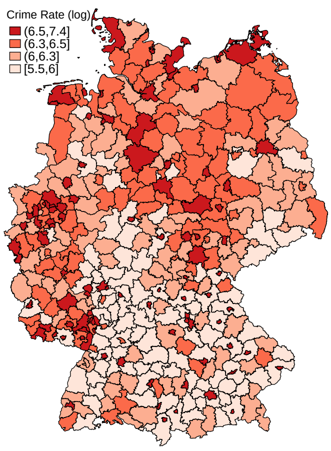
(b) Theft out of cars (log)



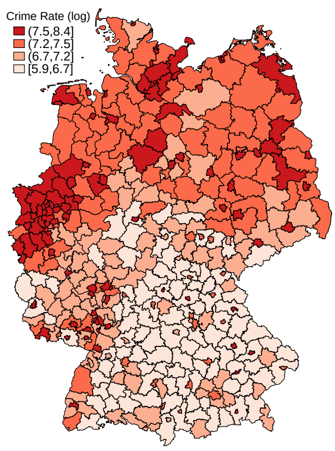
(c) Damage to property (log)



(d) Drug crime (log)



(e) Assault (log)



(f) Street crime (log)

Source: BKA, BKG, own calculations

Figure 3: Crimes per 100,00 inhabitants (log), averages over time, county level

Here we can clearly see a fair amount of clustering associated with positive spatial autocorrelation (compare also to Figure 11 in the Appendix A). This is especially true for burglaries, theft from cars, damage to property and street crime, while it is less pronounced for assault and drug crimes. It is important to note, however, that these maps depict the average over time for each region. When I disaggregate this and look at such maps for each year, which I omit here for the sake of space, we can see this type of pattern for drug crimes as well, while assault is still the odd one out. Also, the classes used for coloring the maps are somewhat arbitrary, in this case each represents a quartile of the overall distribution, which of course could be changed to obtain different results. However, with the results at hand, it is interesting that these patterns look quite similar for the different types of crime. We can observe a high-value cluster in the Rhine-Ruhr region, in the North around Hamburg and in the East around Berlin, while Bavaria and to a lesser degree Baden-Württemeberg exhibit clusters with low crime rates. Looking at these maps, it also seems to matter whether a region borders another country. There seems to be a particularly large high-value cluster of damage to property near the Polish border and a one of drug offenses along the border with the Netherlands and Belgium. Another, although not very surprising, result is that especially in maps c)-f), we can clearly see that cities exhibit much higher crime rates than the surrounding country-side. Further, there is no apparent difference between East and West Germany, which is why I will not use an East-West dummy in may analysis, unlike Messner, Teske, et al. (2013). To test the theory of Sah (1991), I also include the one-year lag of the clearance rate of street crime, and to test the broken-window theory, I will use "damage to property", a quite minor offense, as an explanatory variable rather than as an endogenous one.

I've also performed outlier detection with boxplots on these variables, the results of which can be found in Figure 14 in the Appendix A. As can be seen there, some outliers do in fact exist, although not very many considering the 4824 observations. Non-the-less, I've used these and other box-plot results to construct an outlier dummy to include in my regressions.

4.2 Economic Determinants

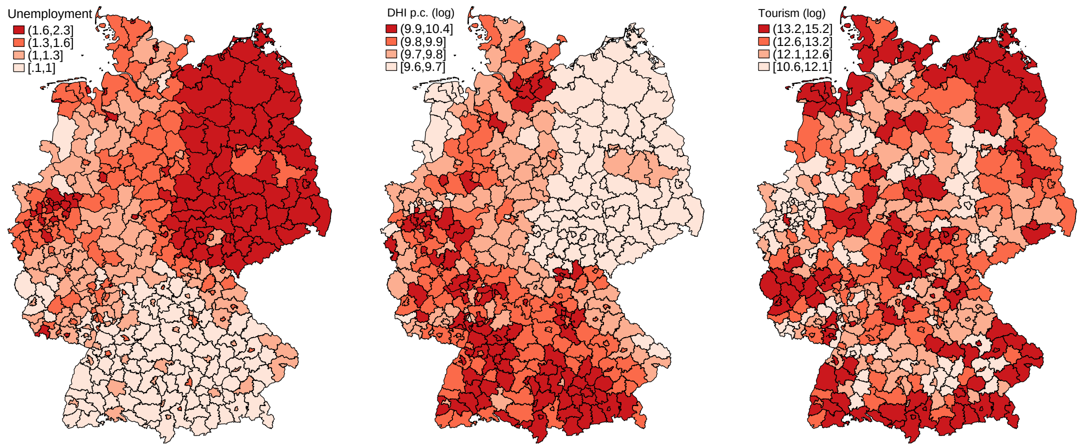
As noted in Chapter 2, economic indicators play a central role in most theories of crime. Yet at the same time it is difficult to choose variables in such a manner that their effect is clear and unidirectional. I will use three economic indicators in my study, a proxy for illegal income opportunities and general wealth of the region, one for legal income opportunities and one for tourism.

For illegal income opportunities/wealth of the region I've considered several variables, namely GDP, disposable household income (DHI), primary household income and the average hourly wage. All these variables were taken from the report "VGR der Länder" by the "Arbeitskreis Volkswirtschaftliche Gesamtrechnung der Länder". Of these, DHI seemed to perform best in my regression, both when considering the AIC/BIC and the R^2-values. It is not surprising that DHI p.c. performed best since DHI is defined as the part of the income of private households that can actually be spent, i.e. the income after taxes, government transfers and other regular payments. For an exact definition see the documentation of the data-set these variables were derived from (Brenner et al. 2015). To make the numbers comparable across regions, I calculated it in Euro per capita (p.c.). To make it comparable across time, I deflated it by the official consumer price index (CPI) with base-year 2010 as reported by the "Statistisches Bundesamt" to obtain real DHI p.c. This is the measure I will refer to from now on when mentioning DHI. As several authors before me have found a strong bi-directional relationship between regional wealth and crime (Entorf and Spengler 2002, Torres-Preciado et al. 2015 etc.), simultaneity might be an issue. To prevent this, I will use the one-year-lag of DHI to preclude any possibility of a bi-directional causality in the Granger sense.

Related to this measure of illegal income opportunities is tourist activity, which is of course also used in the routine activity theory. As a proxy for tourism I use the number of nights visitors stayed in a county. This data is reported by the local "Fremdenverkehrsämter" and collected by the "Statistische Ämter der Länder und des Bundes" (from now on abbreviated "Statistische Ämter". To make it comparable across regions, I've again divided this number by the total population of a county and multiplied it by 100,000. I will from now on refer to this measure as "tourism". Of course, it is also possible that some amount of simultaneity exists with crime and tourism, as high crime numbers might dissuade tourists from coming. However, this would be associated with a negative sign of the coefficient, which is not the case in my regressions.

For legal income opportunities, I will use the unemployment numbers as reported by the "Statistische Ämter". Given previous research (Draca et al. 2015), I have reason to believe that median income or measures of inequality would perform better as a proxy for legal income opportunities. Unfortunately, there is no such data is available on the county-level. Further, while the unemployment numbers are available as rates and as absolute numbers, I have to account for the county reforms mentioned before. Therefore I can't use the rates as reported, but rather have to calculate my own rates. Since the number of people who would be able to work are not reported, I instead calculate unemployment rates as the number of unemployed relative to the number of inhabitants. Assuming that the reasons for not participating in the labor market, such as age, education, raising children, disability etc., are relatively homogeneously distributed across all regions, I find this to be a satisfying approximation. To see whether the hypothesis of Cantor and Land (1985) holds up, I considered also including long-term unemployment as a variable as well. But as this did not produce any result of note, I've instead included the one-year lag of the unemployment rate as done by Ha and Andresen (2017).

As we can see from Figure 4, both unemployment and DHI exhibit quite distinctive clustering, while tourism doesn't seem to. It is apparent at the first glance, that maps a) and b) seem to be the mirror image of the other, which is not surprising, as it just means that



(a) Unemployment (log) (b) DHI p.c. (log) (c) Tourism(log)

Source: Statistisches Bundesamt, Statistische Ämter, BKG, own calculations

Figure 4: Unemployment, DHI and tourism, average over time, county level

unemployment and DHI are negatively correlated as one would expect. The one way there are not similar is that cities tend to have both high unemployment and high DHI p.c., especially in the Rhine-Ruhr area. Also, in contrast to the maps of crime earlier, we can see a clear difference between East and West Germany. As for tourist activity, it seems that especially the border regions and the North Sea are attractive destinations, as well as some of the bigger cities, although except for Cologne none in the Rhine-Ruhr region. As before, I've used box-plots to find outliers for the construction of my outlier-dummy. The results of this can be found in Figure 15 in Appendix A. As can be seen there, especially unemployment but also DHI and tourism have some serious outliers.

4.3 Social Determinants

While it was relatively easy to find suitable variables for the economic side of my model, the variables on the societal/social side took a bit more creativity. The first variable I needed was a measure of government response to crime. This mainly means police deployment, but also youth workers etc. And while the numbers of youth-workers per county are readily available from the "Statistische Ämter", numbers on the size of the police force are not. Therefore I'm grateful to the ministries of the interior of Baden-Württemberg, Bavaria, Saxony, Saxony-Anhalt, Thuringia, Brandenburg, Schleswig-Holstein, Saarland, Bremen and Lower Saxony as well as the statistical office of North-Rhine Westfalia for providing me such numbers. Unfortunately, I didn't end up using this data in my regression for several reasons. For one, I wasn't able to collect such numbers for all states in Germany. For another, they all had very different levels of aggregation, and only some where on the level of police districts ("Polizeidirektion"), which roughly equates to counties. But the most serious problem was that when running my regressions with either the number of police or number of youth-workers per capita, the results showed serious signs of simultaneity, i.e. a

positive relationship between crime and numbers of police/youth-workers. This, of course, resembles the results of Levitt (1995), so that this data doesn't need to go completely to waste. I used it to check whether Levitt's theory might also hold true for Germany and checked whether there is a correlation between number of police-officers p.c. and years with state elections. The resulting correlation coefficient of -0.01 however strongly suggests that there is no relationship at all. I've also used it to plot the development of police-officers p.c. over time for each state where data was available. The results of this, which can be found in Figure 13 in the Appendix A, are not very striking though.
To deal with the issue of simultaneity, I had to find a proxy that did not exhibit signs of simultaneity. For this, I used the number of state employees in each county as reported by the "Statistische Ämter". Specifically, I used the number of tenured ("verbeamtete") full-time state employees as for this subset of government workers the data was most complete. This of course mostly excludes youth and social workers and mainly consist of police officers, teachers and people in the administration and justice system. Of course, *a priori* it is still not possible to exclude simultaneity in this case. For one, it is still possible that the share of police officers among them is so great that it determines the relationship of the entire variable to crime. For another, it is likely that cities, which as we saw exhibit higher crime rates, also have more tenured state employees, since they are administrative centers. However, if this were a serious problem, we would expect the coefficient associated with government employees to be positive, which it is not (see next chapter). Again, I've calculated the number of state employees per 100,000 inhabitants to make it comparable across regions (from now on referred to as "state employees").

Next, I had to find a proxy for the human capital stock among young people. Unfortunately, there is no data available for the educational attainment of all inhabitants in the counties. Instead, I used the number of students leaving school without a degree as reported by the "Statistische Ämter". From this I've calculated the share of students without a degree relative to all finishing school that year, from now on called "drop-out rate". I've also tried using the share of those finishing with a lower- or middle-tier degree (Haupt-/Realschulabschluss") instead, but with less clear results. Machin et al. (2011) point out that there might exist some degree of simultaneity here as well. The idea is that teenagers who "chose" a career of crime are less likely to work on their academic career, while at the same time students who are not doing well in school might be tempted by a career in crime. To preclude this, I again only include the one-year lag of the drop-out rate in my regressions.

For family cohesion, as it is used in the social disorganization theory, I've considered two different proxies, the number of marriages and the number of divorces per 100,000 inhabitants, calculated from numbers by the "Statistisches Bundesamt". Again, there might be an issue with simultaneity, as criminals are much less likely to get married and more likely to divorce (Barnes et al. (2014)). For Germany, this is also confirmed by a survey among inmates, see Entorf (2008). But as only very few people in any county are criminals, even those with the highest crime rate, it cannot be expected to be a major issue for my level of aggregation. I tried using both marriages and divorces on my regressions, and divorces performed better overall. Unfortunately, the divorce numbers are only available on the state level for the entire time frame and only for the year 2015 on the county level. But as I will demean the divorce rate and then add their mean as it's own variable anyway when using the Mundlak-approach described before, I used these two statistics to obtain a time-trend by state (the demeaned state divorce rate) and a sort of county fixed effects by including the numbers from 2015, as reported by the "Statistische Ämter", instead of the means from the state divorce rates. I argue that this comes close enough to finding the *between*- and *within*-effects of divorce, as I would ideally have, if the divorce-rates where available on the county level for the entire period.

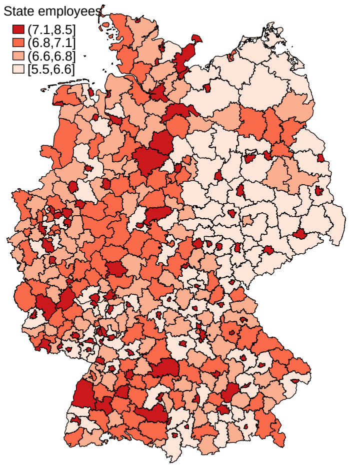
As mentioned before, most other authors before me didn't explicitly include a variable for social cohesion, but rather argued that the other economic and social variables would account for the effect of social capital. In contrast, I will follow Buonanno et al. (2009) when using voter turn-out as a proxy for social cohesion/social capital. The idea behind this is that when people feel a high degree of civic duty or when they generally trust and associate with their neighbors, they are much more likely to vote in an election. Of course, different types of elections always have different voter turn-outs, which makes it difficult to compare results of a national election with a state election, for instance. The solution for this problem could be to just use one type of election, the national parliamentary elections for instance, but that would give me only three data-points per county, as they only happen every four years. To remedy this, I subtract the average voter turn-out to make state, national and European parliamentary elections comparable. As this procedure necessarily creates negative values, and since I want to use mostly logarithmized variables in my regressions, I then add the absolute value of the minimum plus 1 to enforce positive numbers which can be logarithmized. This way, I ensure that every county has about 8-9 observations each. For the years where no new data is available, as no election took place, I just repeat the value from the previous year. The source of this data is again the "Statistische Ämter", who report the absolute number of votes cast and the numbers of eligible voters per county for these three types of elections, from which voter-turnout was calculated. I considered whether there is a relationship between crime and the electoral success of conservative or far-right parties, but no obvious connection emerged. Bateson (2012) notes that simultaneity might be an issue here as well, as survey data suggests that people who where victimized recently are far more likely to participate in politics. This would mean, however, that the relationship between crime and voting should have a positive sign, which it does not in my regressions.

The spatial distribution of the variables from this section (Figure 5), exhibit in each case clear, but very distinct pattering. In the case of state employees, we can again clearly distinguish between East and West Germany. Besides this, it is also apparent that the number of state employees p.c. is especially high in the cities, and in the state capital for that matter, with the interesting exception of Berlin. There is further no apparent clustering here, which makes sense considering the deployment of state employees is a political decision. Contrary, with regards to the drop-out rate, this is not the case. Here there apparently exists a distinct high-value cluster in the North-East and a low value one in the South. Again, we can see that this share is especially high in the bigger cities. This is also true for the divorce rates, where in addition there are far fewer divorces in the East compared to the West. One reason for this is certainly that there also far less marriages in the East. This becomes apparent when looking at a similar map for marriages, which I have omitted here for brevity. Lastly, the (demeaned) voter-turn-out exhibits the strongest clustering of these four. There are several distinct low- and high values clusters, with turn-out generally being higher in the South-West than the North-East. And as before, I have used box-plots for outlier detection, see Figure 15 in the Appendix A. As can be seen there, especially voter turn-out and the drop-out rate have some serious outliers.

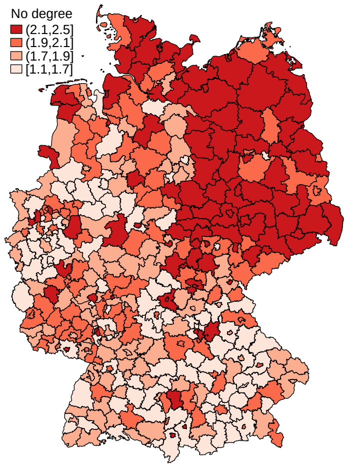
4.4 Other Determinants

Besides these socio-economic determinants mentioned before, there are also some demographic and geographic characteristics that likely need to be controlled for. For one, it is apparent from the maps of both the ex- and the endogenous variables, that it matters whether a county is urban or rural. I've considered two variables to control for this, population density and the county-classifications by the BBSR. The latter sorts all German counties into four categories, major cities, urbanized, rural with some urbanization and rural counties, see Einig et al. (2012) for details. This has some advantages over population density as an indicator, as it also incorporates information on the political and cultural characteristics of a county. There are several disadvantages to this approach, however. For one, this is a categorical variable, which would necessitate the inclusion of three dummies. For another, the BBSR doesn't reclassify counties yearly, which would mean there were only two observations available per county over the time frame. I therefore used population density instead, which also performed better than the BBSR variable with regards to AIC/BIC and R^2, likely because it has more *within*-variance attached to it. This can also be understood as a proxy for urbanization in the sense of the social disorganization theory. The population density was calculated from numbers reported by the "Statistische Ämter" regarding population and area in square kilometers.

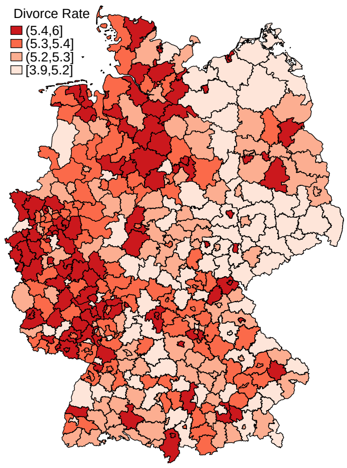
From the same data-source, I also constructed variables regarding the age and gender structure of each county. It is well understood that many types of crime, especially violent crime, are mainly committed by young males. For Germany, this is supported by the aforementioned survey among inmates (Entorf (2008)), which reported that 89% of inmates are male, with an average age of 33. Considering that the crime they were



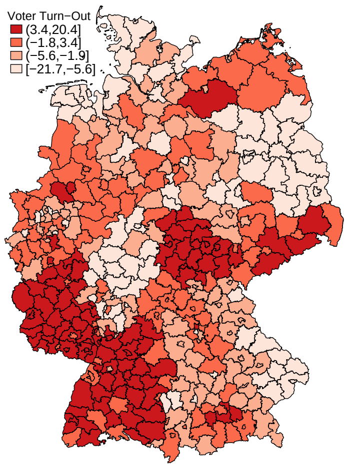
(a) State employees per 100,000 inh. (log)



(b) Dropout rate (log)



(c) Divorce rate in 2015 (log)



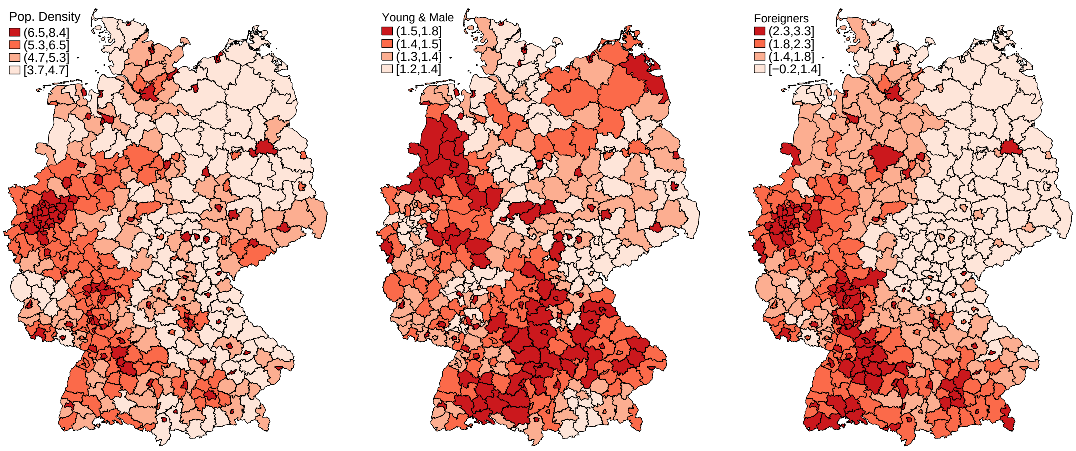
(d) Voter turnout (demeaned)

Source: Statistisches Bundesamt, Statistische Ämter, BKG, own calculations

Figure 5: Social indicators, average over time, county level

convicted for must have obviously taken place before they landed in prison, this suggests that most crimes are committed by fairly young people. There are obviously several different ways I could control for this. But as I indeed only want to control for this, also because this connection is both quite intuitive and well studied, I chose to follow Entorf and Spengler (2000) and constructed a variable "young & male". This is the share of males between 15 and 25 relative to the entire population. It could be argued that these age borders are somewhat arbitrary, but it still tells us something about the general gender/age structure of the county.

Also from the same data-source, I've constructed the variable "share of foreigners", which is the proportion of non-citizens living in a given county. In contrast to "young & male", this variable and its relationship to crime is actually of some interest to me. For one, it is clearly a very politically charged question whether foreigners commit more crimes, having controlled for all other relevant variables. The recent study by Piopiunik and Ruhose (2017) would suggest that in Germany migration does indeed have a strong impact on crime. Of course, this can also be understood as a proxy for "racial heterogeneity" in the sense of the social disorganization theory. Again, there might exist the problem of simultaneity here, as it is possible, that since many non-Germans are relatively poor, they are forced to move to poorer and more crime-ridden neighborhoods. Since this can't be differentiated from foreigners causing crime, I will again use the one-year lag to make sure that the causality only goes one way. But it is also possible that foreigners are suspected more often by the police, and thus more often caught when they have committed a crime. Unfortunately, my data doesn't allow me to say either way, so this has to be left to future research.



(a) Pop. Density (log) (b) Young & male (log) (c) Share of foreigners (log)

Source: Statistische Ämter, BKG, own calculations

Figure 6: Pop. dens., young & male, foreigners, average over time, county level

Lastly, I've constructed border dummies, which indicate whether a county borders a specific country, i.e. Denmark, Poland, the Czech Republic, Austria, Switzerland, France, Luxembourg, Belgium or the Netherlands. From this I also constructed a dummy indicating whether a region is a border region at all to differentiate between a possible increase of crime that comes from any border and country-specific effects.

When looking at the spatial distribution of these variables (Figure 6), the results are non-surprising with regards to population density and share of foreigners. As we would expect, the population density is highest in the cities and lowest in the somewhat underdeveloped parts of Eastern Germany. The same is true for foreigners, who seemingly tend to agglomerate in the larger cities and more in the West than the East. More surprising are the patterns emerging from the "young & male" variable. The results indicate that especially in the South and West there are many young men, with less in the North and the east. Never-the-less, we cannot assume real clustering here, because, while these broad trends exist, there are also many instances of high- and low value counties neighboring each other, which would be associated with negative spatial dependency. Again, I've use box-plots for outlier-detection. The results can be found in Figure 16 in Appendix A. However, only a few minor outliers emerged.

5 Results

Having presented the methods of choice and introduced the data-set, this section will discuss the results. This will be done with particular focus on the five hypotheses formulated in Chapter 2. To reiterate, I hypothesized in H1 that the Becker-Ehrlich model would hold true, H2 asked whether social disorganization theory applies, H3 concerns the routine activity theory, H4 the broken windows theory and H5 regards the existence of spatial dependencies. Before considering H1-4, it should first be examined, whether spatial dependencies actually exist and what form of clustering they result in.

5.1 Spatial Autocorrelation

When looking at spatial dependencies, I had to find a workable definition of neighborhood. As discussed in Chapter 3, I created several different spatial weight matrices (queen-contiguity, distance cut-off, inverse distance squared). Then, following LeSage and Pace (2014), I created a random variable (over only one time period, i.e. with 402 observations) from a standard-normal distribution and used these three spatial weight matrices to calculate their spatial lags and then calculated their correlations to see whether it makes a difference which definition I use.

	Queen contiguity	*Distance cut-off*	*Inverse distance*
Queen contiguity	1.0000	-	-
Distance cut-off	0.7240	1.0000	-
Inverse distance	0.7860	0.6090	1.0000

Table 2: Correlations of spatial lags with different weight matrices

As can be seen from Table 2, the correlations are fairly high across the board, although queen contiguity seems to be the most similar to the two others. When comparing these results with the correlations reported by LeSage and Pace (2014), which are also somewhere around 0.7, it seems fair to assume that the choice of weight matrix doesn't matter much for the rest of my study. Therefore, I will use the simplest definition, queen contiguity, from now on. Here, each region has on average four neighbors. Of course, as mentioned before, the three weight matrices used here are only the most common ones, but the literature knows of a plethora of other definitions. So it is still possible that this is a misspecification, but not al definitions could be tested in the scope of this study.

Variable	*I*	*z-statistic*	*p-value**
Burglaries (log)	0.143	5.513	0.000
Theft from cars (log)	0.125	4.850	0.000
Dmg. to property (log)	0.079	3.103	0.002
Drug crime (log)	0.057	2.249	0.025
Street crime (log)	0.108	4.194	0.000
Assault (log)	0.105	4.066	0.000
Unemployment (log)	0.156	6.027	0.000
Drop-out rate (log)	0.058	2.280	0.023
DHI p.c. (log)	0.133	5.170	0.000
Share of foreigners (log)	0.036	1.464	0.143
Voter turn-out (log)	0.099	3.890	0.000
Divorce-rate 2015 (log)	0.026	1.085	0.278
Tourism (log)	0.031	1.263	0.206
State employees (log)	0.009	0.431	0.667
Pop. density (log)	0.046	1.848	0.065
Young & male (log)	0.024	1.024	0.306

* *two-tailed test*

Table 3: Global Moran's I for the ex- and endogenous variables averaged over time

Having decided on a spatial weight matrix, it is now possible to take a look at the spatial structure of my data. The maps in the previous section already suggest some amount of positive spatial autocorrelation. To confirm this, let us consider first the global Moran's I results reported in Table 3. As we can see here, all crime variables and most exogenous variables exhibit strong positive spatial auto-correlation. Surprisingly, this is even true for drug crimes and assault, where we couldn't see a clear pattern previously. Less surprising is that state employees p.c., share of foreigners and divorce rates don't show significant spatial dependencies, although there seems to be some weak clustering with regards to population density. Finally, neither tourism nor the share of young males show significant spatial dependency. This is surprising, considering there seemed to be some broad spatial trends when mapping them previously.

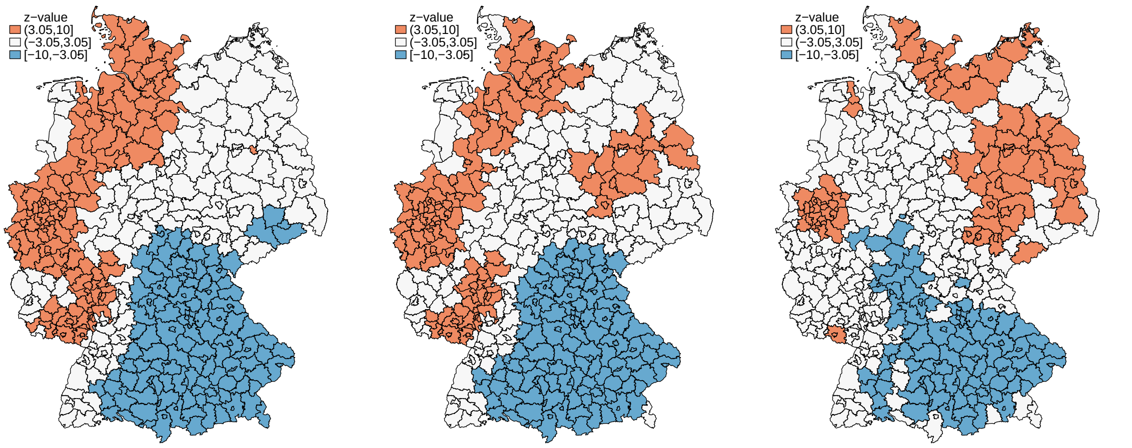
That said, these results already broadly confirm H5, which states that there exist spatial dependencies with crime and also it's various dependent variables. The implications of this are already quite stark. For one it means that, when modeling crime on a granular level, it is absolutely necessary to account for these dependencies. In order to differentiate between spill-overs stemming from spatial dependencies among the explanatory variables and those resulting from dependencies of crime itself, I will include spatial lags of those variables showing significant Moran's Is in my SDM. Secondly, from a policy perspective, it implies that there exist externalities and feedback loops a crime-fighting policy must take into account. Of course from this, one cannot say much about the nature of these externalities and the clustering they result in. We also don't know how stable these relationships are over space and time, while I need to assume homogeneity for my SDM as mentioned before. To check whether this is actually the case, I employed two strategies.

First, I used so-called Moran's scatter plots, which indicate how similar neighboring regions are. The results of this can be found in Figure 17 in Appendix A. As we can see there, heterogeneity of the spatial dependency across space might indeed be an issue. Under homogeneity, one would expect all data-points to be within either the upper right or lower left quadrant, meaning high- and low value clusters. This is mostly the case for burglaries, theft from cars and street crimes, while it is less pronounced with regard to damage to property and completely breaks down for drug crimes and assault. This is an somewhat odd result, as the global Moran's I reported before are the sum of all local Moran's, and both assault and drug crime were significantly positive there. When looking at the box-plots of the local Moran's Is (Figure 18 in Appendix A), there is reason to believe that these contradictions are largely driven by outliers. Given the maps from the previous chapter, and that most counties do exhibt positive spatial autocorrelation, I would argue that the instances of negative dependency largely come from cities being surrounded by rural areas, especially in the South. And since I will control for population density in my regressions, I don't expect this to be a major problem. Non-the-less, I've constructed a new outlier-dummy including regions with abnormally large or small local Moran's I. If I where to include this in the definition of the dummy constructed before, it could be argued that it has too many definitions. And since these two dummies are not highly correlated (0.03), collinearity is not an issue when using both (called "out1" and "out2" in the regression results).

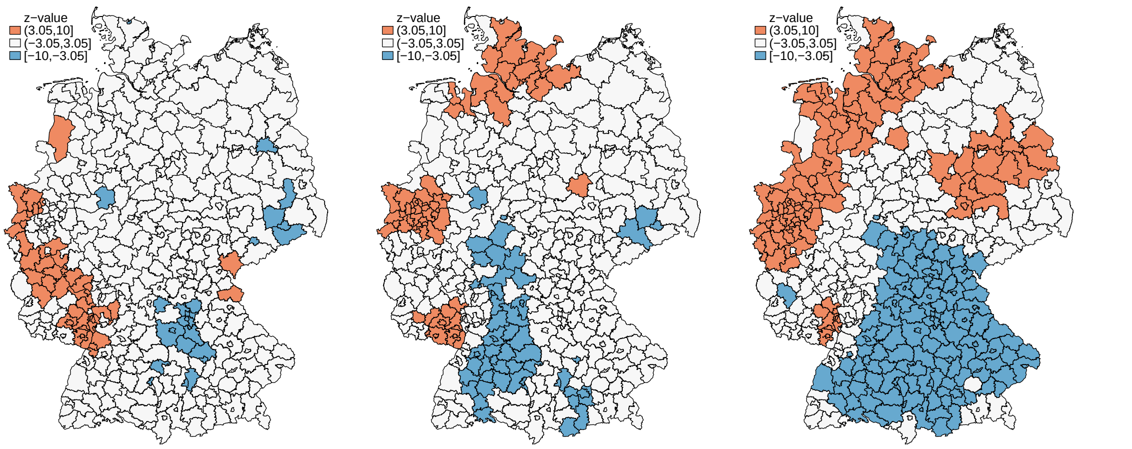
5.2 Patterns & Clusters

Having found evidence for spatial dependency, I'm now interested in the patterns that emerge from this. The maps in the previous chapter already displayed a fair amount of clustering, but it is not clear whether these patterns are really the result of spatial dependency or reflect the clustering of the underlying variables. This kind of causal inference is of course also at the heart of the SDM formulated before, but first I will use some exploratory techniques in the hope they can provide more insight into the matter.

First, I'm interested in finding the clusters that are the result of spatial dependency. For this I use the local Getis-Ord G, as described in Chapter 3. To reiterate, this statistic tells us whether and where low and high value clusters exist that are the result of positive spatial dependency. As also mentioned before, to prevent the problem of multiple inferences, I will use Bonferroni-bounds to decide whether something is a cluster. On the 5-% significance level, this means $\Phi(z) = 1 - 0.05/(2 \cdot 402)$, resulting in the critical values of $z = \pm 3.05$, where z-values smaller than these suggest a small-value cluster and those higher a high-value one. Of course, Getis-Ord G is only sensible to use, when there is reason to believe there actually exists spatial dependency, therefore I will preclude those variables with insignificant global Moran's Is from this analysis.



(a) Burglaries (log) (b) Theft out of cars (log) (c) Damage to property (log)



(d) Drug crime (log) (e) Assault (log) (f) Street crime (log)

Source: BKA, BKG, own calculations

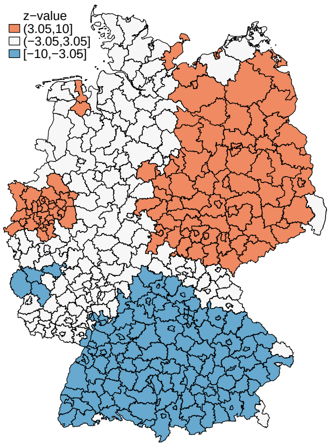
Figure 7: Getis-Ord G z-value, var. crimes averaged over time

The maps in Figure 7 show the results for the six types of crime I'm studying. All in all, they are not very surprising considering the patterns that emerged in the maps from the previous chapter (Figure 3). As we can see, especially the maps for burglaries, theft from cars and street crime look very similar, with one very large low-value cluster in the South/South-East (denoted in blue) and one very large high-value one in the North and West (denoted in orange), while the rest of the republic shows no significant clustering at all (white). These three maps differ slightly in whether there is a cluster in the East, roughly around Berlin. While theft from cars and street crime show some clustering there, burglaries do not. When looking at the results for drug crime and assault, the picture becomes less clear. Assault shows relatively few clusters, one high-value one in the North around Hamburg, one in the Rhine-Ruhr area, a low-value one in the South-West and some smaller ones here or there. The clustering completely breaks apart when considering drug crimes, with only one distinct high-value cluster in the West, near the Dutch border. But as argued before, the numbers for drug crimes have to be taken with a grain of salt, since they are most certainly highly underreported. This might explain why this map shows Berlin to be in a low-value cluster, which contradicts at least anecdotal evidence. And of course this applies to all the maps shown here to some degree, since they are based on averages over time. It is possible that different patterns would emerge were the time-dimension taken into account, but as this would require presenting 12 maps for each variable, it is omitted in this exploratory part of the study.

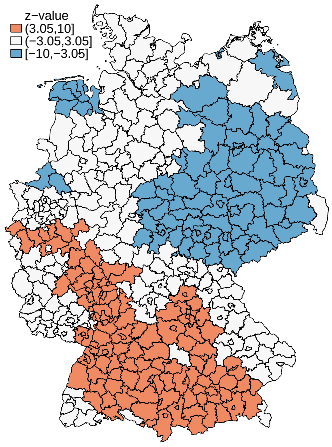
Non-the-less, we have now a better idea what kind of clusters exist within my endogenous variables. In the next step, I'm interested whether similar patterns emerge among the exogenous variables. If this were the case, it would suggest that the clustering shown there is at least partially a result of the spatial dependencies of the explanatory variables. The results from Figure 8 suggest that some relationship does indeed exist. Not surprisingly, the clustering within unemployment and DHI p.c. are largely a mirror image of one-another, with a large high-value cluster of unemployment and a corresponding low-value one of DHI p.c. in the East. A bit more surprising is the fact that, while there is a high-value cluster of unemployment in the Rhine-Ruhr region, there is no corresponding cluster of DHI p.c. there as we have also seen in the maps from the previous chapter. This is likely due to the fact that many large companies have their headquarters there, making the average household income high, even though there is still much unemployment. In the South-West, there is again a very large low-value cluster of unemployment and a high-value one of DHI p.c. The picture of clustering in drop-out rates is somewhat similar, but the high-value cluster in the East also extends to Hamburg and Schleswig-Holstein. Voter turn-out is the odd one out here, with several medium size clusters all over the map.

Comparing these results with the patterns that emerged with crime, there are some obvious similarities. In many cases we can detect distinct clusters in the East, the North, the West and the South. From this, we can already find some evidence for H1-4. As expected, clusters with high unemployment tend to have higher crime rates, while DHI has an ambivalent effect, as some clusters in the West show both high crime rates and DHI, for example in the case of burglaries. The drop-out rate clusters also correspond quite well to the crime clusters, while the relationship between voter turn-out and crime is not obvious.

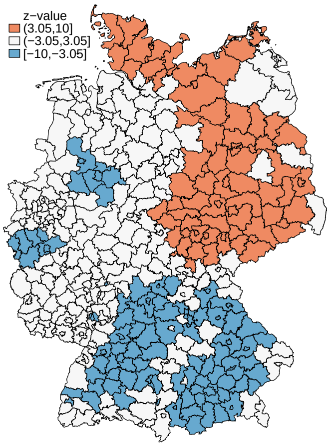
Overall, these results are already quite meaningful. For one, it underlines the finding from the previous section, that there is significant spatial dependency, resulting in clustering, in my data. Secondly, it is a first confirmation of some of my hypothesis regarding causality. The fact that spatial dependencies also exist for some exogenous variables of course is in itself also relevant. For one, it means that it might be sensible to explicitly model these dependencies in my SDM, so that I can differentiate between spatial effects stemming



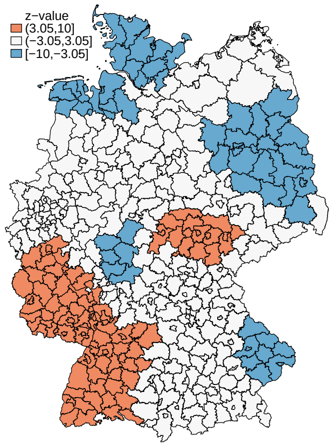
(a) Unemployment (log)



(b) DHI p.c. (log)



(c) Drop out rate (log)



(d) Voter turn-out (log)

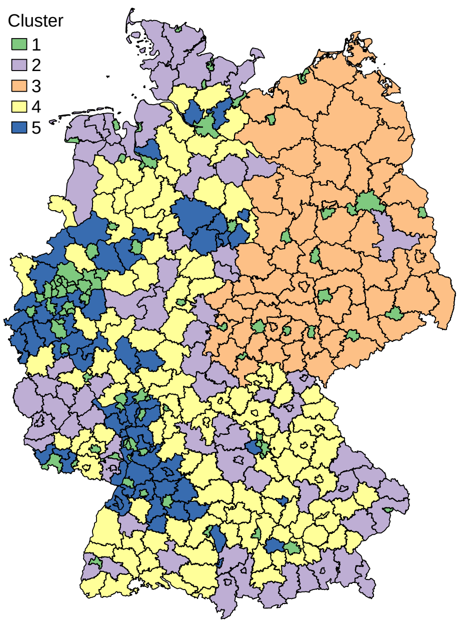
Source: Statistische Ämter, BKG, own calculations

Figure 8: Getis-Ord G z-value, var. determinants averaged over time

from the endogenous and exogenous variables. From a policy perspective, these results are also quite relevant. For one, due to the feedback-loops associated with spatial dependency, it would make sense to have a unified policy within a cluster, as these feedback effects will make it difficult to enact change without coordination, more on this later.

The last exploratory technique I used is cluster analysis of the explanatory variables as described in Chapter 3. The idea here is to find whether there is a latent pattern among counties that might explain the clusters I've found before. Again, this is a non-spatial technique and therefore the clusters that will emerge here have nothing to do with spatial dependency of crime. Instead, it will find counties that have similar socio-economic characteristics and I will see whether this is associated with the spatial clustering of crime shown before. As mentioned, I use two different hierarchical clustering techniques, average linkage and Ward. Finding a stopping rule to get a sensible amount of clusters proofed somewhat tricky though. As can be seen from the dendrograms (Figure 19 in Appendix A), in both cases large jumps in dissimilarity begin to appear after there are only about five clusters left. This would suggest that stopping at five clusters is a good choice, considering the results have to be interpretable, which would become difficult with 10 or more clusters. When looking at the pseudo-F by Caliński and Harabasz (1974), we see that the results of Ward and average linkage are quite similar up to around 5 clusters. After that, the pseudo-F values from using average linkage drop drastically from around 150 when using 5 clusters to about 2 when using two clusters. This would suggest that here, two clusters are the optimal choice. But unfortunately, the two clusters which emerge are the entire country and one single-county cluster. And while this is an interesting result, it is also quite useless. Also, this convexity is not present when using the Ward-method. I therefore choose five clusters as a stopping rule, although the pseudo-F values suggest this isn't optimal for average linkage.

Figure 9 depicts the results of the cluster analysis when using the Ward method. When we compare it to the results from average linkage method (Figure 21 in Appendix A), we see that they are quite similar overall, which suggests that these are sensible results (Rencher 2003). But likely because of its space-dilating properties, average linkage has produced one cluster with only a single county in it, which isn't very useful either. Therefore, and since it is often considered the default method, I will use the Ward results from now on. When Looking at Figure 9, we can see a fairly distinct pattern in space emerging. With



Var. sources, own calculations

Figure 9: Cluster analysis results using Ward

this, and considering the averages by cluster shown in Table 4, interpretation of these

Mean of:	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*
Unemployment (log)	1.59	1.09	1.93	0.99	1.17
DHI p.c. (log)	9.84	9.85	9.7	9.90	9.92
Drop-out rate (log)	1.94	1.80	2.15	1.76	1.73
Tourism (log)	12.40	13.83	12.79	12.56	11.98
State employees p.c. (log)	7.53	6.74	6.32	6.74	6.72
Divorce (log)	5.29	5.30	5.10	5.31	5.36
Voter turn-out (log)	3.10	3.21	3.15	3.26	3.32
Pop. density (log)	7.10	4.70	4.58	5.10	6.05
Share of foreigners (log)	2.26	1.56	0.49	1.81	2.16
Young & male (log)	1.47	1.40	1.38	1.42	1.39

Table 4: Variable-averages by Ward-cluster

Correlation	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*
Burglaries (log)	0.34	-0.19	-0.12	-0.22	0.18
Theft from cars (log)	0.44	-0.25	0.00	-0.30	0.10
Damage to property (log)	0.60	-0.25	0.18	-0.45	-0.08
Drug crime (log)	0.47	-0.05	-0.14	-0.25	-0.07
Street crime p.c. (log)	0.60	-0.26	-0.02	-0.38	0.04
Assault (log)	0.70	-0.15	-0.07	-0.40	-0.13

Table 5: Correlation between crime and cluster-dummies

results becomes quite straight-forward. Cluster 1 seems to consist of the major cities like Hamburg, Berlin, Munich, Frankfurt, cities in the Rhine-Ruhr area etc. These cities show fairly high unemployment, many state-employees p.c., low voter turn-out and a high share of foreigners and young men. Cluster 5 seems somewhat similar and to consist of smaller cities and highly urbanized counties in the West like Hannover, Münster or the Rhein-Main area without Frankfurt. Here unemployment is lower, but still quite high, the same goes for the share of foreigners. Interestingly, these cities have the lowest tourist activity out of all clusters, while having the second highest population density. They also have the highest relative voter turn-out of all clusters.

Cluster 2 seems to consist of poorer rural counties in the West, with low population density and relatively high unemployment and low DHI p.c. compared to the other rural counties in the West (cluster 4). Cluster 3 clearly consists of rural counties in the East, with the highest unemployment, lowest DHI p.c., lowest population density and a very small share of foreigners. Lastly, and as mentioned before, cluster 4 seems to consist of richer rural counties in the West, with the lowest unemployment and second highest DHI p.c. out of all clusters. Considering this is a exploratory technique, these results seem to give a good idea about the spatial structure of my covariates. It would therefore be interesting how these clusters relate to crime rates. For this, I created 5 dummies denoting whether a region belongs to a specific cluster and calculated the correlations between this and the crime rates, the results of which can be found in Table 5. Overall, the results are mainly in line with H1-4. Cluster 1, the big cities with high unemployment and high population density correlates positively with all forms of crime. In contrast, cluster 4, the rich rural counties in the West, correlate negatively with all forms of crime, with the other clusters falling somewhere in between. One interesting case is cluster 3, the rural counties in the East. For one, even though they have the highest unemployment, lowest DHI p.c. and highest drop-out rates, the correlations are mostly negative. For another, the on exception is damage to property, where there is a positive correlation. This goes against the broken window policy, where we would expect more damage to property to cause higher crime rates all around. A similar thing can be seen in cluster 5, where half the correlations have a positive sign and the other half a negative one. When comparing these results with the spatial clustering discussed before, the similarities are limited. We can see a clear East-West divide in the Ward-clusters but not in the spatial crime clusters, while the North-South divide visible there is not in the results from hierarchical cluster analysis. This of course might be due to the algorithm or the stopping-rule I used, which are both arbitrary to some degree. But to me, it suggests that this clustering is not purely the result of the spatial structure of the covariates, but rather the result of the spatial dynamics of both the ex- and endogenous variables. It is impossible to disentangle these relationships without a formal regression model, to the results of which I will turn now.

5.3 Regression Results

As reporting both the regression results as well as the direct, indirect and total effects for each regression would take up a lot of space, I will only report a selection of the estimated average direct and indirect effects that are either significant or otherwise of interest, while listing the rest of the estimation results in Appendix B and omitting total effects completely, as they are just the sum of indirect and direct effects. I will also not report the coefficients associated with the three outlier-dummies (outliers in the data, outliers in Moran's I and problems from merging counties before 2007 in Saxony-Anhalt), although the first two are often significant.

5.3.1 Burglaries

	ρ	*Log-Likelihood*	R^2*-total*	*Hausman*	*Unit-root*	*Wooldridge*	*Mundlak*
Statistic	0.2483	-1889.25	0.6149	646.86	-12.6612	176.305	1468.20
p-value	0.0000	-	-	0.0000	0.0000	0.0000	0.0000

Table 6: Burglaries: Tests and goodness-of-fit measures

Before turning to the results, first a quick word about the test and goodness-of-fit results reported in Table 6. The estimated spatial lag coefficient of the endogenous variable is denoted by ρ. Here, we can infer a very significant positive relationship between burglaries in county i and the neighboring county j, which of course will trickle down through all counties. Further, *Hausman* shows the results of the Hausman test. It is important to note that this is not a post-regression test, as my regression includes time-invariates. Instead it is a test comparing two auxiliary regressions of the

	Direct Effects: Burglaries				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Dmg. to property (log)	-0.2441	0.0450	-5.4247	0.0000	-0.3323,-0.1559
State employees p.c. (log)	-0.3491	0.0548	-6.3748	0.0000	-0.4564,-0.2418
Young & male (log)	0.3267	0.0669	4.8839	0.0000	0.1956,0.4579
Divorce rate (log)	0.3874	0.1246	3.1090	0.0019	0.1432,0.6316
Unemployment (log)	0.1423	0.0324	4.3953	0.0000	0.0788,0.2058
Tourism (log)	0.2272	0.0453	5.0150	0.0000	0.1384,0.3160
Pop. density (log)	1.7280	0.2882	5.9950	0.0000	1.1631,2.2929
Lag unemployment (log)	0.0767	0.0302	2.5400	0.0111	0.0175,0.1360
Lag DHI p.c. (log)	1.4403	0.2122	6.7860	0.0000	1.0243,1.8563
Lag clearance rate (log)	-0.0811	0.0349	-2.3251	0.0201	-0.1494,-0.0127
Border to Switzerland	-0.5614	0.2725	-2.0602	0.0394	-1.0954,-0.0273
Border to Belgium	0.6135	0.2720	2.2556	0.0241	0.0804,1.1466
Border to Luxembourg	0.6555	0.2843	2.3057	0.0211	0.0983,1.2128
Avg. unemployment (log)	0.7213	0.1145	6.2996	0.0000	0.4969,0.9457
Avg. young & male (log)	-1.4315	0.2867	-4.9927	0.0000	-1.9934,-0.8695
Avg. share of foreigners (log)	0.4389	0.0671	6.5406	0.0000	0.3074,0.5704
Avg. dmg. to property (log)	0.4905	0.1203	4.0769	0.0000	0.2547,0.7263
Avg. Clearance rate (log)	-1.0991	0.1081	-10.1661	0.0000	-1.3109,-0.8872
Divorce rate 2015 (log)	0.5635	0.1180	4.7759	0.0000	0.3322,0.7947

Table 7: Selection of avg. direct effects: Burglaries (log)

time-variate variables, one using FE and the other RE, where the approach by Mundlak (1978) is not implemented. As mentioned before, here H_0 is that there is no systematic difference between the two, which we have to reject in our case. Therefore it is crucial to use the Mundlak-approach in my main regression. *Unit root* denotes the results of the unit-root test by Breitung and Das (2005), where the H_0 is that the endogenous variable contains a unit-root, which again has to be strongly rejected here, meaning the data-generating process is likely stationary. *Wooldridge* reports the results of the test for serial correlation by Wooldridge (2010), where under H_0 there is no serial correlation, which has to be rejected again. Therefore it is important to use the robust standard-errors by Cameron et al. (2011). Lastly, *Mundlak* denotes the results of a Wald-test of the coefficients associated with the averages over time. If they are jointly significantly different from zero, we can assume that this regression has the same properties regarding unbiasedness and consistency as an FE estimation (Bell and Jones 2015). In Table 22 (in Appendix B) I also report AIC/BIC and other goodness-of-fit measures. Here it becomes obvious from looking at the within-/ between-R^2 that the explanatory power of my model largely comes from the between dimension, while it struggles to explain variation across time, likely because there is no real observable trend there. Lastly, as can be seen from both the histograms and KDE of the residuals (Figure 22 in Appendix A), the assumption of normality seems to be mostly met. These test results are quite similar across all five estimations, so I won't comment on them again unless something changes.

From the estimated average direct effects reported in Table 7, we can already see that many of my hypothesis are confirmed in the case of burglaries. With regard to the Becker-Ehrlich model (H1), we can conclude that lag of DHI p.c. indeed has a positive impact on the burglary rate, meaning it seems to represent opportunities for burglary rather than the access to resources to fight crime, as the social disorganization theory would have us believe. It is important to remember here that this variable is demeaned, and interestingly the time-average of DHI p.c. is not significant. On the other hand, unemployment seems to strongly impact crime, both the average level as well as the demeaned lag and the current period values. This is further evidence that the Becker-Ehrlich theory works well here, which is especially interesting, as many other previous studies have failed to show this intuitively sensible result (Entorf (2008)). Since the sign for unemployment in the current period is positive, it suggests that the theory by Cantor and Land (1985) has to be rejected for the case of burglaries, as the fact that people are unemployed doesn't seem to increase the vigilance of the inhabitants in a manner that would lower crime. In terms of deterrence, we see that the overall government response to crime, measured by the number of state employees, as well as the clearance rate, in fact lowers crime. It also seems to confirm the theory by Sah (1991), as not only the average, but also the lag of the clearance rate significantly lowers crime. This suggests that potential criminals look at the last period to make a decision whether to commit crime in the current one. In this context also fits that the lag of unemployment is significant. With respect to H2, I already mentioned that DHI p.c. seems to have the wrong sign for the social disorganization theory to be a good fit. As a saving grace for H2, the divorce rate, both over time and between counties, seems to increase crime as expected. But this could of course also taken as conformation for the routine activity theory (H3), which is also supported by the fact that both tourism seems to increase burglaries. It seems likely that this is due to the fact that tourist accommodations are more often empty than other homes. With regard to the broken window theory (H4), the results are somewhat ambiguous. While damage to property averaged over time has a significant positive impact on burglaries, the sign of the coefficient affiliated with the demeaned variable is negative. As mentioned before, damage to property was included as a proxy for general "disorder", and it seems while the general level of disorder increases burglaries, an increase from one year to another lowers it. A possible explanation for this phenomenon is that increases in damage to property might temporarily result in a response by the government, for example in an increase of police presence, that also dissuades potential burglars. However, this has to be investigated further to come to a conclusive result. Lastly, when considering the various control variables, the share of young males shows a similar behavior than the damage to property rate. While the demeaned variable seems to have a significant positive impact, the average over time has a negative one. This is a contradiction I can't quite explain, but it makes sense to assume that burglaries are less sensitive to the share of young males than other crime variables. In contrast, population density behaves like expected, with a higher burglary rate in regions with higher population densities, which also confirms H2. Interestingly, the lag of the share of foreigners wasn't significant at all (see also complete results in Appendix B). Lastly the effects neighboring countries have on the burglary rate are somewhat counter-intuitive. In contrast to popular belief, it is not regions neighboring

	Indirect Effects: Burglaries				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Dmg. to property (log)	-0.0764	0.0152	-5.0357	0.0000	-0.1062,-0.0467
State employees p.c. (log)	-0.1095	0.0202	-5.4238	0.0000	-0.1491,-0.0700
Young & male (log)	0.1028	0.0243	4.2303	0.0000	0.0552,0.1504
Divorce rate (log)	0.1214	0.0403	3.0112	0.0026	0.0424,0.2004
Tourism (log)	0.0713	0.0158	4.5201	0.0000	0.0404,0.1022
Pop. density (log)	0.5416	0.1011	5.3552	0.0000	0.3434,0.7398
Lag unemployment (log)	0.0241	0.0098	2.4611	0.0139	0.0049,0.0432
Lag DHI p.c. (log)	2.3366	0.3541	6.5991	0.0000	1.6426,3.0306
Lag clearance rate (log)	-0.0255	0.0114	-2.2414	0.0250	-0.0478,-0.0032
Border to Switzerland	-0.1760	0.0866	-2.0325	0.0421	-0.3457,-0.0063
Border to Belgium	0.1924	0.0876	2.1975	0.0280	0.0208,0.3640
Border to Luxembourg	0.2057	0.0914	2.2504	0.0244	0.0266,0.3849
Voter turn-out (log)	0.2224	0.0733	3.0319	0.0024	0.0786,0.3661
Avg. young & male (log)	-0.4489	0.0982	-4.5695	0.0000	-0.6415,-0.2564
Avg. share of foreigners (log)	0.1378	0.0253	5.4461	0.0000	0.0882,0.1874
Avg. dmg. to property (log)	0.1538	0.0401	3.8387	0.0001	0.0753,0.2324
Avg. Clearance rate (log)	-0.3449	0.0473	-7.2913	0.0000	-0.4376,-0.2522
Divorce rate 2015 (log)	0.1772	0.0423	4.1910	0.0000	0.0943,0.2600

Table 8: Selection of avg. indirect effects: Burglaries (log)

Eastern European countries that suffer from more burglaries, but rather those bordering on Belgium and Luxembourg, while bordering Switzerland has a negative impact. It should be remembered here that I differentiate between the country-specific effect and the effect of living on the border in general, which didn't turn out to be significant however. This is also largely in line with the findings of Oberwittler and Gerstner (2011) for Baden-Wurttemberg.

When looking at the average indirect effects (Table 8), we can see clear evidence of spill-overs. First of all, this of course again confirms H5, that the feedback loops due to spatial dependencies play a crucial role in explaining crime in a county. Largely, the effect seems to consist of the neighboring county being in a condition predestined to increase crime in their own county, which then radiates out to the neighboring counties. This is implied by the fact that all the same variables proofed to be significant, with the same signs of the coefficients. This is also an interesting result, as it means that all these variables cause the positive spatial auto-correlation of crime noted earlier and we do not see a "displacement" of crime, i.e. criminals moving from one county to the other as enforcement increases , as also rejected by Weisburd et al. (2006). Especially with burglaries, one could have expected that for example the indirect effects of DHI pc. or unemployment could have the opposite sign than the direct effects, as inhabitants of poor counties go to richer counties to rob its inhabitants. Arguably, the reason this can't be observed is due to the fact that income and unemployment are highly clustered themselves, so that very few rich counties border poor ones. Another particular interesting result is that only the lag of unemployment is significant here, which could be suggesting that the spatial spill-over of unemployment, and arguably other variables, needs time to manifest itself. Therefore, it might interesting to model crime with a temporal-spatial model, i.e. a model that also takes time dynamics into account. But this has to be left to future research. Also interesting is that the border effects seem to be so strong that they trickle down through the regions as well, meaning for example that counties which border counties that in turn border Belgium or Luxembourg also suffer higher rates of burglaries.

5.3.2 Theft from Cars

	ρ	*Log-Likelihood*	R^2*-total*	*Hausman*	*Unit-root*	*Wooldridge*	*Mundlak*
Statistic	.4832	-835.01	0.6715	161.45	-12.2707	483.844	1836.75
p-value	0.0000	-	-	0.0000	0.0000	0.0000	0.0000

Table 9: Theft from cars: Tests and goodness-of-fit measures

	Direct Effects: Theft from cars				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	-0.1229	0.0265	-4.6339	0.0000	-0.1750,-0.0709
State employees p.c. (log)	-0.1039	0.0436	-2.3827	0.0172	-0.1894,-0.0184
Lag share of foreigners (log)	0.1091	0.0410	2.6594	0.0078	0.0287,0.1894
Young & male (log)	-0.4321	0.0532	-8.1202	0.0000	-0.5364,-0.3278
Unemployment (log)	0.1571	0.0250	6.2769	0.0000	0.1081,0.2062
Tourism (log)	-0.0896	0.0361	-2.4832	0.0130	-0.1603,-0.0189
Lag drop-out rate (log)	-0.0996	0.0220	-4.5175	0.0000	-0.1428,-0.0564
Lag DHI p.c. (log)	1.5546	0.1695	9.1701	0.0000	1.2223,1.8868
Lag clearance rate (log)	-0.2091	0.0279	-7.5052	0.0000	-0.2637,-0.1545
Border to Austria	-0.4747	0.2155	-2.2030	0.0276	-0.8970,-0.0524
Border to Switzerland	-0.5183	0.2490	-2.0815	0.0374	-1.0064,-0.0303
Border to Luxembourg	0.5251	0.2598	2.0214	0.0432	0.0160,1.0342
Voter turn-out (log)	-0.0646	0.0304	-2.1252	0.0336	-0.1242,-0.0050
Avg. unemployment (log)	0.6531	0.1048	6.2305	0.0000	0.4476,0.8585
Avg. share of foreigners (log)	0.1840	0.0613	3.0029	0.0027	0.0639,0.3042
Avg. dmg. to property (log)	0.4919	0.1100	4.4724	0.0000	0.2763,0.7075
Avg. Clearance rate (log)	-1.2469	0.0987	-12.6369	0.0000	-1.4403,-1.0535
Divorce rate 2015 (log)	0.3934	0.1079	3.6462	0.0003	0.1819,0.6049

Table 10: Selection of avg. direct effects: Theft from cars (log)

The results concerning theft from cars are largely similar to those regarding burglaries. This makes sense, as both are property crimes and probably largely driven by the same motivation. The first notable difference is that the model seems to be a better fit, as suggested by the log-likelihood, R^2 and AIC/BIC (Table 22 in Appendix B). Secondly, here voter turn-out has the hypothesized impact on crime, which makes the social disorganization theory (H2) a better fit. Potentially, this is because theft from a car is more a crime of opportunity compared to a burglary, which makes social cohesion and control more important, as it is not only committed by hardened professionals. Thirdly, the share of foreigners now significantly increases the rate of thefts, which also suggests that burglaries and thefts from cars are different in kind. Other than this, the results reported in Table 10 again largely support the Becker-Ehrlich theory, with clearance rate and it's lag as well as rate of state employees p.c. having a negative effect on crime, while DHI p.c. and unemployment having a positive one. Beside the effect of voter turn-out, H2 is also confirmed by divorces increasing the amount of theft. However, the routine activity theory (H3) doesn't

	Indirect Effects: Theft from cars				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	-0.1025	0.0229	-4.4675	0.0000	-0.1474,-0.0575
State employees p.c. (log)	-0.0866	0.0367	- 2.3584	0.0184	-0.1586,-0.0146
Lag share of foreigners (log)	0.0910	0.0353	2.5771	0.0100	0.0218,0.1603
Young & male (log)	-0.3598	0.0469	-7.6765	0.0000	-0.4516,-0.2679
Unemployment (log)	0.5819	0.0584	9.9599	0.0000	0.4674,0.6964
Tourism (log)	-0.0746	0.0303	-2.4595	0.0139	-0.1341,-0.0152
Lag drop-out rate (log)	-0.1920	0.0618	-3.1072	0.0019	-0.3132,-0.0709
Lag DHI p.c.	3.4987	0.3934	8.8931	0.0000	2.7276,4.2698
Lag clearance rate (log)	-0.1742	0.0254	-6.8661	0.0000	-0.2240,-0.1245
Border to Austria	-0.3950	0.1795	-2.2002	0.0278	-0.7469,-0.0431
Border to Switzerland	-0.4314	0.2070	-2.0846	0.0371	-0.8371,-0.0258
Border to Luxembourg	0.4377	0.2180	2.0076	0.0447	0.0104,0.8650
Avg. share of foreigners (log)	0.1534	0.0519	2.9555	0.0031	0.0517,0.2552
Avg. dmg. to property (log)	0.4100	0.0947	4.3314	0.0000	0.2245,0.5955
Avg. Clearance rate (log)	-1.0391	0.1017	-10.2192	0.0000	-1.2384,-0.8398
Divorce rate 2015 (log)	0.3283	0.0935	3.5121	0.0004	0.1451,0.5115

Table 11: Selection of avg. indirect effects: Theft from cars (log)

seem to work as well. For one, the general level of tourism isn't significant at all, and the within-effect has a negative sign, though being quite small. This is counter-intuitive, but might be related to the relationship between disorder and theft rate, i.e. that high amounts of disorder lower tourist activity while increasing theft from cars. This is supported by the fact that the time average of damage to property again significantly increases the rate of thefts, thus confirming H4 to some degree. Somewhat odd is that the share of young males is again negatively impacting crime, the same as the school drop-out rate. I'm not entirely clear why that is, but it should be noted that these results, as well as in the case of burglaries, are very robust to various different specifications of the model. Lastly, we can see that bordering Austria and Switzerland seems to lower the rate of thefts, while bordering Luxembourg increases it. This is interesting, although no obvious interpretation springs to mind. The average indirect effects (Table 11) are very similar to the direct one, again suggesting a very straight spill-over from one county to the other and not showing any signs of displacement in the sense of Weisburd et al. (2006). One notable difference is that voter turn-out doesn't seem to show such spill-over effects. This makes a certain amount of sense, considering that the social cohesion of a group likely only impacts crime within that group directly.

5.3.3 Drug Crime

	ρ	*Log-Likelihood*	R^2*-total*	*Hausman*	*Unit-root*	*Wooldridge*	*Mundlak*
Statistic	0.1431	-438.66	0.4736	73.28	-12.6636	145.306	1020.61
p-value	0.0000	-	-	0.0000	0.0000	0.0000	0.0000

Table 12: Drug crime: Tests and goodness-of-fit measures

With regard to drug crime, it seems that the model is not as good a fit as before. For one, the coefficient of the spatial AR-term (ρ) is much smaller, while still being highly significant. But also in terms of R^2, the fit is worse, although interestingly both log-likelihood and AIC/BIC (Table 22 in Appendix B) would suggest a better fit. That there is less spatial autocorrelation is of course in line with the findings from Moran's I and Getis-Ord's G, where we saw far less clustering than with other types of crime.

	Direct Effects: Drug crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	0.0934	0.0237	3.9421	0.0001	0.0470,0.1399
State employees p.c. (log)	0.1525	0.0391	3.9048	0.0001	0.0760,0.2291
Lag share of foreigners (log)	0.0824	0.0367	2.2455	0.0247	0.0105,0.1544
Young & male (log)	-0.3379	0.0476	-7.1014	0.0000	-0.4311,-0.2446
Divorce rate (log)	0.3611	0.0888	4.0678	0.0000	0.1871,0.5351
Unemployment (log)	0.0523	0.0233	2.2467	0.0247	0.0067,0.0979
Lag clearance rate	0.0636	0.0249	2.5580	0.0105	0.0149,0.1123
Border to the Netherlands	0.5330	0.1844	2.8907	0.0038	0.1716,0.8944
Border to Denmark	-0.5383	0.2466	-2.1827	0.0291	-1.0217,-0.0549
Voter turn-out (log)	0.1624	0.0270	6.0120	0.0000	0.1094,0.2153
Avg. DHI. p.c.	-0.4801	0.2421	-1.9832	0.0473	-0.9546,-0.0056
Avg. young & male (log)	-0.5302	0.2196	-2.4139	0.0158	-0.9607,-0.0997
Avg. share of foreigners (log)	0.2419	0.0514	4.7031	0.0000	0.1411,0.3426
Avg. state employees p.c. (log)	0.4232	0.0490	8.6393	0.0000	0.3272,0.5193
Avg. dmg. to property (log)	0.3205	0.0922	3.4755	0.0005	0.1398,0.5012
Avg. Clearance rate (log)	0.1962	0.0830	2.3655	0.0180	0.0336,0.3588

Table 13: Selection of avg. direct effects: Drug crime (log)

Secondly, considering the results from Table 13, it seems that the Becker-Ehrlich theory (H1) doesn't apply anymore. Because while unemployment still increases the amount of drug crime, DHI p.c. lowers it, suggesting that it no longer can be considered as a proxy for illegal income opportunities. Instead it could be considered as a proxy for the resources a community has access to in order to organize itself, in the sense of the social disorganization theory (H2). That the Becker-Ehrlich model breaks down here can also be seen from the effect of the deterrence variables, clearance rates and state employees p.c., that both increase the rate of drug crimes. To me, this suggests that there might exist a problem with simultaneity here. As discussed before, drug crimes are notoriously underreported, and so it seems likely that an increase in government action doesn't increases the amount of drug crimes committed but rather the amount of drug crimes detected. Therefore, all the following results have to be taken with a larger grain of salt than usual. For the validity of the social disorganization theory in this case also speaks that the both the divorce rate and the share of foreigners strongly increases the rate of drug crimes. However, voter turn does as well, which I again attribute to the simultaneity problem discussed before, as it seems likely that communities with more cohesion are better at detecting drug crimes, which again would explain why Berlin was in a low drug crime cluster before. The same is true for the share of young men, which seem to lower the amount of drug crimes, which is not sensible at all. However, the broken window theory (H4) seems to be confirmed again, with the rate of damage to property crimes increasing the amount of drug crime. But simultaneity might be a problem here as well, as more drug consumption could likely also lead to more damage to property. A more reasonable result is that the amount of drug crime is very high close to the border to the Netherlands. With respect to the indirect effects (Table 14), the picture is again very similar to the cases before. The same variables that affect drug crime in a county also affect them in the neighboring counties, implying a straight forward spill-over process. Overall, the results for drug crimes have to be disregarded to some degree however, as the presence of simultaneity stemming from the data gathering process makes a good estimation difficult.

	Indirect Effects: Drug crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	0.0152	0.0046	3.2790	0.0010	0.0061,0.0243
State employees p.c. (log)	0.0248	0.0077	3.2300	0.0012	0.0098,0.0399
Lag share of foreigners (log)	0.0135	0.0066	2.0283	0.0425	0.0005,0.0265
Young & male (log)	-0.0549	0.0119	-4.6052	0.0000	-0.0783,-0.0315
Divorce rate (log)	0.0586	0.0169	3.4692	0.0005	0.0255,0.0917
Unemployment (log)	0.3176	0.0367	8.6435	0.0000	0.2456,0.3896
Lag drop-out rate (log)	-0.1327	0.0362	-3.6626	0.0002	-0.2038,-0.0617
Lag clearance rate(log)	0.0104	0.0045	2.2875	0.0222	0.0015,0.0193
Border to the Netherlands	0.0870	0.0343	2.5359	0.0112	0.0198,0.1543
Border to Denmark	-0.0873	0.0421	-2.0734	0.0381	-0.1699,-0.0048
Voter turn-out (log)	0.2958	0.0479	6.1722	0.0000	0.2019,0.3898
Avg. young & male (log)	-0.0863	0.0390	-2.2158	0.0267	-0.1627,-0.0100
Avg. share of foreigners (log)	0.0395	0.0112	3.5363	0.0004	0.0176,0.0614
Avg. state employees p.c. (log)	0.0691	0.0152	4.5399	0.0000	0.0393,0.0989
Avg. dmg. to property (log)	0.0521	0.0172	3.0266	0.0025	0.0184,0.0859
Avg. Clearance rate (log)	0.0320	0.0148	2.1627	0.0306	0.0030,0.0610

Table 14: Selection of avg. indirect effects: Drug crime (log)

5.3.4 Street Crime

	ρ	*Log-Likelihood*	R^2*-total*	*Hausman*	*Unit-root*	*Wooldridge*	*Mundlak*
Statistic	0.1035	3627.15	0.8228	150.32	-12.0008	263.144	3481.641
p-value	0.0000	-	-	0.0000	0.0000	0.0000	0.0000

Table 15: Street crime: Tests and goodness-of-fit measures

As far as street crimes are concerned, the model seems to perform a lot better. Not only is the log-likelihood quite high, but so is R^2. As can be seen from Table 22 in Appendix B, this is also due to the fact that here the model explains the majority of within-variation, which isn't the case in the other regressions. However, the spatial AR-coefficient ρ is lower than in all previous cases, while still being highly significant. The Becker-Ehrlich theory (H1) seems to fit quite well here, although with some limitations. Clearance rates, both lagged, current period and time average, lower crime as one would expect under H1, however the number of state employees p.c. is not significant here and neither is DHI p.c. But since unemployment increases the rate of street crimes, overall this theory still fits well. The same is true for the social disorganization theory (H2), with divorce rates, share of foreigners and population density all increasing the crime rate. The routine activity theory performs less well, with tourism lowering crime and all other variables associated with it not being significant. That tourism lowers crime is again likely due to the fact, that disorder, i.e. it's proxy, damage to property, has a highly significant impact on street crime while likely also reducing the attractiveness of the region for tourists. This of course also confirms the broken window theory (H4). Lastly it is interesting to see that the only border that has a significant impact is the one to Netherlands.

	Direct Effects: Street crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	-0.0392	0.0090	-4.3797	0.0000	-0.0568,-0.0217
Dmg. to property (log)	0.4631	0.0121	38.2135	0.0000	0.4393,0.4869
Lag share of foreigners (log)	0.0327	0.0139	2.3614	0.0182	0.0056,0.0599
Divorce rate (log)	0.3864	0.0341	11.3221	0.0000	0.3195,0.4533
Unemployment (log)	0.0399	0.0088	4.5114	0.0000	0.0226,0.0572
Tourism (log)	-0.0757	0.0122	-6.1961	0.0000	-0.0997,-0.0518
Lag clearance rate(log)	-0.0860	0.0094	-9.1635	0.0000	-0.1044,-0.0676
Border to the Netherlands	0.3263	0.1263	2.5834	0.0098	0.0788,0.5739
Avg. unemployment (log)	0.2190	0.0600	3.6475	0.0003	0.1013,0.3366
Avg. share of foreigners (log)	0.1648	0.0352	4.6884	0.0000	0.0959,0.2337
Avg. dmg. to property (log)	0.9076	0.0631	14.3873	0.0000	0.7840,1.0313
Avg. Clearance rate (log)	-0.5031	0.0568	-8.8564	0.0000	-0.6145,-0.3918
Divorce rate 2015 (log)	0.1665	0.0611	2.7245	0.0064	0.0467,0.2862

Table 16: Selection of avg. direct effects: Street crime (log)

	Indirect Effects: Street crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate (log)	-0.0045	0.0014	-3.2819	0.0010	-0.0071,-0.0018
Dmg. to property (log)	0.0527	0.0106	4.9500	0.0000	0.0318,0.0735
Lag share of foreigners (log)	0.0037	0.0018	2.0604	0.0394	0.0002,0.0073
Divorce rate (log)	0.0438	0.0087	5.0567	0.0000	0.0268,0.0607
Unemployment (log)	0.0732	0.0134	5.4769	0.0000	0.0470,0.0994
Tourism (log)	-0.0086	0.0022	-3.9166	0.0001	-0.0129,-0.0043
Lag drop-out rate (log)	0.0516	0.0134	3.8616	0.0001	0.0254,0.0778
Lag DHI p.c. (log)	0.3696	0.0808	4.5770	0.0000	0.2113,0.5279
Lag clearance rate	-0.0098	0.0023	-4.3025	0.0000	-0.0142,-0.0053
Border to the Netherlands	0.0372	0.0167	2.2277	0.0259	0.0045,0.0699
Avg. share of foreigners (log)	0.0188	0.0055	3.4220	0.0006	0.0080,0.0295
Avg. dmg. to property (log)	0.1032	0.0217	4.7591	0.0000	0.0607,0.1458
Avg. Clearance rate (log)	-0.0572	0.0132	-4.3239	0.0000	-0.0832,-0.0313
Divorce rate 2015 (log)	0.0190	0.0082	2.3272	0.0200	0.0030,0.0350

Table 17: Selection of avg. indirect effects: Street crime (log)

When considering the average indirect effects (Table 17), the results are largely similar to those reported before, with most of the variables determining crime in one's own county spilling over to the neighboring ones. One difference is however that the drop-out rate is now significantly increasing street crime in neighboring counties. This is a very interesting result, as it suggests a spatial mobility of offenders not seen before, i.e. people with low academic performance crossing county lines to commit crimes there. This seems to be the only reasonable explanation for this result, as it seems unlikely that the quality of education in a neighboring county inspires people in the other county to commit crimes. Another interesting difference is that the lag of DHI p.c. also increases crime only indirectly. This is somewhat odd, as one would expect DHI, when taken as a proxy for illegal income opportunities, to effect crime only in the county the crime takes place in, not the other way around. There are several possibilities why this is not the case. It could be that jealousy plays a role here, i.e people in one county comparing themselves to those in another who became richer and therefore deciding to take up crime. It is also possible that this is some kind of displacement effect, i.e. that higher wealth in a county leads to more social organization, driving criminals away into the neighboring one. However, further research is needed to see whether this result holds up and what causes it.

5.3.5 Assault

	ρ	*Log-Likelihood*	R^2*-total*	*Hausman*	*Unit-root*	*Wooldridge*	*Mundlak*
Statistic	0.0399	3504.08	0.7306	118.81	-8.5453	263.144	71.751
p-value	0.0400	-	-	0.0000	0.0000	0.0000	0.0000

Table 18: Assault: Tests and goodness-of-fit measures

	Direct Effects: Assault				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0780	0.0094	-8.3187	0.0000	-0.0964,-0.0596,
Dmg. to property (log)	0.2792	0.0127	21.9416	0.0000	0.2542,0.3041
State employees p.c. (log)	-0.0513	0.0155	-3.3226	0.0009	-0.0816,-0.0211
Lag share of foreigners (log)	0.0427	0.0145	2.9456	0.0032	0.0143,0.0711
Divorce rates (log)	0.1835	0.0354	5.1790	0.0000	0.1141,0.2530
Tourism (log)	0.0436	0.0128	3.4157	0.0006	0.0186,0.0686
Lag clearance rate	-0.0359	0.0098	-3.6490	0.0003	-0.0551,0.0166
Border to Austria	0.2148	0.1049	2.0474	0.0406	0.0092,0.4204
Border to France	0.2083	0.1053	1.9777	0.0480	0.0019,0.4147
Border to Belgium	0.2532	0.1210	2.0930	0.0363	0.0161,0.4903
Border to Denmark	0.2961	0.1430	2.0701	0.0384	0.0158,0.5765
Avg. drop-out rate (log)	0.1466	0.0483	3.0362	0.0024	0.0520,0.2412
Avg. DHI. p.c.	-0.4583	0.1404	-3.2643	0.0011	-0.7335,-0.1831
Avg. population density(log)	0.0542	0.0192	2.8195	0.0048	0.0165,0.0919
Avg. share of foreigners (log)	0.1007	0.0298	3.3821	0.0007	0.0423,0.1591
Avg. state employees p.c. (log)	-0.1457	0.0283	-5.1392	0.0000	-0.2012,-0.0901
Avg. dmg. to property (log)	0.6431	0.0535	12.0273	0.0000	0.5383,0.7479
Avg. Clearance rate(log)	-0.2641	0.0481	-5.4852	0.0000	-0.3585,-0.1697

Table 19: Selection of avg. direct effects: Assault (log)

Lastly, concerning assault, we can see that the spatial dependency plays only a small role, with ρ being close to zero and barely significant. Interestingly, the model still seems to be a good fit, considering the log-likelihood, R^2 and AIC/BIC (Table 22 in Appendix B). In terms of average direct effects, assault seems in some ways similar to drug crime. Like it was the case there, the Becker-Ehrlich model (H1) doesn't seem to work too well. Unemployment for instance has no significant impact on the rate of assaults, and DHI. p.c. even seems to lower it. Again, this suggests that here DHI is not a proxy for illegal income opportunities, that aren't really there in the case of assault anyway. Instead, it seems to be a proxy for the access to resources a community has to organize itself, with the effect that the rate of assaults gets lowered. This is also supported by the fact that the deterrence variables, clearance rates and state employees, in their various forms all effectively lower the assault rates. This of course supports the social disorganization theory and is also in line with the results from Messner, Teske, et al. (2013), who also used assault as one of their two crime variables, but as they didn't model spatial dependency explicitly, this comparison can only go so far. However, in contrast to their findings, the share of young men is not significant in my results.

This, but also the rest of the results, suggests that the social disorganization theory (H2) seems well suited to explain the rate of assaults. Both the share of foreigners as well as population density increase their occurrence, as well as the divorce rate. The last result could of course be also interpreted in favor of the routine activity theory (H3), especially since tourism positively affects the assault rate as well. Lastly, even the broken window theory (H4) seems to largely apply here, as damage to property increases the number of assaults per capita. Obviously, this stands in conflict with the results for street crime, where tourism and damage to property had the opposite effect, which was interpreted as disorder lowering tourist activity, but this doesn't seem to be the case here. Finally, as hypothesized, the drop-out rate increases crime. So interestingly, assault and street crime are the only cases where the drop-out rate seems to play a significant role explaining crime.

	Indirect Effects: Assault				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0032	0.0017	-1.8777	0.0604	-0.0066,0.0001
Dmg. to property (log)	0.0116	0.0060	1.9423	0.0521	-0.0001,0.0234
Divorce rates	0.0076	0.0043	1.7751	0.0759	-0.0008,0.0161
Lag DHI p.c.	-0.1764	0.0809	-2.1798	0.0293	-0.3351,-0.0178
Avg. DHI. p.c.	-0.3364	0.1798	-1.8703	0.0614	-0.6888,0.0161
Avg. share of foreigners (log)	0.0042	0.0026	1.6515	0.0986	-0.0008,0.0093
Avg. state employees p.c. (log)	-0.0061	0.0036	-1.7271	0.0841	-0.0131,0.0008
Avg. dmg. to property (log)	0.0268	0.0139	1.9336	0.0532	-0.0004,0.0539
Avg. Clearance rate	-0.0110	0.0061	-1.8082	0.0706	-0.0230,0.0009

Table 20: Selection of avg. indirect effects: Assault (log)

When comparing the average indirect effects on assault (Table 20) to the other regression results, a clear contrast emerges. Since ρ is far lower, the spill-over effects are far less pronounced, and often only significant on the $\alpha \leq 10\%$ level. But other than this, the nature of spill-overs is still mostly the same as before, again the same variables determining the crime rate in one's own county also affect those in neighboring ones.

5.3.6 Summary of Regression Results

In summary, one could say that the regression results fall into two broad categories: There are those concerning crimes against property, where the Becker-Ehrlich model (H1) takes on much of the explanatory power. This of course makes sense, as this model was especially built to explain property crime, but is still interesting to see confirmed. This is also largely in line with the non-spatial results by Entorf and Spengler (2000). In the other category are crimes not directed against someone else's property, like drug crimes and assault. Here the theory of social disorganization seems to explain regional variation much better. As street crime is a mixture of those two, in makes sense that here the results also do, as both H1 and H2 perform reasonably well. In both categories, the routine activity (H3) theory largely seems to apply as well as the the broken window theory (H4), with the exception of burglaries, where the results were mixed. With respect to the spatial dependencies (H5), all forms of crime exhibited significant spatial lag terms, although of varying size, with assault exhibiting the least spatial dependency. The resulting spill-over effects also were largely similar across crime types, with a few exceptions it was always the same variables that caused crime in one region that also radiated out, causing crime in a neighboring one. Therefore, the theory that crime gets displaced to another county when circumstances or policy lower it in a neighboring one, has to be rejected, as also found by Weisburd et al. (2006). In terms of fit, most models seemed to have a fairly high explanatory power, especially between counties, with the exception of drug crimes. Here it became apparent that the data exhibited strong signs of simultaneity, likely the result of underreporting of crime not being homogeneous across regions but rather being causally linked to clearance rate, unemployment or the number of state employees. Therefore these results have to be interpreted carefully. Lastly, there were a number of results which could be the jump-off point for further research. The burglary rate only seemed to respond to the lagged clearance rate, giving support to the theory by Sah (1991) of crime dynamics. Also, DHI had only an indirect effect on street crime, which could signify a displacement process of crime. Lastly, it is notable that the share of foreigners had a significant positive impact on all types of crime except burglaries. This of course supports the findings of Piopiunik and Ruhose (2017).

6 Discussion

Lastly, let us discuss what these findings mean in terms of policy and what their limitations are. After this, I will then come to a conclusion.

6.1 Policy Implications

The question now becomes what these results means for crime-fighting policy. And there is good news and bad news. For one, it became apparent that crime rates do respond to government action. In most cases, the clearance rate significantly lowers crime, which of course implies that size and training of the police force is a key factor when one wants to lower crime rate. This is also supported by the fact that the share of state employees, as a proxy for government response to crime, significantly lowers crime in most cases, the exception being street crime, where it had no significant impact, and drug crime, which displayed problems with simultaneity. This is of course an intuitive result, but an important one, as the money spent on crime fighting is a very easy thing to change from a policy perspective, especially compared to problems like unemployment or the drop-out rate. But here the spatial aspect also becomes important, as it is not enough to increase clearance rates or government staff in one's own county, the neighboring counties should ideally do the same. And since there is no evidence of displacement, this should be possible without conflicts between counties arising, as more police action in one county doesn't increase but rather lowers crime in neighboring ones. But, as so often in the presence of externalities, the problem of free-riders can arise here. For example, a county i can profit from increased spending in neighboring county j without increasing their own spending. From a general welfare perspective it would obviously be optimal to harness the power of the feedback loops associated with spatial spill-overs by coordinating spending within one of the crime-clusters found using Getis-Ord G. Therefore, it is fortunate that in Germany crime fighting policies are decided on the state level, which drastically decreases the free-riding problem. But since the clusters found also cross state lines, between-state cooperation still seems advisable.

This is even more the case, as the broken window theory seems to apply for basically all types of crime to some degree and also exhibits spill-over behavior. Therefore, it indeed seems to be a good idea to fight disorder as a preventive measure and not treat damage to property as a minor offense. This of course raises questions of fairness, mainly whether it is just to punish someone not for the crime they have committed but rather for the crimes their crime could instigate others to commit. But this is a question I do not feel qualified to answer authoritatively.

Of course deterrence cannot eliminate crime, and likely exhibits a decreasing marginal effect. If one wants to lower crime beyond the point where deterrence ceases to be effective, it becomes important to consider the social and economic causes of crime. My results suggests that a good starting point would be unemployment, especially when it comes to crimes against property. Increasing the chances for employment is of course a social good in itself, but will likely also decrease property crime in ones own county as well as the neighboring ones. And since it is a social good in itself, cooperation to harness positive feedback loops shouldn't be difficult to accomplish as there is no conflict of interest here. The same is true for the drop-out rate, which especially seemed to impact violent crime, i.e. assault. And while unemployment or the drop-out rate are difficult to change as a policy maker, it is even more difficult to change things like social or family cohesion. Especially the latter has proven to impact basically all kinds of crime, either because single parents have less time to supervise their children, because they often have less resources for raising their children, or because the stresses of a divorce make it more likely for the child to turn to crime. If it were the first two, one theoretically could make divorce more difficult and thereby decrease crime, although this of course would be morally and politically problematic. But if it is the ladder, i.e. that children traumatized by a divorce are more likely to be criminal, this of course not a solution, as they would likely also be traumatized living in an unhappy and dysfunctional family. It might therefore be more promising to try to promote social cohesion by supporting local clubs and groups, financially or otherwise. However, my results suggest that the likely pay-out in terms of crime reduction is relatively small. Here, it is again important to remember the spill-over effects, which would make inter-region cooperation on these issues very beneficial.

Other social-economic factors are more of a double-edged sword. DHI p.c. for instance increases property crime, while it decreases drug and violent crime. And of course a high DHI is also desirable for different reasons, so that artificially lowering DHI p.c. in order to decrease property crime is a preposterous idea. But here the externalities become problematic, because a conflict of interests of neighboring counties arises. My results suggest, that an increase in wealth in one county increases property crime there, which then spills over into neighboring ones that didn't enjoy an increase in DHI. This means that the neighboring counties have to bear some of the costs for one county having higher wealth. It is clear that this can cause inefficiency in the Pareto sense, and it might be necessary to compensate the neighboring counties when one becomes wealthier. This of course already happens to some degree, for one since there is much redistribution of tax income via the state or federal government, and for another because as we have seen DHI exhibits fair amount of spatial spill-over itself, meaning that higher DHI in one county increases income in the neighboring ones. This is less true for tourism, which causes the same externality problem as DHI, but without there being any kind of redistribution scheme in place to compensate counties neighboring those with high tourist activity for the increase in crime. It is therefore worth considering whether one should introduce such a scheme.

Likely the politically most explosive finding is that it seems that migration indeed increases crime, with the exception burglaries. As this is a touchy subject, I feel it necessary to make some qualifying remarks here. First, my data is not granular enough to say how this increase takes place. It might be that migrants are more likely to turn to crime, that they are more likely to be caught or that them moving to a county decreases social cohesion there, which makes the inhabitants in that county overall more criminal. Also, again because my data is not granular enough, it is possible that my measures for unemployment and DHI p.c. do not describe the economic situation of migrants well, as it is possible that even though the county is quite rich overall, the migrants living there are quite poor. Non-the-less, this result is so robust that it would be wrong to dismiss it, just because it is politically inconvenient. It seems that, no matter how this happens exactly, a county receiving a large inflow of migrants has to be aware that this might increase the crime rates and prepare accordingly. However, as my data ends in 2014, the large inflow of refugees in 2015/16 hasn't been taken into account here, so that my results can't be generalized for this situation. Of course migration isn't the only event with the potential to increase a crime a county has to prepare or, the same is true for urbanization, i.e. an increase of population density. In both cases there are indirect effects onto neighboring counties, which make again makes it necessary to plan for these events in a coordinated manner, a least within a high-crime cluster.

It should be noted that this need for cooperation within a cluster seems especially urgent with regard to property crimes as well as street crime and less so when considering lowering violent crime, as the spatial spill overs are far less pronounced there. Also, border regions in general don't seem to show higher crime rate, but bordering BeNeLux, Denmark and some other countries often does. There is of course nothing one can do about bordering another country, but it seems likely to me that these effects have something to do with policies in these countries, the most obvious example being the Netherlands with their legalization of marijuana. This might mean that a successful crime fighting policy also relies on international co-operation, as is of course already happening to some extend within the EU.

6.2 Limitations

Over the course of this thesis it has become apparent that there are some limitations, most of them due to data availability. For one, the county level is still quite a large scale of observation, although more granular than most other studies of crime in Germany. This is especially the case as it includes some very large cities such as Hamburg or Berlin as a single observation, which causes the differences between parts of these large cities to be averaged away. Ideally, this study should be repeated with observations being cells on a smalls scale grid, like 500x500 meter cells. This of course would also somewhat alleviate the modified area unit problem (MAUP), as the area units would no longer arbitrarily vary in size and shape and be far more granular. And it would get rid of the measurement error introduced by the fact that Saxony-Anhalt in 2007 merged some of their counties in a non-straightforward way. Unfortunately, no such data currently exists as far as I know. Secondly, it is not ideal that this studies had to rely on police recorded data due to the problem of underreporting discussed before. Especially for drug crimes this caused some major issues of simultaneity I wasn't able to fix. Therefore, survey data might perform better here, or in case of drug crime an analysis of drug content in the sewage of each county, following Commandeur et al. (2014). But again, to my knowledge no such data exists on this granular a level or over this time frame.

With regard to the explanatory variables, it would have been nice to get some indicator of inequality, or an order statistic of income, as it reportedly performs better than unemployment in most studies. But again, no such data was available on the scale needed. It is of course also less than ideal that the yearly divorce rates where only available on the state level, and I therefore had to use the divorces rates of 2015 as a proxy for the time-average of divorce rates, although considering the results I feel this has worked reasonably well. Regarding social cohesion, voter-turn-out has only somewhat worked as a proxy, and

I'm not sure whether this is because social cohesion is not very important, or because the proxy didn't work well. Therefore it might be a good idea to repeat this study with a variable like membership in clubs or something similar, which wasn't available either. Lastly, concerning the choice of model, I'm fairly content with the results, although of course no model is perfect and the problems discussed in Chapter 3 apply. The results also show that it might be a good idea to use a different model for different types of crime, for example burglaries might have been better explained using a temporal-spatial model, even though the Breitung-test suggested that there is no unit root in the data. In general, it seems that models trying to explain crimes against property should largely rely on the Becker-Ehrlich model and those explaining violent crime more in the social disorganization theory. However, overall I still contest that this study is the most exhaustive and granular look at the causes and spatial dependencies of crime in Germany that has been conducted so far, and thus a good jumping-off point for future research.

6.3 Conclusion

In conclusion, this study looked at the question what causes regional variation of crime. The literature suggested a range of possibilities, focusing on economic incentives in the case of the Becker-Ehrlich theory, on the social context in the case of social disorganization and the routine activity theory and on the effect of disorder in the case of the broken window theory. Also, many authors found that crime exhibits spatial dependencies. That this is indeed the case was tested with various measures and largely confirmed, although especially property crime exhibits much spatial autocorrelation and violent crime less so. I was also able to show that this leads to clusters of high and of low crime rates. And that these clusters are indeed the result of spatial dynamics and not simply an echo of the spatial structure of the explanatory variables was shown by the results of the cluster analysis. Therefore, it was crucial to use a spatial model when trying to explain this variation, and since some explanatory variables showed spatial dependencies of their own, I chose to utilize a Spatial Durbin Model. This model seemed to perform reasonably well, even though it mostly explained the between-variation in the data. But as the endogenous variables didn't vary much over time, as seen from plotting them and also the Breitung-test, this was expected. The Becker-Ehrlich model seemed to work well to explain crimes against property, while the social disorganization theory had good explanatory power regarding violent and drug crime. The broken window and routine activity theory seemed to mostly apply to all types of crime. The spatial dependencies observed earlier seem to largely stem from a straight-forward spill-over process and not from displacement, as the same factors causing an increase in crime in one county also increase crime in the neighboring counties. From a policy perspective, this implies externalities that can cause inefficiencies if not remedied by cooperation or compensation. Also, it is important for policy makers to be aware of the effect a change in population density, tourism or the share of foreigners in their or neighboring counties can have on the crime rates and to prepare accordingly.

However, largely the policy response to crime seems to be effective in Germany. Therefore, the easiest way to fight crime is ensuring better staffed and trained workforce countering it.

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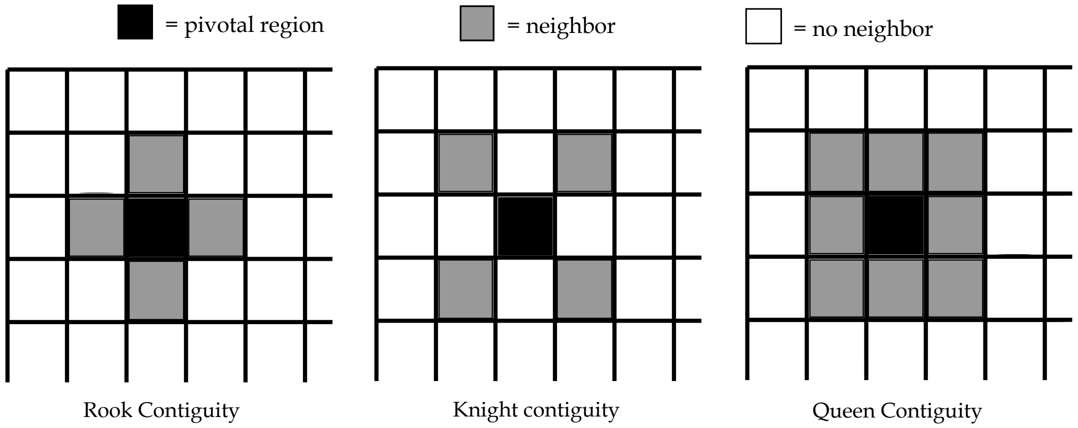
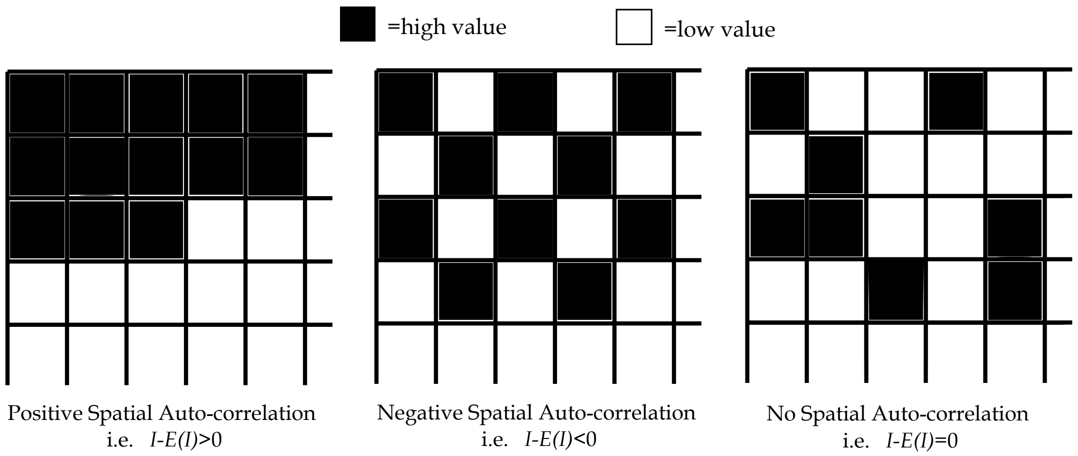
Appendix A: Figures



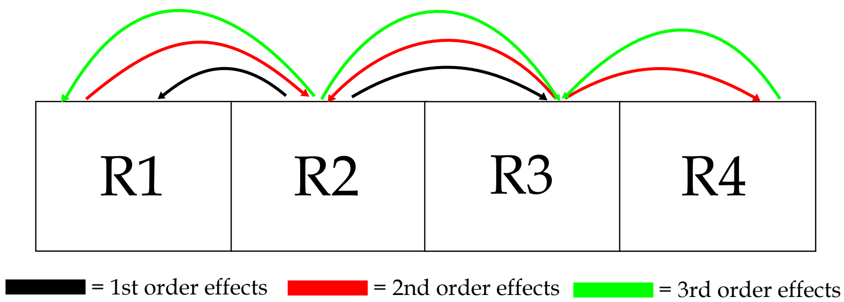
Own representation

Figure 10: Spatial weights: Different definitions of contiguity



Own representation

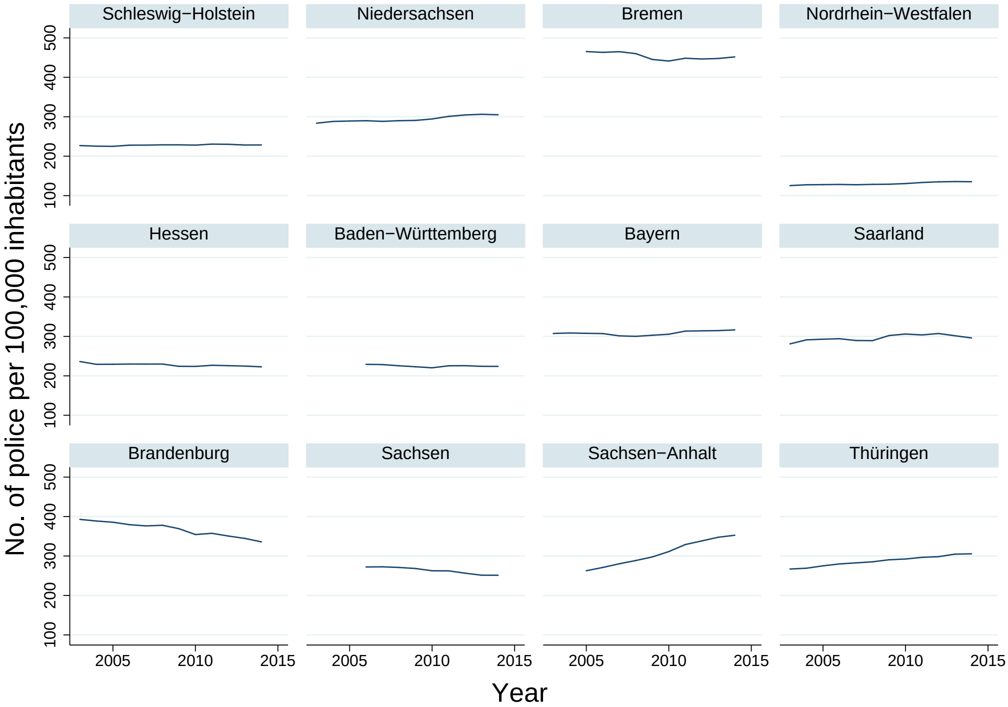
Figure 11: Patterns resulting from spatial auto-correlation (assuming rook contiguity)



Own representation

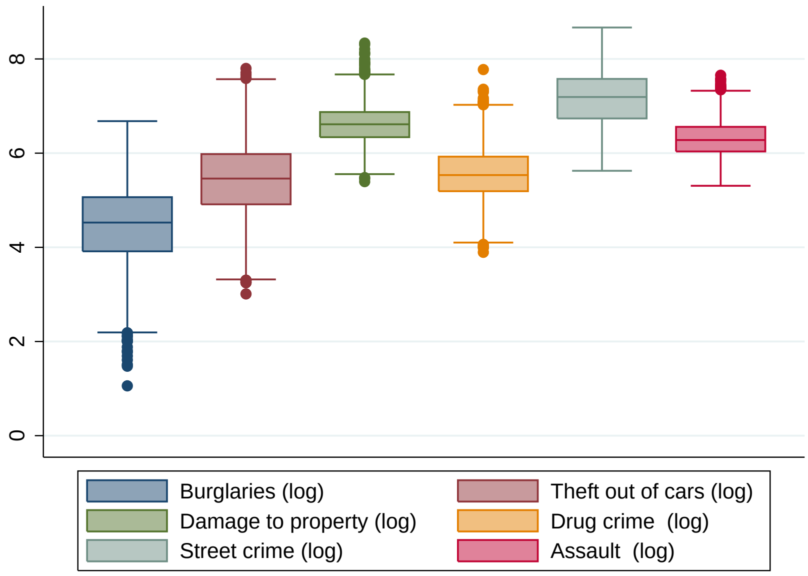
Figure 12: Feedback loop after a change in region 2 in the face of spatial autocorrelation, first three iterations

endfigure



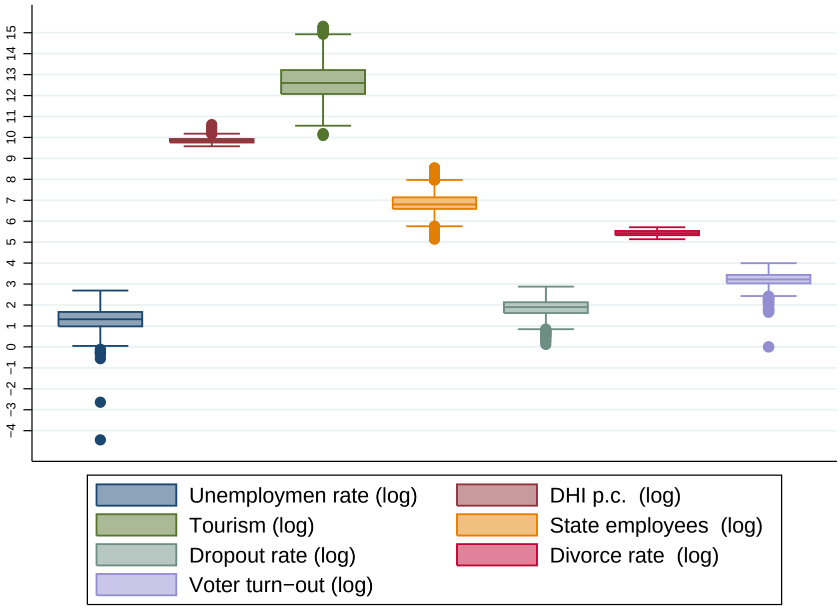
Source: Var. ministries of the interior and statistical offices, own calculations

Figure 13: Number of police officers (full-time equiv.) per 100,000 inhabitants



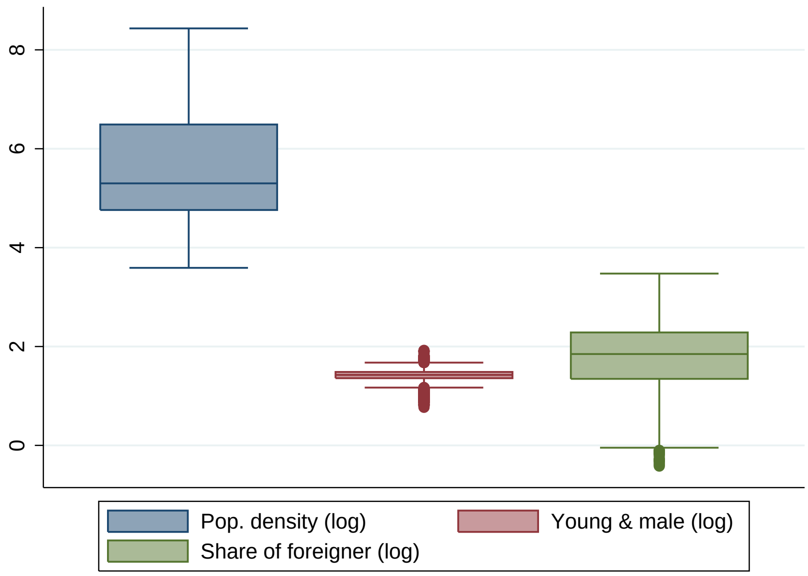
Source: BKA, own calculations

Figure 14: Outlier detection: Boxplots of crime rates



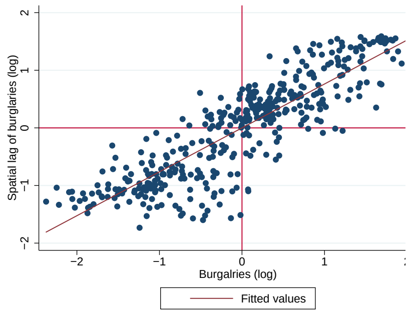
Source: Statistisches Bundesamt, Bundesgentur f. Arbeit, Statistische Ämter der Länder, BKG, own calculations

Figure 15: Outlier detection: Boxplots of economic and social determinants

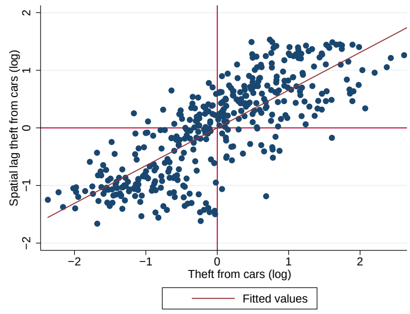


Source: Statistische Ämter der Länder, BKG, own calculations

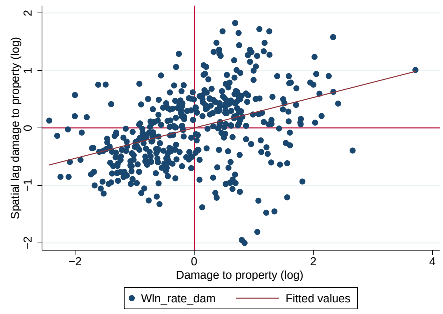
Figure 16: Outlier detection: Boxplots of other determinants



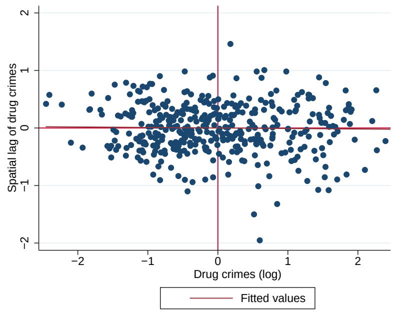
(a) Burglaries (log)



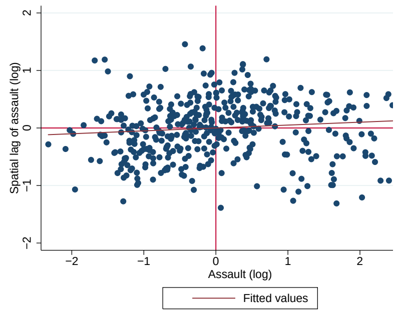
(b) Theft from cars (log)



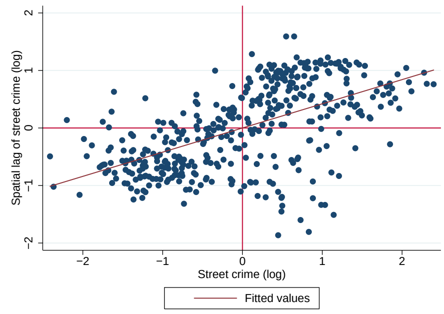
(c) Damage to property (log)



(d) Drug crime (log)



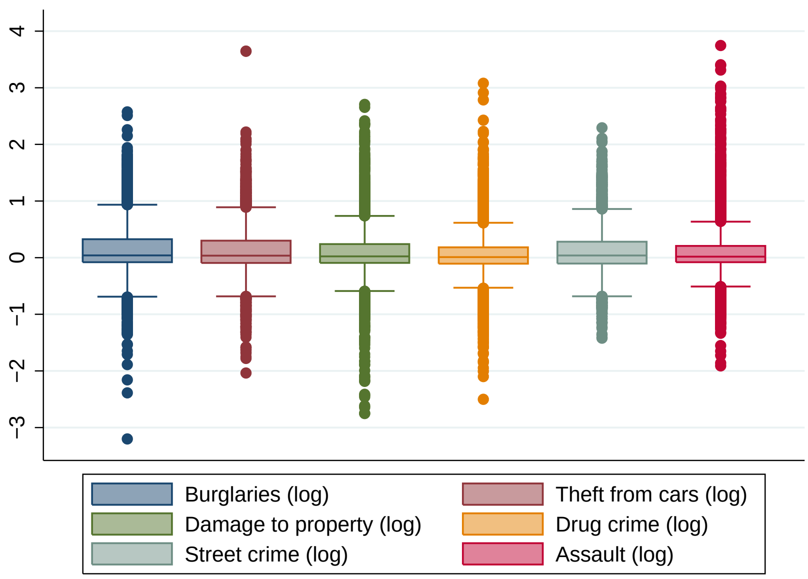
(e) Assault (log)



(f) Street crime (log)

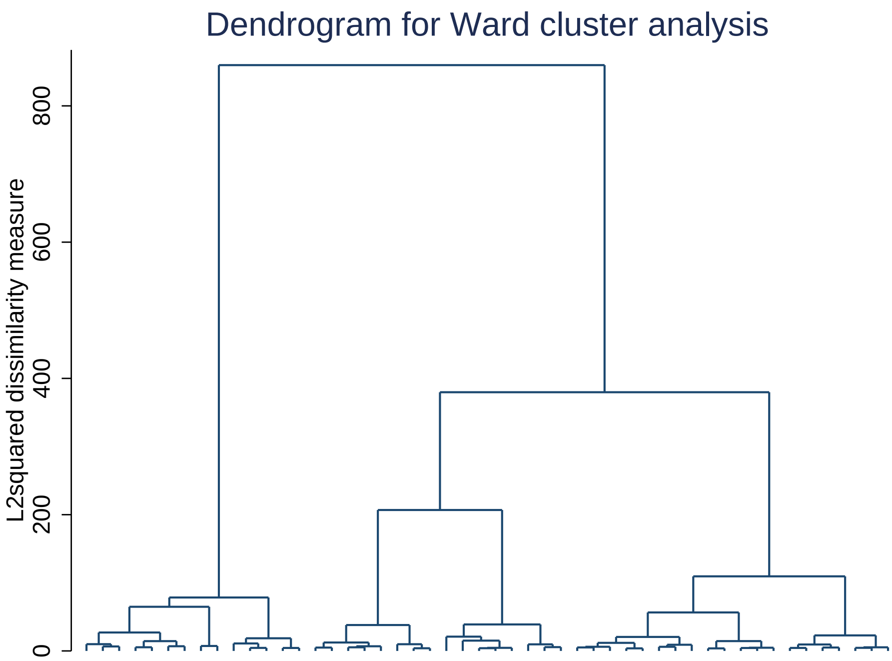
Source: BKA, BKG, own calculations

Figure 17: Moran scatter plots, different types of crime, average over time

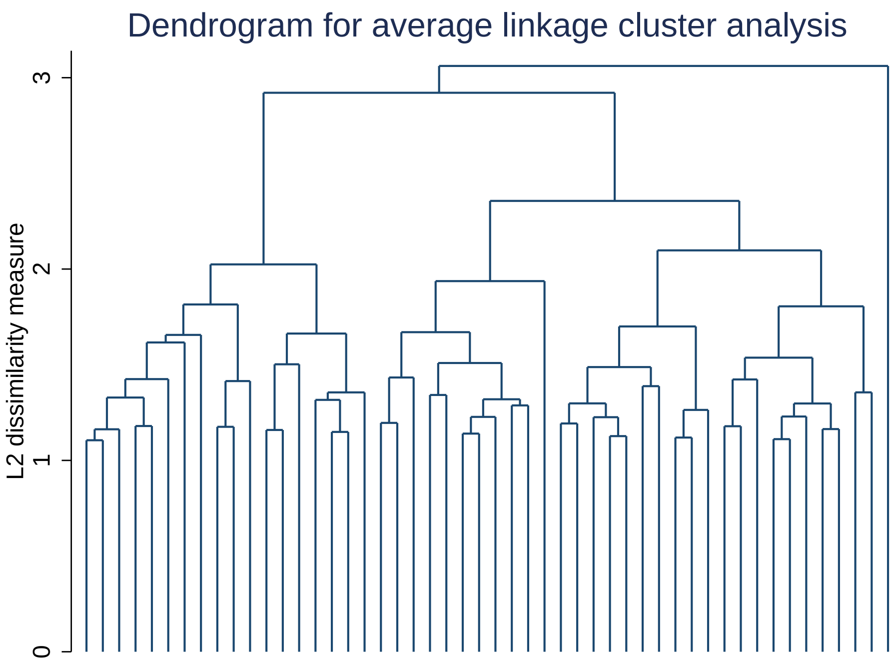


Source: BKA, BKG, own calculations

Figure 18: Boxplots of local Moran's I, different types of crime



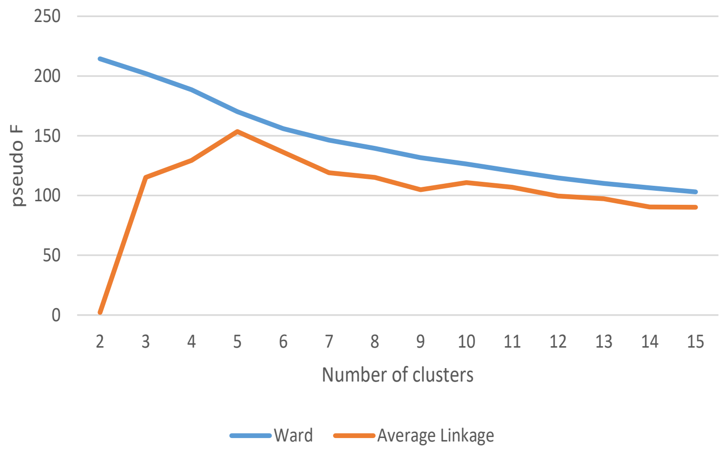
(a) Ward



(b) Average linkage

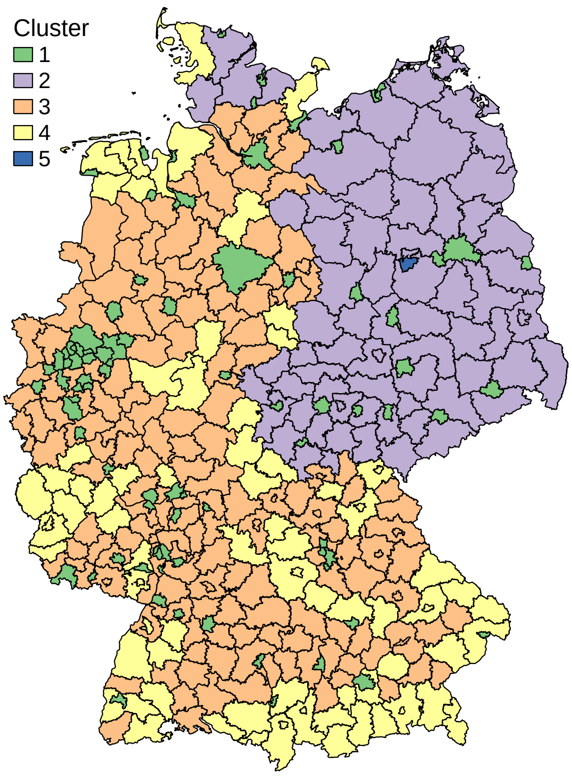
Var. sources, own calculations

Figure 19: Dendrograms, Ward and avg.-linkage cluster analysis , last 50 iterations



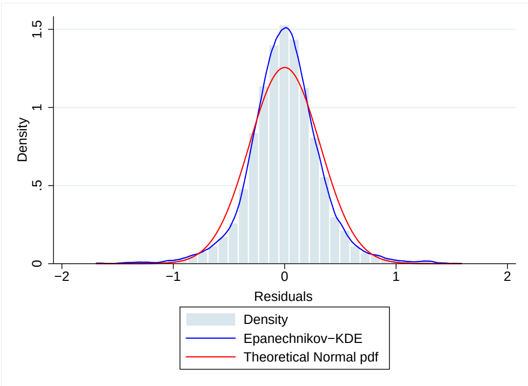
Var. sources, own calculations

Figure 20: Pseudo-F by Caliński and Harabasz (1974) for Ward and average linkage

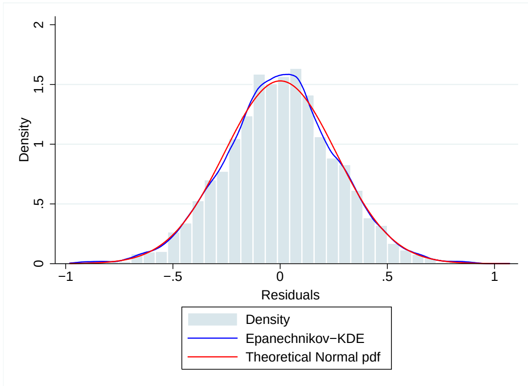


Var. sources, own calculations

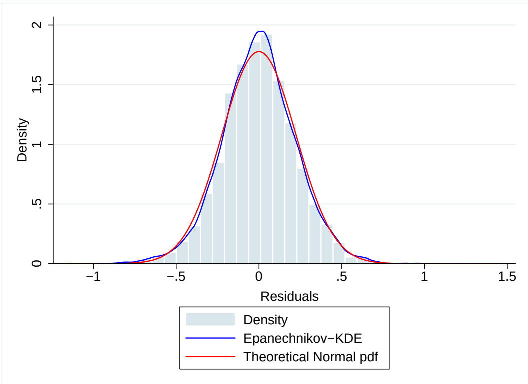
Figure 21: Cluster analysis results using average linkage



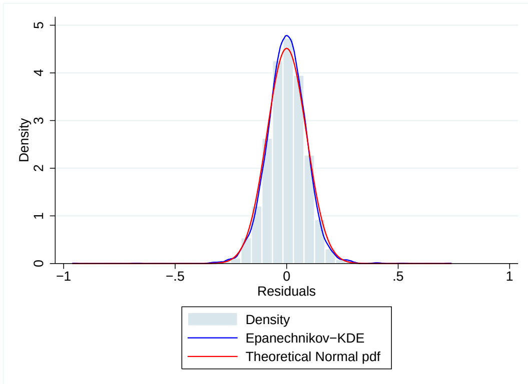
(a) Burglaries (log)



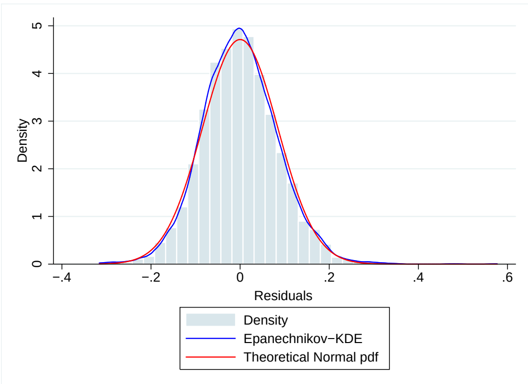
(b) Theft from cars (log)



(c) Drug crime (log)



(d) Assault (log)



(e) Street crime (log)

Var. sources, own calculations

Figure 22: Histograms of regression residuals

Appendix B: Tables

Variable	Share of obs. imputed	Exogenous vars. used	Estimation technique
Unemployment	0.31%	GDP p.c., DHI p.c. and their lags	OLS, White std. errors
Drop out rate	2.61%	GDP p.c., youth workers p.c.	OLS, White std. errors
State employees	1.07%	GDP p.c., DHI p.c, population dens.	OLS, White std. errors
Tourism	0.33%	GDP p.c., border dummies, population dens.	OLS, White std. errors

Table 21: Imputations used to create balanced panel

Endogenous var.	*AIC*	*BIC*	R^2-*within*	R^2-*between*	R^2-*total*
Burglaries (log)	3876.518	4189.841	0.1151	0.7156	0.6149
Theft from cars (log)	1768.011	2081.334	0.3470	0.7432	0.6715
Drug crime (log)	975.311	1288.634	0.1066	0.5677	0.4736
Street crime (log)	-7156.294	-6842.971	0.5928	0.8377	0.8228
Assault (log)	-6910.168	-6596.845	0.2053	0.7682	0.7306

Table 22: Goodness-of-fit measures of the regressions

Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
	Main				
Clearance rate	-0.0117	0.0334	-0.3515	0.7252	-0.0772,0.0537
Dmg. to property (log)	-0.2411	0.0443	-5.4409	0.0000	-0.3279,-0.1542
State employees p.c. (log)	-0.3463	0.0579	-5.9785	0.0000	-0.4598,-0.2328
Lag share of foreigners (log)	0.0270	0.0514	0.5250	0.5996	-0.0737,0.1277
Young & male (log)	0.3199	0.0648	4.9337	0.0000	0.1928,0.4470
Divorce rates	0.3847	0.1201	3.2018	0.0014	0.1492,0.6202
Unemployment (log)	0.1438	0.0336	4.2829	0.0000	0.0780,0.2096
Tourism (log)	0.2265	0.0438	5.1746	0.0000	0.1407,0.3122
Pop. density (log)	1.7108	0.2932	5.8351	0.0000	1.1361,2.2854
Lag drop-out rate (log)	0.0369	0.0279	1.3240	0.1855	-0.0177,0.0916
Lag unemployment (log)	0.0762	0.0303	2.5156	0.0119	0.0168,0.1356
Lag DHI p.c.	1.3470	0.2160	6.2372	0.0000	0.9237,1.7703
Lag clearance rate	-0.0797	0.0321	-2.4817	0.0131	-0.1426,-0.0168
Border region	-0.0895	0.2223	-0.4024	0.6874	-0.5251,0.3462
Border to Poland	-0.0797	0.2461	-0.3238	0.7461	-0.5621,0.4027
Border to the Czech Repub.	-0.2409	0.2214	-1.0881	0.2765	-0.6749,0.1930
Border to Austria	-0.4134	0.2352	-1.7579	0.0788	-0.8743,0.0475
Border to Switzerland	-0.5851	0.2818	-2.0761	0.0379	-1.1374,-0.0327
Border to France	0.2146	0.2329	0.9214	0.3569	-0.2419,0.6711
Border to Belgium	0.5968	0.2580	2.3134	0.0207	0.0912,1.1025
Border to the Netherlands	0.2002	0.2444	0.8192	0.4127	-0.2788,0.6793
Border to Denmark	0.3712	0.3213	1.1552	0.2480	-0.2586,1.0010
Border to Luxembourg	0.6380	0.2699	2.3639	0.0181	0.1090,1.1670
Voter turn-out (log)	0.0097	0.0375	0.2576	0.7967	-0.0639,0.0832
out1	-0.1276	0.0417	-3.0565	0.0022	-0.2094,-0.0458
out2	-0.0927	0.0153	-6.0407	0.0000	-0.1227,-0.0626
lk-ref	-0.0355	0.1517	-0.2343	0.8147	-0.3328,0.2617
Avg. drop-out rate (log)	-0.1257	0.1029	-1.2208	0.2222	-0.3274,0.0761
Avg. DHI. p.c.	-0.4406	0.3038	-1.4500	0.1471	-1.0360,0.1549
Avg. poulation density	-0.0726	0.0425	-1.7070	0.0878	-0.1560,0.0108
Avg. tourism (log)	-0.0217	0.0289	-0.7530	0.4515	-0.0784,0.0349
Avg. unemployment (log)	0.7142	0.1137	6.2823	0.0000	0.4914,0.9371
Avg. young & male (log)	-1.4080	0.2879	-4.8911	0.0000	-1.9723,-0.8438
Avg. share of foreigners (log)	0.4317	0.0655	6.5876	0.0000	0.3032,0.5601
Avg. state employees p.c. (log)	-0.0736	0.0642	-1.1470	0.2514	-0.1994,0.0522
Avg. dmg. to property (log)	0.4856	0.1172	4.1439	0.0000	0.2559,0.7153
Avg. Clearance rate	-1.0797	0.1060	-10.1863	0.0000	-1.2874,-0.8719
Divorce rates 2015	0.5534	0.1099	5.0341	0.0000	0.3379,0.7688
Constant	3.6990	5.0004	0.7397	0.4595	-6.1017,13.4996
	Spatial lags of regressors				
Unemployment (log)	-0.0870	0.0448	-1.9412	0.0522	-0.1749,0.0008
Lag DHI p.c.	1.4906	0.2822	5.2813	0.0000	0.9374,2.0438
Lag drop-out rate (log)	-0.1448	0.0447	-3.2402	0.0012	-0.2325,-0.0572
Voter turn-out (log)	0.1692	0.0592	2.8578	0.0043	0.0532,0.2853
Avg. unemployment (log)	-0.0416	0.1273	-0.3267	0.7439	-0.2911,0.2079
Avg. DHI. p.c.	0.2494	0.3767	0.6621	0.5079	-0.4888,0.9877
Avg. drop-out rate (log)	-0.0556	0.1886	-0.2949	0.7681	-0.4253,0.3140
	Spatial lag of regressand				
ρ	0.2483	0.0190	13.1025	0.0000	0.2112,0.2855

Table 23: Burglaries (log): SDM estimation results

Variable	Direct Effects: Burglaries Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0129	0.0333	-0.3872	0.6986	-0.0781,0.0523
Dmg. to property (log)	-0.2441	0.0450	-5.4247	0.0000	-0.3323,-0.1559
State employees p.c. (log)	-0.3491	0.0548	-6.3748	0.0000	-0.4564,-0.2418
Lag share of foreigners (log)	0.0256	0.0514	0.4980	0.6185	-0.0752,0.1264
Young & male (log)	0.3267	0.0669	4.8839	0.0000	0.1956,0.4579
Divorce rates	0.3874	0.1246	3.1090	0.0019	0.1432,0.6316
Unemployment (log)	0.1423	0.0324	4.3953	0.0000	0.0788,0.2058
Tourism (log)	0.2272	0.0453	5.0150	0.0000	0.1384,0.3160
Pop. density (log)	1.7280	0.2882	5.9950	0.0000	1.1631,2.2929
Lag drop-out rate (log)	0.0304	0.0278	1.0924	0.2747	-0.0242,0.0850
Lag unemployment (log)	0.0767	0.0302	2.5400	0.0111	0.0175,0.1360
Lag DHI p.c.	1.4403	0.2122	6.7860	0.0000	1.0243,1.8563
Lag clearance rate	-0.0811	0.0349	-2.3251	0.0201	-0.1494,-0.0127
Border region	-0.1116	0.2205	-0.5060	0.6129	-0.5437,0.3206
Border to Poland	-0.0709	0.2489	-0.2848	0.7758	-0.5587,0.4169
Border to the Czech Repub.	-0.2316	0.2221	-1.0429	0.2970	-0.6668,0.2037
Border to Austria	-0.4003	0.2358	-1.6978	0.0896	-0.8625,0.0618
Border to Switzerland	-0.5614	0.2725	-2.0602	0.0394	-1.0954,-0.0273
Border to France	0.2342	0.2369	0.9888	0.3228	-0.2300,0.6984
Border to Belgium	0.6135	0.2720	2.2556	0.0241	0.0804,1.1466
Border to the Netherlands	0.2234	0.2405	0.9286	0.3531	-0.2481,0.6948
Border to Denmark	0.3818	0.3217	1.1866	0.2354	-0.2488,1.0124
Border to Luxembourg	0.6555	0.2843	2.3057	0.0211	0.0983,1.2128
Voter turn-out (log)	0.0165	0.0371	0.4459	0.6557	-0.0561,0.0892
out1	-0.1287	0.0440	-2.9274	0.0034	-0.2149,-0.0425
out2	-0.0939	0.0149	-6.2987	0.0000	-0.1232,-0.0647
lk-ref	-0.0376	0.1531	-0.2459	0.8058	-0.3376,0.2624
Avg. drop-out rate (log)	-0.1308	0.1088	-1.2020	0.2294	-0.3441,0.0825
Avg. DHI. p.c.	-0.4410	0.3160	-1.3958	0.1628	-1.0604,0.1783
Avg. poulation density	-0.0758	0.0434	-1.7444	0.0811	-0.1609,0.0094
Avg. tourism (log)	-0.0219	0.0285	-0.7696	0.4416	-0.0777,0.0339
Avg. unemployment (log)	0.7213	0.1145	6.2996	0.0000	0.4969,0.9457
Avg. young & male (log)	-1.4315	0.2867	-4.9927	0.0000	-1.9934,-0.8695
Avg. share of foreigners (log)	0.4389	0.0671	6.5406	0.0000	0.3074,0.5704
Avg. state employees p.c. (log)	-0.0737	0.0639	-1.1537	0.2486	-0.1989,0.0515
Avg. dmg. to property (log)	0.4905	0.1203	4.0769	0.0000	0.2547,0.7263
Avg. Clearance rate	-1.0991	0.1081	-10.1661	0.0000	-1.3109,-0.8872
Divorce rates 2015	0.5635	0.1180	4.7759	0.0000	0.3322,0.7947

Table 24: Avg. direct effects: Burglaries (log)

Variable	Indirect Effects: Burglaries				
	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0040	0.0105	-0.3862	0.6994	-0.0246,0.0165
Dmg. to property (log)	-0.0764	0.0152	-5.0357	0.0000	-0.1062,-0.0467
State employees p.c. (log)	-0.1095	0.0202	-5.4238	0.0000	-0.1491,-0.0700
Lag share of foreigners (log)	0.0081	0.0164	0.4944	0.6210	-0.0241,0.0404
Young & male (log)	0.1028	0.0243	4.2303	0.0000	0.0552,0.1504
Divorce rates	0.1214	0.0403	3.0112	0.0026	0.0424,0.2004
Unemployment (log)	-0.0656	0.0555	-1.1811	0.2376	-0.1743,0.0432
Tourism (log)	0.0713	0.0158	4.5201	0.0000	0.0404,0.1022
Pop. density (log)	0.5416	0.1011	5.3552	0.0000	0.3434,0.7398
Lag drop-out rate (log)	-0.1760	0.0564	-3.1241	0.0018	-0.2865,-0.0656
Lag unemployment (log)	0.0241	0.0098	2.4611	0.0139	0.0049,0.0432
Lag DHI p.c.	2.3366	0.3541	6.5991	0.0000	1.6426,3.0306
Lag clearance rate	-0.0255	0.0114	-2.2414	0.0250	-0.0478,-0.0032
Border region	-0.0354	0.0691	-0.5124	0.6084	-0.1709,0.1000
Border to Poland	-0.0219	0.0780	-0.2804	0.7792	-0.1748,0.1310
Border to the Czech Repub.	-0.0721	0.0688	-1.0481	0.2946	-0.2070,0.0627
Border to Austria	-0.1253	0.0742	-1.6884	0.0913	-0.2708,0.0202
Border to Switzerland	-0.1760	0.0866	-2.0325	0.0421	-0.3457,-0.0063
Border to France	0.0738	0.0748	0.9872	0.3235	-0.0727,0.2203
Border to Belgium	0.1924	0.0876	2.1975	0.0280	0.0208,0.3640
Border to the Netherlands	0.0703	0.0760	0.9256	0.3546	-0.0786,0.2193
Border to Denmark	0.1201	0.1023	1.1740	0.2404	-0.0804,0.3206
Border to Luxembourg	0.2057	0.0914	2.2504	0.0244	0.0266,0.3849
Voter turn-out (log)	0.2224	0.0733	3.0319	0.0024	0.0786,0.3661
out1	-0.0404	0.0144	-2.8077	0.0050	-0.0685,-0.0122
out2	-0.0295	0.0055	-5.3842	0.0000	-0.0402,-0.0187
lk-ref	-0.0123	0.0487	-0.2520	0.8010	-0.1077,0.0831
Avg. drop-out rate (log)	-0.1241	0.2344	-0.5296	0.5964	-0.5836,0.3353
Avg. DHI. p.c.	0.1520	0.4970	0.3059	0.7597	-0.8221,1.1262
Avg. poulation density	-0.0238	0.0140	-1.7045	0.0883	-0.0512,0.0036
Avg. tourism (log)	-0.0068	0.0089	-0.7660	0.4436	-0.0243,0.0106
Avg. unemployment (log)	0.1789	0.1638	1.0921	0.2748	-0.1421,0.4999
Avg. young & male (log)	-0.4489	0.0982	-4.5695	0.0000	-0.6415,-0.2564
Avg. share of foreigners (log)	0.1378	0.0253	5.4461	0.0000	0.0882,0.1874
Avg. state employees p.c. (log)	-0.0230	0.0201	-1.1461	0.2517	-0.0624,0.0164
Avg. dmg. to property (log)	0.1538	0.0401	3.8387	0.0001	0.0753,0.2324
Avg. Clearance rate	-0.3449	0.0473	-7.2913	0.0000	-0.4376,-0.2522
Divorce rates 2015	0.1772	0.0423	4.1910	0.0000	0.0943,0.2600

Table 25: Avg. indirect effects: Burglaries (log)

Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
	Main				
Clearance rate	-0.1157	0.0256	-4.5271	0.0000	-0.1658,-0.0656
Dmg. to property (log)	0.0108	0.0339	0.3194	0.7495	-0.0556,0.0772
State employees p.c. (log)	-0.0972	0.0442	-2.1976	0.0280	-0.1839,-0.0105
Lag share of foreigners (log)	0.1046	0.0393	2.6636	0.0077	0.0276,0.1815
Young & male (log)	-0.4113	0.0498	-8.2634	0.0000	-0.5088,-0.3137
Divorce rates	0.2963	0.0918	3.2257	0.0013	0.1162,0.4763
Unemployment (log)	0.1193	0.0258	4.6287	0.0000	0.0688,0.1698
Tourism (log)	-0.0832	0.0334	-2.4905	0.0128	-0.1487,-0.0177
Pop. density (log)	0.3845	0.2299	1.6724	0.0944	-0.0661,0.8351
Lag drop-out rate (log)	-0.0877	0.0213	-4.1157	0.0000	-0.1295,-0.0460
Lag unemployment (log)	-0.0069	0.0231	-0.3004	0.7639	-0.0523,0.0384
Lag DHI p.c.	1.3318	0.1662	8.0109	0.0000	1.0059,1.6576
Lag clearance rate	-0.1977	0.0246	-8.0494	0.0000	-0.2458,-0.1496
Border region	-0.0083	0.1949	-0.0426	0.9660	-0.3903,0.3737
Border to Poland	0.1057	0.2157	0.4902	0.6240	-0.3171,0.5286
Border to the Czech Repub.	-0.2250	0.1941	-1.1594	0.2463	-0.6054,0.1554
Border to Austria	-0.4654	0.2062	-2.2572	0.0240	-0.8694,-0.0613
Border to Switzerland	-0.5178	0.2471	-2.0956	0.0361	-1.0022,-0.0335
Border to France	0.1150	0.2042	0.5633	0.5732	-0.2852,0.5152
Border to Belgium	0.3962	0.2262	1.7515	0.0799	-0.0472,0.8395
Border to the Netherlands	-0.0160	0.2143	-0.0746	0.9406	-0.4361,0.4041
Border to Denmark	-0.1350	0.2817	-0.4793	0.6318	-0.6871,0.4171
Border to Luxembourg	0.4891	0.2365	2.0678	0.0387	0.0255,0.9527
Voter turn-out (log)	-0.0691	0.0296	-2.3356	0.0195	-0.1271,-0.0111
out1	0.0127	0.0321	0.3941	0.6935	-0.0503,0.0756
out2	-0.0229	0.0118	-1.9343	0.0531	-0.0460,0.0003
lk-ref	-0.1206	0.1241	-0.9713	0.3314	-0.3638,0.1227
Avg. drop-out rate (log)	-0.0516	0.0902	-0.5726	0.5669	-0.2284,0.1251
Avg. DHI. p.c.	-0.4069	0.2662	-1.5285	0.1264	-0.9288,0.1149
Avg. poulation density	0.0435	0.0372	1.1684	0.2427	-0.0295,0.1164
Avg. tourism (log)	0.0232	0.0253	0.9166	0.3594	-0.0264,0.0728
Avg. unemployment (log)	0.6581	0.0996	6.6064	0.0000	0.4629,0.8533
Avg. young & male (log)	-0.1749	0.2522	-0.6933	0.4881	-0.6692,0.3195
Avg. share of foreigners (log)	0.1727	0.0574	3.0077	0.0026	0.0602,0.2853
Avg. state employees p.c. (log)	-0.0744	0.0562	-1.3223	0.1861	-0.1846,0.0359
Avg. dmg. to property (log)	0.4670	0.1027	4.5452	0.0000	0.2656,0.6683
Avg. Clearance rate	-1.1759	0.0929	-12.6572	0.0000	-1.3580,-0.9938
Divorce rates 2015	0.3700	0.0964	3.8398	0.0001	0.1811,0.5588
Constant	1.9583	4.3826	0.4468	0.6550	-6.6313,10.5480
	Spatial lags of regressors				
Unemployment (log)	0.2618	0.0349	7.4979	0.0000	0.1934,0.3302
Lag DHI p.c.	1.2786	0.2239	5.7106	0.0000	0.8398,1.7175
Lag drop-out rate (log)	-0.0617	0.0341	-1.8107	0.0702	-0.1286,0.0051
Voter turn-out (log)	0.0838	0.0466	1.7989	0.0720	-0.0075,0.1750
Avg. unemployment (log)	-0.3652	0.1115	-3.2760	0.0011	-0.5836,-0.1467
Avg. DHI. p.c.	0.2757	0.3297	0.8362	0.4030	-0.3705,0.9220
Avg. drop-out rate (log)	0.1182	0.1652	0.7159	0.4740	-0.2055,0.4419
	Spatial lag of regressand				
ρ	0.4833	0.0153	31.6706	0.0000	0.4533,0.5132

Table 26: Theft from cars (log): SDM estimation results

	Direct Effects: Theft from cars				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.1229	0.0265	-4.6339	0.0000	-0.1750,-0.0709
Dmg. to property (log)	0.0115	0.0359	0.3190	0.7497	-0.0590,0.0819
State employees p.c. (log)	-0.1039	0.0436	-2.3827	0.0172	-0.0184-0.1894
Lag share of foreigners (log)	0.1091	0.0410	2.6594	0.0078	0.0287,0.1894
Young & male (log)	-0.4321	0.0532	-8.1202	0.0000	-0.5364,-0.3278
Divorce rates	0.3110	0.0992	3.1346	0.0017	0.1166,0.5055
Unemployment (log)	0.1571	0.0250	6.2769	0.0000	0.1081,0.2062
Tourism (log)	-0.0896	0.0361	-2.4832	0.0130	-0.1603,-0.0189
Pop. density (log)	0.4024	0.2353	1.7103	0.0872	-0.0587,0.8635
Lag drop-out rate (log)	-0.0996	0.0220	-4.5175	0.0000	-0.1428,-0.0564
Lag unemployment (log)	-0.0077	0.0241	-0.3190	0.7497	-0.0548,0.0395
Lag DHI p.c.	1.5546	0.1695	9.1701	0.0000	1.2223,1.8868
Lag clearance rate	-0.2091	0.0279	-7.5052	0.0000	-0.2637,-0.1545
Border region	-0.0280	0.2015	-0.1388	0.8896	-0.4230,0.3670
Border to Poland	0.1206	0.2275	0.5303	0.5959	-0.3253,0.5666
Border to the Czech Repub.	-0.2263	0.2028	-1.1157	0.2645	-0.6237,0.1712
Border to Austria	-0.4747	0.2155	-2.2030	0.0276	-0.8970,-0.0524
Border to Switzerland	-0.5183	0.2490	-2.0815	0.0374	-1.0064,-0.0303
Border to France	0.1369	0.2165	0.6322	0.5273	-0.2875,0.5612
Border to Belgium	0.4267	0.2487	1.7158	0.0862	-0.0607,0.9141
Border to the Netherlands	0.0019	0.2198	0.0089	0.9929	-0.4289,0.4328
Border to Denmark	-0.1371	0.2940	-0.4664	0.6409	-0.7134,0.4391
Border to Luxembourg	0.5251	0.2598	2.0214	0.0432	0.0160,1.0342
Voter turn-out (log)	-0.0646	0.0304	-2.1252	0.0336	-0.1242,-0.0050
out1	0.0138	0.0353	0.3895	0.6969	-0.0555,0.0830
out2	-0.0242	0.0120	-2.0205	0.0433	-0.0477,-0.0007
lk-ref	-0.1287	0.1307	-0.9844	0.3249	-0.3848,0.1275
Avg. drop-out rate (log)	-0.0421	0.1004	-0.4190	0.6752	-0.2388,0.1547
Avg. DHI. p.c.	-0.4059	0.2900	-1.3998	0.1616	-0.9742,0.1624
Avg. poulation density	0.0438	0.0396	1.1064	0.2685	-0.0338,0.1215
Avg. tourism (log)	0.0246	0.0260	0.9463	0.3440	-0.0264,0.0756
Avg. unemployment (log)	0.6531	0.1048	6.2305	0.0000	0.4476,0.8585
Avg. young & male (log)	-0.1899	0.2620	-0.7249	0.4685	-0.7033,0.3235
Avg. share of foreigners (log)	0.1840	0.0613	3.0029	0.0027	0.0639,0.3042
Avg. state employees p.c. (log)	-0.0777	0.0583	-1.3317	0.1830	-0.1920,0.0366
Avg. dmg. to property (log)	0.4919	0.1100	4.4724	0.0000	0.2763,0.7075
Avg. Clearance rate	-1.2469	0.0987	-12.6369	0.0000	-1.4403,-1.0535
Divorce rates 2015	0.3934	0.1079	3.6462	0.0003	0.1819,0.6049

Table 27: Avg. direct effects: Theft from cars (log)

	Indirect Effects: Theft from cars				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.1025	0.0229	-4.4675	0.0000	-0.1474,-0.0575
Dmg. to property (log)	0.0098	0.0301	0.3264	0.7441	-0.0492,0.0688
State employees p.c. (log)	-0.0866	0.0367	- 2.3584	0.0184	-0.1586,-0.0146
Lag share of foreigners (log)	0.0910	0.0353	2.5771	0.0100	0.0218,0.1603
Young & male (log)	-0.3598	0.0469	-7.6765	0.0000	-0.4516,-0.2679
Divorce rates	0.2585	0.0820	3.1526	0.0016	0.0978,0.4193
Unemployment (log)	0.5819	0.0584	9.9599	0.0000	0.4674,0.6964
Tourism (log)	-0.0746	0.0303	-2.4595	0.0139	-0.1341,-0.0152
Pop. density (log)	0.3337	0.1940	1.7201	0.0854	-0.0465,0.7140
Lag drop-out rate (log)	-0.1920	0.0618	-3.1072	0.0019	-0.3132,-0.0709
Lag unemployment (log)	-0.0064	0.0202	-0.3177	0.7507	-0.0460,0.0332
Lag DHI p.c.	3.4987	0.3934	8.8931	0.0000	2.7276,4.2698
Lag clearance rate	-0.1742	0.0254	-6.8661	0.0000	-0.2240,-0.1245
Border region	-0.0239	0.1674	-0.1431	0.8862	-0.3519,0.3041
Border to Poland	0.1011	0.1899	0.5325	0.5944	-0.2711,0.4733
Border to the Czech Repub.	-0.1877	0.1674	-1.1209	0.2623	-0.5158,0.1405
Border to Austria	-0.3950	0.1795	-2.2002	0.0278	-0.7469,-0.0431
Border to Switzerland	-0.4314	0.2070	-2.0846	0.0371	-0.8371,-0.0258
Border to France	0.1145	0.1809	0.6330	0.5267	-0.2400,0.4690
Border to Belgium	0.3556	0.2085	1.7055	0.0881	-0.0530,0.7643
Border to the Netherlands	0.0020	0.1829	0.0107	0.9915	-0.3566,0.3605
Border to Denmark	-0.1140	0.2449	-0.4654	0.6416	-0.5939,0.3660
Border to Luxembourg	0.4377	0.2180	2.0076	0.0447	0.0104,0.8650
Voter turn-out (log)	0.0940	0.0833	1.1287	0.2590	-0.0692,0.2573
out1	0.0115	0.0295	0.3896	0.6968	-0.0464,0.0694
out2	-0.0202	0.0101	-1.9970	0.0458	-0.0400,-0.0004
lk-ref	-0.1078	0.1103	-0.9772	0.3285	-0.3240,0.1084
Avg. drop-out rate (log)	0.1536	0.2996	0.5127	0.6082	-0.4335,0.7407
Avg. DHI. p.c.	0.1071	0.6492	0.1650	0.8689	-1.1653,1.3795
Avg. poulation density	0.0365	0.0331	1.1022	0.2704	-0.0284,0.1015
Avg. tourism (log)	0.0206	0.0217	0.9474	0.3435	-0.0220,0.0631
Avg. unemployment (log)	-0.0796	0.2151	-0.3703	0.7112	-0.5011,0.3419
Avg. young & male (log)	-0.1579	0.2175	-0.7262	0.4677	-0.5842,0.2683
Avg. share of foreigners (log)	0.1534	0.0519	2.9555	0.0031	0.0517,0.2552
Avg. state employees p.c. (log)	-0.0646	0.0486	-1.3299	0.1835	-0.1598,0.0306
Avg. dmg. to property (log)	0.4100	0.0947	4.3314	0.0000	0.2245,0.5955
Avg. Clearance rate	-1.0391	0.1017	-10.2192	0.0000	-1.2384,-0.8398
Divorce rates 2015	0.3283	0.0935	3.5121	0.0004	0.1451,0.5115

Table 28: Avg. indirect effects: Theft from cars (log)

Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
	Main				
Clearance rate	0.0937	0.0240	3.9051	0.0001	0.0467,0.1408
Dmg. to property (log)	-0.0128	0.0318	-0.4031	0.6869	-0.0751,0.0495
State employees p.c. (log)	0.1508	0.0417	3.6192	0.0003	0.0691,0.2325
Lag share of foreigners (log)	0.0833	0.0370	2.2511	0.0244	0.0108,0.1558
Young & male (log)	-0.3385	0.0466	-7.2640	0.0000	-0.4298,-0.2471
Divorce rates	0.3612	0.0863	4.1833	0.0000	0.1920,0.5304
Unemployment (log)	0.0437	0.0242	1.8069	0.0708	-0.0037,0.0912
Tourism (log)	0.0128	0.0314	0.4079	0.6833	-0.0488,0.0744
Pop. density (log)	-0.0767	0.2129	-0.3601	0.7188	-0.4940,0.3407
Lag drop-out rate (log)	0.0330	0.0201	1.6424	0.1005	-0.0064,0.0723
Lag unemployment (log)	0.0056	0.0218	0.2574	0.7968	-0.0371,0.0483
Lag DHI p.c.	-0.1215	0.1549	-0.7842	0.4329	-0.4251,0.1821
Lag clearance rate	0.0636	0.0231	2.7557	0.0059	0.0184,0.1088
Border region	0.0831	0.1719	0.4838	0.6285	-0.2537,0.4200
Border to Poland	-0.2874	0.1902	-1.5104	0.1309	-0.6602,0.0855
Border to the Czech Repub.	0.1221	0.1712	0.7133	0.4757	-0.2134,0.4576
Border to Austria	0.1540	0.1818	0.8473	0.3968	-0.2023,0.5104
Border to Switzerland	0.3309	0.2179	1.5187	0.1288	-0.0962,0.7579
Border to France	-0.1464	0.1801	-0.8133	0.4160	-0.4994,0.2065
Border to Belgium	0.1326	0.1995	0.6648	0.5062	-0.2583,0.5235
Border to the Netherlands	0.5152	0.1890	2.7258	0.0064	0.1447,0.8856
Border to Denmark	-0.5406	0.2484	-2.1763	0.0295	-1.0275,-0.0537
Border to Luxembourg	0.0140	0.2086	0.0671	0.9465	-0.3948,0.4228
Voter turn-out (log)	0.1565	0.0275	5.6823	0.0000	0.1025,0.2105
out1	0.1503	0.0301	4.9925	0.0000	0.0913,0.2094
out2	-0.0220	0.0111	-1.9810	0.0476	-0.0437,-0.0002
lk-ref	0.1932	0.1135	1.7023	0.0887	-0.0292,0.4156
Avg. drop-out rate (log)	0.1496	0.0796	1.8806	0.0600	-0.0063,0.3055
Avg. DHI. p.c.	-0.4681	0.2348	-1.9935	0.0462	-0.9284,-0.0079
Avg. poulation density	-0.0296	0.0329	-0.9010	0.3676	-0.0940,0.0348
Avg. tourism (log)	0.0357	0.0223	1.5978	0.1101	-0.0081,0.0794
Avg. unemployment (log)	0.0923	0.0879	1.0502	0.2936	-0.0799,0.2645
Avg. young & male (log)	-0.5237	0.2223	-2.3556	0.0185	-0.9594,-0.0879
Avg. share of foreigners (log)	0.2395	0.0506	4.7304	0.0000	0.1403,0.3387
Avg. state employees p.c. (log)	0.4208	0.0496	8.4844	0.0000	0.3236,0.5181
Avg. dmg. to property (log)	0.3202	0.0906	3.5344	0.0004	0.1426,0.4977
Avg. Clearance rate	0.1998	0.0820	2.4365	0.0148	0.0391,0.3605
Divorce rates 2015	-0.1067	0.0850	-1.2556	0.2093	-0.2733,0.0599
Constant	4.7026	3.8644	1.2169	0.2236	-2.8714,12.2766
	Spatial lags of regressors				
Unemployment (log)	0.2725	0.0324	8.4163	0.0000	0.2090,0.3359
Lag DHI p.c.	1.1371	0.2019	5.6324	0.0000	0.7414,1.5328
Lag drop-out rate (log)	-0.1198	0.0321	-3.7333	0.0002	-0.1827,-0.0569
Voter turn-out (log)	0.2355	0.0435	5.4118	0.0000	0.1502,0.3208
Avg. unemployment (log)	0.0383	0.0968	0.3961	0.6920	-0.1514,0.2281
Avg. DHI. p.c.	-0.1639	0.2904	-0.5643	0.5725	-0.7330,0.4053
Avg. drop-out rate (log)	-0.2467	0.1457	-1.6938	0.0903	-0.5322,0.0388
	Spatial lag of regressand				
ρ	0.1431	0.0205	6.9693	0.0000	0.1029,0.1834

Table 29: Drug crime (log): SDM estimation results

Variable	Direct Effects: Drug crime				
	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	0.0934	0.0237	3.9421	0.0001	0.0470,0.1399
Dmg. to property (log)	-0.0128	0.0320	-0.4007	0.6886	-0.0756,0.0499
State employees p.c. (log)	0.1525	0.0391	3.9048	0.0001	0.0760,0.2291
Lag share of foreigners (log)	0.0824	0.0367	2.2455	0.0247	0.0105,0.1544
Young & male (log)	-0.3379	0.0476	-7.1014	0.0000	-0.4311,-0.2446
Divorce rates	0.3611	0.0888	4.0678	0.0000	0.1871,0.5351
Unemployment (log)	0.0523	0.0233	2.2467	0.0247	0.0067,0.0979
Tourism (log)	0.0113	0.0323	0.3516	0.7251	-0.0519,0.0746
Pop. density (log)	-0.0801	0.2077	-0.3857	0.6997	-0.4872,0.3270
Lag drop-out rate (log)	0.0300	0.0199	1.5070	0.1318	-0.0090,0.0691
Lag unemployment (log)	0.0053	0.0215	0.2471	0.8048	-0.0369,0.0475
Lag DHI p.c.	-0.0897	0.1514	-0.5928	0.5533	-0.3865,0.2070
Lag clearance rate	0.0636	0.0249	2.5580	0.0105	0.0149,0.1123
Border region	0.0674	0.1690	0.3988	0.6900	-0.2639,0.3987
Border to Poland	-0.2810	0.1907	-1.4734	0.1406	-0.6549,0.0928
Border to the Czech Repub.	0.1321	0.1702	0.7758	0.4379	-0.2016,0.4657
Border to Austria	0.1687	0.1808	0.9330	0.3508	-0.1857,0.5230
Border to Switzerland	0.3561	0.2090	1.7041	0.0884	-0.0535,0.7657
Border to France	-0.1341	0.1815	-0.7389	0.4600	-0.4899,0.2217
Border to Belgium	0.1401	0.2085	0.6721	0.5015	-0.2686,0.5488
Border to the Netherlands	0.5330	0.1844	2.8907	0.0038	0.1716,0.8944
Border to Denmark	-0.5383	0.2466	-2.1827	0.0291	-1.0217,-0.0549
Border to Luxembourg	0.0213	0.2178	0.0977	0.9222	-0.4056,0.4482
Voter turn-out (log)	-0.1624	0.0270	6.0120	0.0000	-0.1094,-0.2153
out1	0.1513	0.0315	4.8078	0.0000	0.0896,0.2130
out2	-0.0221	0.0107	-2.0693	0.0385	-0.0431,-0.0012
lk-ref	0.1928	0.1135	1.6986	0.0894	-0.0297,0.4153
Avg. drop-out rate (log)	0.1429	0.0833	1.7162	0.0861	-0.0203,0.3061
Avg. DHI. p.c.	-0.4801	0.2421	-1.9832	0.0473	-0.9546,-0.0056
Avg. poulation density	-0.0315	0.0333	-0.9450	0.3447	-0.0967,0.0338
Avg. tourism (log)	0.0359	0.0218	1.6464	0.0997	-0.0068,0.0787
Avg. unemployment (log)	0.0938	0.0878	1.0689	0.2851	-0.0782,0.2659
Avg. young & male (log)	-0.5302	0.2196	-2.4139	0.0158	-0.9607,-0.0997
Avg. share of foreigners (log)	0.2419	0.0514	4.7031	0.0000	0.1411,0.3426
Avg. state employees p.c. (log)	0.4232	0.0490	8.6393	0.0000	0.3272,0.5193
Avg. dmg. to property (log)	0.3205	0.0922	3.4755	0.0005	0.1398,0.5012
Avg. Clearance rate	0.1962	0.0830	2.3655	0.0180	0.0336,0.3588
Divorce rates 2015	-0.1049	0.0904	-1.1602	0.2460	-0.2820,0.0723

Table 30: Avg. direct effects: Drug crime (log)

Variable	Indirect Effects: Drug crime Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	0.0152	0.0046	3.2790	0.0010	0.0061,0.0243
Dmg. to property (log)	-0.0020	0.0052	-0.3779	0.7055	-0.0122,0.0083
State employees p.c. (log)	0.0248	0.0077	3.2300	0.0012	0.0098,0.0399
Lag share of foreigners (log)	0.0135	0.0066	2.0283	0.0425	0.0005,0.0265
Young & male (log)	-0.0549	0.0119	-4.6052	0.0000	-0.0783,-0.0315
Divorce rates	0.0586	0.0169	3.4692	0.0005	0.0255,0.0917
Unemployment (log)	0.3176	0.0367	8.6435	0.0000	0.2456,0.3896
Tourism (log)	0.0018	0.0053	0.3453	0.7299	-0.0086,0.0123
Pop. density (log)	-0.0136	0.0341	-0.3978	0.6908	-0.0803,0.0532
Lag drop-out rate (log)	-0.1327	0.0362	-3.6626	0.0002	-0.2038,-0.0617
Lag unemployment (log)	0.0009	0.0036	0.2387	0.8113	-0.0062,0.0080
Lag DHI p.c.	1.2768	0.2243	5.6923	0.0000	0.8372,1.7164
Lag clearance rate	0.0104	0.0045	2.2875	0.0222	0.0015,0.0193
Border region	0.0107	0.0272	0.3920	0.6950	-0.0426,0.0639
Border to Poland	-0.0455	0.0317	-1.4361	0.1510	-0.1077,0.0166
Border to the Czech Repub.	0.0220	0.0280	0.7831	0.4335	-0.0330,0.0769
Border to Austria	0.0278	0.0302	0.9205	0.3573	-0.0314,0.0869
Border to Switzerland	0.0582	0.0358	1.6256	0.1040	-0.0120,0.1284
Border to France	-0.0216	0.0295	-0.7309	0.4648	-0.0795,0.0363
Border to Belgium	0.0230	0.0345	0.6665	0.5051	-0.0446,0.0906
Border to the Netherlands	0.0870	0.0343	2.5359	0.0112	0.0198,0.1543
Border to Denmark	-0.0873	0.0421	-2.0734	0.0381	-0.1699,-0.0048
Border to Luxembourg	0.0032	0.0358	0.0902	0.9281	-0.0669,0.0733
Voter turn-out (log)	-0.2958	0.0479	6.1722	0.0000	-0.2019,-0.3898
out1	0.0247	0.0067	3.6826	0.0002	0.0115,0.0378
out2	-0.0036	0.0019	-1.9113	0.0560	-0.0073,0.0001
lk-ref	0.0311	0.0193	1.6122	0.1069	-0.0067,0.0690
Avg. drop-out rate (log)	-0.2661	0.1603	-1.6600	0.0969	-0.5804,0.0481
Avg. DHI. p.c.	-0.2811	0.3387	-0.8300	0.4065	-0.9450,0.3827
Avg. poulation density	-0.0052	0.0056	-0.9255	0.3547	-0.0163,0.0058
Avg. tourism (log)	0.0058	0.0037	1.5816	0.1137	-0.0014,0.0131
Avg. unemployment (log)	0.0624	0.1111	0.5616	0.5744	-0.1554,0.2802
Avg. young & male (log)	-0.0863	0.0390	-2.2158	0.0267	-0.1627,-0.0100
Avg. share of foreigners (log)	0.0395	0.0112	3.5363	0.0004	0.0176,0.0614
Avg. state employees p.c. (log)	0.0691	0.0152	4.5399	0.0000	0.0393,0.0989
Avg. dmg. to property (log)	0.0521	0.0172	3.0266	0.0025	0.0184,0.0859
Avg. Clearance rate	0.0320	0.0148	2.1627	0.0306	0.0030,0.0610
Divorce rates 2015	-0.0169	0.0150	-1.1301	0.2584	-0.0463,0.0124

Table 31: Avg. indirect effects: Drug crime (log)

Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
			Main		
Clearance rate	-0.0389	0.0091	-4.2775	0.0000	-0.0567,-0.0211
Dmg. to property (log)	0.4621	0.0121	38.3012	0.0000	0.4385,0.4858
State employees p.c. (log)	0.0111	0.0158	0.7035	0.4817	-0.0198,0.0420
Lag share of foreigners (log)	0.0331	0.0140	2.3664	0.0180	0.0057,0.0605
Young & male (log)	-0.0236	0.0176	-1.3401	0.1802	-0.0582,0.0109
Divorce rates	0.3862	0.0334	11.5566	0.0000	0.3207,0.4517
Unemployment (log)	0.0383	0.0091	4.1908	0.0000	0.0204,0.0562
Tourism (log)	-0.0750	0.0119	-6.2831	0.0000	-0.0984,-0.0516
Pop. density (log)	0.1485	0.0941	1.5776	0.1147	-0.0360,0.3329
Lag drop-out rate (log)	0.0036	0.0076	0.4783	0.6325	-0.0113,0.0186
Lag unemployment (log)	0.0136	0.0082	1.6451	0.1000	-0.0026,0.0297
Lag DHI p.c.	0.0347	0.0585	0.5934	0.5529	-0.0799,0.1493
Lag clearance rate	-0.0857	0.0087	-9.8226	0.0000	-0.1028,-0.0686
Border region	0.0244	0.1180	0.2072	0.8359	-0.2069,0.2558
Border to Poland	0.0350	0.1306	0.2682	0.7885	-0.2209,0.2909
Border to the Czech Repub.	-0.1079	0.1175	-0.9184	0.3584	-0.3382,0.1224
Border to Austria	-0.0701	0.1248	-0.5614	0.5745	-0.3147,0.1746
Border to Switzerland	-0.2676	0.1497	-1.7874	0.0739	-0.5610,0.0258
Border to France	-0.0473	0.1236	-0.3825	0.7021	-0.2894,0.1949
Border to Belgium	0.0406	0.1369	0.2963	0.7670	-0.2278,0.3089
Border to the Netherlands	0.3148	0.1298	2.4256	0.0153	0.0604,0.5692
Border to Denmark	-0.1145	0.1705	-0.6715	0.5019	-0.4488,0.2197
Border to Luxembourg	-0.0610	0.1432	-0.4263	0.6699	-0.3416,0.2195
Voter turn-out (log)	-0.0047	0.0113	-0.4150	0.6781	-0.0270,0.0175
out1	-0.0276	0.0116	-2.3742	0.0176	-0.0504,-0.0048
out2	-0.0090	0.0043	-2.1081	0.0350	-0.0175,-0.0006
lk-ref	-0.0691	0.0531	-1.3004	0.1934	-0.1732,0.0350
Avg. drop-out rate (log)	-0.0786	0.0545	-1.4412	0.1495	-0.1855,0.0283
Avg. DHI. p.c.	-0.3425	0.1611	-2.1258	0.0335	-0.6583,-0.0267
Avg. poulation density	0.0076	0.0224	0.3396	0.7342	-0.0363,0.0516
Avg. tourism (log)	-0.0010	0.0153	-0.0677	0.9460	-0.0310,0.0289
Avg. unemployment (log)	0.2181	0.0602	3.6236	0.0003	0.1001,0.3360
Avg. young & male (log)	-0.1455	0.1526	-0.9531	0.3405	-0.4446,0.1537
Avg. share of foreigners (log)	0.1635	0.0347	4.7090	0.0000	0.0954,0.2315
Avg. state employees p.c. (log)	-0.0054	0.0340	-0.1576	0.8748	-0.0719,0.0612
Avg. dmg. to property (log)	0.9064	0.0622	14.5803	0.0000	0.7846,1.0282
Avg. Clearance rate	-0.4990	0.0562	-8.8804	0.0000	-0.6092,-0.3889
Divorce rates 2015	0.1648	0.0583	2.8261	0.0047	0.0505,0.2790
Constant	1.9525	2.6513	0.7364	0.4615	-3.2440,7.1489
			Spatial lags of regressors		
Unemployment (log)	0.0627	0.0123	5.1165	0.0000	0.0387,0.0868
Lag DHI p.c.	0.3334	0.0763	4.3715	0.0000	0.1839,0.4828
Lag drop-out rate (log)	0.0472	0.0124	3.8184	0.0001	0.0230,0.0715
Voter turn-out (log)	0.0370	0.0177	2.0888	0.0367	0.0023,0.0717
Avg. unemployment (log)	0.0164	0.0682	0.2403	0.8101	-0.1173,0.1501
Avg. DHI. p.c.	0.2074	0.1998	1.0378	0.2994	-0.1843,0.5990
Avg. drop-out rate (log)	0.0491	0.0997	0.4922	0.6226	-0.1464,0.2445
			Spatial lag of regressand		
ρ	0.1035	0.0181	5.7221	0.0000	0.0680,0.1389

Table 32: Street crime (log): SDM estimation results

	Direct Effects: Street crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0392	0.0090	-4.3797	0.0000	-0.0568,-0.0217
Dmg. to property (log)	0.4631	0.0121	38.2135	0.0000	0.4393,0.4869
State employees p.c. (log)	0.0115	0.0148	0.7823	0.4340	-0.0174,0.0405
Lag share of foreigners (log)	0.0327	0.0139	2.3614	0.0182	0.0056,0.0599
Young & male (log)	-0.0230	0.0180	-1.2750	0.2023	-0.0582,0.0123
Divorce rates	0.3864	0.0341	11.3221	0.0000	0.3195,0.4533
Unemployment (log)	0.0399	0.0088	4.5114	0.0000	0.0226,0.0572
Tourism (log)	-0.0757	0.0122	-6.1961	0.0000	-0.0997,-0.0518
Pop. density (log)	0.1476	0.0910	1.6214	0.1049	-0.0308,0.3260
Lag drop-out rate (log)	0.0047	0.0076	0.6213	0.5344	-0.0101,0.0196
Lag unemployment (log)	0.0135	0.0082	1.6535	0.0982	-0.0025,0.0295
Lag DHI p.c.	0.0416	0.0573	0.7265	0.4675	-0.0706,0.1538
Lag clearance rate	-0.0860	0.0094	-9.1635	0.0000	-0.1044,-0.0676
Border region	0.0135	0.1159	0.1163	0.9074	-0.2136,0.2406
Border to Poland	0.0402	0.1307	0.3077	0.7583	-0.2159,0.2963
Border to the Czech Repub.	-0.1016	0.1166	-0.8720	0.3832	-0.3301,0.1268
Border to Austria	-0.0606	0.1239	-0.4893	0.6246	-0.3034,0.1822
Border to Switzerland	-0.2518	0.1434	-1.7561	0.0791	-0.5328,0.0292
Border to France	-0.0385	0.1243	-0.3097	0.7568	-0.2822,0.2052
Border to Belgium	0.0455	0.1428	0.3183	0.7503	-0.2345,0.3254
Border to the Netherlands	0.3263	0.1263	2.5834	0.0098	0.0788,0.5739
Border to Denmark	-0.1116	0.1689	-0.6604	0.5090	-0.4427,0.2195
Border to Luxembourg	-0.0563	0.1491	-0.3774	0.7059	-0.3486,0.2360
Voter turn-out (log)	-0.0045	0.0112	-0.4047	0.6857	-0.0264,0.0174
out1	-0.0275	0.0121	-2.2719	0.0231	-0.0513,-0.0038
out2	-0.0091	0.0041	-2.2036	0.0276	-0.0172,-0.0010
lk-ref	-0.0696	0.0530	-1.3143	0.1888	-0.1735,0.0342
Avg. drop-out rate (log)	-0.0780	0.0570	-1.3697	0.1708	-0.1896,0.0336
Avg. DHI. p.c.	-0.3431	0.1658	-2.0696	0.0385	-0.6679,-0.0182
Avg. poulation density	0.0064	0.0227	0.2821	0.7779	-0.0380,0.0508
Avg. tourism (log)	-0.0010	0.0149	-0.0656	0.9477	-0.0302,0.0282
Avg. unemployment (log)	0.2190	0.0600	3.6475	0.0003	0.1013,0.3366
Avg. young & male (log)	-0.1491	0.1503	-0.9916	0.3214	-0.4437,0.1456
Avg. share of foreigners (log)	0.1648	0.0352	4.6884	0.0000	0.0959,0.2337
Avg. state employees p.c. (log)	-0.0048	0.0334	-0.1440	0.8855	-0.0703,0.0607
Avg. dmg. to property (log)	0.9076	0.0631	14.3873	0.0000	0.7840,1.0313
Avg. Clearance rate	-0.5031	0.0568	-8.8564	0.0000	-0.6145,-0.3918
Divorce rates 2015	0.1665	0.0611	2.7245	0.0064	0.0467,0.2862

Table 33: Avg. direct effects: Street crime (log)

	Indirect Effects: Street crime				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0045	0.0014	-3.2819	0.0010	-0.0071,-0.0018
Dmg. to property (log)	0.0527	0.0106	4.9500	0.0000	0.0318,0.0735
State employees p.c. (log)	0.0013	0.0017	0.7669	0.4431	-0.0021,0.0047
Lag share of foreigners (log)	0.0037	0.0018	2.0604	0.0394	0.0002,0.0073
Young & male (log)	-0.0026	0.0022	-1.1993	0.2304	-0.0069,0.0017
Divorce rates	0.0438	0.0087	5.0567	0.0000	0.0268,0.0607
Unemployment (log)	0.0732	0.0134	5.4769	0.0000	0.0470,0.0994
Tourism (log)	-0.0086	0.0022	-3.9166	0.0001	-0.0129,-0.0043
Pop. density (log)	0.0167	0.0109	1.5406	0.1234	-0.0046,0.0381
Lag drop-out rate (log)	0.0516	0.0134	3.8616	0.0001	0.0254,0.0778
Lag unemployment (log)	0.0015	0.0010	1.5104	0.1309	-0.0005,0.0035
Lag DHI p.c.	0.3696	0.0808	4.5770	0.0000	0.2113,0.5279
Lag clearance rate	-0.0098	0.0023	-4.3025	0.0000	-0.0142,-0.0053
Border region	0.0014	0.0132	0.1058	0.9157	-0.0244,0.0272
Border to Poland	0.0048	0.0152	0.3135	0.7539	-0.0251,0.0346
Border to the Czech Repub.	-0.0114	0.0133	-0.8592	0.3902	-0.0374,0.0146
Border to Austria	-0.0067	0.0142	-0.4733	0.6360	-0.0346,0.0211
Border to Switzerland	-0.0285	0.0173	-1.6522	0.0985	-0.0624,0.0053
Border to France	-0.0043	0.0144	-0.3016	0.7629	-0.0325,0.0239
Border to Belgium	0.0053	0.0163	0.3272	0.7435	-0.0266,0.0373
Border to the Netherlands	0.0372	0.0167	2.2277	0.0259	0.0045,0.0699
Border to Denmark	-0.0127	0.0196	-0.6456	0.5185	-0.0511,0.0258
Border to Luxembourg	-0.0064	0.0172	-0.3746	0.7080	-0.0401,0.0272
Voter turn-out (log)	0.0410	0.0189	2.1714	0.0299	0.0040,0.0779
out1	-0.0031	0.0015	-2.0809	0.0374	-0.0060,-0.0002
out2	-0.0010	0.0005	-1.9436	0.0519	-0.0021,0.0000
lk-ref	-0.0080	0.0065	-1.2319	0.2180	-0.0207,0.0047
Avg. drop-out rate (log)	0.0385	0.1057	0.3638	0.7160	-0.1687,0.2457
Avg. DHI. p.c.	0.1761	0.2251	0.7825	0.4339	-0.2650,0.6173
Avg. poulation density	0.0007	0.0026	0.2743	0.7839	-0.0044,0.0058
Avg. tourism (log)	-0.0001	0.0017	-0.0643	0.9487	-0.0035,0.0033
Avg. unemployment (log)	0.0446	0.0746	0.5981	0.5498	-0.1016,0.1909
Avg. young & male (log)	-0.0168	0.0175	-0.9605	0.3368	-0.0511,0.0175
Avg. share of foreigners (log)	0.0188	0.0055	3.4220	0.0006	0.0080,0.0295
Avg. state employees p.c. (log)	-0.0005	0.0039	-0.1378	0.8904	-0.0081,0.0071
Avg. dmg. to property (log)	0.1032	0.0217	4.7591	0.0000	0.0607,0.1458
Avg. Clearance rate	-0.0572	0.0132	-4.3239	0.0000	-0.0832,-0.0313
Divorce rates 2015	0.0190	0.0082	2.3272	0.0200	0.0030,0.0350

Table 34: Avg. indirect effects: Street crime (log)

Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
			Main		
Clearance rate	-0.0783	0.0095	-8.2089	0.0000	-0.0969,-0.0596
Dmg. to property (log)	0.2791	0.0127	22.0104	0.0000	0.2542,0.3039
State employees p.c. (log)	-0.0509	0.0165	-3.0762	0.0021	-0.0833,-0.0185
Lag share of foreigners (log)	0.0432	0.0147	2.9433	0.0032	0.0144,0.0719
Young & male (log)	0.0214	0.0185	1.1567	0.2474	-0.0149,0.0577
Divorce rates	0.1828	0.0345	5.2951	0.0000	0.1152,0.2505
Unemployment (log)	0.0016	0.0096	0.1687	0.8660	-0.0172,0.0204
Tourism (log)	0.0442	0.0125	3.5408	0.0004	0.0197,0.0686
Pop. density (log)	-0.0373	0.0919	-0.4064	0.6845	-0.2174,0.1428
Lag drop-out rate (log)	0.0006	0.0080	0.0788	0.9372	-0.0150,0.0162
Lag unemployment (log)	0.0128	0.0086	1.4769	0.1397	-0.0042,0.0297
Lag DHI p.c.	-0.1144	0.0614	-1.8628	0.0625	-0.2348,0.0060
Lag clearance rate	-0.0360	0.0092	3.9264	0.0001	-0.0539,-0.0180
Border region	-0.1559	0.1001	-1.5575	0.1194	-0.3521,0.0403
Border to Poland	0.0068	0.1108	0.0614	0.9511	-0.2103,0.2239
Border to the Czech Repub.	0.0832	0.0997	0.8346	0.4039	-0.1122,0.2786
Border to Austria	0.2066	0.1059	1.9508	0.0511	-0.0010,0.4141
Border to Switzerland	0.0321	0.1270	0.2529	0.8003	-0.2167,0.2810
Border to France	0.2007	0.1048	1.9148	0.0555	-0.0047,0.4061
Border to Belgium	0.2491	0.1162	2.1442	0.0320	0.0214,0.4767
Border to the Netherlands	0.1879	0.1101	1.7070	0.0878	-0.0278,0.4037
Border to Denmark	0.2934	0.1446	2.0284	0.0425	0.0099,0.5768
Border to Luxembourg	-0.0054	0.1215	-0.0445	0.9645	-0.2434,0.2326
Voter turn-out (log)	-0.0165	0.0116	-1.4178	0.1563	-0.0393,0.0063
out1	-0.0039	0.0121	-0.3179	0.7506	-0.0276,0.0199
out2	-0.0101	0.0045	-2.2587	0.0239	-0.0189,-0.0013
lk-ref	0.0053	0.0526	0.1012	0.9194	-0.0977,0.1083
Avg. drop-out rate (log)	0.1471	0.0463	3.1781	0.0015	0.0564,0.2378
Avg. DHI. p.c.	-0.4528	0.1367	-3.3125	0.0009	-0.7207,-0.1849
Avg. poulation density	0.0552	0.0190	2.8983	0.0038	0.0179,0.0925
Avg. tourism (log)	0.0083	0.0130	0.6388	0.5229	-0.0172,0.0337
Avg. unemployment (log)	-0.0949	0.0511	-1.8583	0.0631	-0.1950,0.0052
Avg. young & male (log)	-0.1314	0.1294	-1.0153	0.3100	-0.3850,0.1222
Avg. share of foreigners (log)	0.0998	0.0294	3.3900	0.0007	0.0421,0.1576
Avg. state employees p.c. (log)	-0.1452	0.0288	-5.0342	0.0000	-0.2017,-0.0886
Avg. dmg. to property (log)	0.6434	0.0528	12.1976	0.0000	0.5400,0.7468
Avg. Clearance rate	-0.2666	0.0477	-5.5880	0.0000	-0.3600,-0.1731
Divorce rates 2015	-0.0216	0.0495	-0.4374	0.6618	-0.1186,0.0753
Constant	7.1482	2.2503	3.1765	0.0015	2.7377,11.5588
			Spatial lags of regressors		
Unemployment (log)	-0.0042	0.0127	-0.3259	0.7445	-0.0291,0.0208
Lag DHI p.c.	-0.1665	0.0801	-2.0787	0.0376	-0.3235,-0.0095
Lag drop-out rate (log)	0.0166	0.0127	1.2997	0.1937	-0.0084,0.0415
Voter turn-out (log)	-0.0065	0.0183	-0.3541	0.7233	-0.0424,0.0294
Avg. unemployment (log)	-0.0156	0.0568	-0.2742	0.7839	-0.1269,0.0957
Avg. DHI. p.c.	-0.2979	0.1692	-1.7602	0.0784	-0.6296,0.0338
Avg. drop-out rate (log)	-0.0512	0.0847	-0.6043	0.5456	-0.2171,0.1148
			Spatial lag of regressand		
ρ	0.0399	0.0194	2.0584	0.0396	0.0019,0.0779

Table 35: Assault (log): SDM estimation results

	Direct Effects: Assault				
Variable	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0780	0.0094	-8.3187	0.0000	-0.0964,-0.0596,
Dmg. to property (log)	0.2792	0.0127	21.9416	0.0000	0.2542,0.3041
State employees p.c. (log)	-0.0513	0.0155	-3.3226	0.0009	-0.0816,-0.0211
Lag share of foreigners (log)	0.0427	0.0145	2.9456	0.0032	0.0143,0.0711
Young & male (log)	0.0222	0.0188	1.1778	0.2389	-0.0147,0.0591
Divorce rates	0.1835	0.0354	5.1790	0.0000	0.1141,0.2530
Unemployment (log)	0.0019	0.0094	0.2035	0.8388	-0.0164,0.0202
Tourism (log)	0.0436	0.0128	3.4157	0.0006	0.0186,0.0686
Pop. density (log)	-0.0386	0.0890	-0.4337	0.6645	-0.2131,0.1359
Lag drop-out rate (log)	0.0009	0.0079	0.1109	0.9117	-0.0147,0.0164
Lag unemployment (log)	0.0126	0.0085	1.4850	0.1376	-0.0040,0.0293
Lag DHI p.c.	-0.1155	0.0602	-1.9191	0.0550	-0.2334,0.0025
Lag clearance rate	-0.0359	0.0098	-3.6490	0.0003	-0.0551,0.0166
Border region	-0.1653	0.0981	-1.6849	0.0920	-0.3576,0.0270
Border to Poland	0.0111	0.1107	0.1007	0.9198	-0.2058,0.2281
Border to the Czech Repub.	0.0887	0.0987	0.8989	0.3687	-0.1047,0.2822
Border to Austria	0.2148	0.1049	2.0474	0.0406	0.0092,0.4204
Border to Switzerland	0.0460	0.1214	0.3787	0.7049	-0.1919,0.2839
Border to France	0.2083	0.1053	1.9777	0.0480	0.0019,0.4147
Border to Belgium	0.2532	0.1210	2.0930	0.0363	0.0161,0.4903
Border to the Netherlands	0.1972	0.1070	1.8428	0.0654	-0.0125,0.4068
Border to Denmark	0.2961	0.1430	2.0701	0.0384	0.0158,0.5765
Border to Luxembourg	-0.0012	0.1263	-0.0097	0.9922	-0.2488,0.2464
Voter turn-out (log)	-0.0171	0.0115	-1.4952	0.1349	-0.0396,0.0053
out1	-0.0037	0.0126	-0.2949	0.7681	-0.0285,0.0210
out2	-0.0101	0.0043	-2.3597	0.0183	-0.0186,-0.0017
lk-ref	0.0048	0.0524	0.0925	0.9263	-0.0978,0.1075
Avg. drop-out rate (log)	0.1466	0.0483	3.0362	0.0024	0.0520,0.2412
Avg. DHI. p.c.	-0.4583	0.1404	-3.2643	0.0011	-0.7335,-0.1831
Avg. poulation density	0.0542	0.0192	2.8195	0.0048	0.0165,0.0919
Avg. tourism (log)	0.0084	0.0126	0.6612	0.5085	-0.0164,0.0331
Avg. unemployment (log)	-0.0950	0.0509	-1.8664	0.0620	-0.1947,0.0048
Avg. young & male (log)	-0.1341	0.1273	-1.0532	0.2922	-0.3835,0.1154
Avg. share of foreigners (log)	0.1007	0.0298	3.3821	0.0007	0.0423,0.1591
Avg. state employees p.c. (log)	-0.1457	0.0283	-5.1392	0.0000	-0.2012,-0.0901
Avg. dmg. to property (log)	0.6431	0.0535	12.0273	0.0000	0.5383,0.7479
Avg. Clearance rate	-0.2641	0.0481	-5.4852	0.0000	-0.3585,-0.1697
Divorce rates 2015	-0.0204	0.0522	-0.3916	0.6953	-0.1227,0.0818

Table 36: Avg. direct effects: Assault (log)

Variable	Indirect Effects: Assault				
	Coefficient	Std. error	z-value	p-value	95% Conf. Interval
Clearance rate	-0.0032	0.0017	-1.8777	0.0604	-0.0066,0.0001
Dmg. to property (log)	0.0116	0.0060	1.9423	0.0521	-0.0001,0.0234
State employees p.c. (log)	-0.0022	0.0014	-1.5927	0.1112	-0.0048,0.0005
Lag share of foreigners (log)	0.0018	0.0012	1.5435	0.1227	-0.0005,0.0041
Young & male (log)	0.0010	0.0010	0.9328	0.3509	-0.0011,0.0030
Divorce rates	0.0076	0.0043	1.7751	0.0759	-0.0008,0.0161
Unemployment (log)	-0.0042	0.0135	-0.3136	0.7538	-0.0306,0.0222
Tourism (log)	0.0018	0.0011	1.6472	0.0995	-0.0003,0.0040
Pop. density (log)	-0.0017	0.0042	-0.4141	0.6788	-0.0099,0.0064
Lag drop-out rate (log)	0.0166	0.0132	1.2596	0.2078	-0.0092,0.0423
Lag unemployment (log)	0.0005	0.0005	1.0312	0.3025	-0.0005,0.0015
Lag DHI p.c.	-0.1764	0.0809	-2.1798	0.0293	-0.3351,-0.0178
Lag clearance rate	-0.0015	0.0009	-1.6805	0.0929	-0.0032,0.0002
Border region	-0.0070	0.0058	-1.2058	0.2279	-0.0185,0.0044
Border to Poland	0.0006	0.0051	0.1162	0.9075	-0.0094,0.0106
Border to the Czech Repub.	0.0038	0.0048	0.7908	0.4291	-0.0056,0.0132
Border to Austria	0.0091	0.0067	1.3596	0.1740	-0.0040,0.0221
Border to Switzerland	0.0019	0.0056	0.3395	0.7342	-0.0090,0.0128
Border to France	0.0088	0.0067	1.3174	0.1877	-0.0043,0.0218
Border to Belgium	0.0107	0.0078	1.3662	0.1719	-0.0046,0.0260
Border to the Netherlands	0.0083	0.0068	1.2260	0.2202	-0.0050,0.0216
Border to Denmark	0.0125	0.0096	1.3045	0.1921	-0.0063,0.0313
Border to Luxembourg	-0.0001	0.0059	-0.0246	0.9804	-0.0118,0.0115
Voter turn-out (log)	-0.0065	0.0185	-0.3519	0.7249	-0.0428,0.0298
out1	-0.0001	0.0006	-0.2445	0.8068	-0.0013,0.0010
out2	-0.0004	0.0003	-1.4247	0.1542	-0.0010,0.0002
lk-ref	0.0001	0.0025	0.0531	0.9577	-0.0048,0.0051
Avg. drop-out rate (log)	-0.0522	0.0854	-0.6112	0.5410	-0.2196,0.1152
Avg. DHI. p.c.	-0.3364	0.1798	-1.8703	0.0614	-0.6888,0.0161
Avg. poulation density	0.0022	0.0014	1.5875	0.1124	-0.0005,0.0050
Avg. tourism (log)	0.0004	0.0006	0.5728	0.5668	-0.0009,0.0016
Avg. unemployment (log)	-0.0184	0.0594	-0.3090	0.7573	-0.1348,0.0981
Avg. young & male (log)	-0.0056	0.0065	-0.8586	0.3906	-0.0183,0.0071
Avg. share of foreigners (log)	0.0042	0.0026	1.6515	0.0986	-0.0008,0.0093
Avg. state employees p.c. (log)	-0.0061	0.0036	-1.7271	0.0841	-0.0131,0.0008
Avg. dmg. to property (log)	0.0268	0.0139	1.9336	0.0532	-0.0004,0.0539
Avg. Clearance rate	-0.0110	0.0061	-1.8082	0.0706	-0.0230,0.0009
Divorce rates 2015	-0.0008	0.0024	-0.3404	0.7336	-0.0055,0.0038

Table 37: Avg. indirect effects: Assault (log)