Research Proposal: Social Capital and Crime in Germany

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Introduction and theory

Most of crime studies are based on the rational choice assumptions of legal and criminal returns and the importance of deterrence to reduce criminal behaviours (Becker 1968). However, less has been written about the relevance of social interactions explaining criminal behaviours. Some literature, though, has focused on the relationship between violent crimes and social capital. Lederman (Lederman, Loayza, and Menedez 2002) identified that the prevalence of trust on community members has an effect on violent crimes and that the social cohesion through participation and membership in community oranisations only impact violent crime levels depending on the type of religious and social organisation engaged. Additionally, Hanslaimer (Hanslmaier 2015) showed that altruism has a general negative effect on violent crimes, but other indicators of social capital only proved to be related to other types of high impact crime and not to violent crime. Hence, we are interested in responding to the question: How do social networks and bonds in a given community determine the level of violent crime?

Social capital can be summerised as the links, shared values, and understandings in society that enable individuals and groups to trust each other and so work as a group (OECD, n.d.). The concept of social capital gained importance after Robert Putnam used it to describe the anomic state of the American society at the beginning of the 21st century (Putnam 2001). He argued that a decrease in community linkages that once held societies together, translates in a loss of social capital (Putnam 2001).

Additionally, we expect to observe that in societies with anomic and disorganization symptoms there are lower levels of social capital. Within these societies, groups and member interactions find themselves in a disruptive phase, damaging social bonds, norms, values, understandings and commitment. Environments where people lack a strong moral order lead to individual members to behave more egoistically therefore diminishing social capital. Disintegration of members of the community weakens social cohesion and promotes individualism that end in 'Machiavellian' competition, fostering feelings of status insecurity. Moreover, certain social milieus tend to be more vulnerable and respond therefore with violence. In addition, social capital provides means for informal punishment within a given community. Therefore more social capital leads to more abiding to social norms. In contrast communities that lack of social capital can merely punish norm diverging behaviour informally to a lesser extent and therefore are expected to have a higher crime rate.

Our main hypothesis is that the more social capital a community has, the less crime there would be observed as a result of its collective action mechanisms. Thus, we expect to observe that communities with anomic symptoms will tend to have more crime.

Social Capital is a multi-dimensional concept that consist of "varios social elements that promote individual and collective action"(Lederman, Loayza, and Menedez 2002). As a consequence of its high complexity, measuring social capital carries some dificulties. However, researchers have shown consistent results when using indicators for social capital based on participation in community organisations, attitudes of civi action, and the sense of membership to the community (Lederman, Loayza, and Menedez 2002).

With new data available for crime statistics for the years 2013 at the districts' level in Germany it is relevant to study the incidence of high impact crimes and its relation to social capital formation. Results might be meaningful as rational for public intervention using crime reduction strategies that help build-up social capital at the community level (e.g. funding of sport clubs, gathering community, subsidies for staying in a community), instead of more aggressive interventionist policing strategies. Strategies that are less police intensive might have higher public support and might be seen as more legitimate. Social engagement at the local level might also help increase trust levels across community members and encourage more altruistic behaviours among them. Furthermore, social capital investment might be more cost-efficient compared to more aggressive policing tactics, which effects tend to be perceived only in the more immediate time, whereas social capital investments and their effects might stretch out for longer time.

Methodology and analysis

In order to answer the research question, we will apply a linear regression model in R Studio (R Core Team 2015). So far we have used R packages by the following authors: Wickham and Francois (2015), Wickham and Chang (2015), Gandrud (2015), C.-h. Chan et al. (2015) and Wickham (2015). A binominal or multinomial regression model does not qualify, since we have a continuous, interval level dependent variable. Since our data only covers two time periods (t=2) we intend to use pooled OLS regressions. We thereby might run the risk to violate OLS assumptions when the values for a district from one time period are correlated with the observation for this district at the other time period - assuming that the environment remains rather constant and districts with higher crime rates will also experience higher crime rates in the next period. Therefore we need to check statistically, whether our measured estimators are unbiased and efficient (e.g. comparing the results to a panel regression model, dummy for time period, heteroskedasticity).

Data

Our dependent variable crime rate can be obtained from the German Federal Police's crime statistic ("Polizeiliche Kriminalstatistik" PKS) for the years 2013 and 2014 on a district level ("Kreis"). This data is also disaggregated regarding the type of crime. This number, however, is missing the dark figure of crime - the unreported number of crime in this area. Different methods exist to assess the dark figure of crime, but it is difficult to assess their reliability. Hence, depending on the type of crime, the reported numbers might contain a structural bias, i.e. some types of crime are reported at a different rate than others (e.g. when insurance companies require individual reporting). Since we focus on crimes that disrupt the social community, we expect a high level of reporting and this reporting to be consistently high across different types of disruptive crimes. It is possible to focus on one type of crime for our dependent variable, but also to construct a dependent variable summarising different types of crime. The latter approach might prove utile, since this provides greater variance in the dependent variable.
We want to measure different dimensions of our independent variable social capital. We begin with a measurement for the networks and links dimension. This dimension highlights the importance of social bonds and meeting points in a community. We attempt to operationalise this dimension with indicators of marriages and migration. The indicator marriaged couples as a percentage of the population captures the notion that enhanced social ties increase the social capital of a community. Nevertheless this measure might be unreliable, since other forms of cohabitation (that are not measured by official statistics) can generate enhanced social links. In addition we might capture a different underlying concept (e.g. the role of tradition in a region) that is correlated with our dependent variable through a different causal mechanism. The other indicator, migration, aims at capturing the fluctuation of a region with other regions in Germany or with other nations. Since social capital requires time to build up, we expect higher crime rates in areas with high fluctuations.
Moreover we need district level data for other variables to control for local heterogeneity. This data is provided by the German statistical bureau. We want to control for factors that influence the rational choice for committing a crime. First, unemployment changes the opportunity costs of punishment, i.e. imprisonment. Second, the level of income: high income reduces the punishment felt by individuals for minor charges (monetary penalty), but has no predetermined impact on the impact of imprisonment. In addition we want to control for a district's composition in age (younger persons are found to be more involved in crimes), gender (men are found to be more related to crimes), population size (i.e. more people, more expected crimes) and population density (as a proxy for urbanisation). As for now, we expect to obtain measures for some variables only for 2013. It needs to be determined, whether the fluctuation of the variable before 2013 allows to assume identical values for 2014.
On order to conduct the analysis, we need to merge the different datasets. We will use a combination of a unique identifier for the district ("Gemeindeschlüssel") and a year indicator (2013 or 2014).

Conclusion

We expect to confirm our hypothesis: Districts with higher social capital will experience lower levels of crime, whereas districts with lower levels of social capital will experience (ceteris paribus) higher levels of crime. Performing various statistical analyses and obtaining all relevant control variables, we expect high internal validity of the results. Nevertheless the external validity of the results might prove low: Neither can we determine whether these results hold for other time periods in Germany, nor can we extrapolate these results to other regions. However external validity can be argued for, if these results prove to be in line with research that has been conducted in other regions and other time periods.

Regression analysis

Table 1: Regression analysis regarding (non-) violent and total crimes and independent variable FoundationsDensity100k with OLS regressions and negative binominal regression

	Dependent variable:			
	ViolentCrimeRate	NonViolentCrimeRate	CrimeRate	
	OLS	*OLS*	*OLS*	*negative binomial*
	(1)	(2)	(3)	(4)
FoundationsDensity100k	3.80***	20.64***	24.43***	0.002***
	(0.85)	(6.30)	(6.92)	(0.001)
BelieversRate	−0.08***	−0.77***	−0.85***	−0.0001***
	(0.01)	(0.06)	(0.06)	(0.0000)
MarriageRate	−0.23*	−1.15	−1.39	0.0000
	(0.12)	(0.92)	(1.01)	(0.0001)
MaleRate	−84.03***	−884.99***	−969.02***	−0.10***
	(19.94)	(147.01)	(161.46)	(0.02)
YouthRate	29.16***	54.71**	83.87***	0.01***
	(2.90)	(21.38)	(23.48)	(0.003)
UnemployedPercentage	66.83***	824.91***	891.74***	0.10***
	(4.28)	(31.58)	(34.68)	(0.004)
Constant	11,789.58***	122,216.00***	134,005.60***	21.72***
	(1,159.26)	(8,548.98)	(9,388.82)	(1.04)
Observations	393	393	393	393
R^2	0.60	0.75	0.75	
Adjusted R^2	0.59	0.75	0.74	
Log Likelihood				−3,485.04
θ				21.82*** (1.55)
Akaike Inf. Crit.				6,984.09

Note: *p<0.1; **p<0.05; ***p<0.01

This regression output shows the results using 3 different dependent variables and two models

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Table 2: Regression analysis regarding (non-) violent and total crimes and independent variable FlowRate with OLS regressions and negative binominal regression

	Dependent variable:			
	ViolentCrimeRate	NonViolentCrimeRate	CrimeRate	
	OLS	*OLS*	*OLS*	*negative binomial*
	(1)	(2)	(3)	(4)
FlowRate	0.01**	0.08**	0.09**	0.0000***
	(0.01)	(0.04)	(0.04)	(0.0000)
BelieversRate	−0.08***	−0.75***	−0.83***	−0.0001***
	(0.01)	(0.06)	(0.07)	(0.0000)
MarriageRate	−0.20	−1.07	−1.27	−0.0000
	(0.13)	(0.93)	(1.02)	(0.0001)
MaleRate	−102.07***	−979.93***	−1,082.00***	−0.11***
	(19.84)	(144.62)	(159.12)	(0.02)
YouthRate	29.69***	56.16***	85.85***	0.01***
	(2.96)	(21.58)	(23.75)	(0.003)
UnemployedPercentage	67.44***	832.51***	899.95***	0.10***
	(4.46)	(32.52)	(35.78)	(0.004)
Constant	12,617.15***	124,374.70***	136,991.90***	21.01***
	(1,219.13)	(8,886.69)	(9,777.63)	(1.08)
Observations	393	393	393	393
R^2	0.59	0.75	0.74	
Adjusted R^2	0.58	0.74	0.74	
Log Likelihood				−3,481.86
θ				22.17*** (1.57)
Akaike Inf. Crit.				6,977.72
Note:				*p<0.1; **p<0.05; ***p<0.01
	This regression output shows the results using 3 different dependent variables and two models			

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Table 3: Regression analysis regarding (non-) violent and total crimes and independent variable TurnoutPercentage with OLS regressions and negative binominal regression

	Dependent variable:			
	ViolentCrimeRate	NonViolentCrimeRate	CrimeRate	
	OLS	*OLS*	*OLS*	*negative binomial*
	(1)	(2)	(3)	(4)
TurnoutPercentage	-10.76^{***}	-12.54	-23.30	0.001
	(3.63)	(26.75)	(29.42)	(0.003)
BelieversRate	-0.09^{***}	-0.82^{***}	-0.91^{***}	-0.0001^{***}
	(0.01)	(0.05)	(0.06)	(0.0000)
MarriageRate	-0.18	-0.80	-0.98	0.0001
	(0.13)	(0.92)	(1.02)	(0.0001)
MaleRate	-120.64^{***}	$-1,010.89^{***}$	$-1,131.53^{***}$	-0.11^{***}
	(20.54)	(151.45)	(166.60)	(0.02)
YouthRate	25.18^{***}	55.25^{**}	80.43^{***}	0.01^{***}
	(3.41)	(25.15)	(27.66)	(0.003)
UnemployedPercentage	57.28^{***}	807.79^{***}	865.07^{***}	0.10^{***}
	(5.13)	(37.79)	(41.57)	(0.005)
Constant	$15,499.91^{***}$	$134,840.40^{***}$	$150,340.30^{***}$	22.73^{***}
	(1,240.66)	(9,146.89)	(10,062.19)	(1.09)
Observations	393	393	393	393
R^2	0.59	0.74	0.74	
Adjusted R^2	0.58	0.74	0.73	
Log Likelihood				$-3,489.29$
θ				21.36^{***} (1.52)
Akaike Inf. Crit.				6,992.59

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This regression output shows the results using 3 different dependent variables and two models

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Table 4: Regression analysis regarding (non-) violent and total crimes and all independent variables with OLS regressions and negative binominal regression

	Dependent variable:			
	ViolentCrimeRate	NonViolentCrimeRate	CrimeRate	
	OLS	*OLS*	*OLS*	*negative binomial*
	(1)	(2)	(3)	(4)
FoundationsDensity100k	3.89***	19.94***	23.84***	0.002***
	(0.84)	(6.33)	(6.95)	(0.001)
FlowRate	0.01**	0.08**	0.09**	0.0000***
	(0.01)	(0.04)	(0.04)	(0.0000)
TurnoutPercentage	−13.84***	−30.33	−44.17	−0.002
	(3.58)	(26.84)	(29.43)	(0.003)
BelieversRate	−0.07***	−0.71***	−0.78***	−0.0001***
	(0.01)	(0.06)	(0.07)	(0.0000)
MarriageRate	−0.29**	−1.43	−1.72*	−0.0000
	(0.12)	(0.92)	(1.01)	(0.0001)
MaleRate	−103.94***	−926.43***	−1,030.38***	−0.11***
	(20.23)	(151.70)	(166.36)	(0.02)
YouthRate	21.69***	35.43	57.11**	0.01**
	(3.38)	(25.34)	(27.79)	(0.003)
UnemployedPercentage	58.63***	816.05***	874.68***	0.10***
	(4.98)	(37.31)	(40.92)	(0.005)
Constant	12,778.81***	119,640.60***	132,419.40***	20.35***
	(1,314.43)	(9,856.26)	(10,808.72)	(1.17)
Observations	393	393	393	393
R^2	0.62	0.75	0.75	
Adjusted R^2	0.61	0.75	0.74	
Log Likelihood				−3,478.45
θ				22.56*** (1.60)
Akaike Inf. Crit.				6,974.89
Note:				*p<0.1; **p<0.05; ***p<0.01

This regression output shows the results using 3 different dependent variables and two models

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References

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach, 76 J. Pol. Econ. 169 (1968)." *Journal of Political Economy*.

Chan, Chung-hong, Geoffrey CH Chan, Thomas J. Leeper, and Christopher Gandrud. 2015. *Rio: A Swiss-Army Knife for Data I/O*. http://CRAN.R-project.org/package=rio.

Gandrud, Christopher. 2015. *Repmis: Miscellaneous Tools for Reproducible Research*. http://cran.r-project.org/package=repmis.

Hanslmaier, Michael. 2015. "Mehr Sozialkapital–weniger Kriminalität? Eine Makrosoziologische Längsschnittanalyse Bayerischer Landkreise." In *Empirische Forschung über Kriminalität*, 361–404. Springer.

Lederman, Daniel, Norman Loayza, and Maria Menedez. 2002. "Violent Crime: Does Social Captal Matter?" *Economic Development and Cultural Change* 50 (3): 509–39.

OECD. n.d. doi:http://www.oecd.org/insights/37966934.pdf.

Putnam, Robert D. 2001. *Bowling Alone: The Collapse and Revival of American Community*. Simon; Schuster.

R Core Team. 2015. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Wickham, Hadley. 2015. *Tidyr: Easily Tidy Data with 'spread()' and 'gather()' Functions*. http://CRAN.R-project.org/package=tidyr.

Wickham, Hadley, and Winston Chang. 2015. *Ggplot2: An Implementation of the Grammar of Graphics*. http://CRAN.R-project.org/package=ggplot2.

Wickham, Hadley, and Romain Francois. 2015. *Dplyr: A Grammar of Data Manipulation*. http://CRAN.R-project.org/package=dplyr.