Ethnic fractionalisation and social cohesion: the relation between immigration, ethnic fractionalisation and potentials for civic, collective action in Germany

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Chapter 4

Ethno-Categorical and Ethno-Cultural Fractionalisation and Their Impact on Neighbourhood Social Cohesion in Germany

A Test of Six Indices of Ethnic Fractionalisation and Their Change Over Time

Introduction

As we have seen in Chapter 2, the literature on ethnic fractionalisation and social cohesion provides a rich set of empirical findings, but the overall picture is inconclusive. One reason for the state of research is that while a couple of plausible explanations have been proposed, most studies simply test whether the share of ethnic minorities or the common Herfindahl-Hirschman index shows a significant relation to some indicator of social cohesion. Thereby they provide no evidence for the supremacy of one explanation over others. Given this background, some researchers have recently started to investigate more refined and informative measures of ethnic diversity, as for example a linguistically weighted measure of ethnic diversity (Desmet et al., 2009) or a measure of economic inequality between ethnic groups (Baldwin and Huber, 2010). Both extensions yield suggestive evidence on the relevance of certain theoretical explanations, be they concerned with communication problems or unequal resource allocation as in these examples. The few pioneering studies engage in cross-national comparisons. Yet, the earlier discussed research on the effects of ethnic diversity has generated mixed results especially on the sub-national level of European countries.

This paper explores the fruitfulness of such an approach in a sub-national analysis of 55 German regions. In particular, I investigate the impact of a culturally weighted ethnic fractionalisation index, an ethnic polarisation index, an index of ethnic group-based income inequality, a measure of average migrant host-country language skills, and whether the fractionalisation effect is attenuated by the cross-cuttingness between ethnicity and neighbourhood or socio-economic status. I also investigate the change in the different fractionalisation indexes in the two years before the survey was conducted, because research on prejudices has emphasised the role of recent changes in the ethnic composition in driving feelings of threat. As dependent variables, I investigate trust in neighbours and collective efficacy as indicators of the cognitive indicators of social cohesion and associational membership and volunteering as structural indicators.

Theoretical Background

In the second chapter, I defined ethnicity first and foremost as a cognitive category and qualified that it might be accompanied with clustered networks and cultural differences between people identifying with different ethnic categories. I then discussed theoretical explanations of the relation between ethnic fractionalisation and social cohesion that are linked to one of these three aspects of ethnicity. In this chapter, I will focus on those explanations that either draw on ethnicity as a cognitive category or as culture and relate these to different indices that may be regarded as operationalisations of them.[1]

Categorical Diversity and Cognitive Biases

Most studies investigating the operationalisations of ethnic diversity employ indicators that rely on publicly available data of a population's citizenships or racial composition. I propose to call these indices indicators of categorical diversity, because they reflect a population's diversity as measured by statistically available categories. As discussed in Chapter 2, such diversity in ethnic categories can reduce levels of social cohesion according to both social identity and group threat theory, and some scholars claim that "the dynamics of the "we" versus "you" distinction is more powerful than the antagonism generated by the distance between them" (Garcia-Montalvo and Reynal-Querol, 2004, p. 7).

[1] A thorough discussion of and introduction to fractionalisation indices is given by Rao (1982) and Greenberg (1956).

In-Group Favouritism Among others, Alesina et al. (1999) and Alesina and La Ferrara (2002, 2000) refer to social identity theory and argue that since people favour others who are alike, they will be less likely to invest in public goods if out-group members will profit as well. If the statistically available categories reflect the ethnic boundaries people have in mind and of in-group favouritism is the main cause of the ethnic diversity effect, we should find that *the commonly used ethnic diversity index is an adequate predictor of levels of social cohesion (H1).* The reason is that for in-group favouritism it is only the question whether someone belongs to an in-group or out-group member that matters. The most commonly used measure of statistical heterogeneity is the classical Herfindahl-Hirschman Index (Hirschman, 1964) subtracted from unity:

$$ED = 1 - \sum_{i=1}^{k} S_i^2$$

Where S_i denotes the share of ethnic category i and k the number of categories. The ethnic diversity index can be interpreted as the likelihood that two randomly drawn individuals do not share membership in the same ethnic category. It varies between a minimum 0 for regions with only one group and a maximum 1, which is reached in regions where each individual belongs to an own group.

Cross-Cuttingness Cross-cuttingness between categories decreases in-group favouritism, because derogating a person of another ethnicity might compromise the evaluation of another social identity that is shared with this person (Brown, 2000). Recently, Selway (2011) introduced a promising measure of cross-cuttingness and showed that in a cross-national study, the cross-cuttingness between ethnicity, religion, geographical region and income is associated with GDP growth and decreases the negative impact of ethnic fractionalisation. In line with Selway's research, I propose that *the the stronger the cross-cuttingness between ethnicity and other cleavages, the weaker the impact of ethnic diversity (H2).* His measure relies on the idea of a χ^2-test for the dependency between discrete variables and asks how likely it is that if one knows a person's ethnicity, one can infer another characteristic such as his neighbourhood. While the χ^2-test output depends on the overall size of the cross-table, Cramer's V is a normalisation that transforms the output to vary between 0 and 1. Selway's (2011) index of cross-cuttingness makes use of Cramer's normalisation and subtracts it from unity:

$$CC = 1 - \sqrt{\frac{\chi^2}{n\,(m-1)}}$$

Where χ^2 is the common χ^2-test for dependency of discrete variables, n is the sample size, and m is the smaller of either the number of columns or the number of rows. This index reaches 1 if there is no relation between two categorical variables and 0 if one can perfectly infer membership in one category from the other. I estimate two cross-cuttingness indexes. I investigate the cross-cuttingness between socio-economic status and ethnicity, since socio-economic cleavages are a classic cleavage that is contentious in all societies. Secondly I follow Alesina and Zhuravskaya (2011) and estimate the cross-cuttingness between ethnicity and postal code, because they show how ethnic segregation further deepens ethnic cleavages. Schlueter and Scheepers (2010) and Schlueter and Wagner (2008) show that larger percentages of ethnic minorities increase feelings of threat and prejudices, but are also an opportunity for inter-ethnic contacts, which again reduce such feelings. Fractionalized regions with high levels of ethnic segregation offer few opportunities for inter-ethnic contact, but as the social environment is still experienced as fractionalized, levels of social cohesion are low. Integrated diverse regions in contrast, enable personal inter-ethnic contacts and this attenuates cognitive biases via empathy that arises from contact, reduces coordination problems due to understanding that arises from regular interaction, and finally also mitigates asymmetrically distributed preferences, because shared goals arise from frequent exchanges of opinions. As mentioned already in the theory chapter, this is exactly what Biggs and Knauss (2011) find for the likelihood of being a member in the British National Party, or what Rydgren and Ruth (2011) call the *halo effect*; living next to (rather than in) neighbourhoods with many immigrants causes threat.

Group Threat Another approach that deals with cognitive biases cites competition (e.g. Olzak, 1992) or group threat theories (e.g. Bobo, 1999; Blalock, 1967), and argues that the struggle for resources and representation compromises the competitors' trustworthiness and renders collective endeavours unlikely (e.g. Hou and Wu, 2009). Some authors claim that if group threat theory were right, it would not be ethnic diversity per se that undermined trust and cooperation. By contrast, the most contentious situations are those where opponents of equal size face each other. More unclear is the question, whether polarised situations where two equal opponents face each other are more threatening than those with a diversity of equal opponents. Some authors argue for the former and emphasise that: "the notion of polarization is closely linked to the generation of tensions, to the possibility of articulated rebellion and revolt, and to the existence of social unrest in general" (Esteban and Ray, 1994, p. 820). One reason might be that the one line of conflict is more salient in such a situation, whereas in diverse situations many lines of conflict, especially between groups surrounding one's own opponents, are possible. Furthermore in polarised societies all social relations may adjust along the one defining cleavage, which makes the situation especially tense. While Alesina et al. (2003) find polarisation not to be a superior predictor in their cross-national analysis, Dincer (2011) does in her analysis of US federal states and claims that “Conflict is less likely in societies in which fractionalization is minimal or maximal” (Dincer, 2011, p. 291). Moreover, Montalvo and Reynal-Querol (2005) show with a formal rent-seeking model how individuals have the highest interests to devote resources for lobbying for their group in situations where two equal opponents face each other. If these authors are correct in their interpretation of group threat theory, *polarisation is a stronger predictor of social cohesion than ethnic diversity (H3).* From their formal model Montalvo and Reynal-Querol (2005) derive the following index of ethnic polarisation (EP):

$$EP = 1 - \sum_{i=1}^{k} \left(\frac{0.5 - S_i}{0.5}\right)^2 S_i^2 = \sum_{i=1}^{k} s_i^2 \left(1 - S_i^2\right)$$

Where S_i is the share of ethnic category i and k is the number of categories. In this index, if one shifts the population between categories in such a way that two categories become equal in size, the index increases. This is a function of multiplying the index by $(1 - S_2)$, so that it weights down the impact of small categories and becomes largest if two categories of equal size face each other. It also ranges from 0, where all people belong to one category to 1, where there are two opponents of equal size.

Change in Fractionalisation Scholars like Hopkins (2010) have more recently claimed that it is not necessarily the proportion of out-group members that is perceived as threatening, but rather recent increases in the percent of out-group members.[2] Hopkins (2009) builds his assumptions on the work of Kahneman and Tversky (1979), which shows people to be especially attentive to changes rather than states, since information in general is vast. In relation to the discussion on diversity and social cohesion Hopkins therefore argues: “To understand how diversity influences public good provision, we should look to those towns that are diversifying, not those towns that are diverse” (Hopkins, 2009, p. 160). The literature on ethnic fractionalisation and social cohesion has so far mostly ignored such a dynamic perspective on the relation between diversity and social cohesion. Besides Hopkins’ (2011; 2009) and Costa and Kahn’s (2003b) US American Studies, there are only few investigations that follow a dynamic perspective, by either including measures of the change in ethnic fractionalisation (Hooghe et al., 2009; Gesthuizen et al., 2008) in cross-sectional analyses, or by using a longitudinal design (Kesler and Bloemraad, 2010; Rupasingha et al., 2006). The results of these three US sub-national and two cross-national studies are fairly mixed. In any case, no empirical investigation of a dynamic perspective on the relation

[2]Even though studies that explicitly analyse the impact of change in immigration on anti-immigrant sentiments have been conducted long since (e.g. Coenders and Scheepers, 1998)

between diversity and social cohesion exists for the sub-national European case as of yet. However, to the degree that changes are experienced as more threatening and that threat and competition models yield good explanations of why people in fractionalized contexts "hunker down", we should find *changes in diversity to affect social cohesion (H4)*. For this reason, I will not only investigate the impact of different indices of ethnic fractionalisation, but also the change in these indices (below denoted as I) within the two years prior to the data collection.

$$\Delta I = I_t - I_{t-2}$$

Cultural Diversity, Asymmetric Distribution of Preferences and Coordination Problems

What the above-discussed indices might be correlated with, but do not measure is actual cultural diversity in norms, values, preferences as well as shared language and meanings, which are theoretically linked with the cultural dimension of ethnicity. I suggest conceptualising this as cultural diversity, which has two facets, as I laid out in Chapter 2, each of which is associated with a potential explanation of the relation between social cohesion and ethnic diversity.

Asymmetric Distribution of Preferences Seeing culture as a moral system that entails desirable goals and preferences, ethnic fractionalisation could mean disagreement about how a shared community should look like and which public goods should be provided, and could thereby lead to an under-provision of public goods (e.g. Kimenyi, 2006). In addition, Page (2008) has argued from a social choice perspective that asymmetrically distributed preferences may erode trust for the potential of disagreement they cause. In order to measure the asymmetric distribution of preferences that derive from cultural differences between ethnic groups, Baldwin and Huber (2010) rely on an extension of the orthodox ethnic fractionalisation index that is weighted by cultural differences between groups, a culturally weighted ethnic diversity index (CED). If differences in values and norms were central, the *culturally weighted index of ethnic diversity should be a better predictor of social cohesion than common measures of ethnic diversity (H5)*. Originally, Greenberg (1956) proposed this index, which he defined as:

$$CEP = 1 - \sum_{i=1}^{k} \sum_{j=1}^{k} S_i S_j r_{ij}$$

Where S is the share of ethnic category, i or j respectively. k denotes the number of categories and r_{ij} is a measure of the cultural distance between these. r_{ij} ranges between 0 if ethnicities are totally different in cultural terms and 1 if they are similar and thereby functions as a weight. As for the ED measure, CED will take the value of 0 if all groups are similar in values or if there is only one group and 1 if each individual is an own group and they hold most different values. CED will by definition always be smaller or at best as large as the orthodox ethnic diversity index, because ED is a variant of CED in which r_{ij} is always 0 and only r_{ii} 1 (Greenberg 1956). This means, ED assumes maximal differences between all groups.

In theory, asymmetric distributions of preferences originate from cultural differences, but economic differences might also be a cause. As Baldwin and Huber (2010) point out: "Group-based economic differences can lead to different group needs with respect to public goods, feelings of alienation or discrimination by some groups, different attitudes toward redistribution across groups, and different "class" identities by different groups" (Baldwin and Huber, 2010, p 644). According to their study, the negative impact of ethnic fractionalisation as found in cross-national studies is mostly due to economic inequality along ethnic lines. If economic differences along ethnic lines were important in the sub-national European case, *ethnic group-based economic inequality is a better predictor of social cohesion than the orthodox ethnic diversity index (H6).* The measure of ethnic group-based economic inequality is mathematically rather similar to the culturally weighted ethnic diversity index (CED), but different in interpretation:

$$EGI = \sum_{i=1}^{k} \sum_{j=1}^{k} S_i S_j \mid \bar{y}_i - \bar{y}_j \mid$$

Where S is that share of category i or j and k the number of categories. $\bar{y}$ denotes the average income in these categories, meaning that here the average income difference between ethnicities serves as a weight instead of the cultural differences. The EGI can also be understood as a special case of the Gini index (see Champernowne and Cowell, 1998), for which each individual is assigned not his personal income, but his ethnic group's income. Thereby the index calculates the economic inequality between ethnic groups.

Coordination Problems Instead of seeing culture as a moral system, Swidler (1986) proposes to conceive of it as habituated routines of action and ways to do things, which most importantly allow us to interact and communicate with others. A common language, metaphor usage, practices and schemes for example are necessary to communicate about the existence of shared preferences and to successfully coordinate the production of common goods (e.g. Hardin, 1995; Deutsch, 1966). For this reason, some scholars claim ethnic diversity, seen as cultural diversity, leads to problems in the exchange of meaning and hence to coordination problems (e.g. Habyarimana et al., 2007). Following the example of Lancee and

Dronkers (2011), I suggest that in a European context language diversity does not seem to be the best indicator of coordination problems, since there are official first languages. A better way to test the implication of coordination problems in an immigration country is to investigate migrants' average host-country language skills and usage. As, Lev-Ari and Keysar (2010) show already the mere difficulty to understand accented speech compromises the perceived reliability of a speaker. By contrast, as long as most migrants are able to speak and are known to speak the host-country language perfectly, there should be no coordination problems. I hence assume that *the average regional migrant host-country language skills are positively related to social cohesion (H7)*, even though Lancee and Dronkers (2011) could not support this hypothesis for the Dutch case. As a simple measure, I suggest the mean:

$$LSU = \frac{1}{n}\sum_{i=1}^{n} l_i$$

Where l_i is a predicted factor score of the host-country language skills and usage of migrant i, and n is the number of migrants.

Data and Methods

In this paper I analyse four indicators of social cohesion from the EDCA-Survey as was discussed in Chapter 3. The first two are indicators of the cognitive dimension of social cohesion. One is trust in neighbours, which is identical to the measure Putnam (2007) uses. The second measure of cognitive social cohesion is collective efficacy, which was originally developed by Sampson et al. (1999) and is supposed to measure a community's capacity to act collectively to solve neighbourhood problems. In addition, I analyse two indicators of the structural dimension of social cohesion. First, a binary variable indicating whether a person is actively engaged in any association, initiative or something related and second, a binary measure whether persons who are active perform volunteer work. More information, such as descriptive statistics are given in Chapter 3, which deals with the research design.

When regressing these indicators of social cohesion on the different fractionalisation indices, I control for the number of years someone has lived in the neighbourhood, home ownership, education, gender, migration background, dummies indicating the religious confession and age. On the context level I control for a dummy for East Germany and the share of unemployed and the population per square kilometre. The descriptives of all dependent and independent variables, can be found in Chapter 3.

Measuring S_i for the ED, CEF EP, CC and EGI indexes To calculate the ethnic fractionalisation indices, information on the shares of ethnic categories is necessary. Where possible (this means in particular for the indexes of ED, CED and EP), I rely on data of the Federal Office for Migration and Refugees' central register of foreign nationals[3], which represents the most reliable source of information on the foreign population in Germany. The regional shares of people from all 193 fully recognised nations are available. The ethnic categories in this study are thus defined by nationality, which seems sensible in the context of immigration-caused diversity in Germany and stands in congruence with the theory chapter. The downside of this data is that all migrants with German citizenship are seen as German natives. However, data sources like the German micro census, which allow for the identification of migrants with German citizenship, do not yield representative estimates of regional shares of different migrant categories.

In line with Baldwin and Huber (2010), I rely only on groups that make up a significant share of the local population.[4] I set the minimum share to 0.05% of the regional population, so that a category needs to have a share of at least 0.05% in one or more regions of the EDCA-Survey. Since many national categories of interest do not pass this threshold, I summed some categories to form a single category, in order to reach case numbers that pass the threshold. These are North Africans (Moroccans, Tunisians, Algerians and Egyptians), persons from the Middle East (Emirates, Iraqis, Iranians, Jordanians, Kuwaitis, Lebanese, Omanis, Qataris, Syrians and Yemenites) and Afghanistan/Pakistan. Including Germany, this procedure results in 22 ethnic categories that relate to the following countries (or regions): North Africa, Middle East, Afghanistan/Pakistan, Austria, Bosnia and Herzegovina, Bulgaria, Croatia, France, Germany, Greece, Italy, Luxembourg, Netherlands, Poland, Portugal, Romania, Russia, Serbia, South Korea, Spain, Switzerland and Turkey.

For the indexes of cross-cuttingness (CC) and ethnic group-based income inequality (EGI), I used the EDCA-Survey as a data source on ethnic group shares, because the Central Register of Foreigners contains no other information than nationality. For cross-cuttingness the estimation of cross-tables between ethnicity, postal code and socio-economic status are necessary and for group-based income inequality, one needs to know the average income of the ethnicities under investigation. This means, however, that in contrast to the other measures, cross-cuttingness and ethnic income inequality contrast natives to migrants, rather than German citizens to the 21 categories of foreign nationals.

[3]Federal Office for Migration and Refugees: www.bamf.de

[4]I also calculated an ethnic fractionalisation index relying on all 193 national groups. Yet this index hardly differs because the squared group shares of size 0.004 and smaller do not have any numerical leverage. Accordingly the results also remain similar.

Measuring χ^2 for the CC index χ^2 is the central characteristic of the cross-cuttingness index (CC) and denotes the dependence between two discrete variables, in this case between ethnicity and postal code as well as socio-economic status. I operationalise it as an additive scale of three indicators: employment status[5], low education[6] and income below the German poverty line[7]. I also used the single indicators of education, income poverty and employment status, but the results do not differ. To calculate χ^2, I rely only on the EDCAS data, which has at least 100 respondents randomly sampled within each of its 55 surveyed regions. This characteristic of the EDCA-Survey enables the estimation of context level characteristics from the survey. As explained above, I differentiate between migrants and natives and estimate Cramer's V subtracted from unity after a cross-tabulations with the respondent's postal code and socio-economic status. Since I am interested in the overall measure of Cramer's V, the allocation of respondents across single cells in the cross-tab is no of concern. The two indexes of cross-cuttingness specify the degree to which a respondent's migration background allows any conclusions on his neighbourhood and socio-economic status and how this varies across the 55 German regions. The two indices of cross-cuttingness correlate by 0.0191.

Measuring r_{ij} for the CEF index To gain a culturally weighted index of ethnic fractionalisation (CED), a weight r_{ij} denoting cultural differences between all ethnicities is necessary. Of course, the Register of Foreigners does not contain any information that would allow estimating cultural differences between nationalities.

In order to be able to estimate a CED-index as used in recent cross-national research, I employed the World Values Survey (WVS) and European Values Study (EVS) (2009)[8] waves of 1981-2008 to generate a measure of cultural difference between groups. Relying on the latest available data wave, I calculated the mean value on Inglehart and Baker's (2000) traditionalism-secularism (TS) and materialism-post-materialism (PM) scales for each country according to the syntax provided online.[9] Relying on these two scales[10], I calculated the average distances in values between all countries of the 22 ethnic categories of the Ausländer Zentralregister that surpass the 0.05% threshold and participated in the WVS/EVS studies:

$$D = \sqrt{(PM_i - PM_j)^2 + (TS_i - TS_j)^2}$$

[5]respondents were asked about their employment status and had to answer to be full or part time employed

[6]This is defined as ISCED level 2a or lower

[7]Income poverty was derived from the Luxembourg Income Study: www.lisproject.org

[8]World Values Survey (WVS): www.wvsevsdb.com/wvs/WVSData.jsp

[9]World Values Survey (WVS): www.wvsevsdb.com/wvs/WVSIntegratedEVSWVSinstructions.jsp?Idioma=I

[10]I also generated r_{ij} weights from each single scale rather than both combined. Yet, all findings remain the same.

Finally, I standardised D to vary between 0 and 1 and thereby obtained r_{ij}.

This approach relies on the strong assumption that average values of ethnic migrant groups in Germany can be inferred from the values held by persons living in their countries of origin. This assumption is rather crude, especially since the largest group of migrants, Turkish migrants, began migrating to Germany nearly 50 years ago. Since that time processes of value and norm adaption have occurred. I therefore regard the current operationalisation as a proxy that demands for further research. Nevertheless, cultural theories of ethnicity lead one to assume the CEF to be a significant improvement as compared to the orthodox diversity index.

Measuring $\bar{y}$ for the EGI index The differences in income between ethnic groups are the characteristic component of the ethnic group-based economic inequality index (EGI). But since the group sizes of the 22 ethnic groups within each of the 55 regions are too small to estimate the mean income, I decided to consider only the difference in income between native Germans and migrants for this index.

Table 4.1: Descriptive Statistics of the Ethnic Fractionalisation Indices

	Mean	SD	CV	Min	Max
ED	0.16	0.11	0.67	0.01	0.46
Aggregate Level	0.13	0.10	0.76	0.01	0.46
ΔED_{07-09}	0.00	0.01	10.39	-0.01	0.11
Aggregate Level	0.00	0.02	12.00	-0.01	0.11
CED	0.07	0.04	0.66	0.01	0.18
Aggregate Level	0.05	0.04	0.76	0.01	0.18
ΔCED_{07-09}	0.00	0.01	16.99	-0.00	0.05
Aggregate Level	0.00	0.01	13.30	-0.00	0.05
EP	0.07	0.04	0.58	0.01	0.15
Aggregate Level	0.05	0.04	0.65	0.01	0.15
ΔEP_{07-09}	0.00	0.01	12.73	-0.00	0.04
Aggregate Level	0.00	0.01	14.59	-0.00	0.04
LSU	0.02	0.20	9.77	-0.61	0.45
Aggregate Level	0.02	0.23	12.89	-0.61	0.45
EGI	0.01	0.01	0.94	0.00	0.05
Aggregate Level	0.01	0.01	0.95	0.00	0.05
$CC_{Postal\ Code}$	0.48	0.10	0.20	0.30	0.74
Aggregate Level	0.48	0.09	0.19	0.30	0.74
CC_{SES}	0.78	0.08	0.10	0.52	0.97
Aggregate Level	0.78	0.09	0.12	0.52	0.97

Measuring l_i for the LSU index To investigate the importance of average migrant language skills and usage within an region, I built a scale l_i from three items. All respondents of the EDCA-Survey with a migration background were asked how often they had problems when speaking German, how often they speak German with their family members and how often they speak German with friends and acquaintances. An explorative principal components factor analysis shows that all items load on a single factor with factor loadings above 0.6. I use the solution of this factor analysis to predict a factor score for each individual. Note, however, that I did not consider respondents who were oversampled for the Turkish migrant sample, since for this group no weights on their sampling propensity could be estimated. Therefore the LSU measure relies only on the weighted answers of migrants who where sampled randomly. Table 4.1 shows the descriptives of all indices. The descriptives of the other variables used can be found in Chapter 3.

Modelling Strategy Since the data is clustered in 55 regions and the analyses include context level (Kreise) variables, I estimate linear regression models with robust cluster-robust standard errors. As explained Chapter 3, they yield the advantage that the standard errors of parameters of context-level regressors are not underestimated (Angrist and Pischke, 2009, chapter 8.2).

However, 55 clusters hardly allow to investigate the impact of various rather collinear context variables and additional context level control variables, I will run separate models for each of the different diversity measures in combination with their changes within the last two years. I will then compare whether the recently suggested diversity measures yield a better model fit than models estimated with the orthodox ethnic fractionalisation measure. While this procedure does not allow to test the different suggested indexes directly against one another, it informs us about which index yields the highest predictive power. To decide between models I will rely on Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC), as suggested by Weakliem (2004). For both indices lower values indicates a better model fit. The main difference between AIC and BIC is that the BIC assumes that there is a real model that describes reality and thus strongly penalises additional variables that increase model fit only slightly. The AIC assumes that there is no real model, therefore searches for the best prediction and thus only slightly penalises additional predictors (Kuha, 2004).

This strategy results in the estimation of seven models for each of the four dependent variables. The first five models estimate the coefficients of one of the ethnic diversity (ED), ethnic polarisation (EP), culturally weighted ethnic diversity (CED), ethnic group-based income inequality (EGI) and average migrant host-country language skills and usage (LSU) indices along with their changes within the two years preceding the survey. Note that these changes can only be estimated for the first three indices since the others are solely aggregated from the EDCA-Survey itself. The final two models are expansions of Model 1, where a moderation of the ethnic diversity index (ED) by the cross cuttingness (CC) of ethnicity and postal code (Model 6) and ethnicity and socio-economic status (Model 7) is tested.

Results

The results of the analyses are presented in four tables, one for each dependent variable. Tables 4.2 to 4.5 encompass seven models, each of which tests one of the different fractionalisation indices along with its change from 2007 to 2009. Tables C.3 on page 245 and C.4 on page 246 in the appendix show the coefficients of the control variables, which are not shown in the tables for reasons of clarity.

To start from the outset, is there any effect of statistically measured ethnic diversity on social cohesion in Germany? The only other existing study on the German case is Gundelach and Traunmüller's (2010) investigation, which focuses on larger contextual units than this study, and finds effects of ethnic diversity on generalised trust, but not on norms of reciprocity.

Table 4.2: Trust in Neighbours and Competing Fract. Indices (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ED	-0.933*					-3.574*	-3.737
	(0.350)					(1.696)	(2.632)
ΔED_{07-09}	-3.730**					-3.933**	-3.615**
	(0.792)					(0.683)	(0.857)
EP		-2.595*					
		(1.074)					
ΔEP_{07-09}		-8.728**					
		(2.206)					
CED			-2.316*				
			(0.897)				
ΔCED_{07-09}			-9.357**				
			(0.989)				
EGI				-2.948			
				(2.983)			
LSU					0.0842		
					(0.134)		
$CC_{Postal\ Code}$						-1.387*	
						(0.690)	
$ED*CC_{Postal\ Code}$						5.437^{+}	
						(3.186)	
CC_{SES}							-0.829
							(0.745)
$ED*CC_{SES}$							3.541
							(3.356)
Observations	7084	7084	7084	7084	6985	7084	7084
R^2	0.11	0.11	0.11	0.11	0.11	0.11	0.11
AIC	32354.90	32355.94	32354.70	32358.88	31903.73	32353.72	32357.31
BIC	32492.21	32493.26	32492.01	32489.33	32033.91	32504.76	32508.35

Cluster-robust standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Effects of **control variables** are shown in Table C.3 on page 245

Table 4.3: Collective Efficacy and Competing Fract. Indices (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ED	-1.104**					-2.092	-7.116*
	(0.291)					(1.878)	(3.307)
ΔED_{07-09}	-1.452*					-1.532*	-2.215**
	(0.721)					(0.719)	(0.713)
EP		-3.451**					
		(0.924)					
ΔEP_{07-09}		-3.149					
		(1.906)					
CED			-2.810**				
			(0.691)				
ΔCED_{07-09}			-3.199*				
			(1.384)				
EGI				-6.932**			
				(2.277)			
LSU					-0.256^{+}		
					(0.136)		
$CC_{Postal\ Code}$						-0.534	
						(0.712)	
$ED*CC_{Postal\ Code}$						2.049	
						(3.469)	
CC_{SES}							-0.773
							(0.691)
$ED*CC_{SES}$							7.271^{+}
							(3.957)
Observations	6994	6994	6994	6994	6899	6994	6994
R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.07
AIC	32491.93	32491.25	32491.60	32488.74	32066.32	32495.22	32493.80
BIC	32628.99	32628.31	32628.66	32618.94	32196.27	32645.98	32644.56

Cluster-robust standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Effects of **control variables** are shown in Table C.3 on page 245

Table 4.4: Membership in Associations and Competing Fract. Indices (Logistic)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ED	0.902^{+}					0.590	-2.965
	(0.474)					(2.852)	(4.572)
ΔED_{07-09}	1.465					1.220	0.987
	(0.907)					(0.973)	(1.026)
EP		2.768*					
		(1.346)					
ΔEP_{07-09}		3.774					
		(2.348)					
CED			2.581*				
			(1.088)				
ΔCED_{07-09}			2.722^{+}				
			(1.547)				
EGI				0.0448			
				(2.874)			
LSU					0.752**		
					(0.202)		
$CC_{Postal\ Code}$						-0.700	
						(0.972)	
ED*$CC_{Postal\ Code}$						1.142	
						(5.078)	
CC_{SES}							-0.515
							(0.779)
ED*CC_{SES}							4.685
							(5.566)
Observations	7219	7219	7219	7219	7119	7219	7219
Pseudo R^2	0.03	0.03	0.03	0.03	0.04	0.03	0.03
AIC	9661.84	9661.28	9660.23	9665.75	9501.13	9662.16	9664.54
BIC	9799.53	9798.97	9797.92	9796.55	9631.67	9813.62	9816.00

Cluster-robust standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Effects of **control variables** are shown in Table C.4 on page 246

Table 4.5: Voluntary Engagement and Competing Fract. Indices (Logistic)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ED	1.799**					2.227	6.864+
	(0.328)					(2.197)	(3.707)
ΔED_{07-09}	0.852					0.742	1.547*
	(0.728)					(0.801)	(0.713)
EP		5.125**					
		(0.999)					
ΔEP_{07-09}		1.732					
		(1.722)					
CED			4.298**				
			(0.782)				
ΔCED_{07-09}			1.359				
			(1.318)				
EGI				0.607			
				(3.185)			
LSU					0.0109		
					(0.172)		
$\text{CC}_{Postal\ Code}$						-0.135	
						(0.834)	
$\text{ED*CC}_{Postal\ Code}$						-0.556	
						(4.014)	
CC_{SES}							0.590
							(0.767)
ED*CC_{SES}							-6.085
							(4.366)
Observations	3884	3884	3884	3884	3824	3884	3884
Pseudo R^2	0.04	0.04	0.04	0.04	0.04	0.04	0.04
AIC	5171.42	5171.80	5171.97	5180.44	5099.79	5175.07	5174.10
BIC	5296.72	5297.09	5297.27	5299.47	5218.52	5312.89	5311.92

Cluster-robust standard errors in parentheses; $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Effects of **control variables** are shown in Table C.4 on page 246

Focusing on the ethnic diversity index of Model 1 first, I add to the mixed results of the wider debate, just as Gundelach and Traunmüller (2010) do. While I do find a significant negative relation between ethnic diversity and trust in neighbours as well as collective efficacy, there are no such relations with associational membership or volunteering. Quite to the contrary, for the latter two I even find positive associations, a couple of which reach significance.

An explanation for this pattern might lie in the distinction between *cognitive versus structural social cohesion*, with the latter referring to evaluations of one's social environment and the latter to behavioural forms of association with others and volunteering. In this regard, I presented an argument according to which ethnic fractionalisation might also increase levels of structural social cohesion, since people tend to associate with others who are alike and might have an increased interest to do so in ethnically fractionalised regions, especially if they feel threatened and feel a need to mobilise like-minded people. However, my results hold for all kinds of associations and types of volunteering and do not suggest any ethnocentric motivation or competitive collective action. As I will continue to argue in the next chapter, it rather seems to be the case that ethnic fractionalisation results in neighbourhood problems and concerns that mobilise people to engage and work to enhance their community. There is no reason to assume such engagement to have any ethnocentric motive.

Further evidence pointing in the direction of a different fractionalisation effects regarding cognitive and structural social cohesion comes from the investigation of changes in fractionalisation over the past two years, which is also shown in Model 1. First of all, the results support the argument according to which recent changes in the ethnic composition cause declines in social cohesion. Trust in neighbours and collective efficacy are significantly and negatively related to the changes in diversity. Other related variables such as neighbourhood satisfaction also show the significant negative relation (the results are shown in Table C.1 on page 243 in the appendix). This supports the claim that cognitive social cohesion is negatively associated with increases in ethnic fractionalisation.

The opposite seems to be the case for structural indicators of social cohesion. In contrast, both the frequency of membership in associations as well as levels of volunteering seem to be positively associated with increases in ethnic fractionalisation, yet not significanly so. With the data at hand, I can hardly test causal claims, but principally these results support the assumption that cognitive and structural indicators of social cohesion are affected differently bu ethnic fractionalisation.

Turning to the question of the explanatory power of the different fractionalisation indices, I will focus on the cognitive indicators of social cohesion for these show the theoretically expected relation of interest.[11] Models 1 to 5 in Table 4.2 for trust

[11]The principle conclusions are the same for the structural indicators of social cohesion, as

in neighbours and Table 4.3 for collective efficacy respectively, show the results for all fractionalisation indices estimated here. The indices of ethnic diversity (ED), ethnic polarisation (EP) and culturally weighted ethnic diversity (CEF), which are all based on the 22 largest national groups show significantly negative coefficients for both trust in neighbours and collective efficacy. The ethnic group-based income inequality (EGI) differs in operationalisation in that it is based on the shares and income difference of natives in comparison to migrants in general. It is negatively related to both dependant variables, but reaches significance only for collective efficacy. Finally, migrants' average host country language skills (LSU) show no significant relation, a finding that parallels Lancee and Dronkers' (2011) Dutch study. Note however that LSU shows a significant positive relation to membership in associations and voluntarism, which further supports differences between cognitive and structural social cohesion.

Which of the different indices, and hence of the associated explanations, yields the highest explanatory power? To answer this question we need to compare the AIC and BIC values, with lower values of at least two points suggesting a better overall model fit. However, we hardly see any difference between the Models 1 to 5. The common ED index shows the lowest AIC and BIC values for trust in neighbours, yet the difference to the CED, which is the second best fitting, is less than one for both BIC and AIC. For collective efficacy, we see the same picture, with the difference that the EGI shows significantly better model fit than the other indices. Yet since EGI shows no significant relation to trust in neighbours, this is not a robust finding. None of the proposed indices shows any superior explanatory power in the sub-national German comparison. These results refute hypotheses H3 to H7 and yet neither provide clear support for hypothesis H1, which stated that the ethnic diversity index (ED) is a robust predictor if in-group favouritism was the explanation for the fractionalisation effects. While the ethnic diversity index is an adequate predictor, these results do not support in-group favouritism as the main explanation.

Overall, this suggests that at least ED, EP and CED measure the same in the sub-national German comparison and indeed the correlations between the three indices are all above 0.9, which has two reasons. First, the large share of native Germans drives all indices. The different theories (and along with them the indices) assume as ideal-typical extreme scenarios ethnic compositions where there is either a vast amount of ethnic groups (ED), two similarly sized ethnic groups that oppose each other (EP), or a vast amount of groups that are culturally or economically different from one another (CED & EGI). For the European sub-national case these scenarios tend to be implausible, since usually there is a large native majority that dominates the regional ethnic composition. Mathematically, the composition of

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can be inferred from Table 4.4 and 4.5

an immigrant minority that is divided into 22 categories and makes up less than 30 per cent of the population in each region, hardly has any leverage. However culturally distinct or equal in relative size minorities are, this hardly results in any differences in terms of these indices. For this reason, the existing indices basically reflect the regional share of ethnic minorities. This is supported by the results of Table 4.6, which shows the share of foreign nationals and its change over the last two years as predictors. In comparison to the other tables, we see that the results are statistically (in terms of model fit and significance of the coefficients) similar to the fractionalisation indices, the only difference being that they are measured on different scales.

Table 4.6: The Share of Foreign Nationals as Alternative Index

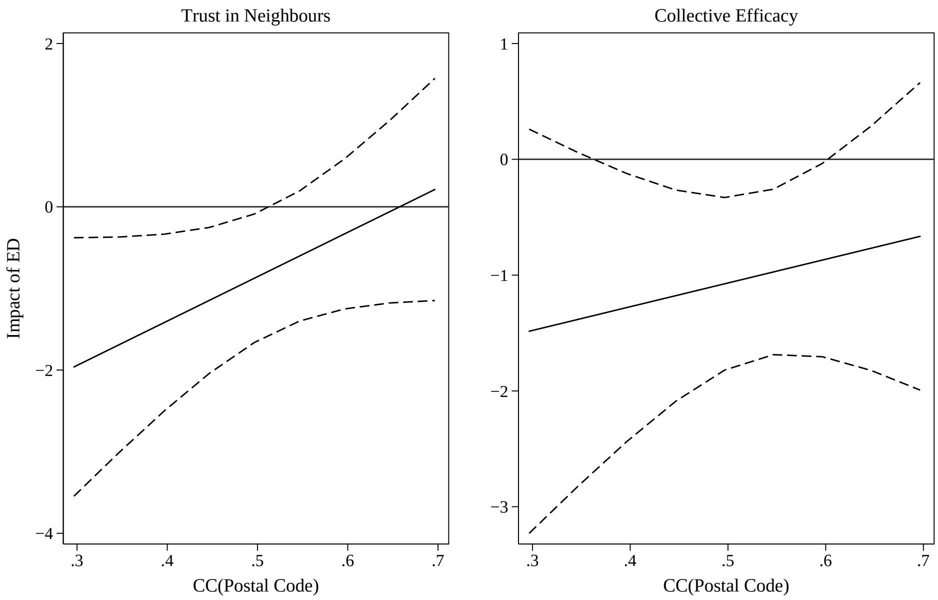
	Trust in Nbhs.	C. Efficacy	A. Member	Volunteering
% Foreign Nationals	-0.0167*	-0.0184**	0.0174*	0.0318**
	(0.00627)	(0.00516)	(0.00818)	(0.00577)
Δ % Foreign Nationals	-0.0563**	-0.0189	0.0221^{+}	0.0159
	(0.00973)	(0.0113)	(0.0132)	(0.0108)
Observations	7084	6994	7219	3884
R^2	0.11	0.07		
Pseudo R^2			0.03	0.04
AIC	32354.60	32492.32	9660.45	5170.37
BIC	32491.91	32629.38	9798.14	5295.66

Cluster-robust standard errors in parentheses; $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$
Effects of **control variables** are shown in Tables C.3 on page 245 and C.4 on page 246

Even so, one would expect a moderately improved model fit, if cultural differences between ethnicities were of any importance. The absence of even a modest improvement suggests secondly that German regions hardly differ in their ethnic composition when it comes to differences in economic and cultural terms. Figuratively speaking, this means that the fewer culturally distant Turks there are in Oberallgäu as compared to Berlin, the fewer culturally similar Poles there are as well. At least the relations stay so similar that both cultural and economic weighting do not make a difference. Alternatively one might assume cultural and economic weighting has simply no effect. But a random weight r_{ij} or $\mid \bar{y}_i - \bar{y}_j \mid$ should actually yield worse results as compared to the common ethnic diversity index (ED), because random weighting introduces measurement error, which drives down the β coefficients, increases the standard error and compromises mode fit. This, however, is not what we see.

Next to these sobering results, which suggest one promising line of cross-national research not to be fruitful for the German and maybe even European sub-national case, we still have the attenuating impact of cross-cuttingness to discuss. On first sight, the results do not seem promising either. There is only one significant interaction between ED and the cross-cuttingness between ethnicity and postal code for trust in neighbours, but none for collective efficacy and none at all

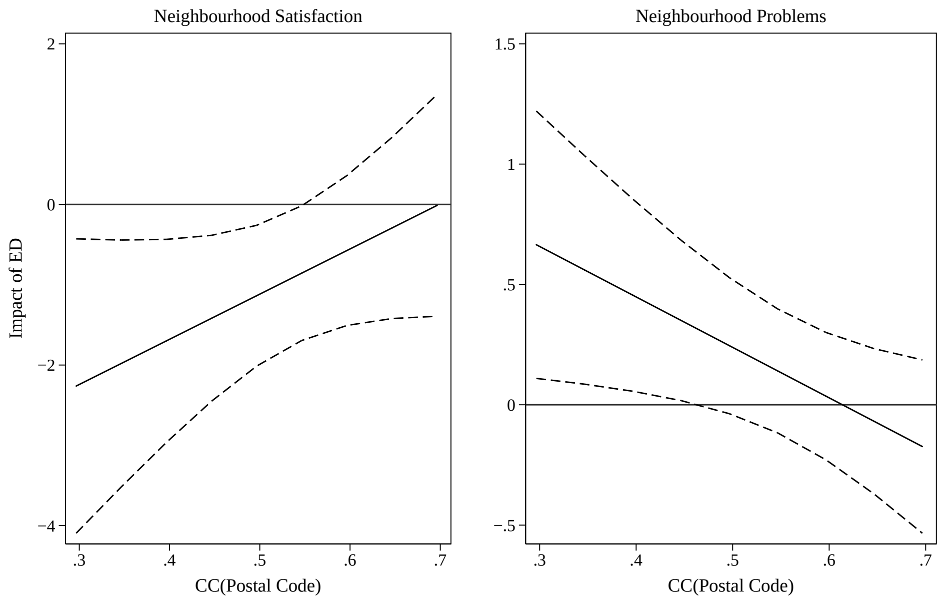
Figure 4.1: Interaction between Ethnic Fract. and Residential Segregation



for the cross-cuttingness between ethnicity and socio-economic status. This result does not differ if I look at the three indicators of socio-economic status (income poverty, low education and employment status) independently. The reason might again be that the socio-economic integration of migrants as compared to natives hardly differs much across the German regions.

The interaction between ED and the cross-cuttingness of ethnicity and postal code also seem to be implausible at first sight, with a negative main effect of cross-cuttingness for both trust in neighbours and collective efficacy. But interactions' main effects show the effects when the other main variable is zero and what should be the effect of cross-cuttingness when there are no migrants to begin with? Overall, the coefficients of interactions are difficult to interpret, because they are only meaningful in assembly, which is why Brambor et al. (2006) suggest to always plot them. Figure 4.1 shows the plotted interactions along with their 95 per cent confidence intervals for both dependent variables. The results suggest that ethnic fractionalisation has negative effects on trust in neighbours where there is no cross-cuttingness between ethnicity and postal code, meaning ethnic segregation. As levels of segregation decrease, however, the negative effect of ethnic fractionalisation vanishes. This result does not hold for collective efficacy, because the slope of the decline in the fractionalisation effect is smaller and the confidence interval gets too sparse in very segregated regions. On the basis

Figure 4.2: Interaction between Ethnic Fract. and Residential Segregation, Additional Results



of these two indicators of cognitive social cohesion it is thus not possible to draw a robust conclusion. For this reason, I conducted additional analyses (results are shown in Tables C.1 on page 243 and C.2 on page 244) on neighbourhood satisfaction and neighbourhood disorder, both of which may also be seen as indicators of neighbourhood based social cohesion as had been argued in Chapter 3. Figure 4.2 visualises how ethnic fractionalisation and ethnic residential segregation jointly affect neighbourhood satisfaction and levels of perceived neighbourhood disorder. The findings parallel those of trust in neighbours and thereby support my claim that there is a robust interaction between ethnic fractionalisation and ethnic residential segregation. The better integrated a region in geographical terms, the less does ethnic fractionalisation affect social cohesion.

This result might seem confusing at first; while inter-ethnic co-existence in the same region decreases social cohesion, inter-ethnic co-existence measured on the level of the postal code reduces this negative effect. However, integrated diverse regions, yield opportunities to establish inter-ethnic contacts whereby cognitive biases, coordination problem and asymmetrically distributed preferences are attenuated.

Conclusion

An ever-growing number of studies investigate the relation between ethnic diversity and social cohesion, but these studies have produced mixed results. In cross-national research, some scholars suggest promising alternative indices that can be regarded as better operationalisations of certain theoretical explanations rather than a general fractionalisation index. A second promising insight of recent research on xenophobia is the investigation of changes in the ethnic composition in addition to the composition itself as a predictor of group threat and prejudices. The aim of this chapter was to test the applicability of both approaches for sub-national European analyses of social cohesion, by comparing 55 sub-national German regions. There are a number of lessons that can be learnt from this analysis, many of which speak directly to arguments that were discussed in the theory chapter.

First of all, I do find a negative relation between ethnic fractionalisation and social cohesion in Germany. This conclusion has to be qualified, however, in that the expected negative relation can only be observed for cognitive indicators of social cohesion, namely trust in neighbours and collective efficacy; for structural indicators I tend to find even the opposite. On a closer reading, Putnam (2007) also shows increased levels of protest participation, political interest and discontent in more diverse communities. This conclusion is further validated by the relation between changes in ethnic composition and cognitive as compared to structural indicators of social cohesion. Nothing suggests, however, that competitive collective action is the appropriate explanation for these differences. Ethnic fractionalisation might result in dissatisfying circumstances that mobilise people to engage for their community without any ethnocentric motivations.

This also concerns the second, comparatively clear-cut lesson that not only ethnic fractionalisation, but in addition also recent changes of the latter are systematically related to social cohesion. The additional effect of changes in the ethnic composition might be another reason for the mixed results of the debate, because changes and absolute levels may sometimes cancel each other out. Imagine declines in ethnic fractionalisation in highly fractionalized regions, parallel to increases in rather homogeneous regions. Usually, migrants move to urban centres and these are also the most fractionalized, suggesting the scenario not to be very realistic, at least for European sub-national regions. But change in ethnic composition is largely an omitted variable and theoretically, the possibility of a bias cannot be excluded.

Another insight concerns the interaction of ethnic fractionalisation and the cross-cuttingness between ethnicity and postal code. Similar to research done by Schlueter and Scheepers (2010) and Schlueter and Wagner (2008), this result suggests that ethnic fractionalisation attenuates its own negative effect by enabling personal inter-ethnic contact. Strong ethnic residential segregation prohibits such personal contacts so that we find a stronger negative relation between fractionalisation and social cohesion in such regions. This supports the classical argument proposed by Allport (1954) nearly 60 years ago, that the most promising solution to problems associated with fractionalisation between populations is personal inter-group contact.

So what drives the ethnic fractionalisation effects? As indicator of coordination problems, the average migrant's host-country language skills shows no systematic relation to cognitive measures of social cohesion. Along with the results of Habyarimana et al. (2007) and Lancee and Dronkers (2011), this rather speaks against coordination problems as a driving force behind the fractionalisation effects. As for the other explanations, a final lesson can be learnt from the fact that none of the alternative indicators of fractionalisation provides a significant improvement over the crude Herfindahl-Hirschman index of ethnic diversity. The different fractionalisation indices that provide promising insights in cross-national comparisons are statistically indistinguishable in my sub-national comparison of 55 German regions. Besides this being an insight in itself, it has a couple of interesting implications. This result is probably due to the fact that the ethnic compositions of German regions, and probably most European sub-national regions in general, are structurally dominated by a native majority. This dominant composition is mostly neglected as a special case by the existing theories on ethnic fractionalisation and rather treated as a common intermediary stage between the ideal-typical situations of total homogeneity and total diversity, polarisation or culturally and economically weighted diversity respectively. Given the sheer absence in most parts of Europe of any other ethnic composition than those dominated by natives, theory development should probably be concerned more with the implications of such typical compositions, rather than non-existent ideal typical ones. The result that the mere percentage of foreign nationals is statistically indistinguishable from any of the fractionalisation indices is telling in this regard. The sub-national European comparison of regions is in principal a comparison of majority/minority relations. However, the indices we use follow the perspective of the native majority, because the percentage of foreign nationals is not a good measure of out-group size for migrants. This suggests that a research program that distinguishes between how fractionalized a context is from the perspective of different ethnicities might yield more promising results especially in the comparison of sub-national European regions. While such a project exceeds the limits of this study, it seems promising for future research.

That said, I want to qualify that the improved indices might actually be worthwhile in a sub-national European analysis that focuses on smaller contextual units. Some neighbourhoods in Amsterdam, Berlin, London, Paris or Brussels surely have an ethnic composition that is not characterised by a clear majority of natives. Whether the indices investigated here show superior explanatory power for such analyses, remains to be investigated, but is for reasons of unavailable public data for the neighbourhood level beyond the scope of this study. However, our data do allows to analyse the question, how fractionalized in ethnic, economic and cultural terms people *perceive* their neighbourhoods to be. This is the topic of the next chapter.