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Refugees (un)welcome – Regional demographic changes and individual attitudes towards refugees

Alyna Paul

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German Socio-Economic Panel (SOEP)
DIW Berlin
Anton-Wilhelm-Amo-Strasse 58
10117 Berlin, Germany
Contact: soeppapers@diw.de

MASTERTHESIS

Refugees (un)welcome – Regional demographic changes and individual attitudes towards refugees

Vorgelegt von:

Alyna Paul

Fakultät für Wirtschafts- und Sozialwissenschaften

Fachbereich Sozialwissenschaften

Studiengang: Soziologie (M.A.)

Erstgutachterin: Prof. Dr. Stefanie Kley

Zweitgutachter: Dr. Theresa M. Entringer

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List of abbreviations

Abbreviation	**Name**
AfD	Alternative for Germany
BBSR	Federal Institute for Research on Building, Urban Affairs and Spatial Development
BMBF	Federal Ministry of Education and Research
CI	Confidence interval
D	Deviance
DIW	German Institute for Economic Research
EU	European Union
FAZ	Frankfurter general newspaper (Frankfurter Allgemeine Zeitung)
FPÖ	Freedom Party of Austria
FRG	Federal Republic of Germany
GDP	Gross Domestic Product
GDR	German Democratic Republic
GVIF	Generalized variance inflation factor
ICC	Intraclass correlation coefficient
INKAR	Indicators, Maps, and Graphics on Spatial and Urban Monitoring
M	mean
NIMBY	Not in my backyard
p	Probability
PE-fit	Person-environment fit
POCs	People of color
SD	Standard deviation
SOEP	German Socio-Economic Panel
SZ	South German newspaper (Süddeutsche Zeitung)
UK	United Kingdom
US	United States of America

Abstract

Background: Many refugees arrived in Germany in 2015 and 2016. At the same time, anti-refugee attitudes among Germans increased. This indicates an association between immigration and attitudes. Now, ten years later, renewed public concern about immigration – while not many immigrate to Germany – highlights the need to identify factors that shape attitudes towards refugees.

Aim: Thus, I tested whether individuals living in counties with high refugee shares and large positive changes in refugee shares tend to hold more negative attitudes towards refugees.

Data: The SOEP and the INKAR provided representative individual-level and county-level panel data for 2016, 2018, and 2020 from Germany. The target population consisted of adults living in Germany who had not moved counties and had not been refugees in 2015 or after. After listwise deletion, 30,266 individuals with 61,444 observations across 398 counties remained for analysis (M_{Age} = 53.07 years, $\%_{Men}$ = 49).

Design: An average five-item score of expected cultural and economic refugee-immigration risks or opportunities formed the outcome variable. Apart from regional-level variables, several individual-level predictors were included in longitudinal and cross-sectional linear multi-level regression models.

Findings: The longitudinal analysis indicated no relationship between regional refugee share or change in refugee share and individual attitudes towards refugees. Although the coefficients pointed in the expected direction, they were very small and only marginally statistically significant, with $\beta_{11} = 0.023$, 95%CI [0.001,0.044] for the share variable and $\beta_{12} = 0.011$, 95%CI [−0.002,0.024] for the change variable. The cross-sectional analysis showed that solely in 2020, the share variable was statistically significant, albeit marginally and unexpectedly negative. Thus, the small longitudinal effect was not stable over time. Instead, education and whether someone had been socialized in East or West Germany were the strongest predictors of attitudes towards refugees.

Conclusions: Negative attitudes towards refugees are independent of the real regional share and change in the share of refugees. This indicates that restricting immigration would not reduce public concern.

1 Introduction

In the autumn of 2014, two Germans offered their spare room to a refugee. This was the start of *Refugees Welcome*, an initiative that helps refugees find an apartment (Soli*dBase, 2024). But *Refugees Welcome* is not just an organization. The term represented a *welcome culture* (Willkommenskultur) that overcame Germany in 2015. That year, due to the Syrian civil war, hundreds of thousands of refugees came to Germany. The country initially intended to help those in need and to ease their integration. A few months later, however, there was a cultural shift. Leading up to the general elections in 2017, the public discussed how many refugees were too many, and the infamous term *refugee crisis* emerged (Liebe et al., 2018, 2).

Survey data showed not only a national culture shift, but also that individual attitudes towards immigration changed. This is surprising, as individuals' attitudes rarely change (Best & Vogel, 2022, p. 31). Nonetheless, the proportion of people concerned about immigration to Germany was unstable. It ranged from approximately 15% to 50% over the last 20 years. During the so-called *refugee crisis* of 2015/2016, nearly 50% of survey participants were very concerned about immigration (Goebel et al., 2023).

Analyzing which factors predict people's attitudes towards refugees is important because those attitudes have consequences. First, they affect the well-being of refugees and other immigrants. Immigrants who experience discrimination tend to report lower mental and physical health (Gihleb et al., 2022, p. 19; Gundacker et al., 2024, p. 1). Second, those attitudes affect people's political behaviors, including voting decisions, trust in politics, and non-electoral political participation (Dinesen & Hjorth, 2024, p. 357). Lastly, public attitudes hold power in politics. Politicians need public support to implement their policies (Ceobanu & Escandell, 2010, p. 324).

Considering that the public again fixates on immigration, identifying factors that drive negative attitudes towards refugees is crucial. Immigration was the most prominent topic in the political debate during the 2025 general election (Ziller, 2025). Public concern peaked, with over 40% of Germans deeming immigration a problem (Ziller, 2025). Understanding attitude-forming processes may reveal ways to help immigrants integrate and enable everyone in Germany to peacefully coexist.

The concurrence of a shift in attitudes and the *refugee crisis* of 2015/2016 leads to the assumption that these two are related. Group-threat theory presumes this association as well. Several studies analyzed whether regional immigrant shares and changes predict residents' attitudes towards immigration (Ceobanu & Escandell, 2010, p. 322; Dinesen & Hjorth, 2024, p. 360; Dustmann et al., 2019, p. 2035; Hainmueller & Hopkins, 2014, p. 236). As I analyzed a subgroup of immigrants – refugees – I tested whether regional refugee shares and changes predict residents' attitudes towards refugees.

The research question was specifically, *if and how regional levels and changes of refugee demographics affect individuals' attitudes towards refugees in Germany*. The expectation was that: (H1) there is a positive relationship between the regional share of refugees and negative attitudes towards refugees; and (H2) there is a positive relationship between the regional change in the share of refugees and negative attitudes towards refugees.

The analysis was built on two data sources: the German Socio-Economic Panel (SOEP) (Goebel et al., 2023), which provided the individual data, and the "Indicators, Maps, and Graphics on Spatial and Urban Monitoring" (INKAR) by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) (BBSR, 2024b), which provided the regional-level demographic and economic data. Both are panel datasets, which rendered the analysis of the effect of changes on attitudes towards refugees possible.

The target population was adults living in a German county (*Kreise* and *kreisfreie Städte*) who had not been refugees themselves in or after 2015 and had not moved counties during the investigation period. The years of interest were the time of and after the *refugee crisis*. Since data on refugee attitudes were available for 2016, 2018, and 2020, the analysis was based on these years. After listwise deletion of cases with missing values, a sample of over 30,000 individuals (N = 30,266) across 398 counties and 61,444 observations was left for analysis.

The dependent variable, attitudes towards refugees (i.e., refugee attitudes) was regressed on the main predictors – the regional share of refugees per 1000 citizens of each county and the change of this share since the year before (i.e., regional refugee demographics) – and several covariates to accurately test the effects in question. Those covariates were gender, age, education, income, socialization in East or West Germany, rurality or urbanity of one's place of residence, one's migration background, and the gross domestic product (GDP) of one's county. To be able to interpret coefficients more easily, numeric predictors were grand-mean-centered and z-score standardized. Multi-level regression models were estimated to account for the data structure. Both stepwise longitudinal and cross-sectional models were used. Analyses were performed with the statistical computing software R Version 4.4 (R Core Team, 2025).

The structure of the paper is as follows: After establishing the theoretical basis (2) and method as well as data (3), I present the results of both the longitudinal and cross-sectional regressions (4) and discuss them relative to the research question (5). The thesis concludes with a summary and outlook for future research objectives (6).

In “Immigration as a threat” (2), I define the concepts of refugee, immigrant, and immigration attitudes. I establish group-threat theory as the theoretical basis to explain how and why people develop negative refugee attitudes. Then, I present previous findings and distinguish them by their level of analysis: micro, meso, or macro. Based on these findings, the present research was conceptualized. I define the hypotheses and elaborate on important methodological considerations, such as the size of the regional context.

The method chapter (3) describes the methodical approach. I introduce both data sources; describe the target population and sample; explain the choice and operationalization of the response variable, the main predictors, and the covariates; and finally, describe the analytical method and strategy.

In the results chapter (4), I present the results of the model assumption tests as well as the longitudinal and cross-sectional regressions of refugee attitudes on individual- and regional-level predictors. I use the determination coefficient R and model comparisons with Chi^2-tests to evaluate each model as a whole.

In the discussion (5), I use the findings to answer the research question. Since the hypotheses cannot be confirmed, I discuss possible explanations for the results. I highlight that temporary variance in attention on the refugee topic – exemplified by media salience, public mood (*Stimmung*), and singular historic events – could influence refugee attitudes, which would explain the residual variance of the regression models and the year-to-year variation left to account for.

The paper concludes (6) with a summary of the findings and limitations. It also suggests profitable lines of action for future research to close the research gaps this analysis has revealed.

2 Immigration as a threat

To analyze what predicts attitudes towards refugees, I need to clarify several theoretical concepts. First, what does it mean to have an attitude? Second, what does it mean to have an attitude towards refugees, and how is that different from attitudes towards immigrants or immigration in general? Lastly, I need a theoretical basis to build hypotheses about what may predict individuals’ attitudes towards refugees.

2.1 Attitudes towards refugees, immigrants and immigration

Attitudes. Starting with the first question, in psychology, there are many definitions for attitudes. They are conceptualized as either opinions formed through contemplation or sentiments based on emotions (Maurer, 2022, pp. 555–556). In this paper, attitudes are not categorized as either rational or emotional. The term is used to describe someone's opinions and feelings. This is to capture a person's view without predetermining how it came to be. Thus, attitudes can result from thoughts or emotions. Even more, the analysis should answer how and why people form their attitudes. Do they develop attitudes based on rational thinking, imagining possible consequences, or are these attitudes based on vague feelings of being threatened?

Attitudes towards immigration. The second question is about the content of attitudes, who and what attitudes are held towards: Attitudes towards refugees, immigrants and immigration are distinct, but related topics of research. In contrast to the other two, attitudes towards immigration are directed at a phenomenon, not at people. Prejudice towards immigrants, however, may increase negative attitudes towards immigration. But the effect does not exist the other way around. People might favor immigration, while still holding negative attitudes towards immigrants (Ceobanu & Escandell, 2010, p. 313). Therefore, it is important to choose one type of attitude while keeping in mind how it might be related to and influenced by the others.

Attitudes towards refugees and immigrants. Attitudes towards refugees and attitudes towards immigrants differ because refugees are a subgroup of immigrants. Previous research determined that reactions to immigrants depend in part on characteristics of these immigrants. Several studies found that longstanding residents hold positive attitudes towards highly educated and skilled immigrants and favor their immigration (Pichl, 2023, p. 516). Contrary to opinions on immigration in general, residents prefer more over less immigration if those immigrants are the 'right kind' of immigrants. Besides educational characteristics, immigrants who share cultural characteristics are also preferred to immigrants with a different cultural or ethnic background. Researchers think that longstanding residents feel the dominance of their own cultural identity to be threatened by immigration (Dinesen & Hjorth, 2024, pp. 374–375). It does not make sense to talk about immigrants as one group, as they are different, and different immigrants get different reactions.

Migration background. Migration background is often used to analyze discrimination against immigrants in Germany. People are considered to be from a migration background when they themselves or at least one parent was not a German citizen by birth (Statistisches Bundesamt, 2025). Using the variable migration background instead of one's own migrant experience permits the analysis of intergenerational integration trajectories. It is, however, not fit to estimate discrimination as discriminatory beliefs and behavior are not directed at people with a migration background per se, but against people with certain religions, appearances, and languages. For example, a Black child living in Germany might face discrimination even though it has no migration background, and a Danish child living in Germany might not (El-Mafaalani, 2023, p. 489).

Types of refugees. Even within the group of refugees in Germany, there are various types of refugees distinguished by legislation. Their status decides whether refugees may work or not, whether they get a residence permit and which one, and whether they can reunify with their family or not. Besides, the legal classification of refugees may coincide with the discrimination that refugees face from the public. For example, some refugees are classified as coming from so-called safe third countries. The public tends to perceive their immigration as unnecessary and therefore unwanted. Those refugees experience more discrimination by Germans than other refugees (Pichl, 2023, pp. 508–510).

These examples show that attitudes towards immigrants are connected to legal and cultural classifications of immigrants and that it is important to distinguish between immigrant groups when analyzing immigrant attitudes. This paper focuses on attitudes towards refugees.

2.2 Group-threat theory

The factors that possibly predict attitudes towards different kinds of immigrants and immigration as a phenomenon are similar (Ceobanu & Escandell, 2010, p. 313). Therefore, I used previous studies on predictors of all these outcomes – attitudes towards refugees, immigrants and immigration – to build hypotheses on what predicts negative refugee attitudes. The different concepts will be summarized as immigrant attitudes, immigration attitudes, or anti-immigrant sentiment. Also, people who hold immigration attitudes will generally be referred to as longstanding residents and, in the case of Germany, as Germans, meaning that they are currently not immigrants themselves. The immigration attitudes of people with a migration background, however, will be discussed as well.

Formation of group-threat. The basis for studies on immigrant attitudes is the group-threat theory or conflict theory (Ceobanu & Escandell, 2010, p. 318). The idea of group-threat theory is that longstanding residents perceive immigrants as a threat, which increases their negative immigration attitudes. The theory emerged in the context of racial discrimination. Blumer (1958) developed the idea of group threat (Gihleb et al., 2022, p. 4). He focused on racial prejudice as a group characteristic instead of the feelings of individual members of a racial group towards those of another. He analyzed how different groups interact to define each other and themselves as racial groups with specific characteristics (Blumer, 1958, p. 3). Blalock (1957) developed the concept of analyzing demographic effects, namely the effect of the population of people of color (POCs) on white people's discriminatory attitudes. He obtained the first evidence supporting the positive effect of the county-level share of POCs in the southern United States (US) on different indicators of discrimination (Blalock, 1957, p. 682). Later, the concept of group threat was applied not just to racial discrimination, but also to anti-immigrant sentiment (Pottie-Sherman & Wilkes, 2017, p. 243).

Context of immigration. In the context of immigration, the group-threat theory states that "the presence of an outgroup in sufficient numbers will generate competition for scarce resources and thus local hostility" (Hopkins, 2010, p. 41). According to the theory, longstanding residents feel that their material (Key Jr, 1949) or cultural (Tajfel, 1978) interests are threatened by immigrants. Thus, in group-threat theory, two types of threat can be distinguished: economic and cultural (Ceobanu & Escandell, 2010, p. 318; Dinesen & Hjorth, 2024, p. 367; Gihleb et al., 2022, p. 5).

Cultural threat. The cultural view suggests that longstanding residents fear their cultural identity could be compromised. As mentioned above, several studies found that negative attitudes are specifically directed towards immigrants who are viewed as different from the country's dominant culture (Dinesen & Hjorth, 2024, pp. 374–375).

Economic threat. The economic view states that negative immigrant attitudes by longstanding residents result from 'material self-interest' (i.e., what is economically best for oneself). Immigration would cross material self-interest either through labor market competition or through fiscal burden (Hainmueller & Hopkins, 2014, p. 227).

Concerning labor market competition, the theory states that the increase in low-skilled immigrants leads to an ample supply of low-skilled workers. This would decrease the wages for low-skill labor while raising the wages for high-skilled workers. Yet, an influx of high-skilled immigrants would lower wages for high-skilled labor and increase those for low-skilled labor (Scheve & Slaughter, 2001, pp. 136–137).

For fiscal burden, low-skilled immigrants – in contrast to high-skilled immigrants – are assumed to burden public finance and incentivize communities to raise taxes. Thus, for their own material interest, longstanding residents would prefer an increase in high-skilled immigrants and would want to control and reduce the immigration of low-skilled workers (Hanson et al., 2007, pp. 7–8).

Real threat? The assumptions of this theory have been heavily debated. The supposedly negative economic consequences of immigration are not substantiated by empirical research. Longstanding residents' wages are determined by a multitude of factors. Considering the different predictors and the relationships in wage construction, the effect of immigration on wages is small to non-existent (Hainmueller & Hopkins, 2014, p. 228). Also, one cannot assume a higher fiscal burden due to more immigration. Between 1990 and 2004, US states that faced a rapid growth in immigrant population increased taxes at a lower rate compared to other states without severe changes in the immigrant demographics. Some of the former even made budget cuts (Hainmueller & Hopkins, 2014, p. 230). Therefore, if there is any effect of immigration on taxes, it is not a straightforward or strong relationship.

Nevertheless, for the group-threat hypothesis, it does not matter whether the threat is real. The theory does not assume positive or negative consequences from immigration to happen. The question is what the longstanding residents think will happen. Negative immigrant attitudes are expected to result even from perceived threats by immigration (Hainmueller & Hopkins, 2014, p. 228).

Measurement. Most studies on immigrant attitudes used the group-threat theory, but they measured it differently. Predictors operate on three analytical levels: the micro, meso, and macro level. Micro-level theories propose the importance of individual characteristics for the development of attitudes towards immigration. Meso-level theories emphasize the role of the region someone lives in. Macro-level theories focus on the importance of national features. Within micro- and meso-level theories, one can also distinguish between the material and the cultural group-threat hypothesis. Table 1 illustrates the different dimensions of group-threat theory. The cells represent the suggested predictors of immigrant attitudes of each type of threat and each level of analysis. I reviewed the research done within each area to derive the hypotheses for my analysis.

Table 1

Dimensions of group-threat theory.

<table>
<tr><th></th><th></th><th colspan="3">Level of analysis</th></tr>
<tr><th></th><th></th><th>Micro</th><th>Meso</th><th>Macro</th></tr>
<tr><td rowspan="2">Type of threat</td><td>Economic</td><td>Material self-interest (socioeconomic status)</td><td>Share and change in the immigrant population</td><td rowspan="2">Media effects (salience, tendency)</td></tr>
<tr><td>Cultural</td><td>Cultural identity and political values</td><td>Type of immigrant group (language and ethnic factors)</td></tr>
</table>

2.2.1 Personal threat: Material self-interest, cultural identity, and values

The version of the group-threat hypothesis that focuses on labor market competition predicts that longstanding residents feel threatened by immigrants with the same educational level and skills. Thus, individual socioeconomic characteristics of longstanding residents should be able to predict their attitudes towards immigration depending on the immigrants' socioeconomic characteristics. Besides, individual characteristics are also used to find evidence for the cultural threat that longstanding residents are said to experience due to immigration.

2.2.1.1 Material self-interest

The majority of studies analyzing the hypothesis of material self-interest on immigration attitudes – whether related to labor market competition or fiscal burden – found no effect that would support the theory (Hainmueller & Hopkins, 2014, p. 240).

Socioeconomic status. They found that people with lower socioeconomic status – meaning lower occupational status, income, and education – have more anti-immigrant attitudes (Jackson et al., 2001, p. 447; Kunovich, 2002, p. 55; Mayda, 2006, p. 510; Semyonov et al., 2008, p. 5). This would support the material self-interest hypothesis if anti-immigrant attitudes by low-skilled residents were directed only towards low-skilled immigrants. In most studies on material self-interest, however, this was not the case (Hainmueller & Hopkins, 2014, p. 240, 2015, p. 529). An experimental study – analyzing the attitudes towards immigrants in 15 European countries before and after the *refugee crisis* of 2015/2016 – found that high-skilled immigrants are preferred to low-skilled immigrants by all longstanding residents, irrespective of their own occupational position. In addition, high-skilled residents approved the immigration of high-skilled workers more than low-skilled residents (Naumann et al., 2018, p. 1009). This contradicts the hypothesis of group-threat theory.

Education. Education is one aspect of socioeconomic status and a variable that was used ubiquitously to measure individual material threat and to predict anti-immigrant sentiment. No matter the methodological approach – whether education was used as the main predictor or solely as a covariate, and whether the US or the European Union (EU) was observed – studies found that people with higher levels of education tend to hold statistically significantly less negative attitudes towards immigrants (Coenders et al., 2008, p. 175; Dražanová et al., 2024, p. 317; Hello et al., 2002, p. 12; Kunovich, 2002, p. 46; Quillian, 1995, p. 597; Rustenbach, 2010, p. 53; Scheepers, 2002, p. 25; Schlueter & Wagner, 2008, p. 167; Schneider, 2007, p. 60; Semyonov et al., 2006, p. 426). Again, this effect is independent of the socioeconomic status of the immigrants. Thus, it does not support the material self-interest hypothesis. Instead, it suggests that there is a simple linear effect of education.

Some studies, however, found no effect for education (Ackermann & Freitag, 2015, p. 36; J. C. Dixon & Ergin, 2010, p. 1343). Besides, education may contain some bias. Education is likely correlated to other attributes that also affect immigration attitudes. The level of education could, for example, coincide with one's level of tolerance, cultural capital, or political correctness, which would be able to explain more positive views on immigration. Even more, the level of education one acquires is determined by the social structure; thus, there are self-selecting processes in place (Hainmueller & Hopkins, 2014, p. 241). These influence the effect of education measured and are not easily dissected from the effect. It is probable that not just higher education, but higher socioeconomic status in general, increases people's opinions of immigrants.

Income. Income is another aspect of individuals' socioeconomic status. Researchers, thus, identified lower individual income as a predictor of anti-immigration attitudes (Coenders et al., 2008, p. 187; Jackson et al., 2001, p. 447; Kehrberg, 2007, p. 272). But the effect did not always appear (Ceobanu & Escandell, 2010, p. 320). Jackson et al. (2001) found that higher income statistically significantly decreases anti-immigration attitudes (Jackson et al., 2001, p. 448). Other studies found no statistically significant effect of income (Semyonov et al., 2006, p. 438; Wilkes et al., 2007, pp. 834–838).

Perceived threat. Ilias et al. (2008) did not measure the threat possibly faced by an individual objectively (e.g., as social status) but subjectively. They asked people to estimate the costs of immigration and found that this estimation was the most important predictor of immigration attitudes (Ilias et al., 2008, p. 741). Their study suggests that immigrant attitudes may result from how threatened people feel based on their understanding of the situation rather than any objectively measurable material cost.

Other demographic characteristics. Beyond socioeconomic variables that indicate material self-interest, other demographic variables were also used as predictors of immigration attitudes. The results suggest that women, younger people, and people living in cities are less prejudiced against immigrants than men, older people, and people living in rural areas (Ceobanu & Escandell, 2010, p. 320; Dražanová et al., 2024, p. 327; Gorodzeisky & Semyonov, 2009, p. 410). A meta-analysis of 144 analyses and over 1000 estimates covering the years from 2009 to 2019 by Dražanová et al. (2024) identified age, aside from education, as the most important predictor of anti-immigrant sentiment. Being older led to a statistically significant increase in opposition to immigration (Dražanová et al., 2024, p. 327). Yet, the authors cautioned against taking the effects of gender and urbanity at face value. Being a man increased anti-immigrant attitudes only marginally and not in a statistically significant way (Dražanová et al., 2024, p. 328). Besides, while the positive effect of living in a city on supporting immigration was statistically significant, it was probably endogenous. Immigrants predominantly live in urban, not rural areas. People in cities thus encounter immigrants more and are more used to immigration, which could moderate the effect. Moreover, one could decide based on one's immigration attitude whether to live in the city or the country. Therefore, self-selection influences the urbanity effect and complicates its interpretation (Dražanová et al., 2024, p. 327).

Migration background. Another demographic predictor of immigration attitudes is one's own migration background. Dražanová et al. (2024) found that immigrants or those belonging to a minority tend to have statistically significantly less negative immigrant attitudes (Dražanová et al., 2024, p. 327). Surprisingly, the time passed since immigration did not affect immigrants' political views. Dancygier and Saunders (2006) found that immigrants do not necessarily align their values with those of longstanding residents over time. The experience of migrating is rather complex, and integration or adaptation processes depend on factors such as language barriers and discrimination, not time. According to the authors, it would be profitable to analyze large samples and differentiate between countries of origin to identify the complex structures within the migrant population (Dancygier & Saunders, 2006, p. 978).

'Race'. McClain et al. (2009) compared three Southern US cities with different racial demographics: one predominantly white, one predominantly Black, and the third 50% each. As immigrants are mainly Hispanic people, immigration changes racial intergroup relations. 'Race' is an important variable specifically in the US South because it predicts social and political outcomes – such as chances in education, legal struggles, and life in general. Based on the importance of racial discrimination, it is to be expected that POCs and white people differ in their immigration attitudes. The authors found that Black people tend to be more threatened materially than white people. But they are less threatened culturally as they recognize cultural identity concerns as racist (McClain et al., 2009, pp. 1–2).

2.2.1.2 Cultural individual threat

The group-threat theory in the cultural vein states that individuals fear their cultural identity and lifestyle to be threatened rather than their economic position. To test this theory, researchers looked at individual characteristics of longstanding residents that supposedly relate to the amount of cultural threat they feel. These characteristics are someone's personality, their beliefs, and their values.

Personality. The construct used to measure personality is usually the Big Five model. It assumes that individuals differ along five dimensions or personality traits. Those are (1) openness, referring to someone's degree of being open and interested to new experiences, (2) conscientiousness, meaning whether someone is efficient and success oriented, (3) extraversion, meaning whether someone is talkative and outgoing, (4) neuroticism, which is the antithesis to emotional stability, and (5) agreeableness, meaning whether someone is kind and friendly (Entringer et al., 2022, p. 43). A meta-analysis of over 70 studies identified openness and agreeableness as key aspects of someone's personality in predicting their prejudice. Low openness increased right-wing authoritarianism, and low agreeableness was associated with a higher social dominance orientation (Sibley & Duckitt, 2008, p. 248).

In contrast, Gallego and Pardos-Prado (2014) who specifically looked at immigration attitudes, found close to no effect of openness (Gallego & Pardos-Prado, 2014, p. 93). They, however, confirmed the importance of agreeableness. The effect remained statistically significant even when other predictors were introduced. Moreover, they showed that neuroticism is positively associated with more anti-immigrant sentiment (Gallego & Pardos-Prado, 2014, p. 92).

Religiosity. Besides the research on personality, several values and beliefs are presumably associated with one's immigration attitudes. One such variable is religion, though the association is not straightforward. Scheepers et al. (2002) found that different measurements of religiosity affect ethnic prejudice in contradictory ways. On the one hand, Catholics and Protestants tended to be more prejudiced than non-religious people. Also, people who attended church more often and who related to religious particularism had more ethnic prejudice than those who did not. On the other hand, people who believed in biblical doctrines, those in whose life religion took a more prominent role, and those who were more spiritual tended to be less prejudiced than the less-believing, less-religious, and less-spiritual ones (Scheepers et al., 2002, p. 242).

Ethnocentrism. Another possible predictor of negative immigrant attitudes is ethnocentrism. The concept was developed by D. R. Kinder and Kam (2009). Ethnocentrism is the habit of dividing society into an ingroup and an outgroup, thus reducing society to us versus them. Therewhile, members of the ingroup are thought of as inherently good, and members of the outgroup are assumed to be bad (D. R. Kinder & Kam, 2009, p. 8). Ethnocentrism does not define who is part of the ingroup and who is not. In some social contexts, groups might be defined based on religion. In others, they might be defined based on ethnic background.

Difference with immigrant attitudes. One might understand ethnocentrism as a form of prejudice or stereotypical thinking and wonder if this is just the same as anti-immigrant attitudes. The phenomena are certainly closely linked, but it is important to remember that immigrants are not necessarily identical with members of an outgroup.

For example, white Americans with strong ethnocentric beliefs would possibly consider white English immigrants as part of their ingroup; they would also consider their ancestors, who were immigrants, part of the ingroup. They would, however, consider Black Americans part of the outgroup wherever they were born. Thus, immigrants can be part of the ingroup and non-immigrants can be part of the outgroup in ethnocentric thinking. The idea is that because ethnocentric people think in these prejudicial, simplified categories, they oppose immigration independent of the actual ethnic composition of the immigrants present.

Ethnocentrism effect. One of the first studies on the effect of ethnocentrism by Burns and Gimpel (2000) found that in 1992, in the US, holding stereotypes against Hispanic and/or Black people was associated with wanting to reduce immigration. The strong, statistically significant effect of racial prejudice is especially interesting because the majority of immigrants into the US was not Black (Burns & Gimpel, 2000, p. 218). The authors also demonstrated that this effect was weaker in 1996, when Hispanic stereotypes played a greater role, suggesting the prejudice was more focused on the major ethnic immigrant group (Burns & Gimpel, 2000, p. 221). Hainmueller and Hopkins (2015) found evidence for the influence of ethnocentrism as well. They revealed that more ethnocentric individuals pay more attention to the country of origin of immigrants when deciding whether they should be allowed to immigrate (Hainmueller & Hopkins, 2015, p. 545). This suggests that they harbor stereotypes for people from countries that they attribute to the outgroup, assuming that those immigrants all show certain characteristics that are bad and thus should not be admitted.

Group-specific stereotypes. Several studies, however, argued that not ethnocentrism, where *everyone else* is part of the outgroup, predicts anti-immigrant attitudes, but rather that they are a result of group-specific stereotypes that differ with each ethnic group (Dinesen & Hjorth, 2024, p. 366). Valentino et al. (2013), for example, showed that while ethnocentrism predicts white Americans' immigration attitudes, most of the effect can be attributed to people's opinions about Hispanic people. The authors also stated that the media moderated the relationship. In the US news coverage, Hispanic people were first associated with immigration in 1994. Since then, stereotypes against Hispanic people have been the main predictor of immigration opinions (Valentino et al., 2013, p. 149). Burns and Gimpel (2000) support this finding.

Situation-specific cues. Moreover, Hopkins (2015) found in his experiment that being a member of the outgroup alone does not prompt opposition to immigration. Rather, the influence depends on certain situation-specific cues. Immigrants who spoke accented English conformed to the imperative of immigrants' assimilation and counteracted the effect. Thus, their assimilation did not foster anti-immigration attitudes (Hopkins, 2015, p. 531). Furthermore, Levy and Wright (2016) showed that prejudice against Hispanic people does not promote anti-immigration attitudes, but that certain beliefs about immigration create prejudicial beliefs about Hispanics. People who strongly oppose illegal immigration hold stereotypes against Hispanic people by linking them to illegal immigrants (Levy & Wright, 2016, p. 1).

Language. Newman et al. (2014) established the importance of social dominance and the ability to transfer the integration effort to the outgroup for emotions towards the outgroup. Social dominance theory states that societies are commonly structured as a hierarchy of different social groups (Newman et al., 2014, p. 167). The authors analyzed white US students' reactions to the introduction of Spanish words into an online chat. Students who did not speak Spanish had to decide whether they were willing to translate the messages on their own – taking on the transcultural transaction costs themselves – or they could request the messenger to translate – leaving the transcultural transaction work to their opponent (Newman et al., 2014, p. 176). The authors inferred that those who believed in a hierarchy of different social groups (i.e., had a high social dominance orientation), but took on the transactional costs anyway were statistically significantly angrier than those with a low social dominance orientation. Moreover, they were even angrier than students who also had a high social dominance orientation, but who transferred the transactional costs to the messenger. The authors explained that by transferring the costs, the student enacted their social dominance and released some of their anger (Newman et al., 2014, p. 181). This experimental design showed the complexity of how intergroup interactions shape personal attitudes.

Again, taking language as an indicator for cultural identity, Hopkins analyzed the response to Spanish by US Americans with different partisanship. The results mirror the analysis of Newman et al. (2014). Whereas Republicans, exposed to Spanish, developed more restrictive attitudes towards immigration, the author detected no such relationship for Democrats (Hopkins, 2014, p. 421). This supports the role of cultural differences of immigrants and non-immigrants and the importance of political orientation in framing experiences.

Political values. Political ideology has been analyzed as a predictor of anti-immigrant sentiment on its own. Several studies found that Conservatives and people who identify more with the political right oppose immigration more often than those who are more liberal or left

(Burns & Gimpel, 2000, p. 219; Chandler & Tsai, 2001, p. 177; Citrin et al., 1997, p. 867; Davidov & Meuleman, 2012, p. 757; Mayda, 2006, p. 514; Newman et al., 2014, p. 174; Newman et al., 2015, p. 127; Wilkes et al., 2008, p. 302; Wright et al., 2016, p. 244).

Also, several researchers detected a relationship between partisanship and immigration attitudes. Republicans are statistically significantly more anti-immigration than Democrats (Campbell et al., 2006, p. 129; Hajnal & Rivera, 2014, p. 773). This effect was observed not only in the US, but also in many European and some developing countries (Mayda, 2006, p. 512).

For the US, Newman (2013) demonstrated that being more authoritarian is associated with being threatened by immigration (Newman, 2013, p. 383). Wright et al. (2016) found that people who adhere to humanitarianism or egalitarianism statistically significantly support immigration more than non-humanitarian and non-egalitarian people (Wright et al., 2016, p. 244).

Socialization in East or West Germany. A predictor of immigration attitudes specific to Germany is whether a person was socialized in East or West Germany. The country was divided from 1949 to 1990 into the socialist German Democratic Republic (GDR) and the capitalist Federal Republic of Germany (FRG). During that time, political and social structures differed between the two states. Different overarching values regarding work ethics or family structure resulted in different lifestyles between East and West Germans (Frese et al., 1996, p. 37; Pfau-Effinger & Smidt, 2011, p. 217).

Those differences still partly exist today (see, e.g., Scheling & Richter, 2021, p. 23). Sack (2016) demonstrated that people’s political values, specifically their democratic value orientation, vary with their socialization in East or West Germany, even 20 years after the reunification (Sack, 2016, p. 1). Therefore, East and West Germany provided culturally different contexts that affected individuals’ behaviors and values. Although the states have been formally reunited for over 30 years, the differences in individual lifestyles and thinking prevail.

Based on the continuing differences, one is likely to assume that people’s immigration attitudes differ between East and West Germany as well, and statistics again and again show that this is the case. East Germans vote for the German anti-immigration, far-right party Alternative for Germany (AfD) twice as often as West Germans. The most important predictor of voting for the AfD is xenophobic beliefs (Schröder, 2018, p. 8), and xenophobia is more common in East than in West Germany (Sturzbecher, 2012, p. 5).

One could also argue that the more negative immigration attitudes in East Germany than in West Germany are not related to their cultural differences but come from their economic differences. On average, East Germans have a lower economic and educational status compared to West Germans (Burkert, 2012, p. 172). No matter where the effect comes from, whether someone is socialized in East or West Germany is important to consider when estimating individual refugee attitudes in Germany.

In **summary**, as demonstrated in this chapter, a lot of research has been done on individual predictors of refugee attitudes. Various kinds were tested: socioeconomic and demographic factors, as well as personality, personal attitudes, and political views. Some – such as education, age, and socialization – seem to statistically significantly affect immigration attitudes, but for others, findings are mixed. But individual factors do not suffice to explain immigration attitudes. Other researchers agree that immigration attitudes are so complex that individual variables alone are unable to predict them (Ceobanu & Escandell, 2010, p. 322).

Problems with individual predictors. Besides unexplained variance in the outcome, there are some theoretical concerns about micro-level predictors. Individual predictors are mostly dispositional and hardly changing variables. Personality is said to change only slowly (Entringer et al., 2022, p. 43). Education levels, once achieved, rarely change. The same goes for one's gender. Because these variables rarely change, they are not able to explain variations of immigration attitudes over time (Dinesen & Hjorth, 2024, p. 366; Hopkins, 2010, p. 43).

But, as described in the beginning, changes in immigration attitudes do happen. Researchers state that, in Germany, the number of hate crimes varies with the number of votes for right-wing extremist parties (Miehlke & Salheiser, 2022, p. 82). Specifically, the strengthening of the AfD in Germany shows that anti-immigrant sentiment has become more mainstream (Miehlke & Salheiser, 2022, p. 81). The sentiment gets visible through violence and voting behavior. Accepting the fact that attitudes did change means that time-varying variables are required to analyze attitudes towards immigrants (Dinesen & Hjorth, 2024, p. 367).

Another concern is that individual characteristics alone do not suffice to test the group-threat hypothesis, as threats to material self-interest and cultural identity, if ever, only appear due to large immigrant populations. Meaning, individuals should be not at all or less threatened if there are few immigrants and more threatened if there are many. The size of the immigrant population should matter in some way. This leads to the next chapter, where the regional amount of immigration is the suggested predictor of individuals' attitudes towards immigration. Regional immigrant demographics are also, in contrast to individual dispositions, time-varying.

2.2.2 Group threat: Regional immigrant population

The original and most common way to test the group-threat theory on a contextual level is to take the size of immigrant groups as a predictor. The theory assumes that a larger group of immigrants in a region makes them more visible and therefore, more likely to be perceived as a threat (Ceobanu & Escandell, 2010, p. 322). Another approach is to use the increase in immigration in a region as a predictor. The change of immigration rates is presumably more noticeable and thus more threatening than solely the size of immigrant groups (Ceobanu & Escandell, 2010, p. 322).

Methodological concerns. What constitutes the region for which immigrant demographics are estimated is an important methodological question. The size of the regions used in previous studies ranges from whole countries to states and counties, to zip-code areas and neighborhoods with a radius of 80 meters. But what size is appropriate?

Another problem is that spatial contexts cannot be manipulated, and people self-sort into regions (Dinesen & Hjorth, 2024, p. 364; Enos, 2014, p. 3699). Immigrants as well as longstanding residents can at least to some degree, choose where they want to live (Dustmann et al., 2019, p. 2035). It can be expected that immigrants choose places with less anti-immigrant sentiment. Anti-immigrant people will again prefer places with fewer immigrants, and people without anti-immigrant attitudes would not mind living in regions with rather high immigrant shares or even specifically want to live there.

The concept "not in my backyard" (NIMBY) is one example of individuals' influence on neighborhoods. This term refers to the opposition of residents to corporate or governmental construction projects near their homes. The idea is that residents do not oppose the projects per se but want the associated burdens to be borne by poor neighborhoods rather than their own. Aside from the indirect class implications of NIMBY, the term also refers to the direct opposition of residents against the settlement of marginalized groups in their neighborhood (e.g., group homes for disabled people or drug-treatment facilities) (P. D. Kinder, 2025; Trischler & Kropp, 2023, p. 23). In this case, one can use NIMBY to refer to the aversion of residents against the settlement of immigrants in their neighborhood.

Mixed findings. The contextual findings of previous research on the group-threat theory are mixed, not to say contradictory (Dinesen & Hjorth, 2024, p. 367; Pottie-Sherman & Wilkes, 2017, p. 218). There are many studies with several different conceptions and measurements of what constitutes group threat. Nonetheless, the variety of conclusions constitutes a problem, as results cannot be traced back to the different kinds of measurements. Even within one type of group-threat indicator and even when the same regions or time frames were observed, different studies came to different conclusions.

Regional level of immigrant demographics. Some studies demonstrated that higher levels of non-EU immigrants into Europe result in increased anti-immigrant sentiment among Europeans (Quillian, 1995, p. 601; Scheepers, 2002, p. 27; Semyonov et al., 2006, p. 426, 2008, p. 5). Dustmann and Preston (2001) observed various counties in England and concluded that a higher share of POCs leads to more negative immigration attitudes (Dustmann & Preston, 2001, p. 371). Many studies analyzed the group-threat theory in the US context. Newman et al. (2015) demonstrated that the share of foreign-born people within a zip-code area predicts the perceived level of immigration, which in turn leads to more negative immigration attitudes (Newman et al., 2015, pp. 126–130). Similarly, Hood and Morris (1998) found a direct, negative correlation between immigrants documented in a region and white Americans' opinions on immigration policies (Hood & Morris, 1998, p. 1).

Dinesen and Sønderskov (2015) were able to measure the share of immigrants and of non-Western immigrants within regions of Denmark, which have a radius of just 80 meters (Dinesen & Sønderskov, 2015, p. 557). In contrast to cross-country examinations, they were able to establish the perceptibility of immigrants rigorously. In line with group-threat theory, the authors find that larger shares of non-Western immigrants decrease social trust. Interestingly, when they looked at larger regional contexts, they no longer found this effect (Dinesen & Sønderskov, 2015, p. 550). Many studies used too large regions to assume that immigrants could be perceived (Dinesen & Hjorth, 2024, p. 369; Dinesen & Sønderskov, 2015, p. 550; Pottie-Sherman & Wilkes, 2017, p. 236). Like Dinesen and Sønderskov (2015), one should try to use small spatial units for the analysis of regional threat effects.

Enos (2014) was able to circumvent the self-selective bias of regional demographics. The author analyzed homogenous communities in the US in which Spanish-speaking confederates were inserted at random. They became part of the daily routines of the white Americans living in these communities. Thus, very direct intergroup contact was established. Subsequently, Enos detected an increase in exclusionary attitudes towards the Spanish-speaking people, supporting the group-threat hypothesis (Enos, 2014, p. 3699).

A few studies, which used not attitudes, but voting behavior as the dependent variable, found substantial evidence for the group-threat theory. Dustmann et al. (2019), like Enos, evaded demographic self-sorting biases. They profited from a policy in Denmark that sorts immigrants into regions at random. Their results demonstrated that in all except the biggest cities, a larger immigrant population increased the proportion of votes for right-wing, anti-immigrant parties (Dustmann et al., 2019, p. 2035). Similarly, Halla et al. (2017) found that the regionally increased share of immigrants in Austria led to statistically significantly larger regional voting shares for the Austrian far-right party, Freedom Party of Austria (FPÖ) (Halla et al., 2017, p. 1341). Barone et al. (2016) similarly found for Italy that higher immigration levels within counties resulted in more votes for the center-right coalition, which holds anti-immigrant positions and promotes policies to reduce immigration (Barone et al., 2016, p. 1).

Distinguishing cultural and economic threats. As with the micro-level predictors of immigration attitudes, one can differentiate meso-level indicators of group threat according to the type of threat: cultural or economic. Longstanding residents may fear negative material consequences of large immigrant populations, or they may fear cultural changes due to large immigrant populations.

Schneider (2007) – analyzing immigration attitudes in Europe – distinguished between cultural and economic threats. She took levels of immigration into Western countries from non-Western countries as an indicator for cultural threat, and the share of low-educated immigrants to measure economic threat (Schneider, 2007, p. 58). She found no evidence that economic factors contribute to perceived group threat, whereas the level of non-Western immigration was a statistically significant predictor of anti-immigrant sentiment (Schneider, 2007, p. 62).

Similarly, Hello et al. (2002) differentiated European countries' cultural context and their demographic context. They took a country's democratic attitudes and religious heterogeneity as an indicator of that country's cultural context and threat, and the share of immigrants as an indicator of the demographic context and economic threat. They also detected a statistically significant effect of cultural threat, but no effect of economic threat on attitudes towards immigrants (Hello et al., 2002, pp. 18–19). Sniderman et al. (2004) also showed that only cultural threats result in increased anti-immigrant attitudes, but perceived economic threats do not (Sniderman et al., 2004, p. 35).

Interactions with individual predictors. Other researchers analyzed individual characteristics of longstanding residents and immigrants, conjoint with regional shares of immigrants, to distinguish between cultural and economic threats.

Hawley (2011) assumed an interaction of context and individual effects. He showed that, in the US, Republicans were more likely to approve immigration restrictions when regional immigration levels were high. Democrats, however, facing the same contextual situation, were less likely to approve immigration restrictions (Hawley, 2011, p. 404). Karreth et al. (2015) found similar evidence for German-speaking countries. Higher immigration levels led to more negative attitudes towards immigrants, but only for longstanding residents who identified with the political right (Karreth et al., 2015, p. 1174). The group-threat hypothesis, thus, seems to hold only for certain types of people.

On the other hand, negative attitudes might only be directed towards certain groups of immigrants. Ha (2010) demonstrated for white Americans that while the presence of Asians in proximity fostered positive immigration attitudes, the opposite effect existed for the presence of Hispanic people. However, Black Americans showed more negative immigration attitudes in response to greater proximity to Asians (Ha, 2010, p. 29). Likewise, Wright and Citrin (2011) analyzed the public response to immigrant-rights protests and found more negative immigration attitudes towards immigrant protesters waving Mexican flags, compared to those waving American flags (Wright & Citrin, 2011, p. 323). These studies highlight the importance of social and identity-related concerns in attitude development. Thus, they suggest that the cultural vein of the group-threat theory is more accurate than the economic vein.

Regional economic performance. Some researchers diverged entirely from measuring regional demographics to estimate contextual indicators of economic group-threat. There is evidence that the regional economic performance is predictive of immigration attitudes (Kunovich, 2004, p. 20; Semyonov et al., 2008, p. 5). The idea is that during economically prosperous times, the perceived material threat is lower, as labor market competition and fiscal burden due to immigration are seen as less severe than in times of economic decline (Ceobanu & Escandell, 2010, p. 322). Other studies, however, found no effect of the regional economic situation on individual attitudes (Hjerm, 2007, p. 1253) or even increased negative attitudes towards immigrants in affluent economies (Mayda, 2006, p. 510).

Contact theory. In the context of meso-level group-threat theory, high levels of immigration are expected to render perceived threats more present and thus to lead to more anti-immigrant attitudes. This assumption is not unchallenged. There is a contradicting theory: contact theory. Contact theory proposes that under certain conditions, living near and interacting with immigrants leads to positive attitudes towards immigration among longstanding residents. Contact is assumed to lead to support and empathy by overcoming prejudices and reducing stereotypical thinking (Dinesen & Hjorth, 2024, p. 367; Gihleb et al., 2022, p. 4). Allport (1954) developed contact theory and specified four conditions under which intergroup contact reduces prejudice: intergroup equality, cooperation, common goals, and authority support (Gihleb et al., 2022, p. 6; Pettigrew, 1998, p. 65).

Group-threat vs. contact theory. Some studies tested group-threat theory against contact theory. Sides and Citrin (2007) found that though the size of the immigrant population does not affect immigration attitudes, contact with immigrants does (Sides & Citrin, 2007, p. 500). This finding supports contact theory but goes against group-threat theory.

Other studies found that the effect of group threat is weakened by interpersonal contact, as larger immigrant populations not only promote fear, but also intergroup interaction. These effects then act against each other, and both affect attitudes towards immigrants (McLaren, 2003, p. 909; Schlueter & Wagner, 2008, p. 153). Wagner et al. (2008; 2006) found also for Germany that group-threat and contact theory effects both exist and act against each other, predicting ethnic prejudice (Wagner et al., 2008, p. 403; Wagner et al., 2006, p. 380).

This finding is questioned. Fetzer (2000) analyzed attitudes towards immigrants as well as attitudes towards immigration. He found, for the US and France, that large local immigrant populations decrease anti-immigrant sentiment – as assumed by contact theory. In Germany, however, he detected the opposite effect – assumed by group-threat theory – that large local immigrant populations increase anti-immigrant sentiment. Notably, in none of these contexts does the immigrant population have any effect on immigration policy preferences. This is unexpected according to contact and group-threat theory (Fetzer, 2000, p. 24; Hainmueller & Hopkins, 2014, p. 236). Thus, contact with immigrants might decrease longstanding residents' prejudice, but not change their political stance on immigration.

Contact effects alone. Some studies only tested contact theory and, therefore, considered intergroup interaction as the main predictor of immigration attitudes (Ellison et al., 2011). A meta-analysis of contact theory research, based on over 500 studies in 38 countries with more than 250,000 subjects, showed that there is an average small negative relationship between intergroup interaction and anti-immigrant sentiment. More than 90% of the studies on contact theory report a negative relationship (Pettigrew et al., 2011, p. 274). Overall, contact theory is well-supported in many different contexts and thus considered to be a good explanation.

Nonetheless, some researchers questioned the support for contact theory. Dustmann and Preston (2001) argued that regional self-selection favors contact theory. As mentioned before, to some extent, people choose where they want to live. Therefore, people with more positive attitudes towards immigrants do not mind or even want to live in regions with higher levels of immigration. This means straightforward regressions tend to confirm the contact hypothesis (Dustmann & Preston, 2001, pp. 370–371).

No effect of the regional share of immigrant demographics. Moreover, there are null findings: Rustenbach (2010) found support for neither group-threat nor contact theory.

According to her, regional demographic composition is unrelated to individual attitudes (Rustenbach, 2010, pp. 65–67).

The data used in this analysis do not allow a test of contact theory. Nonetheless, its implications are important to consider when interpreting the results (Gihleb et al., 2022, p. 6).

Going back to just group-threat theory, some studies found the level of immigration to be insignificant for attitudes towards immigrants. Hjerm (2007) found, for Europe, that neither the perceived number of immigrants nor the actual higher share of immigrants in a country had any statistically significant effect on anti-immigrant attitudes (Hjerm, 2007, p. 1253). Scheepers et al. (2002) analyzed immigration attitudes in Europe and used yearly and periodic averages of the number of refugees in European countries. However, they did not find that greater immigration shares significantly predicted more anti-immigrant attitudes (Scheepers, 2002, p. 27).

Why are the findings mixed? An explanation for the inconsistent contextual evidence for the group-threat theory is that the amount of threat a group poses is mostly measured as the share of this group in a certain region. For minority or migrant groups to be perceived, however, as a threat or just perceived at all, their existence – even in relative proximity – is not enough.

As Hopkins (2010) noted, in the US, immigrants are often not allowed to vote; they work in specific market segments, and live in separate districts. Their encounters with non-immigrants are reduced to a small number of situations, for example, when they are going to the supermarket. Therefore, their visibility should not be assumed. Moreover, these living conditions decrease the possibility of influencing or even threatening the lives of longstanding residents (Hopkins, 2010, p. 40). This holds not only for America in the early 2000s, but for Germany today. There are segregated regions in every part of German cities where only immigrants or only longstanding residents live, respectively (Eksner, 2013, p. 336; El-Mafaalani, 2023, p. 493; Stehle, 2012, p. 167).

Ghettoization. The term ghetto describes the fact that minorities usually live concentrated in a separate settlement. Ghettos derive not only from individual or cultural preferences but external forces, such as market conditions and political decisions (Madanipour, 2012, p. 287). Also, even though individual decisions affect ghettoization, that does not mean that the process is voluntary. Discrimination causes segregated settlements along ethno-racial lines (T. Slater, 2020, p. 161).

Regional change in immigrant demographics. To counter self-selecting biases, the suggestion is not to consider the share of immigrants living in a certain region. Instead, one should use the change in immigrant shares as a predictor of negative immigration attitudes. The idea is that while the actual immigrant population might not be perceivable to longstanding residents, extreme changes would be (Hopkins, 2010, p. 40).

Newman (2013) studied Hispanic immigration into the US. He found a positive, statistically significant relationship between immigration levels and anti-immigration attitudes, but solely for neighborhoods where initially few Hispanic people lived. In neighborhoods with an initially larger Hispanic population, more immigration had the opposite effect, reducing anti-immigrant sentiment (Newman, 2013, p. 374). Similarly, van Klingeren et al. (2015) found for Denmark and the Netherlands that, whereas the size of the immigrant population did not affect anti-immigrant attitudes, the inflow of immigrants had a positive, statistically significant effect (van Klingeren et al., 2015, p. 277).

Some studies conceptualized the change in immigrant shares as the exposure to immigration 'waves'. Dinas et al. (2019) conducted a natural experiment on Greek islands. Some Greek islands experienced sudden increases in the number of refugees in 2015. Whereas the distribution of votes was almost identical across islands before the *refugee crisis*, it changed after the *refugee crisis*. Among islands with a large increase in the number of refugees, vote shares for Europe's most extreme right-wing party, Golden Dawn, increased on average by 44% (Dinas et al., 2019, p. 244).

In **conclusion**, regional effects on immigrant attitudes have their difficulties. Two theories with contradictory hypotheses exist. Research findings also point in different directions. Moreover, the measurement of spatial context is not straightforward. Study designs need to be able to circumvent self-selective biases and dissect possibly contradictory effects to produce interpretable results. As previous findings suggest, the relationship between immigrant demographics and immigrant attitudes is not simple: Other factors possibly moderate or mediate the relationship. One should aim to identify situations where spatial effects exist and the direction they are pointing to.

2.2.3 National threat: Media salience of the immigration issue

Keeping with the threat framework, the third way that immigrants can appear as a threat to longstanding residents is on the macro level, through the media. This line of research is more recent than the other two: The first studies analyzing the effect of media coverage and framing of the immigration topic on people's attitudes towards immigrants appeared in the 2000s (Dinesen & Hjorth, 2024, p. 370).

Media Salience. In general, people base their opinions, specifically their political opinions, on what is presented in the mass media (Iyengar & Simon, 2000, p. 149; D. R. Kinder, 1998, p. 167; Maurer, 2022, p. 555). The media's influence on public opinion operates through different channels. On the one hand, there is an effect of the quantity with which the media reports an issue – media salience. On the other hand, there are certain tendencies of the media in reporting on an issue that affect people's opinions on the topic – media tendencies (Maurer, 2022, p. 560).

Agenda-setting. The quantity of reports on a specific issue affects, for one, what people perceive as relevant. This is called the *agenda-setting effect* (Maurer, 2022, p. 560). The salience of an issue does not influence how people think about things, but what they think about and what they deem important (Cohen, 1963, p. 13). The agenda-setting effect consists of two selection processes: Media outlets select what to report on (i.e., the media agenda), and people select what news to consume (i.e., the public agenda) (Nanz & Matthes, 2022, p. 605). The majority of studies found a positive effect of the media agenda on the public agenda (Luo et al., 2019, p. 150). For example, McCombs and Shaw (1972) found that the agenda of print media outlets during the US presidential election of 1968 coincided with what issues voters regarded as important (McCombs & Shaw, 1972, p. 183).

Priming. The second fact about media salience is that people are inclined to base their political orientation on prominent issues. This is called *priming* (Maurer, 2022, p. 560). The concept stems from an analysis by Iyengar and Kinder (1987). The authors found that, in the US, prominently reported topics in the media were taken more frequently than others as a measure to evaluate the president's performance (Iyengar & Kinder, 1987; Nanz & Matthes, 2022, p. 607). Thus, priming means that salient issues not only seem more important than others, but they also seem more central to political judgements (Nanz & Matthes, 2022, p. 607).

Media tendencies. The tendencies of media coverage can either affect how extreme people's opinions become or direct (*frame*) how people understand a topic (Maurer, 2022, pp. 560–561). There are two approaches explaining how media coverage makes personal attitudes more extreme.

Mainstreaming. Some researchers support the *mainstreaming* theory (Gerbner et al., 1980). Mainstreaming means that all mass media outlets report on a topic in a specific way. They tell the same story, and people who regularly consume mass media develop similar opinions. Besides, they experience their everyday life in a way that is coherent with the media coverage. Then, hearing the same story again and again, while seeing it reflected in one's own experience, leads people to form more rigid and extreme opinions (Gerbner et al., 1980, p. 15).

Reinforcing spirals. The other explanatory approach – the *reinforcing-spirals* model (M. D. Slater, 2007) – assumes a more versatile and sectioned media landscape. The outlets differ in their political orientation and their way of reporting on news topics (Maurer, 2022, p. 560). People can select their source of information and will likely choose media outlets that mirror their own opinions (Iyengar & Hahn, 2009, p. 19). This, in turn, reinforces people's political attitudes, making them more extreme (M. D. Slater, 2007, p. 281).

Framing. Media tendencies can also frame issues. To frame something means to "select some aspects of […] reality and make them more salient […], in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (Entman, 1993, p. 52). In other words, media outlets must select what to report; they define what the problem is, who or what caused it, and who or what could be the solution. In that, they provide a recipe to the audience on how to think about an issue (Entman, 1993, p. 54). By framing, the media thus shapes personal opinions on societal issues.

Media effects on immigration attitudes. These media effects on attitudes are expected to apply to people's immigration attitudes as well. The salience of the issue might render immigration more important and alter people's perception of immigration through agenda-setting and priming. Besides, the media's tendency towards immigration might affect people's opinions on immigrants, by making already prevalent thinking patterns more extreme or by framing immigration (Meltzer et al., 2017, p. 1). The immigration topic is a special case for media effects. Most people lack personal experience with immigrants. Therefore, media coverage as a source of information on immigration is more influential (Dinesen & Hjorth, 2024, p. 370; Meltzer et al., 2017, p. 1).

Previous Findings. Several studies analyzed the effects of media coverage and framing of immigration and immigrants on people's attitudes towards them. The results of these studies are mixed (Dinesen & Hjorth, 2024, p. 371; Eberl et al., 2018, p. 210; Jin, 2024, p. 1).

Agenda-setting effect. Some found that a higher issue salience predicts more anti-immigrant sentiment, which supports the agenda-setting effect (T. L. Dixon, 2008, p. 106; Dunaway et al., 2010, p. 359; Eberl et al., 2017, p. 1125). Issue salience was also shown to increase support for right-wing parties (Boomgaarden & Vliegenthart, 2007, p. 404) and violence against immigrants (Burscher et al., 2015, p. 59; Eberl et al., 2018, p. 210).

Priming effect. Regarding the priming effect, Domke (2001) conducted an experiment analyzing the media discourse of crime and found that if there is information about racial and ethnic groups, it is used to make political judgments (Domke, 2001, p. 772). Besides textual cues, pictures in the news were also shown to have a priming effect. A picture involving POCs leads to an overestimation of how many POCs are affected by the issue described in the news (Abraham & Appiah, 2006, p. 183). Similarly, Dixon (2006) found that when racially prejudiced people are exposed to news where criminal suspects are identified as black, as opposed to no race being specified, they are more likely to support the death penalty. Although stereotypical thinking was already in place, the media coverage activated these stereotypes for the political decision at hand (T. L. Dixon, 2006, p. 162).

Extremizing effect. This finding not only supports the priming hypothesis but also the reinforcing-spirals model. The increase in stereotypical thinking was solely observed for already biased people, but not for those without bias (T. L. Dixon, 2006, p. 162). People did not change their opinion, but their attitudes were reinforced. This effect is supported by other studies (Druckman et al., 2013, p. 57; Knoll et al., 2011, p. 433; Lahav & Courtemanche, 2012, p. 477; Merolla et al., 2013, p. 322; Schneider-Strawczynski & Valette, 2023, p. 1).

Sniderman et al. (2004), however, found that the quantity of negative media coverage of immigrants also changes people's minds. It led to anti-immigrant sentiment in people who previously did not hold conservative opinions (Sniderman et al., 2004, p. 35).

Framing effect. Speaking against the agenda-setting effect, more representation of immigrants in the media as actors coincides with less concern for immigration (Boomgaarden & Vliegenthart, 2009, p. 535). This led to the assumption that it is less about the amount of coverage, but about how immigration is framed and if immigrants appear as media objects, or are actively producing media (Eberl et al., 2018, pp. 210–211).

Boomgarden and de Vreese (2007) analyzing attitude changes following terrorist attacks, found that, although an attack led to anti-immigrant and anti-Islamic attitudes, the media played a significant role in shaping public opinion in the aftermath of an attack. Showing Arab Americans in the media actually improved the opinion towards Muslim people in the US after 9/11 (Boomgaarden & Vreese, 2007, p. 362; Nacos & Torres-Reyna, 2004, p. 255). Schemer (2014) argued that because the media coverage of ethnic minorities is overwhelmingly negative – they are disproportionately often portrayed as poor, disruptive, and criminal (Arendt, 2010, p. 147; Jacobs, 2017, p. 809) – a higher media salience comes with more anti-immigrant attitudes. This is not because of the issue salience, but because the issue is negatively framed, and these frames get repeated over and over (McLaren et al., 2018, 173; Schemer, 2014, p. 531).

Several experimental studies found evidence for the framing hypothesis. They constructed multiple news reports with different frames, exposed their respondents to one of these frames at random, and analyzed their attitudes towards immigrants or some kind of racial or religious outgroup. They found that the respondents differed in their attitudes according to how their stories were framed (Abrajano et al., 2017, p. 5; Brader et al., 2008, p. 959; Cho et al., 2006, p. 136; Domke et al., 1999, p. 570; Hjorth, 2016, p. 3; Richardson, 2005, p. 503).

Erhard et al. (2022) even used SOEP data to measure immigration attitudes from 2001 to 2016. They categorized the media coverage on immigration in Germany into different subcategories or frames and measured the salience of each frame. The authors found that negative frames (e.g., domestic violence) increased immigration concern, whereas positive frames (e.g., scientific studies or soccer) decreased concern (Erhard et al., 2022, p. 629).

Media effects in Germany. Germany is an interesting place to analyze media effects on immigration attitudes because a previous study found that the German political and historical context dampens the effect. Jin (2024) found that politicians and media outlets were more unified on their interpretation and stance regarding immigration around the *refugee crisis* of 2015/2016 and the European election of 2019 than in the United Kingdom (UK). She explained that the dominance of a *welcome culture* prevented the rise of anti-immigrant sentiment. Higher media salience of immigration, then, only led to greater awareness of the issue without increasing prejudice (Jin, 2024, p. 1).

Media salience of immigration in Germany. Maurer et al. (2023) assessed the media salience of refugees in Germany from May 2015 until December 2020 (Maurer et al., 2023). I analyzed the same time frame.

The authors covered six leading German news media outlets, including three newspapers (i.e., *Frankfurter Allgemeine Zeitung* (FAZ), *Süddeutsche Zeitung* (SZ), and *Bild*), as well as three news programmes (i.e., *ARD Tagesschau*, *ZDF heute*, and *RTL Aktuell*). The selection includes different genres with different lines of argument, large audiences, and influence on other smaller news outlets (Maurer et al., 2023, pp. 21–22).

The study's time frame includes several phases of immigration. May 2015 was the start of the *refugee crisis*, with many immigrants coming to Germany. There were times of controversial political debates and decisions about immigration, for example, the agreement between the 2016 EU and Turkey on the readmission of persons residing without authorization, and the Coalition dispute over accelerated transit procedures in 2018. There were public crimes and terrorist attacks where refugees were involved, such as the sexual assaults in Cologne during New Year's Eve 2016 or the attack on the Berlin Christmas market 2016. There were also times when nothing concerning immigration politics happened (Maurer et al., 2023, p. 21).

Figure 1 depicts how many reports were done on refugees per month by the observed outlets. It shows how the salience of the refugee topic changed over the years and that it might explain changes in individuals' refugee attitudes.

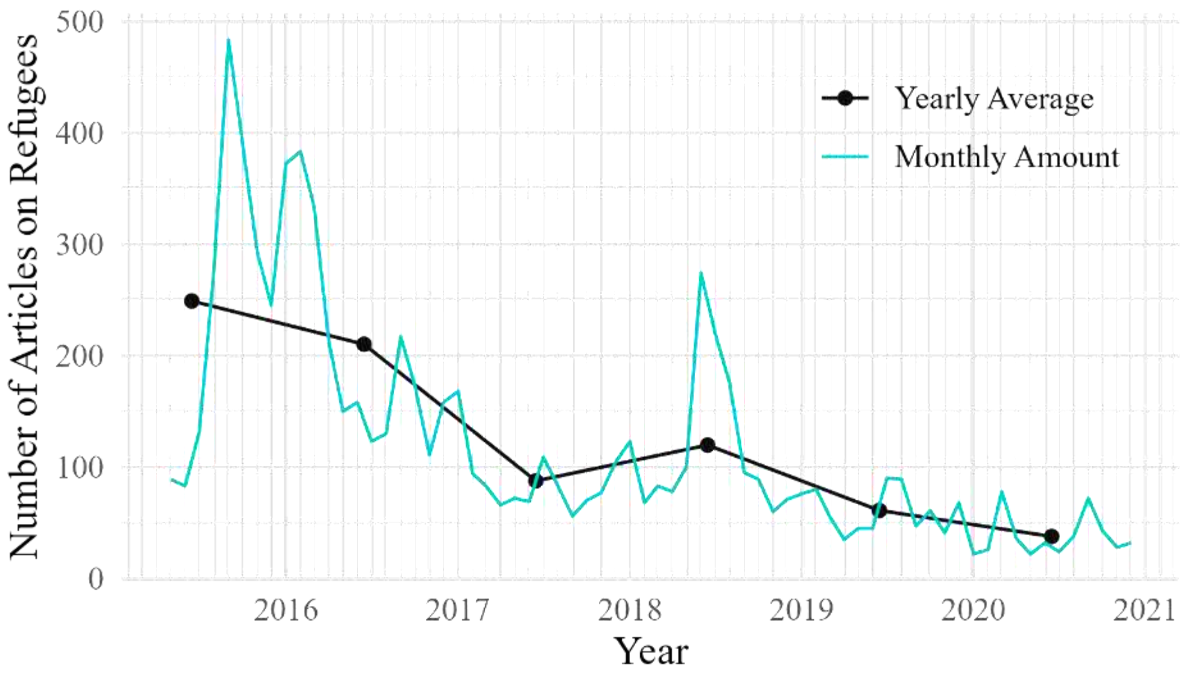

Figure 1: Number of articles on refugees from 2015 to 2020 (N = 8185). Results of a content analysis by Maurer et al. (2023), own depiction.

2.2.4 The interaction of different-level effects: Politicized Places hypothesis

The Politicized Places hypothesis incorporates national media salience and regional immigrant demographics into one theory. It was developed by Hopkins in 2010 and states that "when communities are undergoing sudden demographic changes at the same time that salient national rhetoric politicizes immigration, immigrants can quickly become the targets of local political hostility" (Hopkins, 2010, p. 40). In other words, the change in shares of immigrants is only perceivable and perceivable as a threat if the topic of immigration is nationally salient. According to the theory, the discussion of immigration in the national media leads people to notice demographic changes and to frame these changes as a political issue. Subsequently, it is more probable that people will develop anti-immigrant attitudes (Hopkins, 2010, pp. 40–41).

Politicized Places effect. Hopkins (2010) tested the Politicized Places hypothesis and found evidence to support his theory for the US and the UK (Hopkins, 2010). In the US from 1992 to 2009, Hopkins found that when the national salience of immigration was low, immigration attitudes differed barely between people living in demographically changing compared to non-changing communities. However, during high national salience, the share of people wanting to reduce immigration was 10 percentage points higher in changing counties (Hopkins, 2010, p. 48). In the UK, Hopkins detected different regional effects for the data collected before the general election in England and Wales, where the topic of immigration was extensively used in the political campaigns, compared to the data collected after the election (Hopkins, 2011, p. 515). Whereas the change in the share of immigrants had close to no effect on immigration attitudes pre-election, the predictor became statistically significant post-election (Hopkins, 2011, pp. 518–520).

Interaction effects. Several other studies examined potential interaction effects between regional immigration levels and the salience of the immigration issue. Jones and Martin (2017) found that people from different US states reacted differently to electoral candidates referencing immigration in their 2010 political campaign. In states that experienced a sudden increase in the Hispanic population, immigration cues by the candidates led to more restrictionist views in the population. However, in states that faced no drastic demographic changes, there was no effect of immigration cues (Jones & Martin, 2017, p. 177).

Czymara and Dochow (2018) analyzed the media salience effect for Germany and used SOEP data to measure individual attitudes towards immigration. They took yearly estimates of salience and attitudes covering the time frame of 2001 to 2015. The authors found a statistically significant positive effect of media salience: When the migration topic was salient, the probability of being very concerned about immigration rose by 13 percentage points compared to times of low salience. The effect was more pronounced for people living in a district with a small share of ethnic minorities (Czymara & Dochow, 2018, p. 381).

Schlueter and Davidov (2013) collected news reports and demographic data for Spain from 1996 to 2007. They showed that the quantity of negative reports on immigration increased anti-immigrant sentiment. The strength of the effect depended on the region. In places with a large immigrant population, the effect of media salience was weakened, whereas in places with a small immigrant group size, the effect was pronounced (Schlueter & Davidov, 2013, p. 179). These findings do not directly align with the Politicized Places hypothesis. Both studies suggest that there is a media salience effect, but no effect of the regional immigrant population, not even under certain circumstances of media coverage.

Boomgaarden and Vliegenthart (2009) analyzed the interaction between media and demographic context effects in Germany as well. Alone, the quantity of immigration news had a small positive effect on the perception of immigration as a problem. That changed when the number of asylum applications was considered. In times of many asylum seekers, the media effects became stronger (Boomgaarden & Vliegenthart, 2009, pp. 534–536). This finding supports the proposed interaction of media and demographic effects and the Politicized Places hypothesis. Higher issue salience led to more anti-immigrant sentiment, especially when there were many recent immigrants.

In **summary**, as in the preceding chapters on previous research, findings are mixed. This may be unsatisfying, but it highlights the need to represent apparently complex attitude-building processes in analytical models. Many variables are assumed to predict individual immigrant attitudes. Dissecting if, how, and under which conditions their effect becomes statistically significant is an important task for each analysis.

2.3 The present research: Research question and Hypotheses

Specific immigrant group. This analysis aimed to identify predictors of negative immigration attitudes, more specifically, negative attitudes towards refugees. As was established at the beginning of this chapter, different types of immigrants get different reactions from longstanding residents (Pichl, 2023, p. 516). Some of the studies described also found that anti-immigration attitudes were based more on racist beliefs than on aversion against immigration as a concept (Ceobanu & Escandell, 2010, p. 313).

Analyzing negative refugee attitudes of Germans and thereby focusing on a specific immigrant group that tends to be culturally and ethnically different from what is considered typically German, allows for a clearer understanding of who these attitudes are about. It also means that my analysis can capture possible cultural group-threat effects. For longstanding residents to feel their cultural identity threatened, there must be some form of cultural difference between the ingroup and the outgroup. This is a given with refugees in the years of analysis, not with immigrants in general.

Time frame. The years included in the analysis were 2016, 2018, and 2020 because survey data on refugee attitudes were available for these years. The findings, however, should be generalizable to other periods. During these survey years, the national context regarding immigration changed repeatedly with varying levels of media salience, differing immigration legislation, and crimes with refugee involvement. The time-varying societal context of the refugee topic means that the results can show which factors are stable predictors of negative refugee attitudes and which only become relevant at certain times. Then, these differing contextual factors concerning immigration, for example, the media salience of the refugee topic in Germany, could be starting points to explain why relationships are unstable over time.

Germany. The present research focused on Germany. Much research on refugee attitudes still needs to be done for the country: Over 60% of studies on immigration attitudes were done on US citizens. About 30% of studies were situated in Europe, and the majority of these studies analyzed the UK (Dinesen & Hjorth, 2024, p. 361). Focusing on Germany improves immigration attitude research.

Another advantage of the object of analysis is that, in Germany, detailed regional data were available. One problem with analyzing regional effects on individual characteristics is that the regional units must be relatively small to affect individuals in these units. A critique of many studies on the impact of regional immigrant demographics on individual immigration attitudes is that they compared large regions, such as countries or states. However, due to the segregated living situation of immigrants and longstanding residents, the national immigrant population is invisible to longstanding residents. I increased the probability of perceiving refugee population levels by using German counties.

Regional refugee demographics. As described regarding previous research, although most immigration-attitude studies assumed that longstanding residents feel somehow threatened by immigrants, the factors that were assumed to induce threat and how they were tested were very different. In this analysis, I incorporated various indicators of different analytical levels to separate the effects of these variables. The main variables of interest were the regional-level refugee demographics. It was mentioned earlier that opinions on immigrants and immigration have changed over the last 20 years. Individual characteristics, especially those assumed to be predictive of anti-immigrant sentiment, were mostly stable. The distribution of gender in Germany, for example, did not change in the last 20 years; therefore, how could it explain the change in attitudes?

Regional refugee demographics did change, and they have been a big part of the political debate, especially since the *refugee crisis* of 2015/2016. Thus, it is probable that local refugee populations predict people's individual refugee attitudes.

Research question and hypotheses. In other words, this analysis aimed to answer the research question *of whether and how regional levels and changes of refugee demographics affect individuals' attitudes towards refugees in Germany*. According to the group-threat theory, higher levels of refugee populations correspond to more visibility of refugees and more possibilities for people to feel threatened. I expected that:

> H1: *There is a positive relationship between the regional share of refugees and negative attitudes towards refugees.*

Furthermore, I assumed that regional demographic changes are more perceivable than the number of refugees living within a region. Accordingly, not necessarily higher shares of refugees in the population lead to more anti-refugee sentiment. Rather, great increases in the share of refugees compared to previous years predict negative refugee attitudes:

> H2: *There is a positive relationship between the regional change in the share of refugees and negative attitudes towards refugees.*

3 Methods

The hypotheses described above incorporate two levels of data: individual and regional. The analysis also incorporated two data sources, which are described below. They each provided information for the variables of the analysis. This chapter explains the process of operationalizing and integrating the datasets. I present the resulting structure and characteristics of the sample. Moreover, I explain the analytical strategy of this linear multi-level regression analysis and describe the longitudinal and cross-sectional models estimated.

3.1 Data

SOEP. I took personal data on attitudes towards refugees and immigration, as well as demographic and socioeconomic information from the first data source, the SOEP (Goebel et al., 2023). The SOEP is a longitudinal study. It was initiated in 1984 and has been conducted every year since then. The survey is based at the German Institute for Economic Research (DIW) and funded by the Federal Ministry of Education and Research (BMBF) (Antoni et al., 2023, p. 7; Rathje & Glemser, 2021, p. 6).

The SOEP carries individual and household-level data. The respondents of the individual and household questionnaires are at least 18 years old. There is, however, a youth questionnaire for adolescents of a SOEP household turning 17 during the survey year. Besides, data on children living in a household were obtained via their guardians (Goebel et al., 2019). About 15,000 households and 30,000 individuals living in Germany belong to the survey. The SOEP covers a broad range of topics, such as demographic and socioeconomic attributes, as well as personality and values, for example, well-being, the Big Five model, or political and social attitudes (Goebel et al., 2019, p. 346).

It is a representative study of Germany's resident population. The representation is ensured by the recurring addition of samples to account for panel attrition or to mirror certain influxes to the target population. Besides, immigrants are oversampled to allow analyses on these subpopulations (Goebel et al., 2019, p. 347; Siegers et al., 2022, p. 7).

Generally, the SOEP uses random probability samples, specifically a two-stage stratified sampling procedure. In the first step, sample points were drawn based on federal state and county size. In the second step, households were chosen in each sample point with the random walk procedure (Goebel et al., 2019, p. 348). Due to this sampling procedure with known selection probabilities, design weights were developed and can be used to estimate population characteristics (Goebel et al., 2019, pp. 348–349; Siegers et al., 2022, p. 7).

INKAR. The second data source is a survey of regions in Germany in the subdivision at different regional levels. The INKAR by the BBSR (2024b) includes several indicators that depict a region's educational, demographic, economic, and ecological characteristics. It is longitudinal, as is the SOEP, and thus, can measure differences between regions and also developments within regions over time (BBSR, 2024b). For this analysis, county-level indicators were used.

On the county level, the INKAR captures data for over 400 different regions in Germany. These regions are districts (*Landkreise*) or cities (*kreisfreie Städte*) with at least 100,000 residents. Smaller municipalities under 100,000 residents were integrated with their assigned district into another region-category (*Kreisregion*) (BBSR, 2024a). In the following, these different types of regions are summarized under the term counties and referred to as regions or municipalities. Figure 2 depicts each county within its borders in Germany, illustrating the level of detail of this analysis. The counties are much smaller compared to, for example, federal states, which means the possibility of regional effects on individuals is higher, because the possibility of contact between refugees and non-refugees is higher when smaller regions are used (Dinesen & Hjorth, 2024, p. 369; Dinesen & Sønderskov, 2015, p. 550; Pottie-Sherman & Wilkes, 2017, p. 236).

Figure 2: Map of German counties within borders ($n_{counties}$ = 404), based on INKAR data, own depiction.

The individual data of the SOEP is connected to the regional INKAR data on the county level. Both SOEP and INKAR use the same county codes that allow the merging of these datasets.

3.2 Sample

The target population was people who lived in a German county and had not been refugees in 2015 or after. Because Germany was the object of this analysis, only attitudes of those in Germany were of note. People with a migration background were not excluded from the analysis. Though their attitudes towards immigration and refugees might differ from those of people without a migration background, they were still part of the German population. Thus, their attitudes were of interest here as well.

Due to the data available, this analysis was restricted to attitudes of adults, as is the case for most research in the social sciences (Kratzer & Cwielong, 2014, p. 185; Richter, 1997, p. 95). Relationships may be different for children.

As was mentioned before, data for the outcome were only available for 2016, 2018, and 2020. Besides, cases with invalid data for any observed variables were excluded. After removing data according to these restrictions, 61,444 observations from 30,266 individuals in 398 counties were left for analysis. The sample had an overall unweighted average age of 50.63 years (SD = 16.90) and a roughly balanced gender distribution ($\%_{Men}$ = 46).

3.3 Variables

To test the hypotheses, the SOEP and the INKAR were used to construct several individual- and regional-level variables, which were predictors of immigration attitudes in previous studies. They were formed based on the SOEP Scales Manual (Entringer et al., 2022) and previous papers using the same variables (Gihleb et al., 2022). Besides, Cronbach's α (Cronbach, 1951) was used to measure the internal consistency of constructed scales. This chapter explains how variables were formed and gives descriptive information about these variables.

The summary weights from the SOEP were used for descriptive statistics. At the end of the chapter, Table 2 presents the weighted descriptive statistics with mean, standard deviation, and proportions for each survey year and overall.

Before regression analyses, the numeric predictors were centered near their grand mean to permit interpretation of the intercept and z-score standardized (i.e., scaled by the standard deviation) to render coefficients comparable (Hoffman, 2015, p. 289). The grand mean is unweighted and thus differs slightly from the averages in the summary table. Centering at or near the grand mean is standard practice because it enables interpreting the intercept and the main effects, where most data points are (Hoffman, 2015, pp. 43–44). Furthermore, in hierarchical linear mixed-effects models as were estimated here, grand-mean-centering is preferred to group-mean-centering if one wants to focus on the within-person variance rather than between-person variance (Hoffman, 2015, p. 385). As my main interest was the change in attitudes due to the change in refugee demographics, I focused on within-person variance.

3.3.1 Response Variable: Attitudes towards refugees

The SOEP provides information on several individual values and attitudes. To estimate attitudes towards refugees, respondents were asked five questions in 2016, 2018, and 2020 covering various proposed short- and long-term consequences of refugees immigrating to Germany. Therewhile, the topic was framed as controversial to counteract the effects of social desirability on response patterns (SOEP Group, 2019, p. 56).

Interviewers asked respondents to rate each item on a scale from 1 to 11, with low values indicating negative attitudes towards refugees and high values indicating positive attitudes towards refugees. The questions translated from the original German to English were: (1) "Is it generally good or bad for the German economy that refugees are coming here?" (1 = bad for the economy, 11 = good for the economy), (2) "Will refugees erode or enrich cultural life in Germany?" (1 = erode, 11 = enrich), (3) "Will Germany become a better or worse place to live because of the refugees?" (1 = a worse place, 11 = a better place), (4) "Does a large influx of refugees mean more risks or more opportunities in the short term?" (1 = more risks in the short term, 11 = more opportunities in the short term), (5) "Does a large influx of refugees mean more risks or more opportunities in the long term?" (1 = more risks in the long term, 11 = more opportunities in the long term) (SOEP Group, 2019, p. 56).

The items were recoded so that larger values represented more negative attitudes towards refugees. After that, they were combined into an average score of attitudes towards refugees on a scale from 1 (positive attitudes) to 11 (negative attitudes) per individual and year. Overall weighted mean was 6.79 (*SD* = 2.18). The internal consistency of the scale was very high with Cronbach's $\alpha = 0.91$. Solely, dropping item (4) would have increased α. The increase, however, would have been marginal, and consistency was already very high. Thus, the scale was kept as is.

Figure 3 shows how the average attitudes towards refugees changed over time.

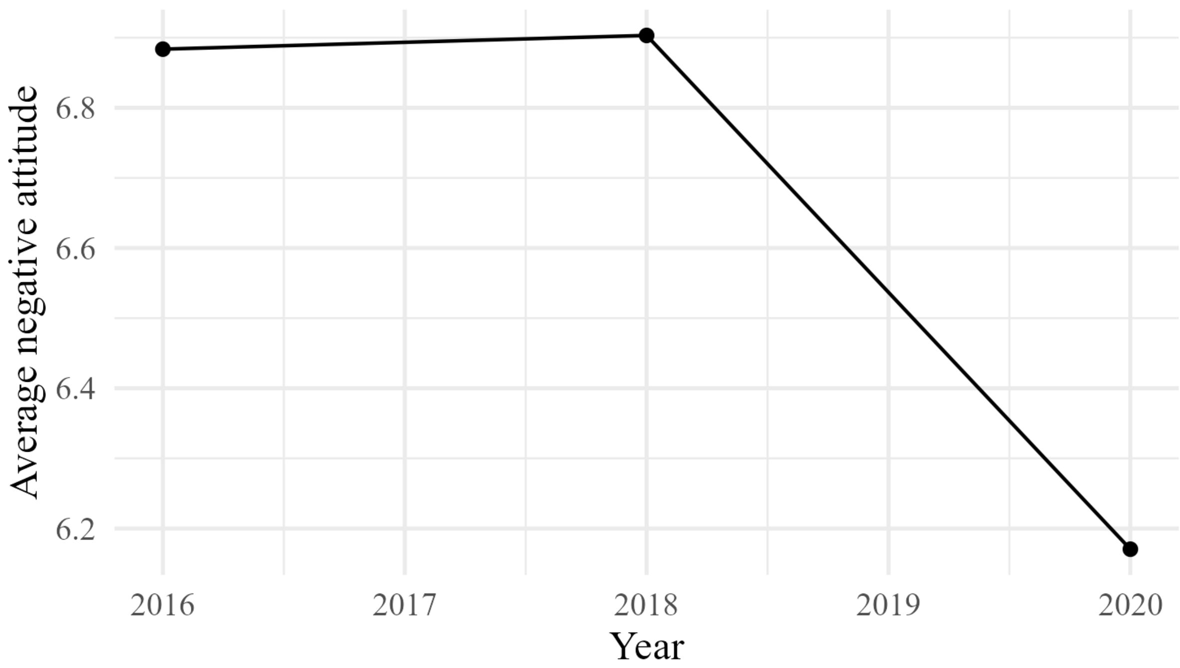

Figure 3: Average attitudes towards refugees per year (N = 30,266; n_{obs} = 61,444; $n_{counties}$ = 398).

Instead of attitudes towards refugees, it would have been possible to analyze attitudes towards immigrants or immigration more generally. The SOEP estimates individual attitudes towards immigration with one question, asking whether people are concerned about immigration to Germany. The response categories are 1 = very concerned, 2 = somewhat concerned, and 3 = not concerned at all (SOEP Group, 2019, p. 55). Those categories are usually recoded into a dummy variable that indicates whether people were very concerned about immigration or not (Gihleb et al., 2022, p. 9). Though the main analyses were done on attitudes towards refugees, this variable was used in a robust analysis to check if similar effects are present for attitudes towards immigration (see Appendix Tables A6 to A8).

3.3.2 Main predictors: Regional refugee demographics

I needed to consider a few things to test the effect of regional immigration demographics on individual attitudes towards refugees. Previous findings affirmed that people react differently to immigration depending on the ethnic and cultural background of these immigrants (Pichl, 2023, p. 516). Thus, regional immigration was measured in a way to explicitly estimate immigrant groups that presumably face the most discrimination, non-Western refugees.

Benefits for asylum seekers. Data for regional immigration was taken from the INKAR database, which tracks the share of people receiving basic social security benefits based on the

Asylum Act. For each county, the variable entails the number of officially recognized asylum seekers per 1000 citizens each year (BBSR, 2024c).

Methodological concerns with benefits for asylum seekers. Having used benefits for asylum seekers as an indicator for refugee demographics excluded any form of 'voluntary' immigration, meaning immigration not motivated by fear of persecution in the country of origin. It especially excluded immigration by fellow Europeans or US Americans who presumably share more cultural values and behaviors with Germans than non-Western immigrants.

By using benefits for asylum seekers, however, I also excluded Western immigrants who are subjected to discrimination based on their ethnic background. Moreover, I did not account for demographic effects beyond international immigration. Racist and nationalist people might develop more negative attitudes towards refugees and immigrants in response to Germans moving to the neighborhood that they consider part of the outgroup (e.g., POCs).

Nonetheless, the measure better captured the number of refugees targeted by discrimination and, therefore, might have predicted negative attitudes towards refugees more accurately than regional shares of foreigners, for example.

Another advantage of estimating immigration demographics as regional benefits for asylum seekers is that it entails an economic dimension. The material self-interest hypothesis states that residents feel threatened by immigration because they expect material negative consequences for themselves, for example, due to tax money being spent on immigrants. The variable measures the amount of money that was spent on the social security of people seeking asylum. Thus, according to the material self-interest hypothesis, it should affect attitudes towards refugees negatively.

It also seems reasonable to predict attitudes towards refugees with the number of refugees, not immigrants in general. Previous research stated, however, that people hold anti-immigrant sentiment also against non-immigrants. It is interesting to analyze how much of the negative refugee attitudes can be connected to the refugees.

Two regional predictors. Furthermore, previous findings highlighted the importance of regional changes in immigration shares rather than the shares themselves. To make separate interpretations of these effects possible, immigrant demographics were estimated in two ways: the regional share of asylum seekers and the regional change in the share of asylum seekers since the year before.

Share of asylum seekers. This variable was taken from the INKAR database as is. The overall weighted average was 5.93 (SD = 3.19) asylum seekers per 1000 citizens within a county. Preceding the analysis with linear mixed-effects regression models, the variable was centered near the grand mean at 6.00 asylum seekers per 1000 citizens and z-score standardized.

Figure 4 depicts the share of asylum seekers per county and year. Darker areas reflect higher shares of asylum seekers. The grey areas represent counties without available data on asylum seekers. These counties could not have been included in the analysis. This exclusion would have biased the results if these areas shared certain characteristics that influence associations between regional immigrant demographics and attitudes towards refugees. The areas excluded, however, were spread throughout Germany, meaning that there were data on counties in all federal states. This indicates that there was no systematic exclusion.

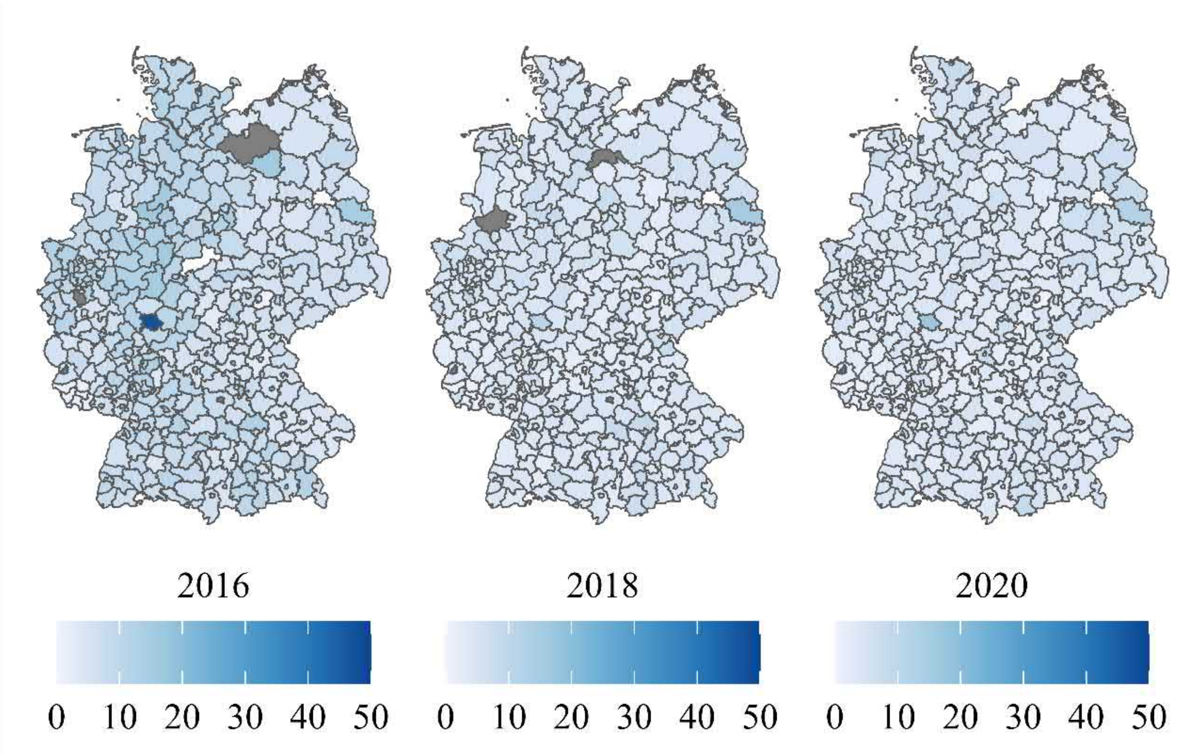

Figure 4: County-level share of asylum seekers of the final sample in 2016 ($n_{counties}$ = 394), 2018 ($n_{counties}$ = 396), and 2020 ($n_{counties}$ = 398).

Change in share of asylum seekers. The change in the share of asylum seekers was operationalized as the difference between the share of asylum seekers in the current year and the share in the previous year. Overall, the weighted average change was −1.71 (SD = 12.87) asylum seekers per 1000 citizens within a county since the previous year. The variable was standardized and recentered at 0.00 before regression analyses. The center was kept at 0.00, because it was near the grand mean and easily interpretable in the context of this variable: no change since the year before.

Figure 5 depicts the changes in the share of asylum seekers per county and year.

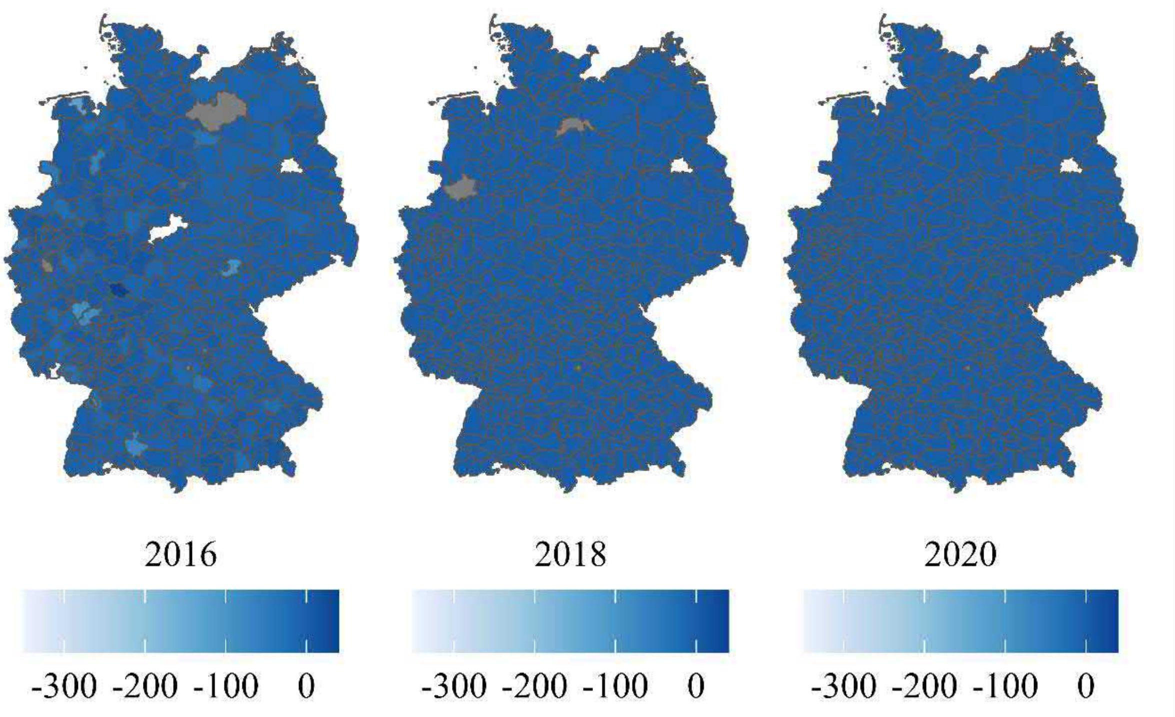

Figure 5: County-level change in share of asylum seekers since the year before of the final sample in 2016 ($n_{counties}$ = 394), 2018 ($n_{counties}$ = 396), and 2020 ($n_{counties}$ = 398).

3.3.3 Covariates

Other possible predictors were included in the analysis to test the effect of regional refugee demographics on individual refugee attitudes rigorously. Therby, I can differentiate between different effects, and do not falsely attribute explanatory power to regional predictors.

Besides standard covariates, such as gender and age, variables that were found to be predictive of refugee attitudes by previous research were included as well. Education and income are classic indicators of someone's level of material threat used to test the labor market competition hypothesis. One's migration background has been shown to influence one's immigration attitudes. Also, whether someone had been socialized in East or West Germany was important to consider while analyzing Germany. Furthermore, this variable reflects different cultural environments, which could affect a person's refugee attitude.

Excluded variables. Other indicators of someone's feeling of cultural threat, such as ethnocentrism or social dominance orientation, were not part of the SOEP data and thus could not be incorporated in the analysis. Those exclusions could limit findings. The way the outcome was estimated, however, entailed various discriminatory beliefs, meaning that even if the inclusion of cultural threat measures had been possible, it would not have been appropriate without inferring a tautological explanation. One should refrain from explaining discriminatory beliefs about immigrants with discriminatory beliefs about immigrants.

Furthermore, personality and religiosity, even though part of the SOEP, were not included in the analysis. Both variables were gathered at irregular intervals and were not available for every year analyzed here (Entringer et al., 2022, p. 44). I would have had to impute estimates. This would have entailed the assumption of stability of these characteristics over time and possibly introduced bias. For those reasons, I decided not to include these factors.

Included variables. The included covariates were formed as follows:

Men. The gender of each individual was taken from the SOEP and operationalized as a dummy variable with 1 = men and 0 = women. 49% (weighted proportion) of the final sample were men.

Age. The age in years for each individual and year was computed as the difference between the person's birth year and the current survey year, both provided by the SOEP. The overall weighted mean age was 53.07 years (*SD* = 17.92 years). Before the analyses, age was centered near the grand mean at 53.00 years and standardized.

Education. The amount of education was measured in the number of years for each individual and year. This variable was provided by the SOEP. They equated an individual's highest school-leaving qualification with a certain number of years (e.g., a high school degree with 13.00 years) and added years for vocational training done (e.g., 1.50 years for an apprenticeship). The overall weighted mean amount of education was 12.23 years (*SD* = 2.65 years). Education was centered near the grand mean at 13.00 years and standardized.

Adjusted Household Income. The income was measured as the adjusted household income in Euros for each individual and year. It was computed by taking the household net income from the SOEP data and dividing it by the square root of the household size. This accounted for the fact that households keep house together. Thus, one's actual individual income is less important than one's household income, and household size matters, though not strictly proportionally (Taylor et al., 2011, p. 37). The overall weighted mean adjusted household income was 2,135.58 € (*SD* = 1,356.12 €). Income was centered near the grand mean at 2,300 € and standardized.

East. The socialization of individuals was taken from the SOEP and operationalized as a dummy variable with 1 = East Germany and 0 = West Germany. 17% (weighted proportion) of the final sample were socialized in East Germany.

Rurality. For this dummy variable, the environment of one's household was categorized as 1 = rural or 0 = urban. The categorization was taken from the SOEP. 34% (weighted proportion) of the final sample lived in a rural area.

Migration Background. One's migration background provided by the SOEP was categorized as a dummy with 0 = no migration background or 1 = migration background. 20% (weighted proportion) of the final sample had a migration background.

Gross domestic product. Besides the individual control variables, the GDP in thousand Euros (€) per county and year was incorporated into analyses as well. The variable was provided by the INKAR database. The overall weighted mean GDP was 16,996,731.54 thousand Euros (*SD* = 25,309,048.83 thousand Euros). The GDP was centered near the grand mean at 14,000,000,000.00 € and standardized.

Figure 6 depicts the GDP in billion Euros per county and year of the final sample.

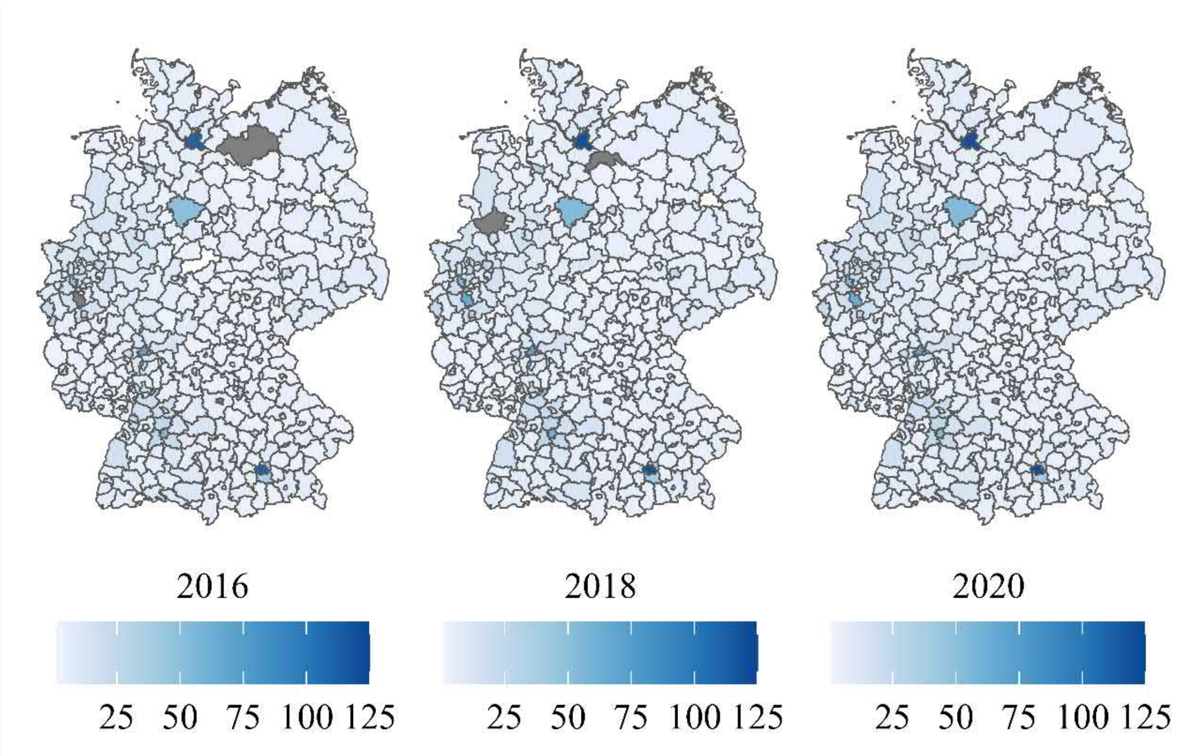

Figure 6: County-level GDP in billion Euros of the final sample in 2016 ($n_{counties}$ = 394), 2018 ($n_{counties}$ = 396), and 2020 ($n_{counties}$ = 398).

Table 2

Weighted share (in %), mean, and standard deviation of the final sample overall and separately for each survey year.

Variable	Overall	2016	2018	2020
	(N = 30,266; n_{obs} = 61,444; $n_{counties}$ = 398)	(N = n_{obs} = 19,846; $n_{counties}$ = 394)	(N = n_{obs} = 21,033; $n_{counties}$ = 396)	(N = n_{obs} = 20,565; $n_{counties}$ = 398)
Attitudes towards Refugees (1.00-11.00)	6.79 (2.18)	6.95 (2.15)	7.00 (2.18)	6.41 (2.17)
Men (ref. Women)	48.86%	49.02%	48.76%	48.81%
East Germany (ref. West)	17.12%	17.20%	17.08%	17.08%
Rural (ref. Urban)	34.12%	34.61%	33.79%	33.95%
Migration Background (ref. None)	19.92%	20.16%	20.62%	18.97%
Age (18.00-103.00)	53.07 (17.92)	52.64 (17.83)	53.14 (17.97)	53.43 (17.95)
Education (7.00-18.00)	12.23 (2.65)	12.13 (2.63)	12.22 (2.65)	12.33 (2.67)
Adj. Household Income (0.00-141,421.36)	2,135.58 (1,356.12)	1,997.21 (1,184.07)	2,129.51 (1,217.80)	2,281.62 (1,613.46)
Gross Domestic Product (1,125,179.00-120,757,272.00)	16,996,731.54 (25,309,048.83)	15,869,763.10 (23,884,952.27)	17,350,317.79 (25,680,017.30)	17,775,241.18 (26,270,031.55)
Share Asylum Seekers (0.05-47.53)	5.93 (3.19)	8.54 (3.73)	4.81 (1.81)	4.44 (1.75)
Change Asylum Seekers (-342.41-39.68)	−1.71 (12.87)	−4.39 (22.00)	−0.72 (1.13)	0.00 (0.80)

Note: Range is in brackets after the name of the variable. For dummy variables, the reference category is specified. Proportions are reported for nominal variables. Mean and standard deviation in brackets are given for numeric variables.

Correlations. For the bivariate analysis, zero-order correlations with Pearson's correlation coefficient *r* (Pearson, 1895) were calculated separately for each year of analysis. Correlation analyses were separated per year, because overall correlation estimates would have been biased. Time-invariant variables, such as Men and East Germany, would have been necessarily more highly correlated than time-varying variables due to repeated observations of the panel data. The results for 2016 are shown below (see Table 3).

Table 3

Zero-order Pearson correlations for 2016 (N = n_{obs} = 19,846; $n_{counties}$ = 394).

Variable	1	2	3	4	5	6	7	8	9	10
1. Attitudes towards Refugees										
2. Men (ref. Women)	.01 [−.00, .02]									
3. East Germany (ref. West)	.12** [.10, .13]	−.00 [−.01, .01]								
4. Rural (ref. Urban)	.09** [.08, .10]	.01 [−.01, .02]	.35** [.34, .36]							
5. Migration Background (ref. None)	.06** [.04, .07]	−.00 [−.02, .01]	−.21** [−.22, −.20]	−.14** [−.15, −.12]						
6. Age	−.00 [−.02, .01]	.03** [.01, .04]	.08** [.07, .09]	.04** [.02, .05]	−.29** [−.30, −.27]					
7. Education	−.29** [−.30, −.28]	.03** [.02, .05]	.05** [.03, .06]	−.07** [−.09, −.06]	−.26** [−.27, −.24]	.01* [.00, .03]				
8. Adj. Household Income	−.17** [−.18, −.16]	.05** [.03, .06]	−.12** [−.14, −.11]	−.11** [−.13, −.10]	−.15** [−.17, −.14]	.07** [.06, .09]	.42** [.40, .43]			
9. Gross Domestic Product	−.09** [−.11, −.08]	−.00 [−.02, .01]	−.19** [−.20, −.18]	−.35** [−.36, −.34]	.12** [.11, .13]	−.04** [−.05, −.03]	.09** [.07, .10]	.11** [.09, .12]		
10. Share Asylum Seekers	−.04** [−.06, −.03]	−.00 [−.01, .01]	−.31** [−.32, −.29]	−.21** [−.22, −.19]	.07** [.06, .09]	−.02** [−.04, −.01]	.00 [−.01, .02]	.02** [.01, .04]	.01 [−.01, .02]	
11. Change Asylum Seekers	−.00 [−.02, .01]	−.00 [−.01, .01]	−.08** [−.09, −.06]	−.09** [−.11, −.08]	.01 [−.01, .02]	−.01 [−.02, .01]	.03** [.02, .05]	.03** [.02, .05]	.15** [.13, .16]	.28** [.27, .30]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

For simplicity reasons, the correlation Tables for 2018 and 2020 are not part of the main text. But they can be seen in the Appendix Tables A2 and A3. The relationships between the individual characteristics did not vary across the years. At every point, education and income ($r \sim .34$) as well as living in a rural environment and East Germany ($r \sim .35$) were positively correlated. Moreover, having a migration background was negatively correlated with someone's age ($r \sim -.27$) and education ($r \sim -.26$) in every year observed.

There was some variation in correlations with time-varying regional variables. The regional share of asylum seekers was negatively correlated with living in rural areas ($r = -.21$), and in East Germany only in 2016 ($r = -.31$). A higher share coincided with a larger positive change in asylum seekers, but only in 2016 ($r = .28$) and 2020 ($r = .28$). The correlations of the regional variables varied specifically with someone's refugee attitude. This instability was reflected in the multivariate analysis.

3.4 Analytical Strategy

The analytical method of choice was a linear mixed-effects regression analysis with a random intercept for individuals nested in counties and fixed effects for the predictors mentioned above.

Mixed-effects model. Mixed-effects models usually estimate the fixed effects of proposed predictors of the outcome and the random effects of grouping variables. Due to the nested model structure, this was not just a mixed-effects model, but more precisely a multi-level model (Higdon, 2013, p. 1386). Mixed-effects analyses adhere to theories and hypotheses where relationships between different analytical levels are assumed. Many researchers uses mixed-effects models because many assume that individuals are influenced by the contexts they are in and the groups they belong to.

Multi-level model. Multi-level models are hierarchical as several data points are nested within groups at a higher analytical level. A common example is people nested in regional contexts (e.g., countries). Even though it is not very intuitive to think of individuals as groups, in longitudinal research, observations from different time points are also thought of as nested within individuals (Hox et al., 2017, p. 1). Here, both a classic grouping of individuals nested in counties and an unintuitive nesting of observations in individuals were present. Multi-level models were particularly suitable for this analysis, because, through this method, it was possible to dissect the effects of individual and regional predictors (Miehlke & Salheiser, 2022, p. 84).

Random intercepts. The random intercepts accounted for the multi-level data structure of observations, individuals, and counties. As there were multiple observations for each individual and multiple individuals per county, observations were grouped in individuals, which in turn were grouped in counties. The hierarchical data structure had, thus, three levels: observations on the first level, individuals on the second, and counties on the third. The data structure was captured by a hierarchical model. In longitudinal mixed-effects models, group memberships have to be constructed as either time-varying or invariant (Hoffman, 2015, p. 493). As most people did not change counties (i.e., 96% of the sample, including movers), membership was constructed as invariant. Thus, people were considered nested in counties. This, however, meant that people who moved had to be excluded from analysis. To test whether this exclusion was influential, a supplementary analysis was carried out where movers were included (see Appendix Tables A11 and A12).

Why no random slopes? In addition, I could have used random slopes. Whereas random intercepts allow the intercept to vary by group, random slopes make group-wise variation of the slope of the regression equation possible (Chung et al., 2013, p. 685). For example, in analyzing the relationship between education and income, one could include a random intercept for gender, assuming that the relationship is the same for men and women, but the level of education differs by gender. Accordingly, one could include a random slope for gender, assuming that, even if the level of education was the same for men and women, the effect of education on income differs.

Here, no random slopes for individuals or counties were introduced because the relationships were assumed to be the same for each individual and each county. Solely their starting points might have been different. As described earlier, it was hypothesized that higher regional shares and changes in refugees are related to more negative refugee attitudes. I did not expect the strength of the relationship to vary per county, but I knew the refugee demographics differed regionally. Therefore, the intercept was allowed to vary.

Besides, the random intercept for individuals was necessary due to the panel data. Someone's previous attitudes are strongly related to their future attitudes. But in the analysis, I need to distinguish between the effect of other variables and one's preceding attitudes. The panel data structure should not influence model estimates. Hence, a random intercept for individuals had to be incorporated. Even more, being able to differentiate between within- and between-person effects is an advantage of a longitudinal analysis such as this (Best & Vogel, 2022, p. 37).

Intraclass coefficient. To test whether a multi-level construction was necessary, the intraclass correlation coefficient (ICC) was calculated (Wenzelburger, 2014, p. 96). The ICC ranges from zero to one: Zero suggests that no variance can be attributed to the class structure in the data, and one indicates that all of the variance results from the differences between groups (Hoffman, 2015, p. 162).

Year. The main models were longitudinal, incorporating a year variable with three categories: 2016, 2018, and 2020. I operationalized time as a nominal, not a continuous variable, because I assumed that refugee attitudes do not change linearly over time. As described at the beginning, in Germany, there were periods of acceptance and aversion. Moreover, media effects and the politicized places hypothesis suggest that current events and reports affect individual attitudes, not that there is a general development in one specific direction. The nominal year variable allowed attitudes to vary across time without assuming linearity.

Longitudinal models. Models were built stepwise: First, (1) a null model with only the random intercept for individuals nested in counties and the fixed effect for the year variable was generated. This unconditional model built the baseline with which conditional models were compared to test the effect of included predictors. This stepwise process corresponds to standard practice (Hoffman, 2015, p. 509). Then, (2) the individual predictors – gender, age, education, income, socialization, rurality, and migration background – were introduced into the model. Finally, (3) regional-level predictors, refugee share and change, as well as GDP, were added to get the full model. The models can be described by these formulas:

(1) $Y_{jik} = \beta_0 + \beta_1 * Year2018 + \beta_2 * Year2020 + u_i + v_{ik} + \varepsilon_{jik}$

(2) $Y_{jik} = \beta_0 + \beta_1 * Year2018 + \beta_2 * Year2020 + \beta_3 * men_{jik} + \beta_4 * east_{jik} + \beta_5 * rural_{jik} + \beta_6 * migration_{jik} + \beta_7 * age_{jik} + \beta_8 * education_{jik} + \beta_9 * income_{jik} + u_i + v_{ik} + \varepsilon_{jik}$

(3) $Y_{jik} = \beta_0 + \beta_1 * Year2018 + \beta_2 * Year2020 + \beta_3 * men_{jik} + \beta_4 * east_{jik} + \beta_5 * rural_{jik} + \beta_6 * migration_{jik} + \beta_7 * age_{jik} + \beta_8 * education_{jik} + \beta_9 * income_{jik} + \beta_{10} * GDP_{jk} + \beta_{11} * share\_asylum_{jk} + \beta_{12} * change\_asylum_{jk} + u_k + v_{ik} + \varepsilon_{jik}$

where Y_{jik} stands for attitudes towards refugees of an individual i, in county k, and in year j. Random effects are specified by u_k for the counties and v_{ik} for individuals within counties. ε_{jik} refers to the unexplained residual variance. Comparing these models meant being able to see if more complicated models entailed a statistically significantly better explanation of refugee attitudes, which would retroactively justify using more predictors.

Cross-sectional models. In addition to the longitudinal models, cross-sectional full models were estimated for each year to better compare effects between years. Since they were cross-sectional, the year variable and the random intercept for individuals were not included.

In each model, there was only one year and one observation per individual. Thus, an inclusion would not have made sense. The cross-sectional models are described by these formulas:

(4) $Y_{2016ik} = \beta_0 + \beta_3 * men_{ik} + \beta_4 * east_{ik} + \beta_5 * rural_{ik} + \beta_6 * migration_{ik} + \beta_7 * age_{ik} + \beta_8 * education_{ik} + \beta_9 * income_{ik} + \beta_{10} * GDP_k + \beta_{11} * share\_asylum_k + \beta_{12} * change\_asylum_k + u_k + \varepsilon_{ik}$

(5) $Y_{2018ik} = \beta_0 + \beta_3 * men_{ik} + \beta_4 * east_{ik} + \beta_5 * rural_{ik} + \beta_6 * migration_{ik} + \beta_7 * age_{ik} + \beta_8 * education_{ik} + \beta_9 * income_{ik} + \beta_{10} * GDP_k + \beta_{11} * share\_asylum_k + \beta_{12} * change\_asylum_k + u_k + \varepsilon_{ik}$

(6) $Y_{2020ik} = \beta_0 + \beta_3 * men_{ik} + \beta_4 * east_{ik} + \beta_5 * rural_{ik} + \beta_6 * migration_{ik} + \beta_7 * age_{ik} + \beta_8 * education_{ik} + \beta_9 * income_{ik} + \beta_{10} * GDP_k + \beta_{11} * share\_asylum_k + \beta_{12} * change\_asylum_k + u_k + \varepsilon_{ik}$

For the full model and the yearly models, trimmed models are presented as well, where inconsequential and therefore unnecessary variables were excluded. This made the models less complicated and more fit to explain refugee attitudes.

Model estimates. The intercept, the random, and the fixed effects estimates were interpreted. The deviance *D* of each model was reported. Chi² tests were performed to compare different models. The goodness of model fit was estimated by the coefficient of determination (R^2). Both marginal and conditional R^2 were calculated. Marginal and conditional R^2 are two types of estimating the variance explained by a model. They were specifically designed for mixed-effects models. Marginal R^2 represents the variance explained by the fixed effects. Conditional R^2 represents the variance explained by both the fixed and the random effects (Nakagawa & Schielzeth, 2013, p. 136).

The model assumptions – normality, homogeneity, no influential observations, linearity, and no multicollinearity – of linear mixed-effects models were tested to ensure the interpretability of model estimates. The analyses were conducted in R version 4.4 (R Core Team, 2025)[1].

[1] R packages used to perform the analysis, most importantly tidyverse and haven, were conceptualised by Bates et al. (2015); Bates et al. (2025); Bolker and Robinson (2024); Csárdi et al. (2024); Fox and Weisberg (2019); Freedman Ellis and Schneider (2024); Gohel et al. (2024); Gohel and Skintzos (2024); Hartig (2024); E. Hughes (2024); J. Hughes and Beiner (2023); Iannone et al. (2024); Kuznetsova et al. (2017); Larmarange (2025); Long (2022); Lüdecke et al. (2021); Ooms (2014); Revelle (2024); Sjoberg et al. (2021); Thériault (2023); Wickham et al. (2019); Wickham et al. (2023); Wickham (2023); Zeileis and Hothorn (2002); Zhang (2024).

4 Results: Modelling attitudes towards refugees

The findings are reported in three steps: First, I describe how I tested linear mixed-effects regression model assumptions to confirm that the analytical strategy was appropriate. Second, I present estimates of the longitudinal linear mixed-effects regression models and quality criteria to compare models. Finally, to better compare the different years and identify stable and time-varying predictors of refugee attitudes, I contrast the cross-sectional linear mixed-effects regression models with each other. Besides, I highlight deviations from the full longitudinal model.

4.1 Compliance with model assumptions

Model assumptions were tested for the full model to ensure safe interpretability of all effects. Because of the multi-level structure of the analysis, residuals were inspected separately for the fixed and the random effects.

Normality. The histogram shows that the fixed effect residuals (level one) seemed to be normally distributed (see Figure 7). However, there were a lot of observations with very low residuals. This means that the model accurately predicted most observed values. Observations that were not predicted as accurately, however, became outliers directly. This was reflected by the large number of influential observations with more than 200 extreme outliers (z-score > 3.29 or z-score < −3.29). The absolute value of 3.29 for the z-score was taken as a threshold for extreme outliers, as many analysts do (Tabachnick & Fidell, 2019, pp. 63–66). Also, the large number of individuals (N = 30,266) might have increased the number of extreme values.

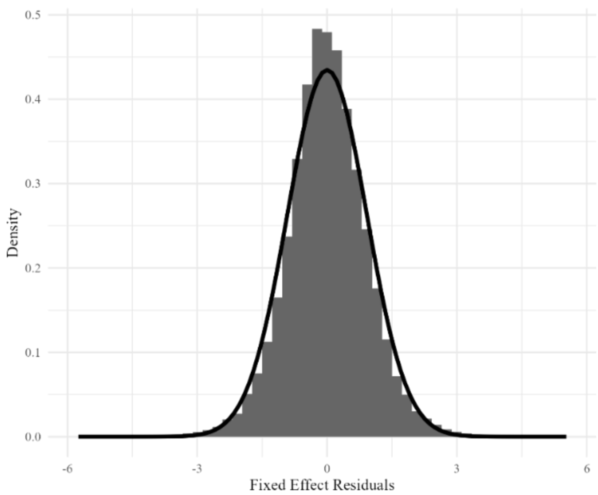

Figure 7: Histogram of fixed effect residuals of the full model.

Moving on to the random intercepts on level two, I observed similar distributions of effect residuals (see Figure 8). Random-intercept effect residuals for individuals within counties appeared to be normally distributed with a high concentration of residual values near zero. Although the effect residuals for the random intercept of counties did not look as close to normal as the fixed-effects residuals, the Shapiro-Wilk test (Shapiro & Wilkenson, 1965) for normality was statistically insignificant (p = 0.688). It did detect statistically significant deviations from normality for the fixed effect residuals and the effect residuals of the random intercept for individuals within counties, although their distributions looked more normal. Therefore, non-normality was no concern for the county's random intercept. The statistically significant normality tests of the other effect residuals were also of secondary concern. Such tests are usually statistically significant when the number of cases is large (Royall, 1986, p. 314). Thus, their significance here could be attributed to the number of individuals and observations, compared to the number of counties. The insignificance of the Shapiro-Wilk test was, thus, seen as an additional assurance of normality.

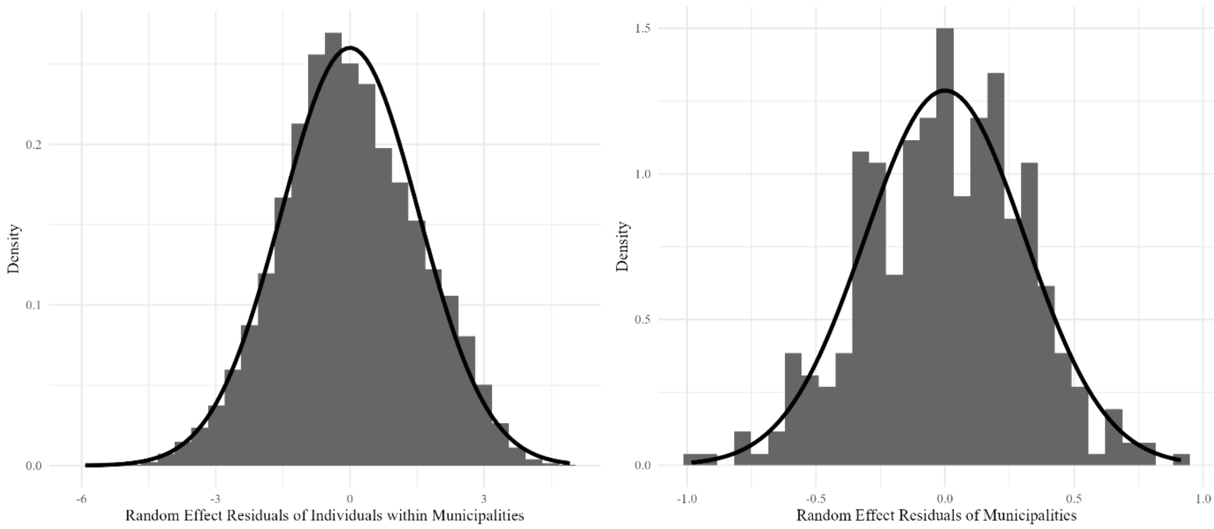

Figure 8: Histograms of random effect residuals of the full model.

Influential observations. Turning to influential observations, there were only a few outliers (for supplementary box plots, see Appendix Figures A4 to A7). For the counties, there were no extreme outliers (|z-score| > 3.29). For the individuals nested within counties, there were four extreme cases (|z-score| > 3.29). This speaks to the model describing the observed clusters well and not failing to account for the observations of certain counties with unique characteristics. Because there were many extreme observations – most of which could be attributed to the accuracy of the model and the number of observations – and since exclusion of certain observations would have needed sufficient justification, outliers were not excluded from analysis. To make sure that this decision did not affect the model fit greatly, robust analyses were conducted without extreme cases. The results did not differ much from those of the main analysis (see Appendix Tables A9 and A10).

Linearity and Homoskedasticity. Plotting fitted against residual values for the model in general helps to detect non-linearity and heteroskedasticity. Non-linearity did not seem to be a problem. The scatterplot (see Figure 9) did not show a curve that would make a transformation of the estimate function appropriate. Therefore, a linear regression was the best choice. Furthermore, heteroskedasticity was also not observed. There was no funneling with larger residuals for larger fitted values. The scatterplot did, however, depict a non-random distribution of residuals. It was parallelogram-shaped. This could be attributed to the observed values. Though some people changed their attitudes towards refugees, which was reflected by different average values over the years, most people did not change their opinion. Thus, the non-random pattern of the plot was produced by the data, not by a model misspecification.

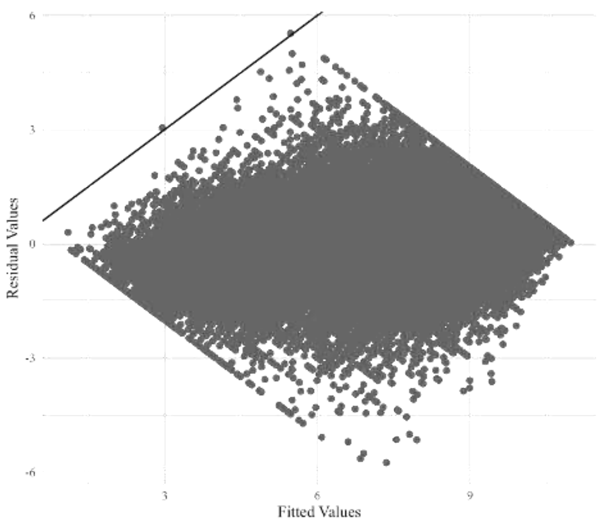

Figure 9: Residual plot for the full model.

Multicollinearity. To rule out multicollinearity, the generalized variance inflation factor (GVIF) (Fox & Monette, 1992) was estimated for each model predictor. Table 4 presents the results. The last column reports the GVIF adjusted for the number of coefficients of a variable. This renders the GVIF comparable across variables of different dimensions. The results indicate that model predictors were not correlated. Adjusted GVIF values were near one, which is the smallest possible value and corresponds to complete independence (Fox & Monette, 1992, p. 178). Critical GVIF values, according to the literature, vary from 4 to 10 (O'brien, 2007, p. 674).

Table 4

GVIF of each model predictor.

	GVIF	Df	GVIF^(1/(2*Df))
Year	1.631194	2	1.130125
Men	1.002969	1	1.001483
East Germany	1.204516	1	1.097504
Migration Background	1.226018	1	1.107257
Rural	1.286590	1	1.134280
Age	1.085296	1	1.041776
Education	1.172500	1	1.082821
Adj. Household Income	1.101273	1	1.049416
Gross Domestic Product	1.176689	1	1.084753
Share Asylum Seekers	1.612554	1	1.269864
Change Asylum Seekers	1.096039	1	1.046919

Although there were many extreme observations, model assumptions were not violated, and the interpretability of model estimates was confirmed.

4.2 Longitudinal regression analysis of attitudes towards refugees

Following listwise deletion, I ran all longitudinal models on the same sample (N = 30,266) for better comparison. Table 5 presents the results of the longitudinal models. The first column incorporates names of predictor variables and model estimates. The second column entails the results for the null model, where only random effects and year fixed effects were used for the estimation of refugee attitudes.

Null model. The adjusted ICC for the null model was 0.727 (ICC_{unadj} = 0.717). This means over 70% of the overall variance was attributable to the variance between classes, namely to the difference between individuals within counties. This value, being well above 0, reinforced the necessity to assume a multi-level regression model. The ICC value was also reflected in the descriptive and model assumption tests results. Most of the variance in refugee attitudes lay between individuals and not within. 73% of the variance in the outcome was explained by the model: random and fixed effects (conditional R^2 = 0.73). There was also some variance explained by the fixed effects of the year variable (marginal R^2 = 0.01).

The intercept represents the expected value of the outcome for a prototypical observation. This is the observation of a random individual in a random county when every predictor variable is zero. Due to the recentering of numeric variables, a prototypical observation was an observation in 2016 of a woman living in West Germany, in an urban environment, without a migration background, who was 53.00 years old, did 13.00 years in the education system, had an adjusted household income of 2,300.00€, and resided in a county with a refugee share of 6.00 asylum seekers per 1000 citizens, a refugee demographic change of 0.00 asylum seekers per 1000 citizens since the year before, and a GDP of 14,000,000,000.00€.

The expected refugee attitude of a prototypical observation of an individual within a county was a little above the midpoint of the refugee attitude scale, β_0 = 6.902, 95%CI [6.839,6.966]. Thus, in general, the attitudes towards refugees were predicted to be more negative than positive. The year coefficients were all statistically significantly related to the outcome (p < 0.001). For 2018, attitudes were expected to be negligibly more negative compared to 2016, β_1 = 0.055, 95%CI [0.030,0.080]. For 2020, refugee attitudes were predicted to be moderately less negative than in 2016, β_2 = −0.513, 95%CI [−0.539,−0.486]. The summed deviation of data points from estimated values was D = 246,516. This value was compared to the deviance value of the following models to see whether more complicated models could statistically significantly reduce model error and enhance fit.

Table 5

Longitudinal linear mixed-effects regressions of attitudes towards refugees on individual and regional demographic characteristics in the final sample (N = 30,266; n_{obs} = 61,444; $n_{counties}$ = 398).

Predictor	**Model 1** Null model	**Model 2** + individual	**Model 3**	Full model
			3.1 Untrimmed	3.2 Trimmed
Intercept	6.902*** [6.839,6.966]	6.553*** [6.482,6.624]	6.529*** [6.455,6.603]	6.551*** [6.486,6.617]
Fixed effects				
Year2018	0.055*** [0.030,0.080]	0.060*** [0.035,0.085]	0.090*** [0.053,0.126]	0.090*** [0.053,0.127]
Year2020	−0.513*** [−0.539,−0.486]	−0.501*** [−0.527,−0.474]	−0.468*** [−0.508,−0.428]	−0.467*** [−0.507,−0.427]
Men		0.046* [0.002,0.091]	0.047* [0.002,0.091]	0.047* [0.003,0.091]
East Germany		0.693*** [0.571,0.815]	0.689*** [0.567,0.811]	0.711*** [0.594,0.829]
Rural		0.113* [0.015,0.211]	0.065 [−0.038,0.168]	

Predictor	**Model 1** Null model	**Model 2** + individual	**Model 3**	Full model
			3.1 Untrimmed	3.2 Trimmed
Migration Background		−0.132*** [−0.189,−0.076]	−0.130*** [−0.187,−0.074]	−0.132*** [−0.189,−0.075]
Age		0.081*** [0.059,0.104]	0.081*** [0.058,0.104]	0.081*** [0.058,0.104]
Education		−0.599*** [−0.624,−0.575]	−0.599*** [−0.623,−0.574]	−0.599*** [−0.624,−0.575]
Adj. Household Income		−0.051*** [−0.068,−0.033]	−0.050*** [−0.068,−0.032]	−0.050*** [−0.068,−0.032]
Gross domestic product			−0.149** [−0.238,−0.059]	−0.166*** [−0.252,−0.080]
Share Asylum Seekers			0.023* [0.001,0.044]	0.023* [0.001,0.044]
Change Asylum Seekers			0.012+ [−0.001,0.025]	0.011+ [−0.002,0.024]
Random effects				
Var. Individual Intercept (*SD*)	3.352 (1.831)	3.007 (1.734)	3.007 (1.734)	3.007 (1.734)
Var. County Intercept (*SD*)	0.303 (0.550)	0.146 (0.382)	0.145 (0.381)	0.147 (0.383)
Residual Variance (*SD*)	1.375 (1.172)	1.381 (1.175)	1.380 (1.175)	1.380 (1.175)
Deviance	246,516	243,875	243,855	243,856
Marginal R^2	0.013	0.103	0.112	0.112
Conditional R^2	0.730	0.727	0.730	0.730

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Individual model. The third column of Table 5 shows the estimates of the individual model with individual-level covariates added to the null model. In the individual model, the variance explained by the random intercept for individuals nested in counties and the fixed effects of the year and individual variables was negligibly lower than in the null model (conditional R^2 = 0.73). This indicates that some variance that was attributed to the data classification could now be explained by fixed effects. 10% of the variance in refugee attitudes was explained by fixed effects (marginal R^2 = 0.10). It was about 9 percentage points higher than in the null model. The expected refugee attitude for a prototypical observation was less negative than in the previous model, but still more negative than positive, β_0 = 6.553, 95%CI [6.482,6.624].

Moving on to the individual predictors added, gender was marginally related to refugee attitudes, with men having slightly more negative attitudes towards refugees than women, β_3 = 0.046, 95%CI [0.002,0.091]. Living in a rural environment was weakly associated with more negative refugee attitudes, β_5 = 0.113, 95% CI [0.015,0.211]. Having a migration background was weakly but highly statistically significantly related to less negative refugee attitudes, β_6 = −0.132, 95%CI [−0.189,−0.076]. Older individuals tended to hold marginally more negative refugee attitudes, β_7 = 0.081, 95%CI [0.059,0.104]. Higher income was weakly associated with less negative refugee attitudes, β_9 = −0.051, 95%CI [−0.068,−0.033]. The individual variables that had the strongest associations with refugee attitudes were socialization and education. Having been socialized in East Germany was positively associated with negative refugee attitudes, β_4 = 0.693, 95%CI [0.571,0.815], and having spent more years on education was negatively associated with negative refugee attitudes, β_8 = −0.599, 95%CI [−0.624,−0.575].

The coefficients for the year fixed effects were roughly the same as in the null model, with more negative attitudes in 2018, β_1 = 0.060, 95%CI [0.035,0.085], and less negative attitudes in 2020, β_2 = −0.501, 95%CI [−0.527,−0.474], compared to 2016. The consistency of the year coefficients in general and the moderate effect of the 2020-year coefficient specifically meant that, though the individual predictors added seemed to improve model fit, there were still year-specific characteristics that affected refugee attitudes that were not captured by the variables added. The model was not apt to predict the sudden decrease in negative refugee attitudes in 2020. The deviance of the individual model was a lot smaller than that of the null model, D = 243,875. The Chi²-test comparing the two models showed that the individual model fit statistically significantly better than the null model ($p < 0.001$) (see Appendix Tables A4 and A5), thus using the more complicated model was justified.

Full model. Finally, adding the regional-level predictors created the full model presented in the fourth column of Table 5. The variance explained by the random intercept of individuals within counties was identical to that of the null model (conditional $R^2 = 0.73$). The variance explained by the fixed effects increased slightly (marginal $R^2 = 0.11$). Thus, an additional percentage point of the variance in refugee attitudes could be explained by the introduction of regional-level predictors. The intercept was again slightly lower than in the previous models, indicating that less negative attitudes towards refugees were expected for a prototypical observation, β_0 = 6.551, 95%CI [6.486,6.617].

Comparing the full and the individual model, the significance and strength of individual coefficients were largely stable. There were weak positive associations of being a man, β_3 = 0.047, 95%CI [0.003,0.091], and being older, β_7 = 0.081, 95%CI [0.058,0.104], with negative refugee attitudes, as well as weak negative associations of having a migration background, $\beta_6 = -0.132$, 95%CI [−0.189,−0.075], and higher income, $\beta_9 = -0.050$, 95%CI [−0.068,−0.032]. Having been socialized in East Germany was still moderately related to more negative refugee attitudes, $\beta_4 = 0.711$, 95%CI [0.594,0.829], and having spent more years on education was moderately related to less negative attitudes towards refugees, $\beta_8 = -0.599$, 95%CI [−0.624,−0.575]. The only individual coefficient that had changed substantially was living in a rural environment. It no longer affected refugee attitudes. The variance in refugee attitudes that had been formerly predicted by the variance in the rurality of someone's environment seemed to be better predicted by the variance of the added regional-level variables.

This is interesting because, although rurality had been formed as an individual variable, it captured characteristics of the environment someone lived in. This variable losing its significance could be interpreted as rurality actually not being predictive of negative refugee attitudes. It was a spurious relationship. The effect had likely been produced by other regional variables that were related to rurality and had been estimated only in the full model. As established in the bivariate analysis, living in a rural area correlated with the regional share of asylum seekers. Also, rural regions tended to have a smaller GDP. Therefore, the cause of negative refugee attitudes probably lay more in the economic and refugee-demographic characteristics of someone's environment than in its rurality.

The newly introduced coefficients were all somewhat statistically significant, although only marginally associated with negative refugee attitudes. Both a higher share of asylum seekers in an individual's county, $\beta_{11} = 0.023$, 95%CI [0.001,0.044], and a larger positive change of the share of asylum seekers since the year before, $\beta_{12} = 0.011$, 95%CI [−0.002,0.024], were marginally related to more negative refugee attitudes. The effect of a county's GDP was larger and more statistically significant. A higher regional GDP was associated with less negative individual attitudes towards refugees, $\beta_{10} = -0.166$, 95%CI [−0.252,−0.080]. The strength of the different fixed effects can be observed more easily with a coefficient plot (see Figure 10).

There was a marginal change in the year estimates that could be interpreted relative to the introduction of the regional-level predictors. The positive effect of the 2018-year coefficient on negative refugee attitudes strengthened, $\beta_1 = 0.090$, 95%CI [0.053,0.127], whereas the negative effect of the 2020-year coefficient weakened, $\beta_2 = -0.467$, 95%CI [−0.507,−0.427]. The inclusion of regional characteristics led to an improved prediction of less negative refugee attitudes in 2020 compared to 2016, which weakened the effect of the year variable. However, the full model was less able to predict more negative refugee attitudes in 2018, compared to

2016. Therefore, even though regional variables seem to account for some variability over the years, there are still unobserved year-specific relationships with refugee attitudes.

The deviance of the full model was slightly lower than that of the individual model, $D = 243,855$. The Chi²-test showed that the improvement of the model fit due to the introduction of the regional-level coefficients was statistically significant ($p < 0.001$).

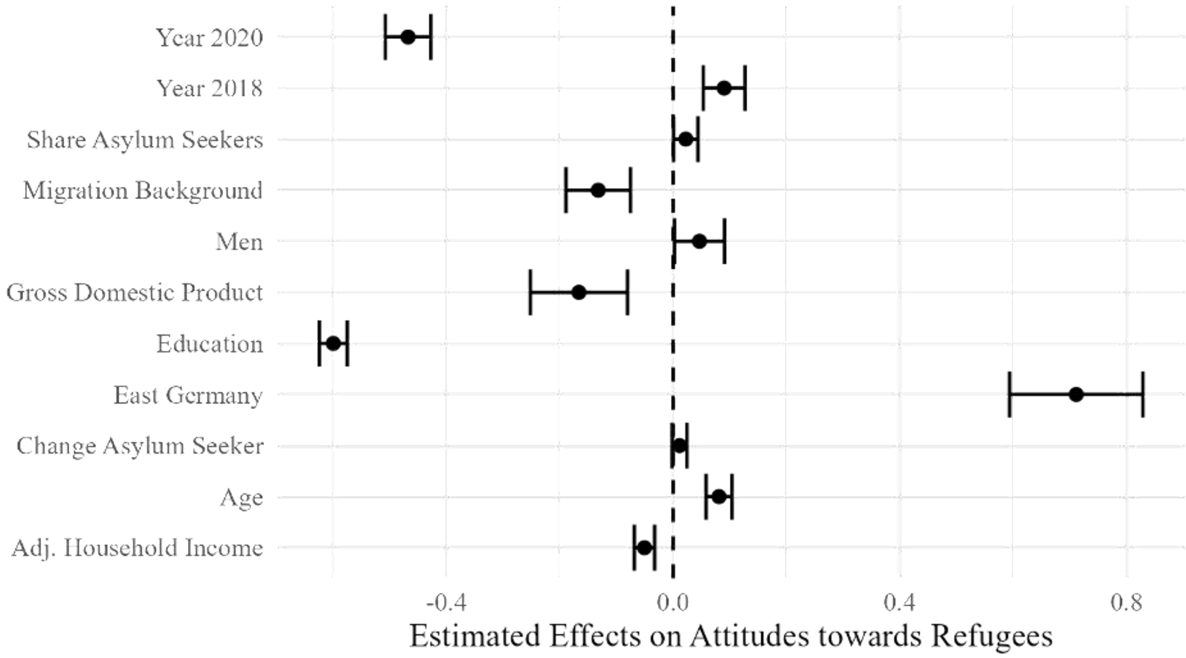

Figure 10: Coefficient plot for the full trimmed longitudinal regression of refugee attitudes.

4.3 Cross-sectional regression analysis of attitudes towards refugees

In addition to the longitudinal analysis, annual regressions compared associations of predictors and refugee attitudes by year. The year coefficients in the previous models consistently showed statistically significant effects, meaning attitudes towards refugees differed statistically significantly between the observed years, even when accounting for possible effects of several individual- and context-level variables. It is probable that not just the refugee attitudes differ between years, but that what affected refugee attitudes and how it affected these attitudes changed year by year. I performed annual regression models to inspect which predictors are stable over time and which are not.

Table 6 shows the results for the cross-sectional models for 2016, 2018, and 2020. For each year, I reduced the sample to observations of that year, which were about $N = 20,000$ each. The models did not contain a random intercept for the individuals anymore, as each year contains only one observation per person and variable. The random intercept for the county remained.

Model fit and intercept. In the annual models, about 13-15% of the variance in refugee attitudes was explained by the random intercept for counties and the fixed effects. Keeping in mind that in the longitudinal analysis, the value for conditional R^2 was consistently over 70% means that this was largely due to the lack of variance within individuals, not because counties were internally very homogenous. About 10-12% of the variance of the outcome could be attributed to the fixed effects. Meaning, the explanatory power of these smaller, annual models was equal to that of the full longitudinal model. The estimated refugee attitude for a prototypical observation did not differ largely from the intercept of the longitudinal model. Only the intercept for 2020 was lower than those in 2016 and 2018, $\beta_0 = 6.027$, 95%CI [5.951,6.104]. The less negative attitudes towards refugees in 2020 were, thus, reflected in the cross-sectional models.

Individual predictors. Though model fit and intercept were stable over the years, fixed effects estimates were largely not. Starting with the individual-level predictors, being a man was consistently marginally positively associated with negative refugee attitudes in the longitudinal models. Whereas this relationship prevailed for 2016 and 2018, $\beta_3 = 0.099$, 95%CI [0.042,0.157], and $\beta_3 = 0.114$, 95%CI [0.058,0.169], in 2020, gender had no statistically significant effect on refugee attitudes, and the direction of the relationship was reversed.

Similarly, for age, estimates for 2018 and 2020 were comparable to those of the longitudinal model, $\beta_7 = 0.046$, 95%CI [0.017,0.075], and $\beta_7 = 0.074$, 95%CI [0.043,0.105]. However, in 2016, the relationship was reversed: Older individuals tended to hold less negative refugee attitudes. This, however, was statistically insignificant.

The largest contrast was in the effect of having a migration background. In 2016, having a migration background was positively associated with negative refugee attitudes, $\beta_6 = 0.074$, 95%CI [0.001,0.146]. The relationship was weak, but statistically significant. In 2018 and 2020, people with migration background statistically significantly tended to hold less negative refugee attitudes, $\beta_6 = -0.077$, 95%CI [−0.151,−0.004], and $\beta_6 = -0.189$, 95%CI [−0.265,−0.113].

Individual predictors that were stable throughout the years were education, $\beta_8 \sim -0.600$, $p < 0.001$ (each year), income, $\beta_9 \sim -0.100$, $p < 0.001$ (each year), and socialization, $\beta_4 \sim 0.650$, $p < 0.001$ (each year). Having been socialized in East Germany was the strongest predictor of negative refugee attitudes every year. Another relatively stable predictor was rurality. The effect of living in a rural environment on negative refugee attitudes was consistently weakly positive, although only marginally statistically significant in 2018, $\beta_{11} = 0.097$, 95%CI [−0.019,0.212].

Regional predictors. Moving on to the regional-level predictors, a higher regional GDP consistently tended to predict less negative refugee attitudes, $\beta_{10} \sim -0.100$, p ~ 0.100. However, the relationship was weak and only marginally statistically significant in 2018 and 2020.

The regional share of asylum seekers in a county only had a marginally statistically significant negative effect on the outcome in 2020. Unexpectedly, individuals living in counties with higher regional shares of asylum seekers tended to report less negative attitudes towards refugees, $\beta_{11} = -0.078$, 95%CI [−0.157,0.000].

The change in the share of asylum seekers of a county had no statistically significant effect on refugee attitudes in any of the years observed. In 2016, the change in asylum seeker demographics coefficient was close to being statistically significant, $\beta_{12} = 0.022$, 95%CI [−0.006,0.050], $p = 0.129$ (see Table 6, Model 6.1). The relationship is positive, as expected, people living in counties with higher positive changes in shares of asylum seekers tended to hold more negative refugee attitudes. However, as mentioned before, the effect was statistically insignificant in 2016 and even more so in 2018 and 2020.

Table 6

Cross-sectional linear mixed-effects regressions of attitudes towards refugees on individual and regional demographic characteristics in the final sample for 2016, 2018, and 2020.

	Model 4 **2016** (N = n_{obs} = 19,846; $n_{counties}$ = 394)		**Model 5** **2018** (N = n_{obs} = 21,033; $n_{counties}$ = 396)		**Model 6** **2020** (N = n_{obs} = 20,565; $n_{counties}$ = 398)	
Predictor	4.1 Untrimmed	4.2 Trimmed	5.1 Untrimmed	5.2 Trimmed	6.1 Untrimmed	6.2 Trimmed
Intercept	6.561*** [6.461,6.661]	6.566*** [6.495,6.637]	6.584*** [6.494,6.674]	6.599*** [6.521,6.677]	6.019*** [5.929,6.110]	6.027*** [5.951,6.104]
Fixed effects						
Men	0.099*** [0.042,0.157]	0.099*** [0.042,0.157]	0.114*** [0.058,0.169]	0.114*** [0.058,0.169]	−0.002 [−0.060,0.056]	
East Germany	0.566*** [0.415,0.717]	0.637*** [0.496,0.778]	0.751*** [0.615,0.886]	0.746*** [0.611,0.882]	0.743*** [0.602,0.884]	0.752*** [0.618,0.886]
Rural	0.079 [−0.045,0.204]		0.102+ [−0.014,0.219]	0.097 [−0.019,0.212]	0.026 [−0.093,0.145]	
Migration Background	0.076* [0.001,0.152]	0.074* [0.001,0.146]	−0.077* [−0.151,−0.004]	−0.077* [−0.151,−0.004]	−0.189*** [−0.264,−0.113]	−0.189*** [−0.265,−0.113]
Age	−0.005 [−0.036,0.025]		0.046** [0.016,0.075]	0.046** [0.017,0.075]	0.074*** [0.043,0.105]	0.074*** [0.043,0.105]
Education	−0.623*** [−0.658,−0.588]	−0.624*** [−0.659,−0.590]	−0.647*** [−0.680,−0.615]	−0.647*** [−0.680,−0.615]	−0.604*** [−0.636,−0.572]	−0.604*** [−0.636,−0.572]

	Model 4 2016 (N = n_{obs} = 19,846; $n_{counties}$ = 394)		Model 5 2018 (N = n_{obs} = 21,033; $n_{counties}$ = 396)		Model 6 2020 (N = n_{obs} = 20,565; $n_{counties}$ = 398)	
Predictor	4.1 Untrimmed	4.2 Trimmed	5.1 Untrimmed	5.2 Trimmed	6.1 Untrimmed	6.2 Trimmed
Income	−0.139*** [−0.198,−0.080]	−0.141*** [−0.200,−0.083]	−0.125*** [−0.177,−0.073]	−0.125*** [−0.177,−0.072]	−0.059*** [−0.079,−0.039]	−0.059*** [−0.079,−0.039]
Gross domestic product	−0.086 [−0.206,0.035]		−0.123* [−0.222,−0.024]	−0.121* [−0.221,−0.022]	−0.099+ [−0.201,0.003]	−0.106* [−0.203,−0.009]
Share Asylum Seekers	−0.033 [−0.082,0.016]		0.010 [−0.068,0.088]		−0.078+ [−0.159,0.002]	−0.078 [−0.157,0.000]
Change Asylum Seekers	0.022 [−0.006,0.050]		−0.238 [−0.727,0.251]		0.002 [−0.704,0.708]	
Random effects						
Var. County Intercept (*SD*)	0.188 (0.433)	0.442	0.158 (0.398)	0.399	0.167 (0.408)	0.409
Residual Variance (*SD*)	4.224 (2.055)	2.055	4.159 (2.039)	2.039	4.442 (2.108)	2.107
Deviance	85,326	85,334	90,054	90,055	89,402	89,402
Marginal R^2	0.100	0.096	0.120	0.120	0.099	0.099
Conditional R^2	0.139	0.136	0.152	0.152	0.131	0.132

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

5 Discussion

My question in this analysis was whether and how regional levels and changes of refugee demographics affect individuals' attitudes towards refugees in Germany.

Share of asylum seekers. For one, I hypothesized that higher regional shares of refugees correspond to more negative refugee attitudes. Looking at the longitudinal models, this hypothesis seemed to be confirmed. There was a statistically significant positive relationship between the shares of asylum seekers in a county and the negative refugee attitudes of individuals living in this county. However, the effect was minimal, and the level of statistical significance was not very high. Meaning, if regional levels of the refugee population affected refugee attitudes, then it would not be the only nor the main influence.

Considering the results of the cross-sectional models, the instability of the effect became even more apparent. The relationship between refugee share and attitudes was solely statistically significant in 2020, but, contrary to the longitudinal models, it was negative.

Therefore, taking all the findings into account, the hypothesis could not be confirmed. Though some of the results aligned with previous expectations, others were not just statistically insignificant: They pointed in the opposite direction.

Change in share of asylum seekers. The second hypothesis was that increases in the regional share of refugees correspond to more negative refugee attitudes. Like in the first part of the research question, the longitudinal models supported this hypothesis. There was a positive relationship between the change in the share of regional refugee demographics and negative refugee attitudes. The effect, however, was only marginally statistically significant and very weak. It is questionable to even call this an effect.

Going over to the cross-sectional models, it became more apparent that there is no relationship between the refugee demographic change and attitudes, and that the hypothesis must be rejected. None of the year effects of the change in the refugee population were statistically significant, and they pointed in different directions.

In **summary**, the findings lead me to reject both hypotheses and answer the research question by stating that, based on these results, regional refugee demographics do not affect individual refugee attitudes. However, instead of rejecting group-threat theory because of a single analysis, it is wiser to make sense of these results.

5.1 Possible biases of regional demographic effects

Multicollinearity. One could argue that the regional predictors are correlated, which then influences their effect. There was, however, no multicollinearity detected, and the regional change variable only had a weak correlation with the share variable. This could not have diminished their effects. The share variable was mainly correlated with whether a person was socialized in East or West Germany. This reflects the fact that fewer refugees live in the former GDR. But this correlation was also very weak and could not explain why there was no visible effect of refugee demographics.

Contact theory. Thinking back to the theories on immigration attitudes described before, these findings could be the result of the contradictory effects assumed by group-threat and contact theory. According to contact theory, higher levels of immigration promote interaction with immigrants, which then reduces stereotypes and improves the opinions of longstanding residents on immigrants. Whereas group-threat theory suggests that larger immigrant populations make it more likely for longstanding residents to view immigrants as a threat. It is possible that both effects exist and counteract each other, explaining the mixed empirical results of this analysis.

Self-selective bias. One could also argue that regional demographics are not ideal variables to test the group-threat theory. There are several possible sources of measurement bias, for example, the self-selection bias. People with more negative attitudes towards refugees would try to avoid living in areas where many refugees live. People with more positive attitudes towards refugees would not mind living in areas with larger refugee populations. Hence, if there is a positive relationship between regional refugee demographics and negative refugee attitudes, individual choices of residency would counteract and weaken the effect.

Perceivability. Also, perceivability complicates measurement. Here, rather small regional units were used. Still, it is possible that regional refugee populations are not visible, particularly if the number of immigrants is small and if the residences of longstanding residents and immigrants are separated as usual (Hopkins, 2010, p. 40).

Furthermore, it was established that anti-immigrant sentiment is often made up of racist and xenophobic beliefs that are not directed at immigrants specifically, but at everyone who is considered part of the outgroup. Even though the methodical approach specifically measured immigration by people traditionally pushed to the outgroup and disregarded immigrants that are part of the ingroup, it did not account for non-immigrants who are excluded from the ingroup. Keeping that in mind, negative refugee attitudes could derive from the number of people categorized as the outgroup, not directly from refugee demographics. Future studies should test this relationship.

5.2 Influence of socialization and cultural context

In addition, one can use other variables beyond regional demographics to test group-threat theory. Individual characteristics have been assumed to predict refugee attitudes for a long time. Here, the results replicated findings of previous studies.

Education. The negative effect of education on anti-refugee attitudes was statistically significant in every model estimated. But the question remains what this effect reflects. Do people learn in school how to be welcoming to immigrants, and the longer they go to school, the more welcoming they are? Or is better education connected to a person's socioeconomic status and social milieu, which predict more positive refugee attitudes? Or, and this would support group-threat theory, do the less negative refugee attitudes indicate that better-educated longstanding residents feel less threatened by immigrants because they do not expect to compete with immigrants on the labor market? These questions cannot be answered by a regression of attitudes on educational level. It needs qualitative analyses of refugee attitudes in the future.

Socialization in East or West Germany. The variable with the largest effect across all the longitudinal and cross-sectional models was whether someone was socialized in East or West Germany. This is interesting as the variable is strongly connected to this research's target, Germany. Most studies on immigration attitudes are situated in the US or the UK, where this variable would neither be relevant nor applicable. This finding highlights the importance of consciously choosing subjects of analysis, because the national, cultural, and historical context matters. Especially in the field of immigration attitudes, it is important to consider the local specifics of the country people immigrate to.

Taking the different refugee attitudes in East and West Germany into account, it would be interesting to estimate regression models for the two samples separately. Variables may statistically significantly affect refugee attitudes in one sample, but not the other. Maybe, in East Germany, where immigration levels are historically low, sudden immigration changes lead to anti-immigrant sentiment, whereas in West Germany, where immigration has historically more precedents, there might be no effect. Another explanation would be that the regional economic situation – worse in East Germany (Burkert, 2012, p. 172) – leads East Germans to hold worse refugee attitudes.

Person-environment fit. The social context can also affect individual attitudes through the people who surround you. Person-environment fit (PE-fit) theory suggests that people tend to share characteristics with those around them, that they tend to feel better when they fit their environment, and that they tend to adapt to their environment if there is a misfit. The theory originates from the biological concept of niches. A niche refers to the environmental conditions an organism needs to survive, meaning the features of the environment need to match the needs of a species (Lewis, 2009, p. 411).

This idea found its way to social studies (Su et al., 2015, p. 81). The findings suggest that people tend to match the religiosity (Stavrova et al., 2013, p. 90; Ugur & Aydın, 2023, p. 156), personality (Bleidorn et al., 2016, p. 419; McCann, 2022, p. 1), and lifestyle (Esposito & Calanchini, 2022, p. 1; Torche & Abufhele, 2021, p. 931) of those around them, and that they tend to be happier when there is PE-fit in these dimensions.

Another dimension of PE-fit is political ideology and partisanship. In the US, conservatives and Republicans are happier in conservative, respectively Republican states (Ebert et al., 2023, p. 1192; Stavrova & Luhmann, 2016, p. 29). People also tend to have a higher sense of belonging when those around them favor the same party (Gimpel & Hui, 2018, p. 883). Finally, people tend to move when there is a PE-misfit in political values (Motyl, 2014, p. 123).

Political and refugee attitudes. Throughout this paper, I described how political opinions and attitudes towards refugees are connected. In Germany, someone's opinion on immigration is the main reason for supporting the AfD (Schröder, 2018, p. 8). Vice versa, someone's party affiliation is predictive of their immigration attitudes. Various studies even analyzed people's voting behavior as an outcome rather than the attitudes towards immigrants themselves. Considering, it would be logical if immigration attitudes were also an influential PE-fit dimension. In other words, people might share immigration attitudes with those around them, they might be happier if they do, and they might align these attitudes with their environment or move to contexts that fit their attitudes.

No-go-areas. Aside from the interindividual social context, another source of the positive effect of being socialized in East Germany could be that regional structures and opportunities increase anti-immigration sentiment. Some researchers observed the popularity of right-wing extremist thinking from a spatial sociological perspective. They argued that globalization and the failure to integrate urban and rural contexts lead to anomic conditions. This normative vacuum would make the implementation of new norms possible. Regions were characterized as arenas where unofficial laws – how to interact with others, what to do, and who belongs to the ingroup – are instated and fought about (Eckardt, 2022, pp. 204–205). The rise of nationalistic and racist paradigms is, thus, thought of as a spatial expansion of right-wing extremist ideas. Those ideas structure what is possible and appropriate in a place and thereby influence the people inhabiting that place.

Eisenach. Eckardt (2022) illustrates this process with the example of the German city Eisenach. There, right-wing extremists gained space through constant presence. They launched youth programs and sports clubs. Thus, they offered leisure activities while forming the young generation according to their beliefs (Eckardt, 2022, p. 208). They also threatened with and performed acts of violence in an increasingly public way, normalizing discriminatory violence (Eckardt, 2022, p. 210). Besides, they achieved spatial expansion by dominating the city's appearance with stickers and graffiti (Eckardt, 2022, p. 215). Through the spatial occupation by right-wing extremist norms, so-called *No-go-areas* (*Angsträume*) are formed, which are feared and avoided by those considered part of the outgroup (here, people on the political left and marginalized groups) (Eckardt, 2022, p. 204). Such areas build contextual conditions where anti-immigration sentiment can flourish. Even more, anti-immigrant attitudes are expected and necessary for integration.

In **summary**, these individual characteristics, education, and socialization point to interindividual and structural context conditions that affect refugee attitudes. Therefore, beyond the individual predictors, one should also include regional-level independent variables. Also, as I mentioned earlier, many individual characteristics do not change over time. This applies to education and socialization as well. Hence, those variables cannot account for a person's change in refugee attitudes. Even more, globally, educational levels have continuously improved over the last 50 years, and this finding applies to Germany as well (Drewelies et al., 2019, p. 1023; Schaie, 2011, p. 41). Therefore, refugee attitudes should be better than before, but they are not.

Regional economic performance. One possible time-varying regional indicator that could also test the group-threat hypothesis is the regional economic performance. It is assumed to affect longstanding residents' feelings of economic threat. In times of low regional economic performance, individuals would regard immigrants more as a threat, not in terms of labor market competition as is expected based on someone's income, but as a fiscal burden to the general economy. The results here are in line with this argument, as the regional GDP consistently coincided with more negative refugee attitudes. Even though the negative relationship was not statistically significant in every model, this finding can be seen as evidence for the economic threat hypothesis, which supports the group-threat theory at least in the economic vein.

5.3 Explanations for time-variance of effects

Another important finding in this analysis is the inconsistency of effects, namely the coefficients for the regional demographics as well as several individual-level effects. In the cross-sectional models, some coefficients lost their statistical significance, or their direction was reversed. One could infer that these variables do not predict refugee attitudes at all. One could argue that relationships get statistically significant more easily in regression models with many observations than when the sample is small (Royall, 1986, p. 314). If one considers, then, that some effects were very weak, those coefficients, although statistically significant, should rather be ignored than overinterpreted. This is especially true for the regional-level effects, as well as rurality and age. The strength and statistical significance of these effects are negligible.

The other variables, however, might predict refugee attitudes only under certain conditions. I already mentioned that contextual variables may affect which factors become relevant for refugee attitudes. The regional economic situation and immigration regulations can affect attitudes towards immigrants. Political decisions about which countries are 'safe' determine which refugees face discrimination (Marx, 2023, p. 426; Pichl, 2023, p. 516). Besides, there might be an overall culture of acceptance or aversion concerning refugees, which influences individual refugee attitudes (Bock, 2017, p. 2).

Welcome culture. For example, in Germany, contrary to other spatial contexts, at the beginning of the *refugee crisis* in 2015, a moral imperative to care for refugees was almost unanimously adopted (Jin, 2024, p. 685). The *welcome culture* dominated the civil society as well as the political conduct. Many citizens helped refugees by donating money or providing places of residence (Liebe et al., 2018, 2). Grassroots organizations such as R*efugees Welcome* were formed, formalizing civic commitment to refugee assistance (Soli*dBase, 2024). Angela Merkel famously said "We can do this" ("Wir schaffen das"), opening the German borders and paving the way for above-average uptake of refugees compared to other European countries (Laubenthal, 2019, p. 412).

But, as influential as the *welcome culture* might have been in 2015, it was gone just a few years later (Liebe et al., 2018, 2). The time-varying cultural context could influence people's opinions (Liebe et al., 2018, 9). This would explain why individual refugee attitudes were more negative in 2018, although there was less immigration than before.

Other national-level predictors. In the chapter on national-level predictors of immigration attitudes, I described several other possible time-varying influences on individual attitudes. Because they function on a national level, they could affect other predictors of anti-immigrant sentiment and explain the differences between the three cross-sectional models estimated here.

Events. For one, events and how these events are discussed in the media may affect individual attitudes (Czymara, 2024, p. 50). Also, media salience on the topic of refugees could affect the opinion of longstanding residents on refugees, and to what extent they see immigrants and immigration as a political issue (Czymara, 2024, p. 50). Events such as the sexual harassment of women on New Year's Eve 2016 in Cologne and the media coverage on that, fueled right-wing opposition and anti-refugee violence (Hermanni & Neumann, 2019, p. 349). Probably, such incidents also promote stereotypes against immigrants and increase individual-level anti-immigrant sentiment. In this case, feelings of threat might be fostered, particularly in women. Interestingly, in this analysis, the gender difference in refugee attitudes is less pronounced in 2016 than in 2018. This could be an indicator that women had more negative refugee attitudes immediately after the event than two years later. However, being a man, compared to being a woman, was still associated with more negative refugee attitudes. To accurately test the effect of such events, a quasi-experimental design is necessary.

There is already one example of a causal study of the influence of events. Stephan and Schürmann (2025) analyzed, with a difference-in-difference design, the effect of anti-racist protest campaigns in response to the 2020 Hanau racist terrorist attack and the coming to light of mass deportation plans by the German far-right party, AfD, in 2024. They found a causal positive relationship between the prevalence of local anti-racist protests and less anti- and more pro-immigration voting behavior, meaning fewer people voted for AfD and more people voted for the Green party (Stephan & Schürmann, 2025). Thus, there is causal evidence for the effect of events on individual attitudes. In the future, research on refugee attitudes would profit from similar designs.

Media salience. It was also shown that the salience of the refugee topic was very variable from 2015 to 2020. In 2020, there were rather few articles about refugees compared to 2016, and the findings aligned with the suggested relationship, because refugee attitudes were statistically significantly better in 2020 compared to 2016.

Politicized Places. It is possible that media salience not only affects refugee attitudes directly, but also indirectly by influencing other predictors. The Politicized Places hypothesis suggests that immigrant demographics only become visible in times of high issue salience and therefore, the effects of regional demographics only appear then. The relationship could not be confirmed by this analysis. Regional share and change of asylum seekers did not get statistically significant in 2016 when the salience of the refugee topic was high in Germany. However, the relationship between the change in refugee demographics and attitudes towards refugees is closest to being statistically significant in 2016 (p = 0.129). This year has the highest salience of the survey years analyzed. As I said before, maybe nitpicking these estimates means overinterpreting the results. But one should also not withhold possibly interesting information.

Other mediators. Aside from the Politicized Places hypothesis, there are other relationships imaginable where issue salience indirectly affects refugee attitudes. For example, the statistically significant negative relationship between adjusted household income and refugee attitudes was more pronounced in 2016, when media salience was high, than in 2020, when it was low. This could be evidence for the group-threat hypothesis. The amount of attention on the topic of refugees in the early survey years might have accentuated the positive effect of a person's low economic status on negative refugee attitudes. The perceived economic threat was larger because immigration seemed to be highly prevalent and politically relevant.

Furthermore, the statistically significant effect of having a migration background was positive in 2016, but negative in 2018 and 2020. Hence, having a migration background was associated with more negative attitudes in 2016 and less negative attitudes otherwise. This finding could indicate a group-threat effect. Possibly, people with a migration background fear labor market competition with immigrants, or rather refugees, not because of their economic or educational status, but because of their own background.

Migration background. Migration background is an interesting variable on its own. Several studies showed that attitudes towards immigrants and immigration by former immigrants differ statistically significantly from those of non-immigrants. Analyzing immigrants' attitudes towards immigrants is therefore an important task for future research. Therewhile it must be said that those attitudes might differ depending on immigration status, country of origin, and ethnic affiliation (Dancygier & Saunders, 2006, pp. 977–978; Dražanová et al., 2024, p. 327).

Stimmung. Besides media salience, there is also the concept of S*timmung,* which was not part of this analysis but could be another explanation for temporal variations in individual refugee attitudes. *Stimmung* translates loosely to mood, atmosphere, or feeling, and refers to an overarching public opinion or public mood (Borneman & Ghassem-Fachandi, 2017, p. 106). Concerning German refugee attitudes, it was established that after many refugees came to Germany in 2015 and 2016, a mood shift occurred. The *Stimmung* changed from a xenophilic *welcome culture* to a xenophobic mood (Borneman & Ghassem-Fachandi, 2017, p. 110). *Stimmung,* or public opinion, is said to be politically influential. Politicians try to mobilize voters by adhering to public opinion, and if parties fail to capture the current *Stimmung,* they generally lose elections (Borneman & Ghassem-Fachandi, 2017, p. 110). Researchers argued that not capturing the *Stimmung* caused the great losses Angela Merkel received in the 2016 general election (Borneman & Ghassem-Fachandi, 2017, p. 106). Beyond the political influence, the current *Stimmung* also affects individuals' opinions. People register mood shifts when they interact with people of a different mood (Borneman & Ghassem-Fachandi, 2017, p. 109). Such interactions may provoke people to align their opinions with those of their counterparts. At least, in interactions, people will recognize the *Stimmung* in its prevalence and influence.

Besides media salience, other contextual factors could indirectly affect the relationships between individual as well as regional predictors and individual refugee attitudes. Future studies should aim to find and test such factors.

Stable attitudes. Another important finding is that most people did not change their opinion. This corroborates previous findings, which state that immigration attitudes are relatively stable over time. If the goal is to create a welcoming society without prejudice towards refugees, one should not only find stable individual characteristics that correlate with more positive immigration attitudes. It is also important to identify the rare situations where people change their opinion, how these changes come to be, and if and how they could be promoted on a larger scale.

5.4 Comparison with robust analyses

One important indicator for the generalizability of findings is robustness checks. Here, three robustness checks were done to test the stability of the regression results.

Without outliers and with movers. For two of them, only the sample was changed; methods and variables remained the same (Appendix Tables A9 to A12). Both the regressions in the sample without outliers and the sample where people who changed counties were included showed no major differences from the main regression results. All the coefficients pointed in the same direction, and the strength of the effects was almost identical. This suggests that the findings for the prediction of refugee attitudes are stable across various samples of the population. Considering that the sample was also random and representative of the adult German population. The findings are generalizable to Germany.

Attitudes towards immigration. The last robustness check (Appendix Tables A6 to A8) differed from the main regression analysis not just in the sample constitution, but in the dependent variable. Here, not attitudes towards refugees were analyzed, but someone's concern about immigration. Thus, it was about attitudes towards a phenomenon, not people. Also, this variable did not differentiate between different types of immigration, but it described the amount of aversion against all immigration. As I said at the beginning, these concepts are different. Nonetheless, they are expected to relate to the same variables. Therefore, this robustness check had the purpose of seeing whether the relationships apply to a broader conception of immigration attitudes. If they do not, either the predictors of refugee attitudes are not ideal yet, or, contrary to prior belief, there are different predictors of refugee and immigration attitudes.

Methodically, this check also differed from the main analysis. On the one hand, data for every year between 2015 and 2020 were available for this variable. On the other hand, it was necessary to use a binomial generalized linear mixed-effects model with a logit-link because the outcome was binary.

The results were rather similar. Being socialized in East Germany and lower education remain the most important and consistent predictors of negative immigration attitudes. In the longitudinal models, some variables that had been statistically significant for the refugee attitudes were not significant for concern about immigration – gender, rurality, and income, as well as all regional-level predictors. These variables had been unstable and weak in the refugee attitude analysis as well. This might mean that they are not relevant for immigration attitudes at all.

In the cross-sectional models, someone's income was a statistically significant predictor, but not in 2019. The negative relationship was moderately strong at its maximum in 2015 with $\beta_9 = -0.518$, 95%CI [−0.715,−0.321]. It was only weak in 2016 and 2020. The GDP and the change in refugee demographics were not statistically significant in any of the annual models. The regional share of asylum seekers had a weak, positive, statistically significant effect on refugee attitudes in 2017 and 2018. This finding differs slightly from the main analysis. It suggests that some unobserved factors became relevant in these years, which moderated the effect of regional refugee demographics on attitudes towards immigration but not towards refugees. The robustness check showed that although the relationships and predictors of various types of immigration attitudes were similar, they were not identical, and it made sense to analyze them separately.

6 Conclusion

In this paper, I analyzed the individual- and regional-level predictors of individuals' refugee attitudes in Germany. I introduced the concept of threat and the group-threat hypothesis as the theoretical background for the analysis. I established that even though researchers agreed that longstanding residents somehow feel threatened by immigrants and immigration, what constitutes the threat is unclear – either people feel their economic situation or their cultural identity to be threatened. Also, it was debated how the threat could be measured.

I presented the findings of studies with various measurements on individual, regional, and national levels:

As an individual indicator of threat for someone's material self-interest, education turned out to be a stable predictor of immigration attitudes. For the other socioeconomic and demographic characteristics (i.e., income, gender, age, and migration background), the evidence was mixed. Several studies used individual indicators of someone's felt cultural threat as predictors of immigration attitudes (i.e., personality, values, and political ideology). The findings suggested that people who are more open, more liberal, and less prejudiced against immigrants have less restrictive opinions on immigration.

As compensation for the inability of stable individual variables to explain individual changes in attitudes, regional-level immigration demographics were introduced as indicators of the amount of group threat and possible predictors of refugee attitudes. The regional-level group threat was measured as a level and a dynamic variable (i.e., the regional immigrant share & the change in the regional immigrant share). Findings were mixed: some supported the group-threat hypothesis, others supported the opposing hypothesis of contact theory, and again others found no effect.

On the national level, media characteristics were examined as predictors of immigrant attitudes. As these types of predictors are new, there are only a few studies on the relationship between national media and individual attitudes. These indicated that the quantity and quality of media articles affect individuals' perception of the immigration topic and, therefore, their immigration attitudes.

Based on the literature on immigration attitudes and the goal to explain increases in anti-immigrant sentiment in Germany, regional demographics were chosen as the main predictors of interest. I posed the research question of whether and how regional levels and changes of refugee demographics affect individuals' attitudes towards refugees in Germany. I hypothesized that the higher share and the change of refugee demographics correspond to more negative refugee attitudes.

I used two data sources to answer the research question. On the one hand, the SOEP provided yearly data on individual attitudes and demographic characteristics of a representative sample of the German population. On the other hand, the INKAR database tracked regional demographic and socioeconomic information for counties in Germany.

In addition to a level and a change measurement of regional refugee demographics, several individual- and regional-level predictors were included as possible covariates. The sample was reduced to people with valid data for all variables who did not change their county and were not refugees themselves in or after 2015. The sample size was $N = 30{,}266$ individuals in 398 counties with 61,444 observations. The descriptive analysis revealed that individuals' attitudes rarely changed. Also, the regional refugee demographics differed from county to county.

I estimated longitudinal and cross-sectional models to test the hypotheses. For the longitudinal models, I performed linear hierarchical regressions of refugee attitudes with a random intercept for individuals nested in counties and stepwise inclusion of predictor groups. The null model included solely the random intercept and a factor variable for time. In the second step, I added the individual predictors, and lastly, the regional-level variables. For the cross-sectional models, linear mixed-effects regressions of refugee attitudes on all predictors were performed for 2016, 2018, and 2020 separately with a random intercept for someone's county. Trimmed models were presented as well to focus on the statistically significant coefficients.

Results of the multivariate analysis revealed only very weak and not consistently statistically significant positive effects of regional refugee demographics on negative refugee attitudes (i.e., β_{11} = 0.023, 95%CI [0.001,0.044] and β_{12} = 0.011, 95%CI [−0.002,0.024]). Circling back to the research question, one can say that regional refugee demographics are contrary to expectations, not predictive of attitudes towards refugees. The effect was too weak to be an actual influence.

This is an interesting finding, since it means that Germans' attitudes towards refugees are independent of the number of refugees living in a county and the increase or decrease of the number of refugees in that county. As was described in the methods chapter, the refugee-attitudes variable was formed by people's opinions on whether and how much negative or positive consequences refugees have on German society. Now, these attitudes are uncoupled from any objectively measurable and personally perceivable number of possible consequences for the German society. In other words, attitudes about the influence of the immigration of refugees have nothing to do with the actual immigration of refugees.

The variables that mainly predicted refugee attitudes are education and socialization, as well as the survey year. On the one hand, these individual predictors showed that what a person thinks about refugees is more about themselves than about refugees. Education and being from East or West Germany are both indicators of that person's socioeconomic status and cultural context. It is evidence for the group-threat hypothesis in the material self-interest vein that less educated and low-income longstanding residents are more prejudiced towards refugees who largely share their socioeconomic position. Besides, the effect of socialization suggests that it is less about the own income than about the regional economic situation. This is supported by the fact that the regional GDP affected refugee attitudes.

Furthermore, that living in East Germany was associated with more negative refugee attitudes also indicates that the cultural context matters. In this analysis, no variables of the cultural or social context of a county were measured. This could be a goal for future analyses. One can only speculate about the underlying relationships. A possible explanation, as proposed by PE-fit theory, would be that the opinions of family, friends, or people within one's region affect one's own attitudes. Another explanation would be that regional socialization structures and opportunities further anti-immigration sentiment, as was illustrated with Eisenach.

On the other hand, the effects of the survey years and the fact that relationships differed between the cross-sectional models point to specific temporal contexts that influence refugee attitudes. Again, what these time-specific factors are is a question for future research. Here, I found some evidence for the effect of national media salience.

In general, the findings indicate that there are still unobserved variables that affect refugee attitudes. Education and socialization consistently affected refugee attitudes moderately strongly and statistically significantly. However, all the models only explained about 10% of the variance in the outcome. Most of the variance in the outcome is explained by the random intercepts, meaning – even with the individual and regional predictors – the models cannot completely explain the differences between individuals within counties.

Even though failing to explain the variable of interest is unsatisfying, the finding that actual refugee demographics do not predict refugee attitudes is very important. Politicians and other participants of the public discourse claim that immigration must be limited because the local German communities and institutions are overburdened by the number of immigrants (Liebe et al., 2018, 2). They also say that, if German administrations do not address these problems, right extremist parties such as the AfD will become more popular (Borneman & Ghassem-Fachandi, 2017, p. 110; Hermanni & Neumann, 2019, p. 349; Salomo et al., 2025, p. 1190; Stöss, 2007, p. 54). In turn, the German government – especially the last and current administration – minimized immigration, in the hope of soothing people concerned about immigration, and to earn back votes from the AfD (Ziller, 2025). But considering that the immigration demographics do not affect people's opinion on immigration, this course of action is bound to fail. Instead, restrictive immigration policies seem to validate and thereby reinforce anti-immigrant sentiment (Ziller, 2025). Preventing right extremist parties from gaining power needs a different approach. It should draw from scientific evidence about immigration attitudes rather than adopting radical views to please the prejudiced.

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Data reference

Socio-Economic Panel (SOEP), version 39, data from 1984-2022 (SOEP-Core v39, Onsite Edition). 2024. DOI: 10.5684/soep.core.v39o

Appendix

A.1 Additional figures to test model assumptions

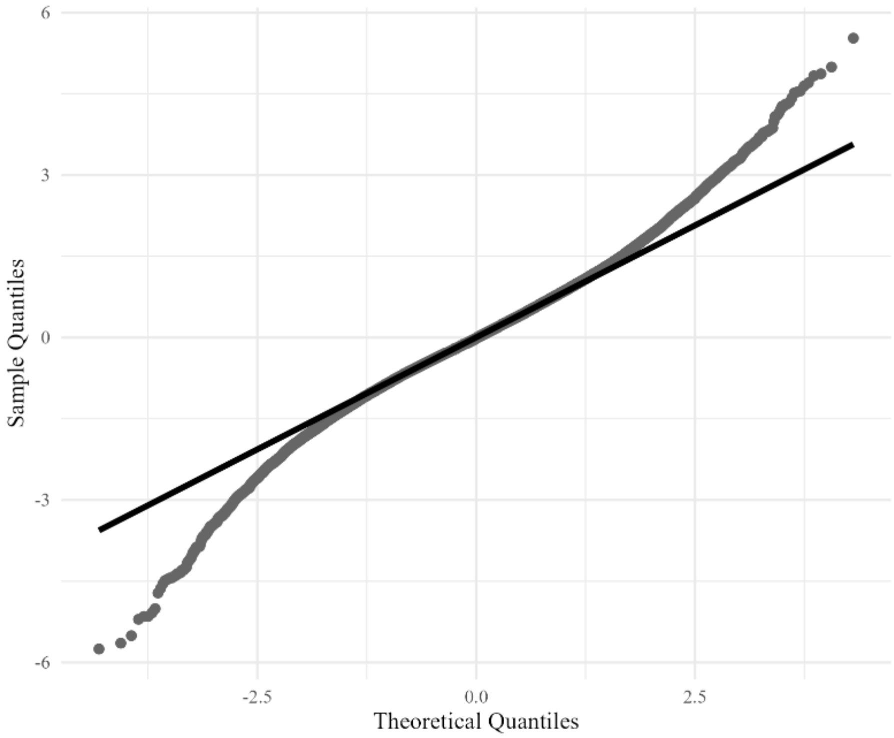

Figure A1: QQ-plot of the fixed effect residuals of the full model.

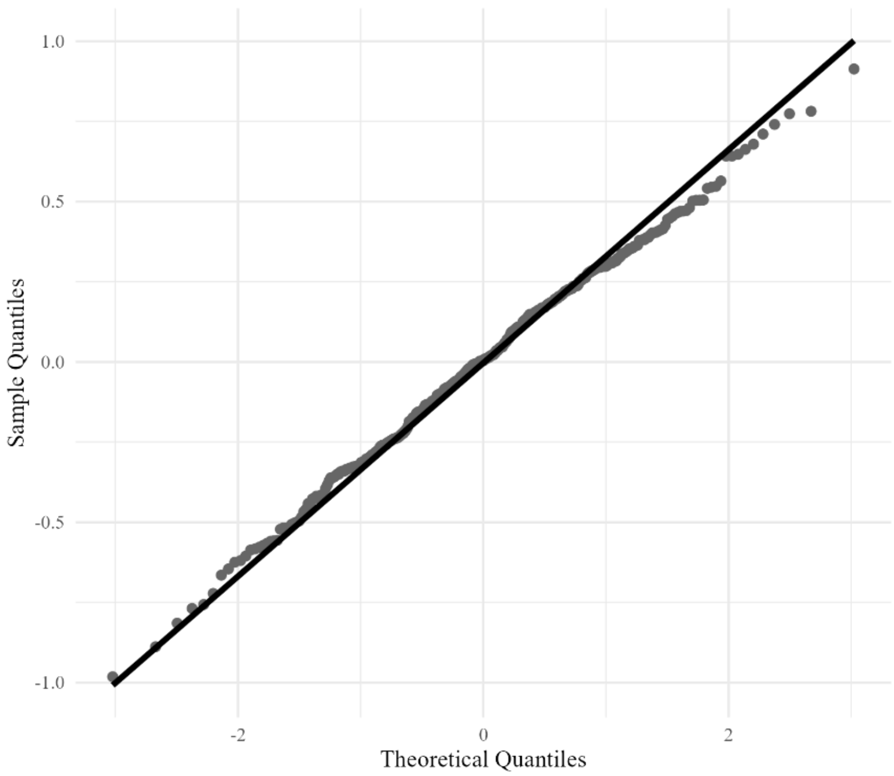

Figure A2: QQ-plot of the random effect residuals of counties of the full model.

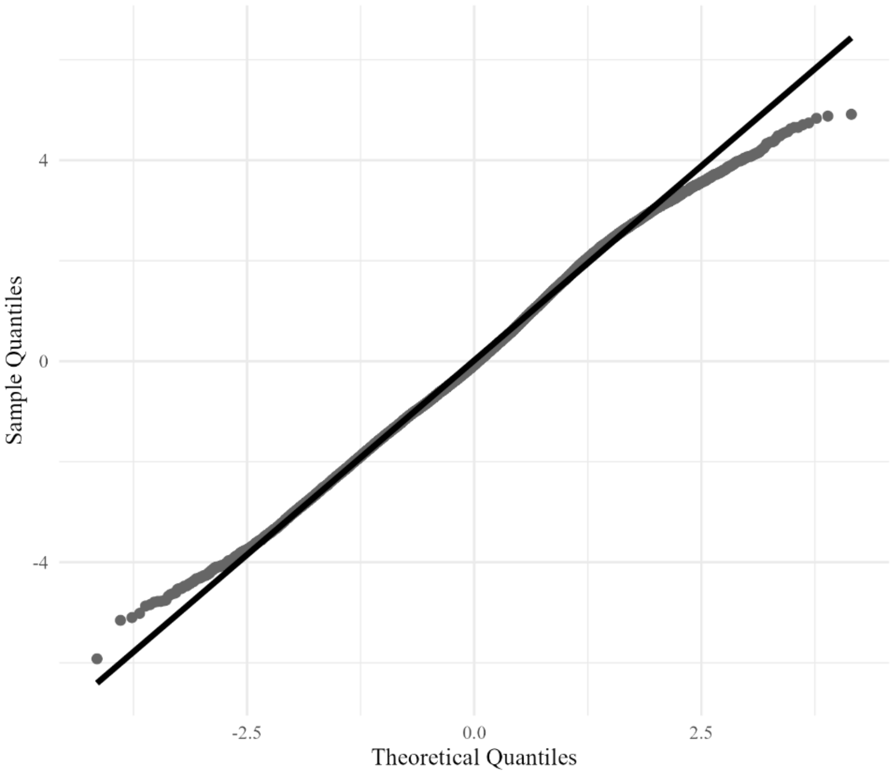

Figure A3: QQ-plot of the random effect residuals of individuals within counties of the full model.

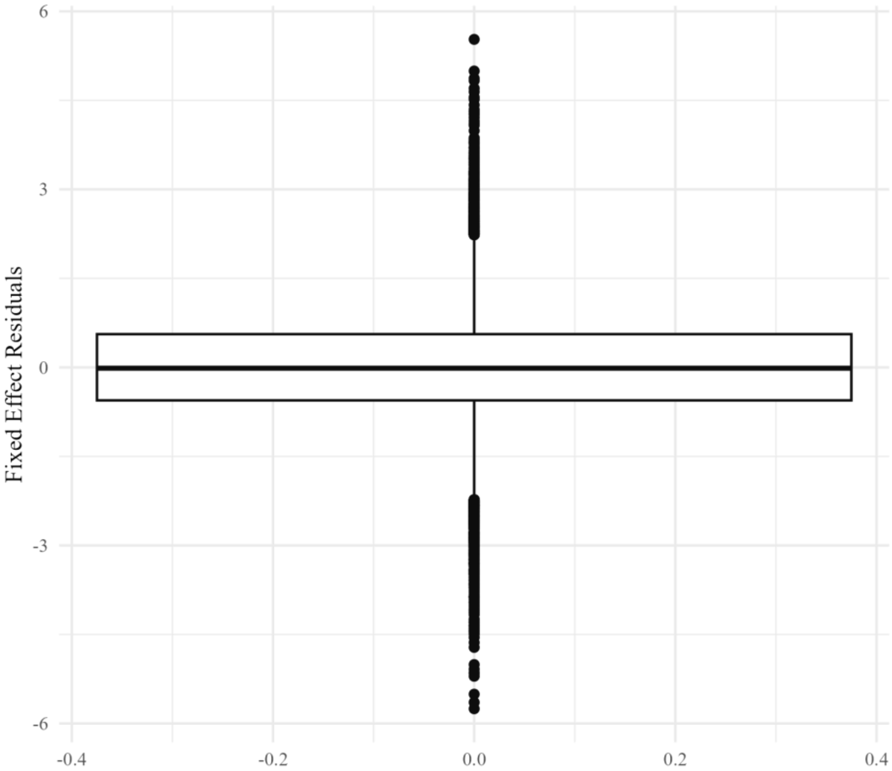

Figure A4: Boxplot of the fixed effect residuals of the full model.

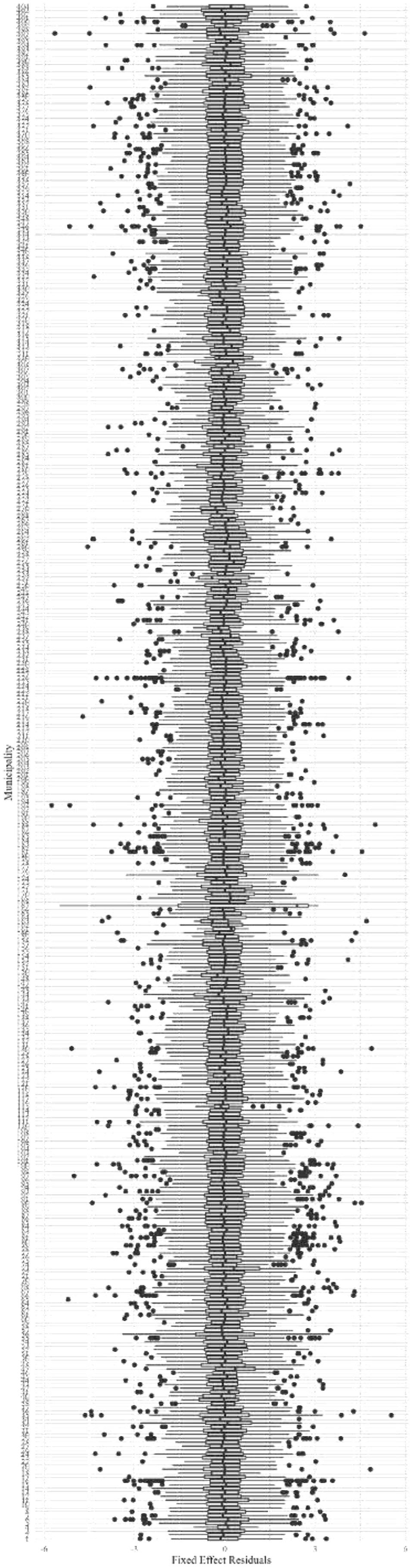

Figure A5: Boxplot of the fixed effect residuals per county of the full model.

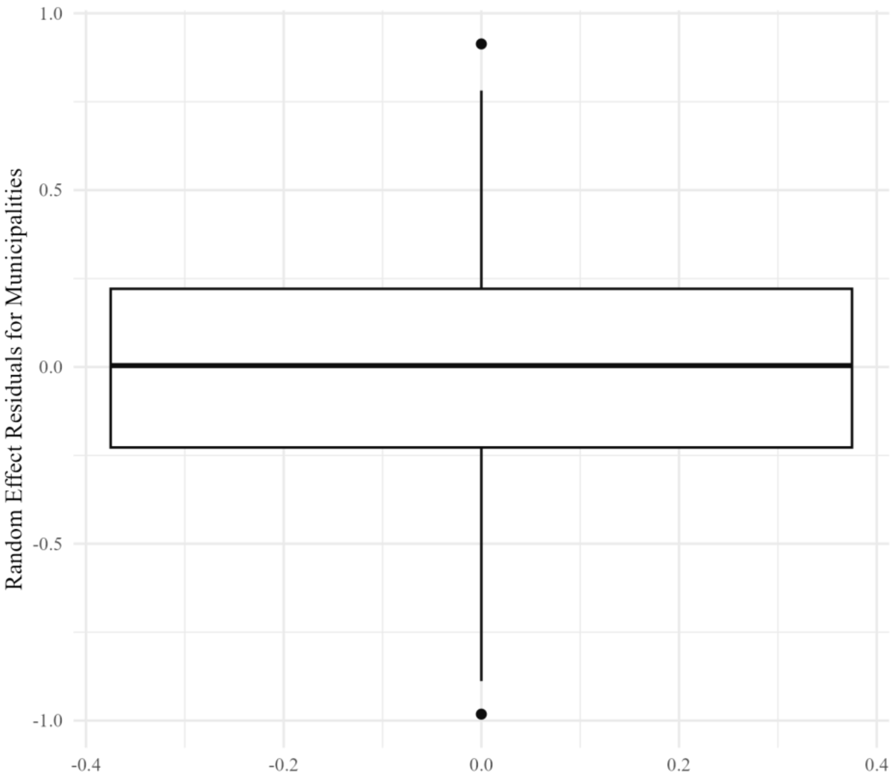

Figure A6: Boxplot of the random effect residuals of counties of the full model.

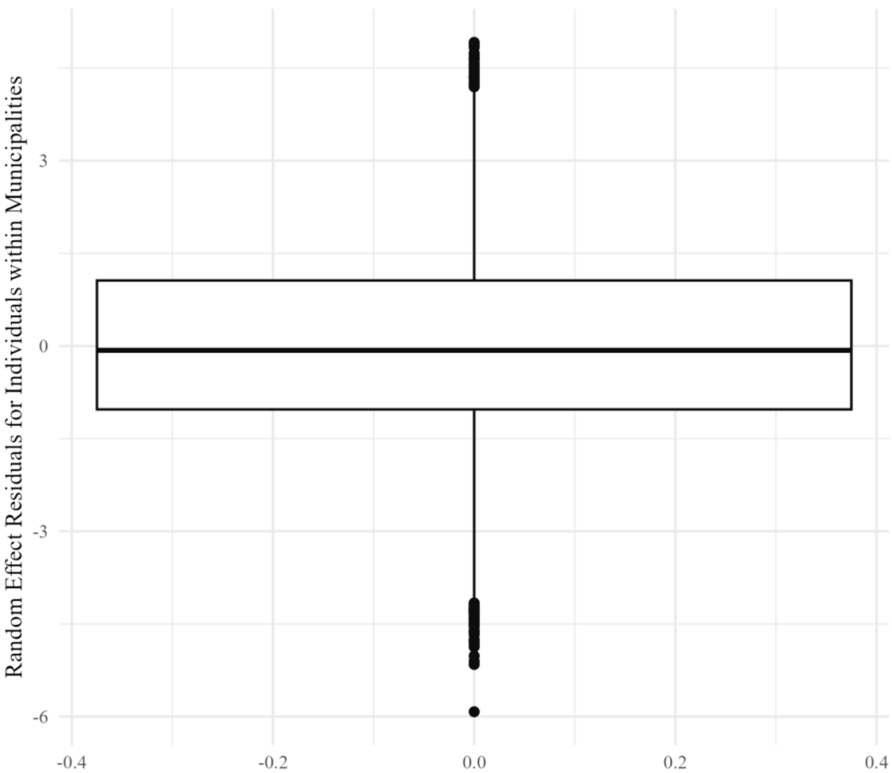

Figure A7: Boxplot of the random effect residuals of individuals within counties of the full model.

A.2 Additional correlation tables

Table A1

Zero-order Pearson correlations with confidence intervals for 2016 (N = 19,846; n_{obs} = 19,846; $n_{counties}$ = 394).

Variable	1	2	3	4	5	6	7	8	9	10
1. Attitudes towards Refugees										
2. Men (ref. Women)	.01 [−.00, .02]									
3. East Germany (ref. West)	.12** [.10, .13]	−.00 [−.01, .01]								
4. Rural (ref. Urban)	.09** [.08, .10]	.01 [−.01, .02]	.35** [.34, .36]							
5. Migration Background (ref. None)	.06** [.04, .07]	−.00 [−.02, .01]	−.21** [−.22, −.20]	−.14** [−.15, −.12]						
6. Age	−.00 [−.02, .01]	.03** [.01, .04]	.08** [.07, .09]	.04** [.02, .05]	−.29** [−.30, −.27]					
7. Education	−.29** [−.30, −.28]	.03** [.02, .05]	.05** [.03, .06]	−.07** [−.09, −.06]	−.26** [−.27, −.24]	.01* [.00, .03]				
8. Adj. Household Income	−.17** [−.18, −.16]	.05** [.03, .06]	−.12** [−.14, −.11]	−.11** [−.13, −.10]	−.15** [−.17, −.14]	.07** [.06, .09]	.42** [.40, .43]			

9. Gross Domestic Product	−.09**	−.00	−.19**	−.35**	.12**	−.04**	.09**	.11**		
	[−.11, −.08]	[−.02, .01]	[−.20, −.18]	[−.36, −.34]	[.11, .13]	[−.05, −.03]	[.07, .10]	[.09, .12]		
10. Share Asylum Seekers	−.04**	−.00	−.31**	−.21**	.07**	−.02**	.00	.02**	.01	
	[−.06, −.03]	[−.01, .01]	[−.32, −.29]	[−.22, −.19]	[.06, .09]	[−.04, −.01]	[−.01, .02]	[.01, .04]	[−.01, .02]	
11. Change Asylum Seekers	−.00	−.00	−.08**	−.09**	.01	−.01	.03**	.03**	.15**	.28**
	[−.02, .01]	[−.01, .01]	[−.09, −.06]	[−.11, −.08]	[−.01, .02]	[−.02, .01]	[.02, .05]	[.02, .05]	[.13, .16]	[.27, .30]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Table A2

Zero-order Pearson correlations with confidence intervals for 2018 ($N = n_{obs} = 21{,}033$; $n_{counties} = 396$).

Variable	1	2	3	4	5	6	7	8	9	10
1. Attitudes towards Refugees										
2. Men (ref. Women)	.02*									
	[.00, .03]									
3. East Germany (ref. West)	.16**	.00								
	[.15, .17]	[−.01, .01]								
4. Rural (ref. Urban)	.12**	.01	.35**							

	[.11, .13]	[−.01, .02]	[.34, .36]							
5. Migration Background (ref. None)	.02*	−.01	−.20**	−.14**						
	[.00, .03]	[−.02, .00]	[−.21, −.18]	[−.15, −.12]						
6. Age	.03**	.02**	.06**	.04**	−.23**					
	[.02, .04]	[.01, .04]	[.05, .08]	[.02, .05]	[−.25, −.22]					
7. Education	−.30**	.03**	.03**	−.08**	−.24**	.01				
	[−.31, −.29]	[.02, .05]	[.01, .04]	[−.09, −.07]	[−.25, −.23]	[−.01, .02]				
8. Adj. Household Income	−.17**	.05**	−.13**	−.11**	−.15**	.06**	.40**			
	[−.18, −.16]	[.04, .06]	[−.14, −.11]	[−.12, −.09]	[−.16, −.13]	[.05, .08]	[.39, .41]			
9. Gross Domestic Product	−.11**	−.00	−.21**	−.36**	.12**	−.03**	.09**	.10**		
	[−.13, −.10]	[−.02, .01]	[−.22, −.19]	[−.37, −.35]	[.11, .14]	[−.05, −.02]	[.07, .10]	[.08, .11]		
10. Share Asylum Seekers	−.02**	.01	−.06**	−.06**	.03**	−.01	.02**	.01	.07**	
	[−.03, −.01]	[−.01, .02]	[−.07, −.04]	[−.08, −.05]	[.01, .04]	[−.02, .00]	[.01, .04]	[−.01, .02]	[.05, .08]	
11. Change Asylum Seekers	.02**	.01	.14**	.16**	−.03**	.00	−.01	−.04**	.00	.13**
	[.00, .03]	[−.01, .02]	[.13, .15]	[.15, .17]	[−.05, −.02]	[−.01, .01]	[−.02, .01]	[−.05, −.03]	[−.01, .02]	[.12, .14]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Table A3

Zero-order Pearson correlations with confidence intervals for 2020 (N = n_{obs} = 20,565; $n_{counties}$ = 398).

Variable	1	2	3	4	5	6	7	8	9	10
1. Attitudes towards Refugees										
2. Men (ref. Women)	−.01 [−.02, .00]									
3. East Germany (ref. West)	.15** [.13, .16]	−.00 [−.02, .01]								
4. Rural (ref. Urban)	.11** [.09, .12]	.00 [−.01, .02]	.36** [.35, .37]							
5. Migration Background (ref. None)	−.00 [−.02, .01]	.01 [−.01, .02]	−.19** [−.20, −.18]	−.13** [−.15, −.12]						
6. Age	.04** [.03, .06]	.02* [.00, .03]	.08** [.07, .10]	.05** [.04, .06]	−.30** [−.31, −.28]					
7. Education	−.26** [−.27, −.25]	.03** [.01, .04]	.04** [.03, .06]	−.08** [−.09, −.06]	−.29** [−.30, −.28]	.06** [.05, .07]				
8. Adj. Household Income	−.10** [−.12, −.09]	.04** [.02, .05]	−.05** [−.06, −.03]	−.05** [−.06, −.03]	−.08** [−.09, −.07]	.04** [.03, .06]	.21** [.20, .22]			
9. Gross Domestic Product	−.10**	.00	−.20**	−.36**	.11**	−.04**	.09**	.06**		

	[−.12, −.09]	[−.01, .02]	[−.22, −.19]	[−.37, −.34]	[.09, .12]	[−.05, −.02]	[.07, .10]	[.05, .08]		
10. Share Asylum Seekers	−.02**	.00	.06**	−.01*	.01	−.00	.02**	.01	.08**	
	[−.04, −.01]	[−.01, .02]	[.05, .08]	[−.03, −.00]	[−.00, .02]	[−.01, .01]	[.01, .03]	[−.01, .02]	[.07, .09]	
11. Change Asylum Seekers	−.00	−.01	.14**	.05**	−.06**	.04**	.03**	.01	.09**	.28**
	[−.02, .01]	[−.02, .00]	[.12, .15]	[.04, .06]	[−.07, −.05]	[.03, .05]	[.02, .04]	[−.01, .02]	[.08, .10]	[.27, .30]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

A.3 Model comparison

Table A4

Chi²-test to compare the null and the individual model.

Model	n_{par}	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Null	6	246527.7	246581.8	−123257.8	246515.7			
+individual	13	243901.1	244018.4	−121937.5	243875.1	2640.587	7	0.000***

Table A5

Chi²-test to compare the individual and the full trimmed model.

Model	n_{par}	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
+individual	13	243901.1	244018.4	−121937.5	243875.1			
Full	15	243886.3	244021.7	−121928.1	243856.3	18.78867	2	0.0001***

A.4 Robustness checks

A.4.1 Robustness check for worry about immigration

Table A6

Longitudinal binomial generalized mixed linear regressions of worry about immigration on individual and regional demographic characteristics (N = 34,042; n_{obs} = 122,847; $n_{counties}$ = 398).

Predictor	**Robust Model 1.1** Null Model	**Robust Model 1.2** + individual		**Robust Model 1.3** Full Model	
		1.2.1 Untrimmed	1.2.2 Trimmed	1.3.1 Untrimmed	1.3.2 Trimmed
Intercept	−1.531*** [−1.616,−1.446]	−1.845*** [−1.937,−1.753]	−1.846*** [−1.923,−1.769]	−1.854*** [−1.947,−1.761]	−1.846*** [−1.923,−1.769]
Fixed effects					
Year2016	1.174*** [1.115,1.233]	1.172*** [1.113,1.231]	1.172*** [1.113,1.231]	1.189*** [1.126,1.252]	1.172*** [1.113,1.231]
Year2017	0.593*** [0.535,0.651]	0.591*** [0.533,0.648]	0.591*** [0.533,0.649]	0.605*** [0.543,0.666]	0.591*** [0.533,0.649]
Year2018	0.001 [−0.059,0.060]	−0.018 [−0.078,0.042]	−0.018 [−0.077,0.042]	−0.007 [−0.070,0.056]	−0.018 [−0.077,0.042]
Year2019	−0.152*** [−0.213,−0.091]	−0.158*** [−0.219,−0.096]	−0.157*** [−0.219,−0.096]	−0.146*** [−0.212,−0.081]	−0.157*** [−0.219,−0.096]
Year2020	−0.490*** [−0.553,−0.427]	−0.502*** [−0.566,−0.439]	−0.502*** [−0.566,−0.439]	−0.493*** [−0.560,−0.426]	−0.502*** [−0.566,−0.439]
Men		−0.049 [−0.113,0.015]		−0.049 [−0.113,0.015]	
East Germany		0.922*** [0.788,1.057]	0.945*** [0.818,1.073]	0.916*** [0.783,1.050]	0.945*** [0.818,1.073]
Rural		0.060 [−0.050,0.169]		0.034 [−0.080,0.148]	

Predictor	**Robust Model 1.1** Null Model	**Robust Model 1.2** + individual		**Robust Model 1.3** Full Model	
		1.2.1 Untrimmed	1.2.2 Trimmed	1.3.1 Untrimmed	1.3.2 Trimmed
Migration Background		−0.495*** [−0.577,−0.412]	−0.498*** [−0.580,−0.416]	−0.492*** [−0.575,−0.410]	−0.498*** [−0.580,−0.416]
Age		0.251*** [0.219,0.284]	0.251*** [0.218,0.284]	0.252*** [0.219,0.284]	0.251*** [0.218,0.284]
Education		−0.898*** [−0.936,−0.860]	−0.899*** [−0.937,−0.861]	−0.897*** [−0.935,−0.859]	−0.899*** [−0.937,−0.861]
Adj. Household Income		0.008 [−0.013,0.029]		0.008 [−0.013,0.029]	
Gross Domestic Product				−0.068 [−0.159,0.023]	
Share Asylum Seekers				−0.008 [−0.039,0.024]	
Change Asylum Seekers				0.017 [−0.010,0.044]	
Random effects					
Var. Individual Intercept (*SD*)	5.173 (2.274)	4.890 (2.211)	4.886 (2.210)	4.896 (2.213)	4.886 (2.210)
Var. County Intercept (*SD*)	0.394 (0.628)	0.133 (0.364)	0.134 (0.366)	0.128 (0.358)	0.134 (0.366)
Deviance	73,699	73,369	73,380	73,355	73,380
Marginal R^2	0.032	0.134	0.133	0.136	0.133
Conditional R^2	0.640	0.657	0.657	0.658	0.657

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A7

Untrimmed cross-sectional binomial generalized linear mixed effects regressions of worry about immigration on individual and regional demographic characteristics for the years from 2015 to 2020.

	Robust Model 1.4 **2015** ($N=n_{obs}$= 20,280; $n_{counties}$ = 393)	**Robust Model 1.5** **2016** ($N=n_{obs}$= 19,470; $n_{counties}$ = 394)	**Robust Model 1.6** **2017** ($N=n_{obs}$= 21,682; $n_{counties}$ = 396)	**Robust Model 1.7** **2018** ($N=n_{obs}$= 20,710; $n_{counties}$ = 396)	**Robust Model 1.8** **2019** ($N=n_{obs}$= 20,263; $n_{counties}$ = 397)	**Robust Model 1.9** **2020** ($N=n_{obs}$= 20,442; $n_{counties}$ = 398)
Predictor	1.4.1 Untrimmed	1.5.1 Untrimmed	1.6.1 Untrimmed	1.7.1 Untrimmed	1.8.1 Untrimmed	1.9.1 Untrimmed
Intercept	−0.911*** [−1.003,−0.819]	−0.276*** [−0.369,−0.184]	−0.684*** [−0.789,−0.578]	−1.059*** [−1.149,−0.969]	−1.195*** [−1.282,−1.108]	−1.321*** [−1.411,−1.232]
Fixed effects						
Men	−0.038 [−0.099,0.024]	−0.038 [−0.097,0.021]	−0.019 [−0.077,0.038]	0.041 [−0.021,0.103]	0.059+ [−0.004,0.123]	0.016 [−0.050,0.083]
East Germany	0.380*** [0.248,0.511]	0.430*** [0.293,0.567]	0.472*** [0.339,0.605]	0.597*** [0.468,0.726]	0.647*** [0.525,0.770]	0.589*** [0.463,0.714]
Rural	−0.043 [−0.155,0.070]	0.002 [−0.112,0.115]	0.049 [−0.061,0.160]	−0.027 [−0.140,0.086]	0.007 [−0.101,0.115]	0.016 [−0.094,0.126]
Migration Background	−0.411*** [−0.494,−0.328]	−0.284*** [−0.362,−0.206]	−0.142*** [−0.218,−0.065]	−0.262*** [−0.345,−0.179]	−0.157*** [−0.243,−0.071]	−0.367*** [−0.457,−0.278]
Age	−0.048** [−0.080,−0.016]	0.135*** [0.103,0.166]	0.154*** [0.124,0.185]	0.147*** [0.115,0.178]	0.109*** [0.076,0.143]	0.185*** [0.151,0.220]
Education	−0.464*** [−0.505,−0.423]	−0.459*** [−0.496,−0.421]	−0.463*** [−0.500,−0.426]	−0.528*** [−0.569,−0.487]	−0.580*** [−0.619,−0.542]	−0.512*** [−0.555,−0.469]
Adj. Household Income	−0.518*** [−0.715,−0.321]	−0.154+ [−0.316,0.009]	−0.370*** [−0.535,−0.204]	−0.449*** [−0.635,−0.263]	0.009 [−0.007,0.025]	−0.262*** [−0.398,−0.126]
Gross Domestic Product	−0.076 [−0.181,0.029]	−0.051 [−0.154,0.051]	−0.041 [−0.133,0.051]	−0.076+ [−0.165,0.013]	−0.032 [−0.112,0.048]	−0.039 [−0.122,0.043]

	Robust Model 1.4 2015 (N=n_{obs}= 20,280; $n_{counties}$ = 393)	Robust Model 1.5 2016 (N=n_{obs}= 19,470; $n_{counties}$ = 394)	Robust Model 1.6 2017 (N=n_{obs}= 21,682; $n_{counties}$ = 396)	Robust Model 1.7 2018 (N=n_{obs}= 20,710; $n_{counties}$ = 396)	Robust Model 1.8 2019 (N=n_{obs}= 20,263; $n_{counties}$ = 397)	Robust Model 1.9 2020 (N=n_{obs}= 20,442; $n_{counties}$ = 398)
Predictor	1.4.1 Untrimmed	1.5.1 Untrimmed	1.6.1 Untrimmed	1.7.1 Untrimmed	1.8.1 Untrimmed	1.9.1 Untrimmed
Share Asylum Seekers	0.129 [−0.058,0.316]	−0.068 [−0.178,0.043]	0.205* [0.030,0.380]	0.250* [0.060,0.441]	0.178+ [−0.021,0.376]	0.069 [−0.126,0.264]
Change Asylum Seekers	−0.181 [−0.438,0.076]	0.020 [−0.006,0.047]	0.065 [−0.144,0.274]	−0.399 [−0.879,0.082]	−0.465+ [−0.970,0.039]	−0.258 [−0.933,0.417]
Random effects						
Var. County Intercept (*SD*)	0.126 (0.355)	0.133 (0.365)	0.129 (0.359)	0.122 (0.349)	0.099 (0.315)	0.097 (0.311)
Deviance	23,761	24,984	26,783	23,690	22,568	21,147
Marginal R^2	0.077	0.073	0.084	0.108	0.107	0.109
Conditional R^2	0.111	0.109	0.119	0.140	0.133	0.135

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A8

Trimmed cross-sectional binomial generalized linear mixed effects regressions of worry about immigration on individual and regional demographic characteristics for the years from 2015 to 2020.

	Robust Model 1.4 **2015** ($N=n_{obs}$= 20,280; $n_{counties}$ = 393)	**Robust Model 1.5** **2016** ($N=n_{obs}$= 19,470; $n_{counties}$ = 394)	**Robust Model 1.6** **2017** ($N=n_{obs}$= 21,682; $n_{counties}$ = 396)	**Robust Model 1.7** **2018** ($N=n_{obs}$= 20,710; $n_{counties}$ = 396)	**Robust Model 1.8** **2019** ($N=n_{obs}$= 20,263; $n_{counties}$ = 397)	**Robust Model 1.9** **2020** ($N=n_{obs}$= 20,442; $n_{counties}$ = 398)
Predictor	1.4.2 Trimmed	1.5.2 Trimmed	1.6.2 Trimmed	1.7.2 Trimmed	1.8.2 Trimmed	1.9.2 Trimmed
Intercept	−0.965*** [−1.027,−0.903]	−0.320*** [−0.381,−0.260]	−0.691*** [−0.751,−0.631]	−1.025*** [−1.094,−0.956]	−1.190*** [−1.269,−1.111]	−1.318*** [−1.380,−1.256]
Fixed effects						
Men					0.060+ [−0.003,0.123]	
East Germany	0.379*** [0.254,0.505]	0.461*** [0.334,0.588]	0.511*** [0.389,0.634]	0.577*** [0.454,0.701]	0.657*** [0.542,0.773]	0.602*** [0.484,0.719]
Rural						
Migration Background	−0.414*** [−0.497,−0.331]	−0.288*** [−0.366,−0.210]	−0.146*** [−0.223,−0.070]	−0.260*** [−0.343,−0.177]	−0.160*** [−0.246,−0.074]	−0.369*** [−0.458,−0.280]
Age	−0.048** [−0.080,−0.016]	0.134*** [0.103,0.165]	0.154*** [0.124,0.184]	0.147*** [0.115,0.179]	0.109*** [0.076,0.143]	0.185*** [0.151,0.220]
Education	−0.464*** [−0.506,−0.423]	−0.460*** [−0.497,−0.422]	−0.465*** [−0.501,−0.428]	−0.527*** [−0.569,−0.486]	−0.580*** [−0.619,−0.542]	−0.513*** [−0.556,−0.470]
Adj. Household Income	−0.527*** [−0.724,−0.331]	−0.159+ [−0.321,0.004]	−0.375*** [−0.541,−0.209]	−0.441*** [−0.627,−0.256]		−0.261*** [−0.397,−0.126]
Gross Domestic Product				−0.065 [−0.150,0.020]		

	Robust Model 1.4 2015 (N=n_{obs}= 20,280; $n_{counties}$ = 393)	Robust Model 1.5 2016 (N=n_{obs}= 19,470; $n_{counties}$ = 394)	Robust Model 1.6 2017 (N =n_{obs}= 21,682; $n_{counties}$ = 396)	Robust Model 1.7 2018 (N=n_{obs}= 20,710; $n_{counties}$ = 396)	Robust Model 1.8 2019 (N=n_{obs}= 20,263; $n_{counties}$ = 397)	Robust Model 1.9 2020 (N=n_{obs}= 20,442; $n_{counties}$ = 398)
Predictor	1.4.2 Trimmed	1.5.2 Trimmed	1.6.2 Trimmed	1.7.2 Trimmed	1.8.2 Trimmed	1.9.2 Trimmed
Share Asylum Seekers			0.182* [0.010,0.354]	0.230* [0.040,0.419]	0.173+ [−0.026,0.371]	
Change Asylum Seekers					−0.464+ [−0.970,0.042]	
Random effects						
Var. County Intercept (*SD*)	0.131 (0.361)	0.137 (0.370)	0.131 (0.362)	0.124 (0.352)	0.100 (0.316)	0.099 (0.315)
Deviance	23,757	24,982	26,781	23,689	22,568	21,144
Marginal R^2	0.074	0.071	0.081	0.107	0.105	0.107
Conditional R^2	0.109	0.108	0.117	0.140	0.132	0.133

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

A.4.2 Robustness check for the sample without outliers

Table A9

Longitudinal linear mixed effects regressions of attitudes towards refugees on individual and regional demographic characteristics of the sample without outliers ($N = 30{,}226$; $n_{obs} = 61{,}045$; $n_{counties} = 398$).

Predictor	**Robust Model 2.1** Null Model	**Robust Model 2.2** + individual	**Robust Model 2.3** Full Model	
			2.3.1 Untrimmed	2.3.2 Trimmed
Fixed effects				
Year2018	0.061*** [0.038,0.085]	0.065*** [0.042,0.089]	0.108*** [0.074,0.143]	0.116*** [0.082,0.149]
Year2020	−0.499*** [−0.524,−0.475]	−0.489*** [−0.514,−0.464]	−0.442*** [−0.480,−0.405]	−0.434*** [−0.470,−0.398]
Men		0.047* [0.003,0.092]	0.048* [0.003,0.092]	0.048* [0.003,0.092]
East Germany		0.696*** [0.573,0.819]	0.694*** [0.570,0.818]	0.718*** [0.599,0.837]
Rural		0.118* [0.019,0.217]	0.069 [−0.035,0.173]	
Migration Background		−0.131*** [−0.188,−0.074]	−0.129*** [−0.186,−0.072]	−0.131*** [−0.188,−0.074]
Age		0.083*** [0.060,0.106]	0.083*** [0.060,0.106]	0.083*** [0.060,0.106]
Education		−0.603*** [−0.628,−0.579]	−0.603*** [−0.627,−0.578]	−0.603*** [−0.628,−0.579]
Adj. Household Income		−0.049*** [−0.067,−0.031]	−0.049*** [−0.067,−0.031]	−0.049*** [−0.067,−0.031]

Predictor	Robust Model 2.1 Null Model	Robust Model 2.2 + individual	Robust Model 2.3 Full Model	
			2.3.1 Untrimmed	2.3.2 Trimmed
Gross Domestic Product			−0.152*** [−0.242,−0.062]	−0.172*** [−0.259,−0.086]
Share Asylum Seekers			0.033** [0.012,0.053]	0.036*** [0.016,0.056]
Change Asylum Seekers			0.009 [−0.004,0.021]	
Random effects				
Var. Individual Intercept (*SD*)	3.481 (1.866)	3.131 (1.769)	3.131 (1.769)	3.131 (1.769)
Var. County Intercept (*SD*)	0.308 (0.555)	0.149 (0.386)	0.150 (0.387)	0.152 (0.390)
Residual Variance (*SD*)	1.189 (1.090)	1.194 (1.093)	1.193 (1.092)	1.193 (1.092)
Deviance	240,724	238,064	238,038	238,042
Marginal R^2	0.013	0.105	0.114	0.115
Conditional R^2	0.764	0.761	0.764	0.764

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A10

Cross-sectional linear mixed effects regressions of attitudes towards refugees on individual and regional demographic characteristics of the sample without outliers for 2016, 2018, and 2020.

	Robust Model 2.4 **2016** ($N = n_{obs}$ = 19,704; $n_{counties}$ = 394)		**Robust Model 2.5** **2018** ($N = n_{obs}$ = 20,894; $n_{counties}$ = 395)		**Robust Model 2.6** **2020** ($N = n_{obs}$ = 20,447; $n_{counties}$ = 397)	
Predictor	2.4.1 Untrimmed	2.4.2 Trimmed	2.5.1 Untrimmed	2.5.2 Trimmed	2.6.1 Untrimmed	2.6.2 Trimmed
Intercept	6.560*** [6.460,6.660]	6.571*** [6.501,6.642]	6.589*** [6.499,6.680]	6.617*** [6.551,6.683]	6.008*** [5.917,6.099]	6.026*** [5.949,6.102]
Fixed effects						
Men	0.099*** [0.041,0.156]	0.098*** [0.041,0.156]	0.114*** [0.059,0.169]	0.114*** [0.059,0.169]	0.008 [−0.049,0.066]	
East Germany	0.576*** [0.425,0.727]	0.641*** [0.500,0.782]	0.761*** [0.625,0.898]	0.796*** [0.666,0.927]	0.750*** [0.609,0.892]	0.765*** [0.630,0.900]
Rural	0.079 [−0.046,0.203]		0.093 [−0.023,0.210]		0.040 [−0.079,0.160]	
Migration Background	0.069+ [−0.006,0.144]	0.069+ [−0.003,0.141]	−0.061 [−0.134,0.012]		−0.182*** [−0.258,−0.107]	−0.183*** [−0.259,−0.108]
Age	−0.009 [−0.039,0.022]		0.041** [0.012,0.070]	0.047** [0.018,0.075]	0.080*** [0.049,0.111]	0.080*** [0.050,0.111]
Education	−0.629*** [−0.664,−0.595]	−0.630*** [−0.664,−0.596]	−0.656*** [−0.689,−0.624]	−0.651*** [−0.683,−0.619]	−0.611*** [−0.643,−0.579]	−0.612*** [−0.643,−0.580]
Adj. Household Income	−0.138*** [−0.196,−0.079]	−0.140*** [−0.198,−0.082]	−0.120*** [−0.172,−0.068]	−0.117*** [−0.169,−0.065]	−0.059*** [−0.078,−0.039]	−0.059*** [−0.078,−0.039]

	Robust Model 2.4 2016 (N = n_{obs} = 19,704; $n_{counties}$ = 394)		Robust Model 2.5 2018 (N = n_{obs} = 20,894; $n_{counties}$ = 395)		Robust Model 2.6 2020 (N = n_{obs} = 20,447; $n_{counties}$ = 397)	
Predictor	2.4.1 Untrimmed	2.4.2 Trimmed	2.5.1 Untrimmed	2.5.2 Trimmed	2.6.1 Untrimmed	2.6.2 Trimmed
Gross Domestic Product	−0.086 [−0.206,0.034]		−0.127* [−0.227,−0.027]	−0.154** [−0.249,−0.058]	−0.095+ [−0.197,0.008]	−0.105* [−0.203,−0.008]
Share Asylum Seekers	−0.026 [−0.075,0.022]		0.012 [−0.066,0.090]		−0.073+ [−0.154,0.007]	−0.073+ [−0.151,0.006]
Change Asylum Seekers	0.021 [−0.007,0.049]		−0.203 [−0.694,0.289]		0.023 [−0.685,0.730]	
Random effects						
Var. County Intercept (*SD*)	0.188 (0.433)	0.195 (0.441)	0.162 (0.402)	0.165 (0.406)	0.169 (0.411)	0.170 (0.412)
Residual Variance (*SD*)	4.134 (2.033)	4.134 (2.033)	4.077 (2.019)	4.078 (2.019)	4.374 (2.092)	4.374 (2.091)
Deviance	84,295	84,303	89,055	89,060	88,586	88,586
Marginal R^2	0.104	0.099	0.124	0.124	0.102	0.102
Conditional R^2	0.142	0.139	0.158	0.158	0.136	0.136

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

A.4.3 Robustness check for people who changed county

Table A11

Longitudinal linear mixed effects regressions of attitudes towards refugees on individual and regional demographic characteristics of the sample with people who changed county (N = 31,546; n_{obs} = 64,493; $n_{counties}$ = 401).

Predictor	**Robust Model 3.1** Null Model	**Robust Model 3.2** + individual	**Robust Model 3.3** Full Model	
			3.3.1 Untrimmed	3.3.2 Trimmed
Fixed effects				
Year2018	0.051*** [0.026,0.075]	0.056*** [0.032,0.081]	0.078*** [0.042,0.114]	0.086*** [0.052,0.121]
Year2020	−0.513*** [−0.538,−0.487]	−0.498*** [−0.525,−0.472]	−0.475*** [−0.514,−0.436]	−0.466*** [−0.503,−0.428]
Men		0.039+ [−0.004,0.082]	0.039+ [−0.004,0.082]	0.039+ [−0.004,0.082]
East Germany		0.650*** [0.533,0.767]	0.651*** [0.534,0.767]	0.652*** [0.535,0.768]
Rural		0.106* [0.017,0.196]	0.081+ [−0.011,0.174]	0.081+ [−0.012,0.174]
Migration Background		−0.123*** [−0.178,−0.068]	−0.123*** [−0.178,−0.068]	−0.123*** [−0.178,−0.067]
Age		0.096*** [0.074,0.119]	0.096*** [0.074,0.118]	0.096*** [0.074,0.118]
Education		−0.609*** [−0.632,−0.585]	−0.608*** [−0.632,−0.584]	−0.608*** [−0.632,−0.584]
Adj. Household Income		−0.048*** [−0.066,−0.031]	−0.048*** [−0.066,−0.031]	−0.048*** [−0.066,−0.031]

Predictor	**Robust Model 3.1** Null Model	**Robust Model 3.2** + individual	**Robust Model 3.3** Full Model	
			3.3.1 Untrimmed	3.3.2 Trimmed
Gross Domestic Product			−0.068* [−0.129,−0.006]	−0.068* [−0.130,−0.007]
Share Asylum Seekers			0.019+ [−0.002,0.039]	0.022* [0.002,0.043]
Change Asylum Seekers			0.010 [−0.003,0.023]	
Random effects				
Var. Individual Intercept (*SD*)	3.381 (1.839)	3.016 (1.737)	3.016 (1.737)	3.016 (1.737)
Var. County Intercept (*SD*)	0.310 (0.557)	0.150 (0.387)	0.149 (0.385)	0.149 (0.386)
Residual Variance (*SD*)	1.378 (1.174)	1.385 (1.177)	1.385 (1.177)	1.385 (1.177)
Deviance	259,335	256,433	256,421	256,423
Marginal R^2	0.013	0.104	0.107	0.107
Conditional R^2	0.732	0.727	0.728	0.728

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table A12

Cross-sectional linear mixed effects regressions of attitudes towards refugees on individual and regional demographic characteristics of the sample with people who changed county for 2016, 2018, and 2020.

	Robust Model 3.4 2016 (N = n_{obs} = 20,700; $n_{counties}$ = 395)		**Robust Model 3.5 2018** (N = n_{obs} = 22,162; $n_{counties}$ = 400)		**Robust Model 3.6 2020** (N = n_{obs} = 21,631; $n_{counties}$ = 400)	
Predictor	3.4.1 Untrimmed	3.4.2 Trimmed	3.5.1 Untrimmed	3.5.2 Trimmed	3.6.1 Untrimmed	3.6.2 Trimmed
Intercept	6.559*** [6.459,6.659]	6.563*** [6.492,6.633]	6.576*** [6.487,6.664]	6.624*** [6.557,6.690]	6.006*** [5.919,6.093]	6.019*** [5.946,6.092]
Fixed effects						
Men	0.089** [0.032,0.145]	0.089** [0.033,0.146]	0.104*** [0.050,0.158]	0.104*** [0.050,0.158]	−0.003 [−0.059,0.054]	
East Germany	0.556*** [0.405,0.708]	0.629*** [0.488,0.770]	0.739*** [0.604,0.874]	0.762*** [0.632,0.892]	0.747*** [0.611,0.883]	0.765*** [0.635,0.894]
Rural	0.082 [−0.043,0.206]		0.085 [−0.028,0.198]		0.037 [−0.074,0.149]	
Migration Background	0.074* [0.001,0.148]	0.064+ [−0.007,0.135]	−0.069+ [−0.141,0.002]	−0.071+ [−0.143,0.000]	−0.187*** [−0.261,−0.113]	−0.188*** [−0.262,−0.115]
Age	0.008 [−0.022,0.038]		0.068*** [0.039,0.096]	0.068*** [0.039,0.097]	0.082*** [0.052,0.112]	0.082*** [0.052,0.112]
Education	−0.633*** [−0.667,−0.599]	−0.636*** [−0.670,−0.602]	−0.659*** [−0.691,−0.627]	−0.660*** [−0.692,−0.628]	−0.614*** [−0.645,−0.583]	−0.615*** [−0.646,−0.584]
Adj. Household Income	−0.132*** [−0.188,−0.075]	−0.132*** [−0.189,−0.076]	−0.114*** [−0.165,−0.064]	−0.115*** [−0.165,−0.064]	−0.056*** [−0.076,−0.037]	−0.056*** [−0.076,−0.037]

	Robust Model 3.4 2016 (N = n_{obs} = 20,700; $n_{counties}$ = 395)		Robust Model 3.5 2018 (N = n_{obs} = 22,162; $n_{counties}$ = 400)		Robust Model 3.6 2020 (N = n_{obs} = 21,631; $n_{counties}$ = 400)	
Predictor	3.4.1 Untrimmed	3.4.2 Trimmed	3.5.1 Untrimmed	3.5.2 Trimmed	3.6.1 Untrimmed	3.6.2 Trimmed
Gross Domestic Product	−0.079 [−0.200,0.043]		−0.167*** [−0.254,−0.080]	−0.185*** [−0.268,−0.101]	−0.087* [−0.168,−0.006]	−0.094* [−0.171,−0.017]
Share Asylum Seekers	−0.034 [−0.083,0.015]		−0.003 [−0.079,0.073]		−0.087* [−0.162,−0.011]	−0.082* [−0.155,−0.008]
Change Asylum Seekers	0.019 [−0.009,0.047]		−0.251 [−0.724,0.223]		0.186 [−0.472,0.843]	
Random effects						
Var. County Intercept (*SD*)	0.192 (0.438)	0.198 (0.445)	0.163 (0.404)	0.165 (0.407)	0.162 (0.403)	0.162 (0.403)
Residual Variance (*SD*)	4.231 (2.057)	4.231 (2.057)	4.184 (2.046)	4.184 (2.046)	4.452 (2.110)	4.452 (2.110)
Deviance	89,028	89,036	95,020	95,023	94,075	94,075
Marginal R^2	0.102	0.097	0.126	0.126	0.101	0.101
Conditional R^2	0.141	0.138	0.158	0.159	0.133	0.133

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$