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Refugees Welcome? Understanding the Regional Heterogeneity of Anti-Foreigner Hate Crimes in Germany

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Refugees Welcome? Understanding the Regional Heterogeneity of Anti-Foreigner Hate Crimes in Germany*

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Abstract

In this article, we examine anti-foreigner hate crime in the wake of the large influx of asylum seekers to Germany in 2014 and 2015. By exploiting the quasi-experimental assignment of asylum seekers to German regions, we estimate the causal effect of an unexpected and sudden change in the share of the foreign-born population on anti-foreigner hate crime. Our county-level analysis shows that not simply the size of regional asylum seeker inflows drives the increase in hate crime, but the rapid compositional change of the residential population: Areas with previously low shares of foreign-born inhabitants that face large-scale immigration of asylum seekers witness the strongest upsurge in hate crime. Economically deprived regions and regions with a legacy of anti-foreigner hate crimes are also found to be prone to hate crime against refugees. However, when we explicitly control for East–West German differences, the predominance of native-born residents at the local level stands out as the single most important factor explaining the sudden increase in hate crime.

Keywords: hate crime; immigration; natural experiment; regional conditions
JEL classification: J15, R23, K42

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1 Introduction

Immigration and anti-foreigner crimes increased dramatically in recent years in Western countries. Germany, as a prime destination country for international refugees in Europe, registered 890,000 incoming asylum seekers in 2015 alone (Bundesministerium des Innern, 2016b),—a more than one percent increase in population size. During the same time, 923 criminal offenses were perpetrated against asylum seekers and their accommodations, more than a five-fold increase from 2014 (Bundesministerium des Innern, 2016a). This sharp increase in hate crimes directed at foreigners was largely unexpected. Hate crimes, the most severe form of openly expressed anti-foreigner hatred, carry economic and social costs and are thus relevant for policy makers. They affect immigrants' integration efforts and strain social cohesion, not only between native residents and immigrants, but also among the native resident population (Gould and Klor, 2016; Deole, 2018; Steinhardt, 2018). Despite the severity, salience, and relevance of these incidents, limited empirical evidence exists on the nature and causes of hate crimes. Why do these hate crimes arise? Are there underlying patterns in the sudden increase of these incidents?

In this article, we elucidate the question of how the large influx of asylum seekers in 2014 and 2015 spurred anti-foreigner hate crime in Germany. Using detailed panel data at the county level, we analyze how the size of the inflow of asylum seekers is associated with attacks against this group. Moreover, we investigate the influence of regional conditions to cover and better understand the high heterogeneity of hate crimes across Germany. Using a quasi-experimental design, we identify the causal effects of the regional inflow of asylum seekers on the rise in anti-foreigner hate crime. Since a government quota system is used to distribute asylum seekers among German regions, the usual problem of the residential self-selection of immigrants can be alleviated. Our setting provides a unique example of the large-scale immigration of ethnically different migrants from primarily Middle Eastern and African countries to German regions. Some of these regions were previously widely unpopular and avoided by immigrants. This natural experiment allows us to observe and quantify the otherwise latent, intangible anti-foreigner attitudes of the incumbent local population.

We contribute to the economic literature on crime against minorities by accounting for the motivations of hate crime offenders. Similar to Krueger and Pischke (1997) and Falk, Kuhn, and Zweimüller (2011), we consider economic hardship or strain as a factor influencing the rise in hate crimes. The paper most similar to ours is by Krueger and Pischke (1997), which addresses the question of whether the regional variance in economic hardship, measured by unemployment at the county level, can explain the unequal distribution of hate crimes in Germany in the beginning of the 1990s. They found that local unemployment rates (and most other explanatory variables) became statistically insignificant after including dummy variables for East and West Germany. We use their striking result as a point of departure and reexamine whether there are indeed no other explanations for hate crime in Germany besides the (East-West) differences rooted in German history.

However, unlike Krueger and Pischke (1997), who assembled a data set on hate crimes at the county level based on newspaper reports, and also different from Falk et al. (2011), who used time series data of the German federal states, our study is based on recent official administrative hate crime records at the county level.[1] Moreover, and perhaps even more important, we go beyond previous contributions by evaluating alternative explanations of hate crime, building on the work of McDevitt and Levin (1993) and McDevitt, Levin, and Bennett (2002), who discuss potential background factors and develop a typology of hate criminals. Specifically, we focus on the roles of economic conditions, change in the ethnic composition of the local population, and importance of a hate crime legacy.

Among the considered hypotheses, we analyze Green, Strolovitch, and Wong's (1998) theory of defended neighborhoods. In their model, hate crime victimization tends to be higher when a rapid increase in ethnically different migrants occurs in a previously homogenous area with a predominant racial group of incumbents. Inhabitants of regions with only limited previous experience of immigration might react more vehemently to incoming foreigners than those living in areas with a high share of preexisting migrants.

[1] Counties in Germany are classified as the NUTS 3 level, comparable to counties in the United States.

Our results provide no evidence of a simple homogeneous effect of asylum seeker inflows on the emergence of hate crimes in Germany. Instead, we find that regional differences account heavily for the rise in hate crimes. Our first-difference estimates show that hate crime increases most pronounced in areas that now have large inflows of asylum seekers, but previously only had a limited number of foreigners. In addition, our evidence indicates that counties with a slack labor market or that had already witnessed hate crimes in the 1990s are now predominantly experiencing a rise in local hate crime. Moreover, we confirm large differences in hate crimes between East and West Germany. Different from Krueger and Pischke (1997), our results reveal that these differences can be explained by the interplay of immigrant inflows and regional variations in the ethnic composition of the incumbent population. Economic conditions or a legacy of hate crime cannot explain the grave differences between the former two parts of Germany.

The remainder of this article is organized as follows. The next section provides information on the context of our study and addresses the related literature. We describe our data on asylum seeker assignments, hate crimes, and other socio-demographic and socio-economic variables at the regional level in section 3. We then describe the German asylum seeker dispersal policy and our identification strategy, followed by the econometric approach in section 5. Section 6 presents the main estimation results and section 7 the additional sensitivity analyses. In section 8, we discuss the relevance of our findings and provide our conclusions.

2 Context and Related Literature

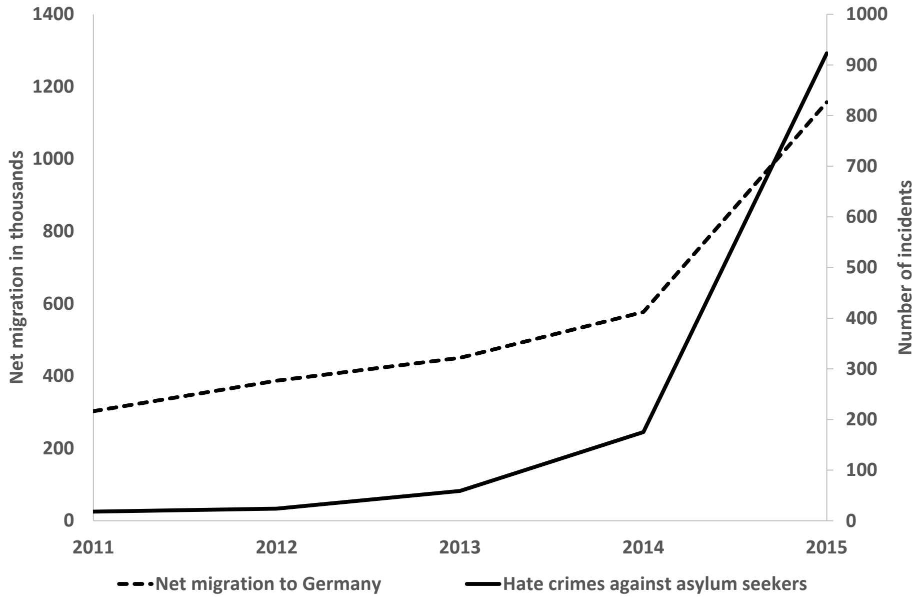
Episodes of violence against minorities and in particular, against foreigners have long been part of German history. Outbursts range from medieval times over Nazi-Germany to post-unification periods (Voigtländer and Voth, 2012; Krueger and Pischke, 1997; Falk et al., 2011). The last well documented attacks against foreigners before the current wave of violence against asylum seekers occurred in the beginning of the 1990s, after the reunification of East and West Germany. While pogrom-like attacks against refugees in Hoyerswerda in 1991 and Rostock-Lichtenhagen in 1992 led to worldwide dismay, they were only two drastic examples of a widespread phenomenon. In this period, the upsurge of anti-foreigner violence was accompanied by the large-scale immigration of ethnic Germans from former USSR countries and asylum seekers fleeing the Yugoslavian civil war.

Similar to the 1990s, when immigration and attacks against foreigners increased sharply and simultaneously, the latest and largest increase in immigration to Germany spurred xenophobic attacks. In 2014 and 2015, more than one million asylum seekers, primarily from the Middle East, entered Germany to seek asylum. The largest portion of immigrants came from countries riddled with civil war such as Syria (36.9%), Afghanistan (17.6%), and Iraq (13.3%), and were mostly young (73.8% are aged under 30 years) and male (65.7%) (BAMF, 2017). The inflow of people with a different ethnic origin dominates the sharp increase in net migration to Germany. Figure 1 depicts the net foreign migration to Germany and hate crime against asylum seekers from 2011 to 2015 on the left and right axes respectively. While hate crime against asylum seekers was almost absent in 2011, it increased in the following years, jumping sharply in 2015. Contemporary to the high net migration in 2015, hate crime against asylum seekers peaked with 923 incidents that year. These figures clearly show that hate crime is increasing in Germany, and that this trend is strongly correlated with the recent inflow of asylum seekers to the country.

However, hate crime incidents are not limited to Germany, but a widespread phenomenon in many industrialized countries. In England and Wales, the British Home Office reported 49,419 racially motivated hate crimes in 2015/16, an increase of 15 percent from 2014/15 (Corcoran, Lader, and Smith, 2015). For the United States, according to estimates of the U.S. Department of Justice (2014), 293,800 incidents of nonfatal violent and property hate crime victimization occurred in 2012 against persons aged 12 years or older residing in US households. Similar to experiences in other countries, the majority of victims perceived that the offender was motivated by bias against their ethnicity (51 percent) or race (46 percent; the survey allowed multiple responses).[2] Van Kesteren (2016), who analyzed survey data on hate crime victimization from

[2]The general problem with published hate crime figures is that the share of undocumented crimes might be high. The U.S. Department of Justice (2014) estimated that about 60 percent of total and violent hate crime victimization were not reported to the police. This has consequences for an econometric analysis of hate crime, which must consider that documented hate crime figures might represent only the tip of the iceberg.

Figure 1: Foreign net migration and hate crime in Germany from 2011 to 2015



Source: Data on foreign net migration is from the Federal Statistical Office. Data on hate crime against asylum seekers is from the Federal Criminal Police Office. Own depiction.

14 Western European countries, notes that in all countries, immigrants are disproportionately exposed to hate crimes.

Given the emergent importance of hate crime, this topic has been studied in various scientific disciplines and theoretical explanations are manifold. The important difference between hate crime and regular crime is the restricted motivation of offenders, which is based on prejudice toward minorities of a different race, religion, or sexual orientation. Green, McFalls, and Smith (2001) defined hate crime as "... unlawful, violent, destructive, or threatening conduct in which the perpetrator is motivated by prejudice toward the victims putative social group". Moreover, they classified hate crime, providing psychological, social-psychological, historical-cultural, sociological, economic, and political explanations at the individual or societal level of analysis. At the individual level, one influential explanation is based on the social identity theory, according to which people obtain their self-esteem from the groups they belong to (in-groups) and tend to have negative views about other groups (out-groups). Tajfel and Turner (1979) link this to the emergence of prejudice: Individuals try to enhance their self-image by enhancing the status of the group to which they belong through prejudiced views and by discriminatory behavior against members of the out-group. Akerlof and Kranton's (2000; 2005) approach of identity economics and its fundamental notion of the utility of identity is grounded in similar ideas. Allowing racial identities, Antecol and Cobb-Clark (2008) use this theoretical framework to explain racially motivated offensive behavior among US military personnel.

Other prominent explanations relate to the societal level.[3] We focus on three major hypotheses for the occurrence of hate crime: economic hardship, changes in the ethnic composition of the local population, and the long shadow of previous hate crime events.

The most widely debated question in the economic literature on hate crime is the relevance of economic conditions in the formation of anti-foreigner violence. The main argument is that aggression against out-groups (such as refugees and immigrants) is harsher the more intense the competition for resources, i.e., the more unfavorable are economic conditions. Previous German evidence on the impact of economic conditions yields mixed evidence. Krueger and Pischke (1997) and Falk et al. (2011) analyzed right-wing extremist crimes in Germany in the aftermath of the Yugoslavian civil war in the 1990s. Using state-level data from 1996 to 1999, Falk et al. (2011) found a significant link between unemployment as a measure of economic conditions and right-wing hate crime. However, based on newspaper incident data, Krueger and Pischke (1997) did not find a significant relationship between anti-foreigner hate crime and economic variables. In their paper, the only significant explanation of hate crime was the East Germany dummy, i.e., as the region with little previous interactions between migrants and non-migrants.

Green et al. (1998) and Hopkins (2010) propose explanation other than economic strain for increased hate crime. They argue that hate crimes against minorities are a consequence of whites' resistance against the sudden influx of minorities. Green et al. (1998) stress that hate crime rises in previously culturally and ethnically homogenous areas that are now experiencing a drastic change in the composition of residents. They confirm their model of "defended neighborhoods"

[3]Detailed surveys on existing theories are provided by Green et al. (2001), Dustmann, Fabbri, and Preston (2011), and Mocan and Raschke (2016), among others.

for crimes against Asians, Hispanics, and Blacks in predominantly white areas in New York City in the years 1987-1995, while no relationship was found between racially motivated crime and labor market conditions. Hopkins (2010) adds to the theory of defended neighborhoods the notion of a broad anti-minority climate at the national level, which is important in explaining nationwide increases in hate crimes.

Furthermore, convincing empirical evidence demonstrates the importance of historic events and adoption of institutions for modern-day attitudes and behavior (e.g., Grosjean, 2014; Couttenier, Grosjean, and Sangnier, 2017; Satyanath, Voigtländer, and Voth, 2017). Most related to our study is the work by Voigtländer and Voth (2012). They analyze the legacy of anti-Semitic hate crimes in interwar Germany, finding that indicators of twentieth-century anti-Semitism are significantly and positively correlated with medieval pogroms. Interestingly, their findings are related to defending-neighborhood explanations. Their results show that areas with lower hate crime persistence were those with higher levels of trade and persistent immigration, as predicted by the defended neighborhood hypothesis, in combination with the explanation of (a lack of) economic hardship.

Following the scientific debate on anti-foreigner sentiment, until now, no unified literature exists on the causes of this phenomenon. We contribute to the various strands of the literature by addressing several potential explanations of hate crime in a unified empirical framework. We extend previous analyses, which mainly focused on the economic reasons for hate crime, by accounting for alternative hypotheses such as defended neighborhoods and the legacy of hate crimes. We do so by investigating the increase in hate crimes after massive immigration of ethnically different asylum seekers to an industrialized country. Most important, we estimate the effect of hosting newly arrived immigrants on the rise in hate crime, enabling for a causal interpretation of the relationship between immigration and upsurge in hate crimes.

3 Data and Descriptive Statistics

3.1 Hate Crime Statistics

We employ data on attacks against asylum seekers for the years 2013 to 2015. Relying on administrative police records, we observe all registered incidents of hate crimes against asylum seekers' accommodations and the asylum seekers living in these. Since the police do not register victims' residence status, hate crimes against asylum seekers can only be identified by the place where the crime was committed, i.e. in other words, against persons living in asylum seeker accommodations. Thus, we can only observe the lower bound of attacks against this group. However, recorded incidents at asylum seeker accommodations can be considered as undoubtedly targeted against this group of recently immigrated foreigners, since these accommodations are salient and likely known to perpetrators. In addition, in time period under investigation asylum seekers had just arrived in Germany, making it likely that they are centering on their accommodations.

Following a xenophobic incident at an asylum seeker accommodation, the local police administration note the event as hate crime against asylum seekers. All these events were reported to the Criminal Police Offices of the German states (Landeskriminalämter) and finally to the Federal Criminal Police Office (Bundeskriminalamt, BKA). Each entry entails information on the time, place, and type of attack.[4] We collected this data using the replies of the Federal Government to several parliamentary inquiries of DIE LINKE party for 2013 to 2015 (see for instance Deutscher Bundestag, 2014).

In contrast to many other studies relying on survey or newspaper data (Krueger and Pischke, 1997; Jäckle and König, 2017; Müller and Schwarz, 2018), we employ official hate crime records. These, like most other crime statistics, are prone to under-reporting. However, compared to Jäckle and König (2017), who use a data set on attacks against asylum seekers based on newspaper reports collected by the Amadeu Antonio Foundation in 2015, our data set includes almost

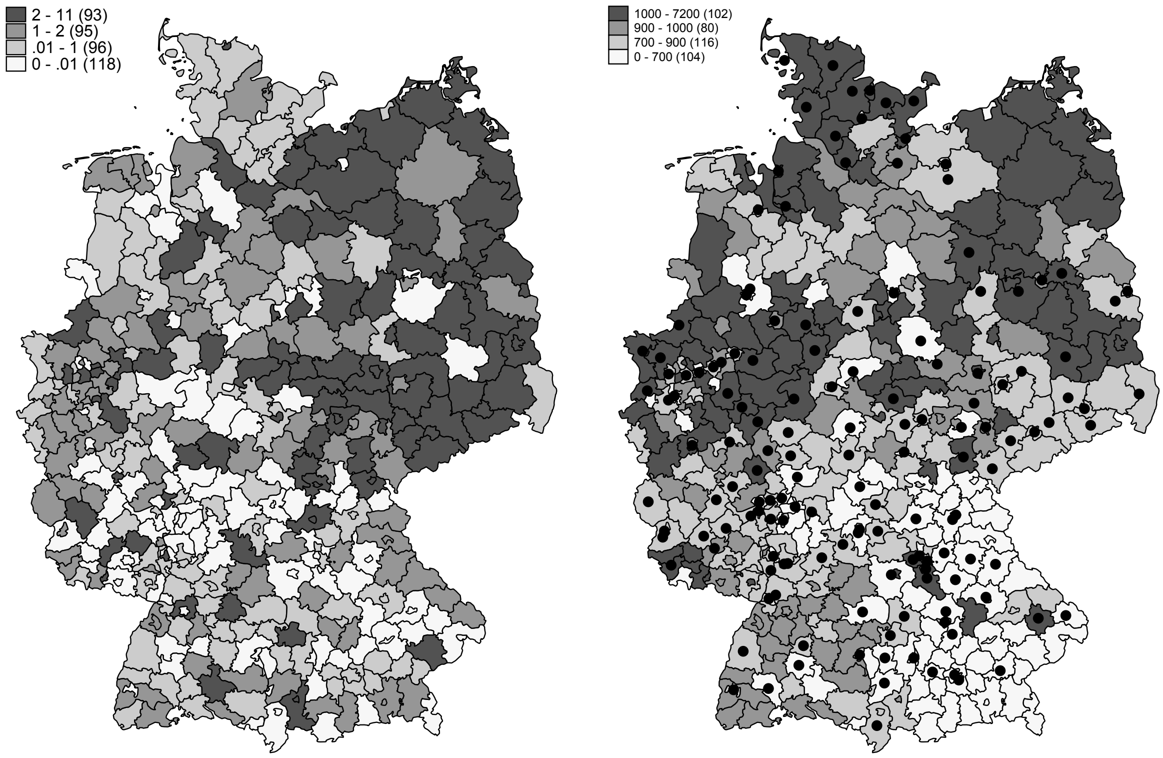
[4]Figure A1 in the appendix visualizes the number of hate crime incidents by type.

50 percent more entries than does their database. By using administrative data, we avoid the shortcomings of alternative data sources, such as selective media attention, to report only shocking incidents of anti-foreigner hate crime. This type of under-reporting could be especially problematic in regions where negative attitudes against foreigners are dominant, thus biasing the regional documentation of hate crimes. Since our analysis relies on variation between counties, this is crucial for our identification strategy. Furthermore, the strict regulations in police reporting, mean that this bias in administrative police records is considerably unlikely.

We use all attacks labeled as right-wing extremist hate crimes. By that, we exclude the possibility of including intra-refugee community hate crimes such as between Iraqis and Iranians living in the same group accommodation. As a robustness check in section 7, we restrict the analysis to violent hate crimes including arson attacks and assaults to focus on salient crimes, which are less prone to under-reporting biases. All other non-violent but clearly xenophobic actions constitute a widely ranged measure of anti-foreigner, mostly racist, and extreme right political behavior directed at threatening, insulting, or defaming asylum seekers. Examples of non-violent hate crimes are swastika graffiti at asylum seeker accommodations or threatening their lives at gunpoint. Ultimately, we use 1,155 incidents for the whole of Germany from 2013 to 2015. In 2014, 171 cases of hate crimes against asylum seekers occurred. When asylum seekers' immigration to Germany spiked in 2015, hate crime incidents peaked at 925, of which 74 were arson attacks and 63 assaults.

Panel (a) in Figure 2 depicts the distribution of attacks per 100,000 residents. Almost 72 percent of the German counties experienced at least one attack against asylum seekers from 2013 to 2015, and almost one quarter encountered a minimum of one violent attack. In 2015, after adjusting for population size, every most-affected region was in the eastern part of Germany. The rural area of Sächsische Schweiz-Osterzgebirge in Saxony had the most incidents with 9.76 attacks per 100,000 residents in 2015, followed by the counties of Uckermark and Saale with 8.24 and 7.99 attacks per 100,000 residents respectively.

Figure 2: Attacks against and assignment of asylum seekers per 100,000 residents



(a) Hate crimes

(b) Asylum seeker assignments

Note: Panel (a) displays the regional distribution of hate crimes against asylum seekers in 2013–2015 normalized by 100,000 residents. Panel (b) shows the regional distribution of the number of assigned asylum seekers in 2015 normalized by 100,000 residents. The black dots mark the presence of a state-run large-scale asylum seeker reception center.

3.2 Asylum Seeker Data

Our source of asylum seeker data is Gehrsitz and Ungerer (2016), who collected data from the States Ministries of Interior on the assignment of asylum seekers to counties. Their data provide information on the number of asylum seekers assigned to subordinate counties by the States Ministries of Interior in 2014 and 2015. In our main analysis, we estimate Intention-to-Treat (ITT) effects on the rise in hate crimes against asylum seekers. Using the number of assigned asylum seekers alleviates concerns regarding the potential endogeneity of asylum seeker location choices or about counties trying to influence the actual number of asylum seekers hosted. However, subordinate counties may have tried to influence assignments from the state authorities. We empirically investigate this concern in section 4.

In addition, we use information on the presence of a large-scale asylum seeker reception center (EAE), also collected by Gehrsitz and Ungerer (2016). These centers have high visibility and might be more likely to be chosen as hate crime targets. We investigate whether the existence of a local EAE is associated with more hate crime against asylum seekers.

The map in Panel (b) in Figure 2 presents the assignment of asylum seekers to counties per 100,000 residents in 2015. Darker areas indicate a larger number of assignments per 100,000 residents. The black dots mark the presence of an EAE. The range of newly assigned asylum seekers spans from none to almost 7,200 asylum seekers per 100,000 residents.[5]

3.3 Regional Characteristics by Occurrence of Hate Crime

To understand the relation between attacks against asylum seekers and regional characteristics, we calculate the means and standard deviations of several socio-demographic and economic indicators by the occurrence and non-occurrence of attacks in the counties. Table 1 presents these statistics using data (i) of all counties in Germany; (ii) for counties that experienced at least one attack in 2013, 2014, or 2015; and (iii) for counties without a single recorded attack in these years. The last column in Table 1 reports the differences in means between counties with and without attacks against asylum seekers. The asterisks highlight statistically significant differences. Panel A shows the average number of attacks per county and Panel B general demographic statistics. Panel C to E give first impressions on how potential explanations for anti-foreigner hate crime are distributed across counties with and without attacks.

Data at the county level for 2013 to 2015 are supplied by the Federal Statistical Office of Germany (Statistisches Bundesamt), Federal Returning Officer (Bundeswahlleiter), and the BKA.

[5]The State of Bavaria (south-east) stands out on the map as hosting relatively few asylum seekers. This is for two reasons. First, Bavaria tends to not distribute asylum seekers to regions immediately, but keeps them for a longer time in state-administered reception centers. Second, since almost all asylum seekers entered Germany by the so-called Balkan route, they arrived in Bavaria first. Because of the administrative costs involved in registering asylum seekers at the Bavarian-Austrian border, the number of asylum seekers Bavaria was to host was reduced.

With the exception of variables only available for a certain period (e.g., election outcomes), all county statistics in Table 1 are averaged over our estimation period of 2014 and 2015.

Panel A in Table 1 shows that on average, 1.36 attacks occurred per county, of which 0.20 were registered as violent hate crimes. When normalizing the number of attacks by population size, the respective frequencies are 0.67 attacks and 0.08 per 100,000 residents. These figures indicate that hate crimes against asylum seekers are not frequent, but rare and extreme cases of anti-foreigner hatred.

Regarding the demographics in panel B, the resident population of counties with and without attacks differs greatly, but only marginally in terms of population density. Counties without any attacks have fewer residents, but a higher density. As mentioned, attacks happen disproportionately often in counties belonging to the former territory of the German Democratic Republic. Among all counties that experienced at least one attack, about one fourth are located in the East (the share of eastern counties among all counties is 18.88 percent). In comparison, of the 118 counties without attack, only 4 (or 3.38 percent) are part of eastern Germany. We also examined the migration patterns of natives within Germany. Counties with and without attacks do not seem to have different residential turnovers in our estimation period. According to Willems, Eckert, Würtz, and Steinmetz (1993), hate crime perpetrators are predominantly young males with low scholarly achievement. Thus, we report the share of males aged less than 35 years and share of school dropouts. P-values of the tests of equality of means suggest that on average, counties with attacks have more school dropouts, but a lower share of males aged less than 35 years. There is no statistical difference between the affected and non-affected groups of counties in terms of violent crime records. Note that the share of foreign-born crime suspects is considerably higher in counties without attacks.

Regarding panel C, counties facing attacks against asylum seekers have a statistically significant higher share of citizens with German nationality than those without attacks. This supports the notion that immigrants usually bypass areas in which they expect hostile behavior from the resident population. Notably, there is no statistically significant difference in the number of

Table 1: Summary statistics by counties with and without attacks

	Total		With attack		Without attack		Diff.
	mean	sd	mean	sd	mean	sd	
Panel A: Attacks on asylum seekers							
Number of attacks	1.36	3.08	1.93	3.52	–	–	–
Number of violent attacks	0.20	0.71	0.28	0.83	–	–	–
Attacks per 100k residents	0.67	1.17	0.94	1.29	–	–	–
Violent attacks per 100k residents	0.08	0.27	0.12	0.32	–	–	–
Panel B: Demographics							
Number of residents in thousands	203.20	235.25	230.89	270.64	136.55	77.82	94.35***
Residents per km^2	523.74	687.07	497.24	710.35	587.51	624.35	-90.27*
Share of Cities over 100k residents in %	16.52	37.16	16.20	36.87	17.30	37.90	-1.10
Share of counties in the East in %	18.88	39.16	25.35	43.54	3.38	18.10	21.98***
Net internal migration of natives %	-0.03	0.29	-0.02	0.29	-0.04	0.29	0.02
Share of males under 35 in %	18.48	1.79	18.27	1.84	18.98	1.57	-0.72***
Share of school dropouts in %	5.69	2.27	5.93	2.38	5.13	1.88	0.79***
Share of vacant private housing	5.60	2.95	5.90	3.08	4.89	2.48	1.00***
Violent crimes per 100k residents	188.63	98.34	185.67	93.15	195.74	109.72	-10.07
Share of non-German crime suspects in %	25.62	11.58	24.34	11.45	28.70	11.33	-4.36***
Panel C: Immigration							
Share of natives in %	91.72	4.82	92.36	4.62	90.20	4.95	2.16***
Assigned asylum seekers per 100k residents	546.62	455.29	553.80	386.27	529.32	589.82	24.48
Share of counties with refugee reception center in 2015	36.77	48.25	35.92	48.02	38.82	48.84	-2.90
Panel D: Economy							
GDP per capita in 1k Euro	34.11	14.55	32.80	14.26	37.26	14.77	-4.47***
Unemployed persons per 1k residents	32.51	14.33	33.93	14.60	29.09	13.07	4.84***
German Index of Socioeconomic Deprivation in 2012	44.55	16.95	46.10	17.17	40.81	15.83	5.29***
Panel E: Voting							
Voter turnout in 2013 federal election in %	71.62	3.82	71.66	3.73	71.48	4.20	0.18
Extreme right vote shares in 2013 federal election in %	1.49	0.84	1.51	0.90	1.40	0.59	0.11***
AfD vote shares in 2017 federal election in %	12.59	5.27	12.72	5.68	12.03	3.02	0.69***
N	804		568		236		804

Notes: The first two columns show the mean and standard deviation (sd) of county variables for all counties. Columns three and four display the mean and standard deviation of county variables only for counties with at least one recorded attack against asylum seekers in 2014 or 2015. Columns five and six display the mean and standard deviation of county variables only for counties without any recorded attack against asylum seekers between 2013 and 2015. Column seven displays the difference in means between columns five and three. Statistical significant differences are indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

assigned asylum seekers. This may indicate that the German dispersal policy was not undermined by attacks against asylum seekers. Finally, both groups of counties have approximately the same share of those hosting a refugee reception center.

Panel D suggests that economic conditions matter, since there are statistically significant differences between counties with and without attacks. GDP per capita is higher and unemployment figures lower in regions without hate crime attacks. We confirm this differential using an index of socioeconomic deprivation (GISD).[6] The higher the index, the more deprived the area under consideration.

Panel E includes two statistics regarding the federal election in 2013. The timing of the election is convenient, since it was conducted the year before the large-scale immigration of asylum seekers began. The immigration of asylum seekers was not on the top of the political agenda, and did not mobilize masses of voters. Counties with attacks against asylum seekers do not statistically differ in terms of voter turnout. However, voters living in counties with hate crimes against asylum seekers cast slightly more votes for extreme-right parties.[7] The same is true for votes for the party "Alternative für Deutschland" (AfD). At the federal election in 2017, they ran an election campaign based solely on anti-immigration and anti-asylum seeker sentiments. In doing so, they mobilized many voters and garnered more than 12 percent of the votes cast.

To summarize, there are strong differences between counties with and without hate crimes against asylum seekers in terms of economic conditions, demographics, and ethnic composition. However, we do not find any indication of selection mechanisms that may have directed asylum seeker assignments to regions in which they would be at a lower risk of being a victim of a hate crime.

[6]The index was introduced by Germanys Federal Institute for Research on Building, Urban Affairs and Spatial Development (Kroll, Schumann, Hoebel, and Lampert, 2017), and is based on a (factor analytic) weighted average of the three dimensions of education, occupation, and income.

[7]We classified the National Democratic Party, Republicans, and The Right as extreme right parties.

4 Asylum Seeker Dispersal Policy in Germany

To attach a causal interpretation to our estimates of local asylum seeker inflows and regional conditions on the emergence of hate crime attacks, we rely on the exogeneity of the assignment of asylum seekers with respect to regional characteristics influencing hate crime. For this exogeneity assumption to hold, it is required that asylum seekers cannot choose their place of residence and that counties cannot decide on the number of asylum seekers they want to host. Both conditions are likely to be fulfilled in the German context of asylum immigration because of a national dispersal policy. Based on the federal system in Germany, asylum seekers are assigned to different locations in a two or three-stage procedure. In the first stage, newly arriving asylum seekers are assigned to a state. Then, within a state, they are either allocated to a county and then to a municipality or directly to a municipality.

The typical way asylum seekers move through the German assignment scheme in the time of the large influx of asylum seekers was as follows (see also BAMF, 2016). When asylum seekers passed the German border, they were picked up by police officers and registered at the closest reception center incorporating a local branch of the Federal Office for Migration and Refugees (BAMF). At these centers, asylum seekers were assigned to one of the German states (Länder) based on a quota regulating the division of federal financial burdens between the states.[8] The quota is based on two thirds of the relative tax revenues and one third of the relative population sizes of the states. A computer program called EASY (Erstverteilung der Asylbegehrenden) assigns asylum seekers to reception centers in a particular state according to the rules of this quota.

In the second step, asylum seekers are assigned either to counties or directly to municipalities within the state.[9] This process varies by state, since each has its own law on how to organize the

[8]This quota is called "Königsteiner Schlüssel" and was originally designed to regulate the financial contributions of the states to federal institutions of research and education. Nowadays, it is widely applied to several topics including the allocation of asylum seekers. The shares for each state are published annually in the Bundesanzeiger from the Federal Ministry of Justice and Consumer Protection.

[9]Exceptions are the city-states Berlin and Hamburg, which do not further assign asylum seekers to subordinate authorities, but allocate them within the city.

allocation of asylum seekers. The majority of states first assign asylum seekers to counties and then to municipalities within the county (see Wendel, 2014). State-to-county or state-to-municipality assignments are primarily based on the population size of counties and municipalities. This is directly stated in the respective state law or implicitly demonstrated by the rules implemented based on the population size of the subordinate level.[10]

In our analysis, we employ the assignment to counties. Therefore, we take the first stage of the assignment process—from the federal to state level—as given, and use variations in the local treatment intensity of hosting asylum seekers. Since we use the county-level aggregate inflow of asylum seekers in our approach, it does not matter whether states assign asylum seekers to counties first and then to municipalities or directly to municipalities.

Asylum seekers are bound to stay at their assigned places as long as no final decision on the application for asylum has been made. Non-compliance is sanctioned with a fine, and if repeatedly disobeyed, with a prison sentence of up to one year. More important, asylum seekers receive monetary benefits and free housing at their assigned place. Since most asylum seekers depend on these benefits, non-compliance is highly unlikely.

County-Level Assignments of Asylum Seekers

Variations in the intensity of hosting asylum seekers stem from the administrative assignments of asylum seekers to counties. By using the administrative assignments from states to subordinate counties, we overcome selection based on the preferences of asylum seekers or non-compliance of hosting regions. However, given the population-based quota system of the German states, a population-normalized measure of the inflow of asylum seekers (as we use it) should have no variation between counties in the same state.

However, we observe within-state variation in our assignment data (see Panel (b) in Figure 2). Although asylum seekers should be assigned according to the population size of the counties,

[10]Two states have additional criteria. North Rhine-Westphalia assigns asylum seekers to municipalities at 90 percent by population size and 10 percent by land size. Brandenburg does the same, but adds a component reflecting the state of the local labor market. An overview on these allocation schemes by state is provided by Geis and Orth (2016).

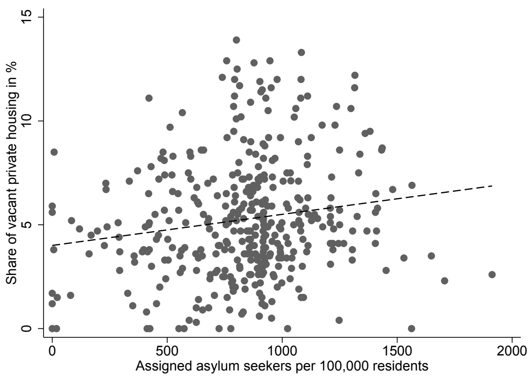
some counties were assigned more asylum seekers per 100,000 residents than others in the same state. Gehrsitz and Ungerer (2016) conclude that the sheer mass of the inflow in 2015 stretched the allocation scheme to its maximum. As a result, decisions on the place where asylum seekers were ultimately hosted were often determined by the availability of group accommodations. In informal talks with the authorities involved in the allocation process, many told us that they adjusted the assignments because of a lack of suitable accommodations in the counties. In some states, the possibility to deviate from the original quota because of a local lack of housing is explicitly stated in the respective state laws. Thus, it seems that both population sizes and readily available group accommodations governed the distribution of asylum seekers.

In our empirical analysis, we use the population-normalized number of assignments as a source of exogenous variation for the intensity of hosting recently arrived asylum seekers. For this approach to be feasible, counties should not impact the number of asylum seekers hosted. Although imposing any influence is highly unlikely given the hierarchical federal structure in Germany, subordinate counties could perhaps have argued for fewer assignments based on (a) available housing capacities, (b) their economic condition, (c) problems with criminal activity, or (d) a tense political situation. In Figure 3 and Table 2, we provide empirical evidence that most of these arguments seem to not be the case.

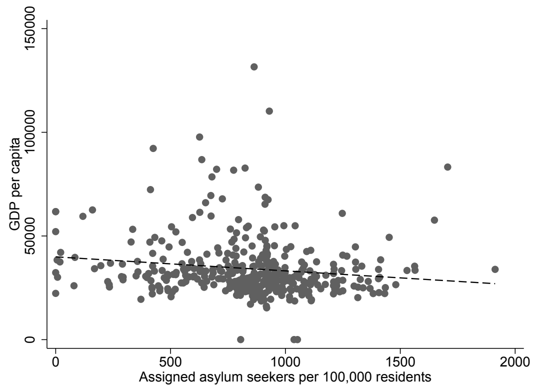
Figure 3 depicts the correlation between the number of assigned asylum seekers per 100,000 residents and four county-level variables. In Panel (a), the share of vacant private housing is indeed positively correlated with the number of assigned asylum seekers. This supports the claims of the state authorities. In addition, as visible in Panels (b), (c), and (d), the assignment of asylum seekers does not seem to be correlated with GDP per capita, crime rates, or the vote shares of extreme right-wing parties.

Especially Panel (d) is important for the case of hate crime against asylum seekers as an outcome variable. If, for instance, counties with known or supposed high levels of hostility against foreigners were able to reduce their share of assigned asylum seekers or if state authorities decided to spare these counties, the correlation between the two measures is expected to be negative.

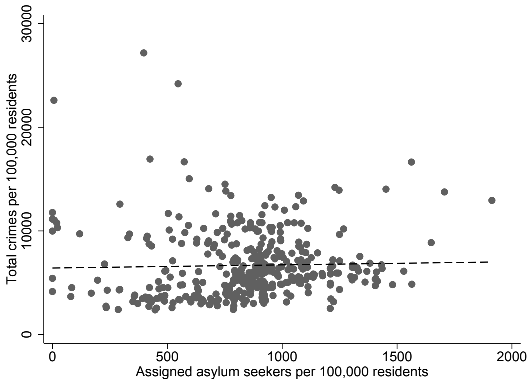
Figure 3: Correlation between the number of assigned asylum seekers per 100,000 residents (X-axis) and county-level characteristics (Y-axis)



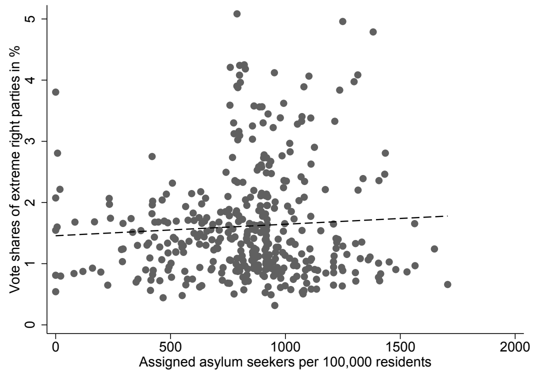
(a) Vacant private housing



(b) GDP per capita



(c) Total crimes



(d) Extreme right-wing vote shares

Note: The Figure displays the correlation between the number of assigned asylum seekers to counties in 2015 per 100,000 residents and (a) the share of vacant private housing in 2015, (b) GDP per capita in 2015, (c) number of total crimes per 100,000 residents in 2015, and (d) county-level vote shares of extreme right-wing parties at the 2013 federal election.

That is, strong political anti-foreigner support would have led to fewer asylum seekers in a county. Panel (d), however, suggests that there is no systematic relationship between asylum seeker assignments and the vote shares of parties with a clear anti-immigration agenda. Although severe protests against the intake of asylum seekers occurred in some places, there is no documented evidence about any acknowledgment of anti-foreigner sentiment in the assignment process.

We can more formally test this proposition by regressing the local assignment of asylum seekers per 100,000 residents on measures of latent xenophobia. Column (1) in Table 2 presents

Table 2: Determinants of Asylum Seeker Assignment

	Assigned asylum seekers per 100,000 residents		
Extreme-right vote share$_{2013}$ (%)	18.750		-6.928
	(17.727)		(19.917)
Hate crimes per 100k residents$_{\text{t-2}}$		1.361	2.693
		(3.680)	(3.713)
County in the East			-146.136
			(90.182)
City with more than 100k residents			-77.678**
			(34.886)
GDP per capita$_{\text{t}}$ in 1k EUR			5.337
			(3.450)
Unemployment per 1k residents$_{\text{t}}$			2.124
			(2.286)
Reception center$_{\text{t}}$ (EAE)			-17.377
			(27.957)
Vacant housing$_{\text{t}}$ (%)			19.502***
			(6.472)
Violent crimes per 100k residents$_{\text{t}}$			-0.280
			(0.318)
Constant	301.169***	315.102***	100.608
	(48.213)	(47.385)	(163.686)
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
adj. R^2	0.503	0.502	0.519
N	788	788	788

Note: Columns one to three show the OLS estimates of the determinants of asylum seeker assignments to counties in 2014 and 2015. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the results of a linear regression including extreme-right parties vote shares as a measure of latent xenophobia. As an alternative measure, we also use hate crimes against asylum seekers in 2012 and 2013, i.e., before the recent large influx. The rationale is the same as in the case of extreme-right voting: Regions that previously experienced incidents of anti-asylum seeker hatred might be able to argue in favor of receiving (relatively) less asylum seekers. The estimated coefficients for extreme right-wing voting and for hate crimes in previous years are statistically insignificant. The coefficient for extreme right-wing voting is large, but positive, indicating that, if at all, more votes for extremist right parties would be associated with *more* asylum seekers. This suggests that pre-existing local hostility against asylum seekers did not drive or influence their assignment.

The result holds when controlling for other factors that might have influenced the assignment of asylum seekers (Table 2, column three). German asylum authorities claim that the availability of housing capacities is one main driver explaining the variation in asylum seeker assignments. Furthermore, cities with a population of more than 100,000 residents were on average assigned about 77 asylum seekers per 100,000 residents less than other counties. Since housing possibilities in big cities are scarce, this again reflects the importance of the availability of accommodations for the assignment of asylum seekers.

Thus, we conclude that the evidence provided in Figure 3 and Table 2 supports the assumption regarding the orthogonality of the assignment of asylum seekers to county characteristics prior to the influx. Relying on this assumption and by conditioning the factors determining the assignment, we are able to estimate and identify a causal ITT effect of asylum seeker inflows on the increase in hate crimes.

5 Econometric Approach

We want to test the hypothesis that the recent influx of asylum seekers to Germany has led to a significant increase in attacks. In particular, we want to investigate why some regions are more prone to hate crime against asylum seekers than others. The analysis considers several channels of influence and focuses on economic, demographic, and social conditions.

As suggested by the reflections and conjectures in previous sections, the link between hate crime and asylum seekers may be non-linear and dependent on interactions with third factors such as the preexisting ratio of incumbent natives relative to foreigners. Therefore, we are interested in the following relationship:

$$\begin{aligned} hate\ crime_{ct} = {} & \delta asylum\ seekers_{ct} + \phi CC_{2013} + \gamma asylum\ seekers_{ct} \times CC_{2013} \\ & + X_{ct}\beta + \theta_c + \theta_s + \theta_t + u_{ct}\,, \end{aligned} \tag{1}$$

where *hate crime* is measured as the total number of attacks against asylum seekers in county c in year t normalized by 1,000,000 residents in 2013. The main explanatory variable $asylum\ seekers_{ct}$ is normalized by 1,000 residents in 2013.[11] CC denotes the potential county-level characteristic of interest, which will differ according to the respective hypothesis under consideration. The parameters δ and γ are the main coefficients of interest to evaluate the influences of asylum seekers and county-level characteristics on the formation of anti-foreigner hate crime in Germany. For the analysis of county-level characteristics, we use interacting explanatory variables only for 2013, the year prior to the main inflow of asylum seekers, to avoid any endogenous changes in regional characteristics in response to the immigration shock.

To interpret δ and γ as causal parameters, we estimate first-differenced regression equations to eliminate time-constant unobserved heterogeneity between the counties (θ_c). This is important, since regions are subject to long-lasting structural attributes, which are not perfectly covered by socio-demographic and socio-economic variables. Moreover, the nature of unexpected inflows of asylum seekers suggests a natural foundation of a first-difference specification. The estimation equation takes the following form:

$$\begin{aligned} \Delta hate\ crime_{ct} = {} & \delta \Delta asylum\ seekers_{ct} + \gamma \Delta asylum\ seekers_{ct} \times CC_{2013} \\ & + \Delta X_{ct}\beta + \Delta\theta_t + \Delta u_{ct}\,, \end{aligned} \tag{2}$$

where we use the annual difference between the periods 2013–2015, resulting in a panel of $T = 2,\ t = 2014, 2015$ with all $n = 402$ counties in Germany. Since we do not have information on the stock of asylum seekers, we take the annual county-level assignments in 2014 and 2015 as a measure of $\Delta asylum\ seekers_{ct}$. To be even more restrictive, we retain state fixed effects (θ_s) to control for state-specific trends; for example, to control for potential changes in police spending or asylum policies between states.

As motivated in the introduction, CC represents the variables constituting the hypotheses of defended neighborhoods, economic hardship, and legacy of hate crime. For instance, the question

[11] The different scales of the dependent and main independent variable were selected to facilitate the interpretation of the estimated coefficients in section 6.

regarding the validity of the theory of defended neighborhoods is whether hate crime is most pronounced in areas where few foreigners lived before and which is now exposed to a large and sudden influx of asylum seekers. Our empirical model enables testing this hypothesis, since we can explicitly incorporate the interaction of county-specific inflow of asylum seekers with the pre-influx share of native-born residents as of 2013. Evidence for the validity of this hypothesis is obtained if the average marginal effect of asylum seekers on hate crime and estimated parameter γ are positive, and the marginal effect increases with the share of natives (indicators of economic hardship and hate crime legacy are considered analogously).

X constitutes a vector of time-varying covariates, including annual changes in the share of German-born residents, unemployed persons per 1,000 residents, GDP per capita, as well as the net internal migration of natives and share of foreign-born alleged offenders of violent crimes. Since the literature on hate crime perpetrators suggests that young male adults or adolescents with low scholastic achievement perform the majority of hate crimes (Willems et al., 1993), X also includes annual changes in the share of males younger than 35 years and in the share of school dropouts in each county. To be diligent about omitted regressors that correlate with our main explanatory variable "assignment of asylum seekers" (see section 4), we also control for the share of vacant housing and presence of large-scale reception centers. In addition, we include dummies for states and years, and cluster standard errors at the county level.

6 Results

6.1 Simply more Hate Crimes due to an Increasing Number of Potential Hate Crime Victims?

We first present the results of regressing hate crimes on asylum seeker inflows without explicitly considering differences in regional conditions. We do this to isolate the victim supply effect, namely the effect of a mere increase in the number of asylum seekers in a particular county on hate crime against asylum seekers in this area. Table 3 provides the results of this regression in column

(1) without and (2) with additional covariates and state and year fixed effects. We estimate the ITT effect, which informs us about the effect of asylum seeker inflows when these (strictly) follow administrative assignments. The unconditional baseline regression shows a statistically significant parameter estimate of 0.937, indicating that the inflow of one additional asylum seeker per 1,000 residents would have led to approximately one additional attack per one million residents. After controlling for covariates and including state and year fixed effects, the ITT effect is reduced by two thirds of its original magnitude (0.325), losing its statistical significance. This result suggests that, conditional on county characteristics and state and year fixed effects, no direct and linear link exists between the size of asylum seeker inflows and hate crime attacks–a surprising result. Generally, it is expected that a higher supply of potential victims per capita should lead to more observed acts of hate crime against this group. An explanation for this finding may be that a certain threshold of incoming asylum seekers must be passed before potential perpetrators lash out against newcomers (analogous to tipping-point models, see Card, Mas, and Rothstein, 2008). In addition, asylum seeker accommodations must be salient to be attacked by aggressors. A lack of visibility of local group accommodations might reduce the probability of attacks. To investigate both potential explanations for the non-significance of the effect of asylum seeker inflows on hate crime, we focus on counties with very high inflows of asylum seekers (exceeding a threshold) or that run large-scale asylum seeker reception centers (high salience).

The models in columns (3) to (4) show the estimated coefficients for asylum seeker inflows and the interaction effect of asylum seeker inflows with dummy variable D, which takes on the value 1 if the county is located in the upper quartile of asylum seeker assignments and 0 otherwise. For both specifications, we find positive, but only marginally statistically significant main effects and negative statistically insignificant interaction effects. It thus seems that counties in the upper end of the asylum seeker distribution do not experience more attacks against asylum seekers than those with less asylum seekers per capita.[12] Columns (5) to (6) show the estimates for the interaction with dummy variable EAE, which takes on the value 1 if the county hosts a

[12]The same holds true when we split counties at the median instead of at the 75^{th} percentile.

Table 3: The Effect of Inflow Size and Reception Centers on Hate Crime

	(1)	(2)	(3)	(4)	(5)	(6)
Asylum Seekers	0.937***	0.325	0.572*	0.571*	0.707***	0.756***
	(0.137)	(0.198)	(0.331)	(0.309)	(0.191)	(0.188)
Asylum Seekers × D$\left[\text{ Inflow} \geqslant \text{Q}_4\right]$			-0.231	-0.217		
			(0.198)	(0.196)		
Asylum Seekers × EAE					-0.508***	-0.534***
					(0.136)	(0.134)
Covariates	No	Yes	No	Yes	No	Yes
State Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
adj. R^2	0.27	0.39	0.37	0.40	0.36	0.39
N	804	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents and interacted with dummy variable *EAE*, which takes on the value of 1 if the county has a large-scale reception center and 0 otherwise, or with dummy variable D, which takes on the value of 1 if the county is within the fourth quartile of asylum seeker assignments and 0 otherwise. Covariates include first-differences of GDP per capita, unemployed per 1,000 residents, and the shares of natives, net internal migration of natives, males aged less than 35 years, school dropouts, foreign suspects of violent crimes, vacant private housing, and an indicator for EAEs (except for columns (5) and (6)). Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

large-scale reception center and 0 otherwise. For counties hosting an EAE, we find *fewer* attacks on asylum seekers. A high salience of asylum seeker accommodations seems not to be driving the results. Instead, this finding indicates that counties with smaller, more spatially fragmented, and decentralized forms of housing experience more attacks against asylum seekers.

We conclude from the regression analyses that the size of the inflow of asylum seekers and a high salience of accommodations do not automatically translate into higher numbers of attacks against this group. Thus, it is crucial to study the local interplay of the size of the influx and prevailing ethnic composition, as well as the economic and social situation to better understand the regional heterogeneity of hate crime offenses. As clarified in subsequent sections, even a small number of asylum seekers in responsive regions might have larger effects than a massive inflow to regions with low levels of anti-foreigner sentiment.

6.2 Regional Factors Determining Hate Crime

In this subsection, we analyze whether the effect of asylum seeker inflows on hate crimes is magnified by local ethnic composition or economic or historical characteristics. We refer to these hypotheses as defended neighborhoods, economic hardship, and the legacy of hate crime respectively.

Columns (1) and (2) in Table 4 present the tests of the defended neighborhood hypothesis. We empirically test the hypothesis by interacting the local inflow of asylum seekers with the share of German-born residents in the county as of 2013. We then construct a measure capturing both the size of the arriving ethnically different inflow and local predominance of the incumbent population. Statistically significant negative coefficient estimates of asylum seeker inflows and statistically significant positive estimates of the interaction with the pre-existing share of natives are visible in both models. This implies that the number of attacks against asylum seekers is higher in regions with relatively larger shares of incumbent natives, and lower in regions with an already relatively large share of foreigners. As the average marginal effects (AME) are positive, we conclude that the results are in line with the defended neighborhood hypothesis. Furthermore, the magnitudes of the AME exceed the corresponding values of the baseline regression without interactions (0.459 instead of 0.325, see column (2) in Table 3). Evidently, what matters is not purely the absolute size of incoming asylum seekers, but the encounter of unaccustomed natives with massive inflows of (ethnically different) foreigners.

Columns (3) and (4) in Table 4 report the effects of asylum seeker inflows on hate crime depending on the extent of economic hardship. We expect that in regions with poor labor market conditions, asylum seekers are considered as competitors of local job seekers or for welfare benefits, specifically for those who are low-skilled and unemployed. In most of the empirical literature, economic hardship is measured by unemployment.[13] To ensure that we cover the economic situation at the time before the massive inflow of asylum seekers, we use the unemployment

[13] In section 6.4 we discuss an alternative measure of economic hardship, an indicator of the relative deprivation of counties (cf. Kroll et al., 2017).

Table 4: Effect of Inflows and Regional Conditions on Hate Crime

	Defended Neighborhoods		Economic Hardship		Legacy of Hate Crimes	
	(1)	(2)	(3)	(4)	(5)	(6)
Asylum Seekers	-10.323***	-6.177***	-0.172	-0.437	0.521***	0.212
	(2.008)	(1.449)	(0.277)	(0.307)	(0.169)	(0.143)
Asylum Seekers						
× Share of natives	12.126***	7.143***				
	(2.171)	(1.631)				
× Unemployment			0.030***	0.022***		
			(0.007)	(0.008)		
× Attacks90s					0.736***	0.457***
					(0.198)	(0.127)
AME[Asylum Seekers]	0.944***	0.459***	0.871***	0.318*	0.980***	0.500***
	(0.083)	(0.133)	(0.121)	(0.192)	(0.091)	(0.149)
Covariates	No	Yes	No	Yes	No	Yes
State Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
adj. R^2	0.35	0.41	0.33	0.41	0.31	0.40
N	804	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents interacted either with the share of Germans living in the county in 2013 (Defended Neighborhoods), number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or a dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993, and 0 otherwise (Legacy of Hate Crimes). For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

figures as of 2013. Because registered unemployment rates depend on the size of the labor force, which depends on the participation rate and potentially high number of people out of the labor force, we instead use the number of unemployed per 1,000 residents as our interaction variable.[14]

As before in columns (1) and (2), we obtain a statistically significant estimate of the interaction parameter γ for the economic hardship hypothesis. The nonlinear effect depending on the local unemployment situation is as expected: One additional asylum seeker in a region with a large number of unemployed persons has a higher marginal effect on attacks against asylum seekers than in a region where the number of jobless people is small (cf. the negative sign of δ, and positive

[14] Using the number of unemployed persons per residents instead of the unemployment rates does not alter our results quantitatively or qualitatively.

one of γ). However, after adding controls, the AME, though still marginally significant, does not differ much from the baseline coefficient in Table 3. Thus, on average, economic conditions might not play a great role in explaining the rise in hat crime, but may be relevant in regions where a high number of asylum seeker coincides with a high number of unemployed persons.

Using data by Krueger and Pischke (1997), who investigated the high and rising rate of anti-foreigner hate crimes during the early 1990s, we test whether historical patterns of hate crime have amplified current aggression against asylum seekers. To do so, we interact the inflow of asylum seekers with a dummy variable, which takes on the value 1 if hate crime events were already documented in the years 1991–1993 in the county, and 0 otherwise. Columns (5) to (6) in Table 4 confirm that regions with former anti-foreigner incidents, which happened 25 years ago, face significantly more attacks than those without attacks at that time. The AME substantially increases from 0.325 in Table 3 to 0.500 after considering previous regional patterns of hate crime. This important finding shows that the current upsurge in hate crimes is not only related to the contemporary factors of ethnic composition or economic conditions, but also rooted in the legacy of the long-lasting xenophobic attitudes that have persisted in affected regions up to today.

6.3 Differences between East and West Germany

The previous section elucidated the regional factors explaining hate crime against asylum seekers. Germany's distinct history of division into two countries with different political systems means it is important to more closely examine at regional subsamples. Moreover, panel (a) in Figure 2 shows that different levels of hate crime rates between the two former parts of Germany exist. In this section, we estimate separate coefficients for East and West Germany, acknowledging the historic and prevailing differences. This exercise seems especially important, as previous and current anti-foreigner attacks are predominantly located in the East of Germany (see section 3 as well as Krueger and Pischke, 1997).

We introduce the dummy variable *East*, which takes on the value 1 if the county is located in the area of the former communist German Democratic Republic (GDR), and 0 otherwise. Column

Table 5: East-West Effects of Regional Conditions on Hate Crime

	Baseline (1)	Defended Neighbor-hoods (2)	Economic Hardship (3)	Legacy of Hate Crimes (4)	Unified Frame-work (5)
Asylum Seekers	0.178	-2.482**	-0.049	0.090	-3.653***
	(0.133)	(1.252)	(0.211)	(0.090)	(1.259)
Asylum Seekers					
× East	1.673***	-3.425	1.440	2.161***	-0.382
	(0.355)	(12.043)	(1.218)	(0.518)	(13.855)
× Share of natives		2.939**			3.816***
		(1.390)			(1.331)
× Share of natives × East		5.052			2.056
		(12.394)			(14.015)
× Unemployment			0.007		0.009
			(0.005)		(0.006)
× Unemployment × East			0.001		0.001
			(0.024)		(0.024)
× Attacks90s				0.377***	0.357***
				(0.104)	(0.104)
× Attacks90s × East				-0.771	-0.750
				(0.553)	(0.600)
AME[Asylum Seekers]		0.524***	0.467***	0.595***	0.620***
		(0.117)	(0.135)	(0.119)	(0.115)
AME[Asylum Seekers] if East=0		0.230**	0.175	0.310***	0.420***
		(0.110)	(0.131)	(0.107)	(0.116)
AME[Asylum Seekers] if East=1		1.515**	1.660***	2.004***	1.533*
		(0.627)	(0.501)	(0.355)	(0.817)
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.43	0.43	0.43	0.44	0.44
N	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or a dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993, and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(1) of Table 5 represents the baseline regression without any interactions with county-level characteristics. There are strong differences in the effect of asylum seeker inflows on hate crime offenses between East and West Germany. While the effect for West German counties is quite small and statistically insignificant, in the East, it is large and statistically significant. In East Germany, for one additional asylum seeker per 1,000 residents, there will be almost two additional attacks against asylum seekers per one million residents in East Germany. The probability of a newly arriving asylum seeker becoming a victim of a hate crime in East Germany is ten times greater than in West Germany. This striking difference makes it necessary to analyze the impact of defended neighborhoods, economic hardship, and the legacy of hate crimes separately for East and West Germany. In particular, because of native dominance, high unemployment and historical hate crime incidents are phenomena mostly prevalent in the eastern part of Germany.

Taking East-West differences into account, we reconsider the test of the defended neighborhood hypothesis. Column (2) in Table 5 displays the parameter estimates of the defended neighborhood hypothesis separately for East and West Germany. The estimated coefficient confirms the significance of the relationship between asylum seeker inflows and hate crime in Table 4: Larger shares of German-born residents are associated with steeper increases in hate crime. The coefficient of the interaction of asylum seeker inflows and the dummy for counties in the east is statistically insignificant. This noteworthy result implies no particular East-specific effect of asylum seeker inflows on hate crime after taking differences in the ethnic predominance of natives into account. As differences between East and West of the average marginal effects are still large, the reason they persist must be evident in the East-West differences of the regional shares of natives, i.e., the constituting explanatory factor of the defended neighborhood hypothesis.

To visualize the stark differences between the previously separated parts of Germany, Figure A2 presents contour plots of predicted hate crime events for county combinations of asylum seeker inflows and the share of German-born residents. As is clearly visible, the number of hate crime incidents increases with the share of natives and with asylum seeker inflows. Furthermore, the number of predicted hate crime events is much larger for any combination of inflows and share of natives in the East than in the West.

Column (3) in Table 5 presents coefficient estimates of the economic hardship hypothesis when allowing for East-West differences. As with the analysis of defended neighborhoods, the AMEs of asylum seeker inflows are substantially larger in the East. However, the AMEs for East and West Germany are considerably smaller than in the case of defended neighborhoods. In addition, the parameter estimate of γ is contrary to previous estimates on economic hardship (see Table 4) statistically insignificant. Thus, it seems that controlling for East-West differences picks up the variation in unemployment, rendering coefficient estimates insignificant. This result suggests that tensions on local labor markets do not drive the huge difference in hate crimes between East and West Germany. A surprising result given the ever-present idea of a direct relationship between economic conditions and xenophobia. We conclude that anti-foreigner hate crime, as the most severe measure of xenophobia, is seemingly influenced by non-economic motives.

The bottom row of Figure A2 visualizes the impact of unemployment and asylum seeker inflows on hate crime. While for West Germany unemployment and the size of the inflow seem relevant for hate crime events, the number of predicted hate crimes only slightly varies with unemployment in the East.

Turning to the hypothesis of hate crime legacy (Table 5, column (4)), we confirm the large differences between the AMEs in the East and West. Moreover, the coefficient of the interaction of asylum seekers and attacks in the 1990s is large and highly significant. Different from previous estimations, the coefficient of $Asylum\ Seekers \times East$ is very large and highly statistically significant (2.161), indicating a pure East German shift. Thus, present-day differences in hate crime between East and West Germany cannot be explained solely by historical hate crime patterns. We conclude from this analysis that hate crime in the 1990s is an important explanatory variable of present-day hate crime (as also shown in Table 4), but is not sufficient to explain the upsurge of hate crime today.

After separately inspecting the hypotheses of defended neighborhoods, economic hardship, and legacy of hate crimes separately, we test whether some explanations are possibly superior to others. We do so by including the full set of interactions of all competing hypotheses into a single regression model. As evident in column (5) in Table 5, our results are closely aligned with previous findings. The coefficients of the interaction terms including the share of natives are magnified when compared to single estimates (3.816 instead of 2.939). We consider this a strong confirmation of the validity of the defended neighborhood hypothesis. The estimated coefficient of the interaction of asylum seeker inflows with unemployment remains statistically insignificant. The high statistical significance of the coefficient of the interaction with hate crimes in the 1990s pertains in the full model, indicating that its significance in Column (4) does not result from omitting unemployment and the share of natives. All coefficient estimates of regressors including an *East* interaction are statistically insignificant. These outcomes corroborate findings on the validity of all the hypotheses, but especially strengthen the relevance of the explanation of defended neighborhoods.

6.4 Further Influences and Hypotheses

The public debate on hate crime in Germany revolves around the roles of deprivation and right-wing attitudes as potential sources of frustration and anti-foreigner crime in East Germany. Indeed, deprivation seems related to the formation of hate groups and extremist parties, as has been shown by Dustmann et al. (2011) and Adamczyk, Gruenewald, Chermak, and Freilich (2014). Evidence provided by Müller and Schwarz (2018) suggests that hate speech and right-wing anti-refugee sentiment spread by the AfD via social media (Facebook) predicts violent crimes against refugees. Another cause for hate crime could be the motive of retaliation. Evidence in favor of retaliatory behavior has been reported by Hanes and Machin (2014). We thus include a regional index of deprivation, the share of foreign-born suspects of violent crimes, and the vote shares of right-wing extremist parties as further potential explanations of hate crime.

An unexpected finding of our previous analysis is the lack of importance of economic conditions in the rise of hate crime. One concern could be that in times of a booming German economy, unemployment figures might not fully capture economic conditions. Therefore, in this section, we use an alternative indicator of economic hardship, namely the German Index of Socioeconomic Deprivation (GISD). Social and economic deprivation refers to limited access to economic and social opportunities and participation because of poverty, a lack of access to jobs, political voice, or exclusion from general progress (see Kroll et al., 2017, for more information on the dimensions and conceptualization).

Column (1) in Table A1 provides the main findings concerning regional deprivation. As in section 6.3, we explicitly incorporate East-West differences. The results of the regression using the GISD indicator rather than unemployment figures are fairly similar (recall Table 5). The AMEs are very near the baseline effects, suggesting that both unemployment and the deprivation index do not add much explanatory power to the rise in hate crime.

Another channel, which explain the upsurge in hate crimes, could be the motive of retaliation. Unfortunately, we cannot directly test this hypothesis, because we do not have information on victim-offender relations when asylum seekers are the perpetrators. In addition, we have no information regarding whether the perpetrators of anti-foreigner hate crime have been victims of asylum seekers before. However, the literature on the victim-offender overlap (Haidt, 2003; Jacobs and Wright, 2010) points out that retaliation is not necessarily addressed against the perpetrator. Through the random redirection of hate, any available person of the out-group can be victimized, leading to a general climate of violence and fear. Moreover, the motive of retaliation can be reinforced if there are many salient cases among the majority population. We try to uncover a potential "climate" of retaliatory motives by merging data on foreign crime suspects[15] from the German Police Statistics (Polizeiliche Kriminalstatistik, PKS) with our existing county-level database. We focus on the share of foreign-born suspects among all suspects involved in a violent crime, since these crimes most likely provoke retaliatory behavior.

In column (2) in Table A1, we display the ITT estimates of interactions with the share of foreign-born suspects of violent crimes. The parameter estimates of the interactions with

[15] A suspect is the outcome of the police investigation of a crime. Suspects can be viewed as alleged criminals, as they are not charged or convicted. However, from the perspective of the police, they are very likely to have committed the crime under consideration.

foreign-born suspects are both negative, marginally statistically significant in the case of γ and statistically insignificant for the specific additional East effect. Although the effect of asylum seeker inflows remains positive on average (see the AMEs), it is higher in regions with relatively smaller shares of foreign-born crime suspects. Thus, the hypothesis of retaliation cannot be confirmed with the data at hand. The negative sign initially seems counterintuitive; however, note that a relatively small share of crimes committed by foreigners are observed when the portion of foreigners in the population is relatively small and the share of natives high. This outcome is analogous to that of the defended neighborhoods hypothesis: High shares of incumbent inhabitants are associated with higher rates of hate crime. Nonetheless, the major East-West differences cannot be explained by our measure of retaliatory behavior as the coefficient of *Asylum Seekers* $\times$ *East* is large and statistically significant.

Finally, we expect to observe more hate crimes against asylum seekers in regions with a relatively large number of right-wing nationalists, who tend to openly express their hostile attitudes against foreigners. We measure the existence of extreme right-wing attitudes using the local vote shares of extreme right-wing parties at the federal election in 2013. Focusing on the federal election in 2013, we obtain an indicator of already existing latent anti-foreigner attitudes prior to the large influx of asylum seekers. As seen in column (3) in Table A1, the results concerning the AMEs are within the usual range of other models. Contrary to expectations, we could not detect a statistically significant association between rising hate crime and asylum seeker inflows. We conclude from this analysis that hate crime does not seem to be a phenomenon limited to areas with a high salience of right-wing extremist views. It must be understood in a more general setting.

7 Sensitivity Analysis

In the previous section, we confirmed that the hypotheses of defended neighborhoods and legacy of hate crime incidents largely explain the upsurge in hate crimes. However, there has been no convincing support for the hypothesis of economic hardship. We now explore the robustness of these findings by considering different estimation models, looking at the subset of violent hate crimes, and controlling for additional potentially confounding variables.

7.1 Count Data Estimation

Since hate crime events are the most extreme expressions of anti-foreigner attitudes, their frequency is small. Therefore, as an alternative approach to analyzing the upsurge in hate crime, these events can be treated as count data. In Table A2, we report the negative binomial regression results of a model using the number of hate crime incidents as the dependent variable instead of the first-differenced population normalized hate crime statistics used thus far. To control for the size of the counties, we include the population size as of 2013 as an additional regressor. The results in Table A2 confirm our previous results from section 6.3. Coefficient estimates in the models capturing defended neighborhoods and the legacy of hate crime events are in line with both hypotheses. The hypothesis of economic hardship is again not supported by the estimates. Likelihood Ratio tests of the Poisson model restriction of mean dispersion are rejected for every model, favoring the chosen negative binomial model over a standard Poisson model.

7.2 Violent Hate Crimes

Thus far, *hate crime* comprised all types of hate-related criminal incidents directed against asylum seeker accommodations and their inhabitants. As the inclination of violent perpetrators to express hatred against foreigners should be more intense than for non-violent hate crime offenders, we examine whether our results also hold for violent hate crimes such as arson and assaults. As committing a violent hate crime means crossing the threshold from an aggressive attitude to aggressive action, these incidents are relatively rare. At the same time, they are more noticeable to the public and therefore, considerably less likely to be under-reported than non-violent xenophobic incidents.

Table A3 provides the results of the regression of the three main hypotheses, now with violent hate crime as the dependent variable. As violent incidents occur less frequently than non-violent hate crimes, the estimated coefficients are smaller than in previous tables. Column (1) presents the regression results for the baseline specification including the East Germany dummy. Again, as in the analysis comprising all hate crime incidents, there is a stronger effect in the East than in the West. Columns (2) to (4) show the regression estimates and average marginal effects for the hypotheses of defended neighborhoods, economic hardship, and legacy of hate crime respectively. Only the coefficient estimate for the defended neighborhoods hypothesis retains its sign and statistical significance when compared to the results based on the total number of hate crimes (see Table 5). That is, the interaction between asylum seeker inflows and the share of natives in the incumbent population is confirmed as a driver of violent hate crime incidents. The hypotheses of economic hardship and hate crime legacy do not explain the rise in violent hate crimes. As before, the defended neighborhood hypothesis seems the most stable explanation for the rise in hate crime in East and West Germany in recent years.

7.3 Further Sensitivity Analyses

In appendix A.1, we provide evidence that the results obtained thus far are not driven by outliers, clustering of standard errors, or omitted variable bias. Table A4 presents the results of our main analysis, but excluding Berlin. Since Berlin is the largest city in (East) Germany and witnesses a high number of hate crime events, the results, especially for East Germany, could be driven by this outlier. However, the regression results appear to be insensitive to the exclusion of Berlin.

Table A5 shows the regression results of our main analysis using standard errors clustered at the state level. This procedure allows for correlation of the error terms within states, but reduces the number of clusters substantially to 16 (the number of German states). Again, statistical significance is not driven by the choice at which level standard errors are clustered.

In the regression analyses presented in Tables A6, A7, and A8, we control for potentially confounding variables. Table A6 includes the local clear-up rates of all crimes and violent crimes as a measure of local police force efficiency. Following Zenou (2003) and Piopiunik and Ruhose (2017), we include spatial lags of hate crime as control variables to capture potential spatial spillovers of hate crime. Specifically, we construct spatially lagged outcome variables as the sum of first-differenced hate crimes per one million residents weighted either with travel time by car (Table A7) or jump distance (Table A8) between county centroids. It seems the regression results from section 6.3 were not affected by the inclusion of these additional control variables.

8 Conclusion

Germany's "refugees welcome" enthusiasm on the one hand and attacks against asylum seeker shelters throughout the country on the other indicates the two faces of Germany's response to Europe's escalating experience of refugee immigration. In this article, we analyze the association of the size and regional distribution of the inflow of asylum seekers with the spatial upsurge of attacks against this group. We adopt three hypotheses from different disciplines regarding the causes of hate crime. Specifically, this study focuses on the hypotheses of defended neighborhoods, economic hardship, and the legacy of hate crime events.

To identify the influence of exogenous asylum seeker inflows, we use a quota system in Germany, which is used to distribute asylum-seekers across German regions. We employ data on administrative assignments to estimate the intention-to-treat effects of asylum seeker inflows on the rise in anti-foreigner hate crime in Germany.

Our results reveal that there has been no homogeneous link between asylum seeker intake and hate crime. We find that the size of the inflow does not automatically translate into a higher number of attacks against asylum seekers. Recent inflows of asylum seekers only impact the rise in hate crimes when they were assigned to areas with a previously very low share of foreign-born inhabitants, to regions under economic strain, or to those with a legacy of anti-foreigner hate crimes. Similar to Krueger and Pischke (1997), we confirm a much larger upsurge in hate crimes in East than in West Germany—a phenomenon still present, 25 years after German reunification. The defended neighborhood hypothesis of Green et al. (1998) stands out as the most robust explanation of the rise in hate crime in both regions of Germany. Thus, we are able to contribute to explanations of the larger average hostile reaction to immigration in East Germany.

In addition, we analyze the robustness of our findings and examine further channels through which hate crime might evolve. When analyzing violent hate crimes only, the hypothesis on defended neighborhoods retains its explanatory power. We further consider retaliation motives and study the correlation between hate crime and extreme right-wing voting behavior. None convincingly explain the rise in hate crime, but implicitly corroborate the relevance of the defended neighborhood hypothesis.

Our findings at the regional level can be rationalized by a severe out-group bias at the individual level. Grattet (2009) pointed out that the reason for such hatred might be that ethnic outsiders pose a significant challenge to the shared cultural identity of the neighborhood. Card, Dustmann, and Preston (2012) similarly argue (economically) that a loss of compositional amenities is reducing the approval of immigration. Policy makers might consider the results of our study by raising awareness and compassion when assigning asylum seekers to areas with limited experience of immigration. Information campaigns and increased public funds for these areas might reduce latent out-group biases and compensate for a potential loss in compositional amenities.

Our study documents and explains the regional variation in outbursts of extreme anti-foreigner attitudes against the newly arrived group of asylum seekers. As our data and empirical analyses are at the regional level, we cannot elucidate the individual characteristics of victims and perpetrators such as educational background and unemployment experience. However, given the importance of the question regarding *where* attacks take place, which is emphasized by many hypotheses in the fields of economics, social sciences, criminology, psychology, and political science, we believe that the causal empirical evidence from this study significantly contributes to understanding the rise in hate crime.

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A Appendix

A.1 Tables

Table A1: East-West Effects of Inflows and Further Regional Conditions on Hate Crime

	Deprivation (1)	Retaliation (2)	Ext. Right Voting (3)
Asylum Seekers	-0.110	0.474**	0.374*
	(0.196)	(0.197)	(0.213)
Asylum Seekers			
× East	0.962	1.927***	1.579
	(1.217)	(0.627)	(0.972)
× GISD	0.007*		
	(0.004)		
× GISD × East	0.009		
	(0.019)		
× Share foreign suspects		-0.011*	
		(0.006)	
× Share foreign suspects × East		-0.047	
		(0.044)	
× Ext.right vote share			-13.068
			(11.838)
× Ext.right vote share × East			10.384
			(32.488)
AME[Asylum Seekers]	0.475***	0.511***	0.508***
	(0.126)	(0.121)	(0.129)
AME[Asylum Seekers] if East=0	0.184	0.214*	0.152
	(0.119)	(0.115)	(0.115)
AME[Asylum Seekers] if East=1	1.549***	1.170**	1.904***
	(0.467)	(0.508)	(0.547)
Covariates	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
adj. R^2	0.44	0.44	0.43
N	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the German Index of Socioeconomic Deprivation from 2012 (Deprivation), the share of foreign-born suspects for violent crimes in 2013 (Retaliation), or the vote shares of extreme right parties at the federal election in 2013 (Ext. Right Voting). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Negative Binomial Estimates of Inflows and Regional Conditions on Hate Crime

	Defended Neighborhoods (1)	Economic Hardship (2)	Legacy of Hate Crimes (3)	Unified Framework (4)
Asylum Seekers	-0.473**	0.022	0.006	-0.644***
	(0.193)	(0.023)	(0.014)	(0.232)
Asylum Seekers				
× East	-0.559	-0.026	0.022	-0.395
	(0.344)	(0.057)	(0.032)	(0.392)
× Share of natives	0.537**			0.681***
	(0.210)			(0.241)
× Share of natives × East	0.535			0.394
	(0.367)			(0.402)
× Unemployment		-0.000		0.001
		(0.001)		(0.001)
× Unemployment × East		0.000		-0.000
		(0.001)		(0.001)
× Attacks90s			0.044***	0.045***
			(0.014)	(0.014)
× Attacks90s × East			-0.053*	-0.044
			(0.028)	(0.030)
Covariates	Yes	Yes	Yes	Yes
Counties' Population Size	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Test of Poisson restrictions	55.74	90.58	85.68	51.72
[p-value]	[0.00]	[0.00]	[0.00]	[0.00]
pseudo R^2	0.23	0.22	0.23	0.23
N	804	804	804	804

Note: The table shows the negative binomial regression results. The number of hate crimes against asylum seekers is used as dependent variable. The main independent variable assigned asylum seekers per 1,000 residents is either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: East-West Effects of Inflows and Regional Characteristics on Violent Hate Crime

	Baseline (1)	Defended Neighbor-hoods (2)	Economic Hardship (3)	Legacy of Hate Crimes (4)	Unified Frame-work (5)
Asylum Seekers	0.040	-0.636**	0.048	0.041	-0.698**
	(0.027)	(0.313)	(0.059)	(0.028)	(0.349)
Asylum Seekers					
× East	0.227**	-2.055	0.236	0.135	-2.659
	(0.100)	(1.816)	(0.296)	(0.156)	(2.111)
× Share of natives		0.747**			0.798**
		(0.351)			(0.367)
× Share of natives × East		2.293			2.849
		(1.916)			(2.153)
× Unemployment			-0.000		0.001
			(0.002)		(0.002)
× Unemployment × East			-0.000		-0.001
			(0.005)		(0.005)
× Attacks90s				0.002	0.000
				(0.032)	(0.032)
× Attacks90s × East				0.110	0.150
				(0.157)	(0.177)
AME[Asylum Seekers]		0.090***	0.081***	0.081**	0.093***
		(0.026)	(0.028)	(0.032)	(0.030)
AME[Asylum Seekers] if East=0		0.053**	0.034	0.035	0.055**
		(0.023)	(0.024)	(0.029)	(0.028)
AME[Asylum Seekers] if East=1		0.134	0.272*	0.246**	0.092
		(0.093)	(0.143)	(0.102)	(0.146)
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.18	0.19	0.18	0.18	0.18
N	804	804	804	804	804

Note: The table shows the first-difference regression results of violent hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: East-West Effects of Inflows and Regional Conditions on Hate Crime (excluding Berlin)

	Baseline (1)	Defended Neighbor-hoods (2)	Economic Hardship (3)	Legacy of Hate Crimes (4)	Unified Frame-work (5)
Asylum Seekers	0.181	-2.240*	-0.052	0.092	-3.441***
	(0.134)	(1.278)	(0.211)	(0.091)	(1.272)
Asylum Seekers					
× East	1.759***	14.216	1.467	2.208***	20.978
	(0.357)	(17.493)	(1.213)	(0.519)	(19.201)
× Share of natives		2.674*			3.561***
		(1.414)			(1.345)
× Share of natives × East		-12.872			-19.667
		(17.920)			(19.546)
× Unemployment			0.007		0.010*
			(0.005)		(0.006)
× Unemployment × East			0.002		0.004
			(0.024)		(0.024)
× Attacks90s				0.379***	0.362***
				(0.104)	(0.104)
× Attacks90s × East				-0.727	-0.894
				(0.555)	(0.607)
AME[Asylum Seekers]		0.539***	0.482***	0.613***	0.634***
		(0.118)	(0.135)	(0.119)	(0.114)
AME[Asylum Seekers] if East=0		0.227**	0.178	0.315***	0.420***
		(0.112)	(0.132)	(0.107)	(0.115)
AME[Asylum Seekers] if East=1		2.490***	1.723***	2.082***	2.685***
		(0.910)	(0.497)	(0.357)	(1.036)
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.44	0.44	0.44	0.44	0.45
N	802	802	802	802	802

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. Berlin is excluded from the estimation sample. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: East-West Effects of Inflows and Regional Conditions on Hate Crime (with State-Level Clustered Standard Errors)

	Baseline (1)	Defended Neighbor-hoods (2)	Economic Hardship (3)	Legacy of Hate Crimes (4)	Unified Frame-work (5)
Asylum Seekers	0.178	-2.482*	-0.049	0.090	-3.653***
	(0.118)	(1.335)	(0.179)	(0.071)	(1.115)
Asylum Seekers					
× East	1.673***	-3.425	1.440	2.161***	-0.382
	(0.317)	(14.336)	(1.271)	(0.221)	(16.099)
× Share of natives		2.939*			3.816***
		(1.478)			(1.159)
× Share of natives × East		5.052			2.056
		(14.705)			(17.081)
× Unemployment			0.007		0.009
			(0.006)		(0.007)
× Unemployment × East			0.001		0.001
			(0.024)		(0.024)
× Attacks90s				0.377***	0.357***
				(0.055)	(0.066)
× Attacks90s × East				-0.771	-0.750
				(0.448)	(0.483)
AME[Asylum Seekers]		0.524***	0.467***	0.595***	0.620***
		(0.057)	(0.068)	(0.055)	(0.052)
AME[Asylum Seekers] if East=0		0.230**	0.175	0.310***	0.420***
		(0.096)	(0.111)	(0.088)	(0.086)
AME[Asylum Seekers] if East=1		1.515*	1.660***	2.004***	1.533**
		(0.725)	(0.508)	(0.214)	(0.670)
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.43	0.43	0.43	0.44	0.44
N	804	804	804	804	804

Note: The table shows first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1000 residents in 2013 (Economic Hardship), or a dummy variable *Attacks90s* which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve a dummy variable *East* which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For covariates see Table 3. Standard errors are clustered at the state level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: East-West Effects of Inflows and Regional Conditions on Hate Crime Controlling for Clear-up Rates

	Baseline (1)	Defended Neighborhoods (2)	Economic Hardship (3)	Legacy of Hate Crimes (4)	Unified Framework (5)
Asylum Seekers	0.204	-2.326*	-0.015	0.116	-3.483***
	(0.126)	(1.213)	(0.212)	(0.093)	(1.276)
Asylum Seekers					
× East	1.643***	-4.147	1.452	2.160***	-0.894
	(0.362)	(11.986)	(1.231)	(0.520)	(13.775)
× Share of natives		2.794**			3.665***
		(1.343)			(1.334)
× Share of natives × East		5.769			2.614
		(12.333)			(13.932)
× Unemployment			0.007		0.009
			(0.005)		(0.006)
× Unemployment × East			0.000		0.001
			(0.024)		(0.025)
× Attacks90s				0.361***	0.343***
				(0.104)	(0.103)
× Attacks90s × East				-0.794	-0.767
				(0.557)	(0.603)
AME[Asylum Seekers]		0.543***	0.488***	0.608***	0.631***
		(0.113)	(0.129)	(0.117)	(0.115)
AME[Asylum Seekers] if East=0		0.253**	0.200	0.328***	0.432***
		(0.109)	(0.126)	(0.108)	(0.118)
AME[Asylum Seekers] if East=1		1.482**	1.676***	2.005***	1.528*
		(0.625)	(0.503)	(0.355)	(0.817)
Clear-up rates for violent and total crime	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.43	0.44	0.43	0.44	0.44
N	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: East-West Effects of Inflows and Regional Conditions on Hate Crime Controlling for Spatial Spillovers by Car Driving Time

	Baseline	Defended Neigh-borhoods	Economic Hardship	Legacy of Hate Crimes	Unified Frame-work
	(1)	(2)	(3)	(4)	(5)
Asylum Seekers	0.172	-2.473**	-0.038	0.088	-3.671***
	(0.135)	(1.245)	(0.209)	(0.093)	(1.301)
Asylum Seekers					
× East	1.658***	-3.753	1.406	2.154***	-0.312
	(0.358)	(12.102)	(1.225)	(0.518)	(14.030)
× Share of natives		2.922**			3.831***
		(1.383)			(1.368)
× Share of natives × East		5.371			1.994
		(12.448)			(14.171)
× Unemployment			0.007		0.009
			(0.006)		(0.006)
× Unemployment × East			0.002		0.001
			(0.024)		(0.025)
× Attacks90s				0.374***	0.357***
				(0.108)	(0.106)
× Attacks90s × East				-0.770	-0.750
				(0.553)	(0.601)
AME[Asylum Seekers]		0.517***	0.465***	0.592***	0.622***
		(0.122)	(0.139)	(0.128)	(0.123)
AME[Asylum Seekers] if East=0		0.225**	0.172	0.308***	0.422***
		(0.113)	(0.135)	(0.114)	(0.128)
AME[Asylum Seekers] if East=1		1.485**	1.650***	1.997***	1.542*
		(0.644)	(0.506)	(0.365)	(0.837)
Spatially lagged outcome by driving time	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.43	0.43	0.43	0.44	0.44
N	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occured in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

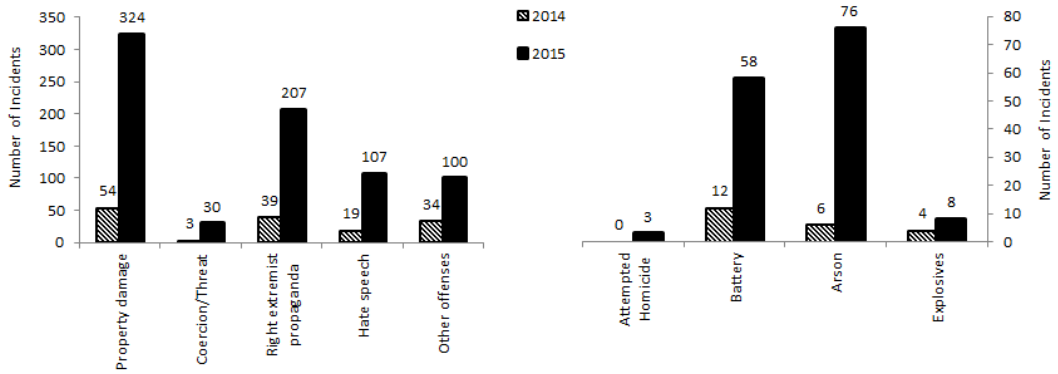
Table A8: East-West Effects of Inflows and Regional Conditions on Hate Crime Controlling for Spatial Spillovers by Jump Distance

	Baseline	Defended Neigh-bor-hoods	Economic Hard-ship	Legacy of Hate Crimes	Unified Frame-work
	(1)	(2)	(3)	(4)	(5)
Asylum Seekers	0.177	-2.476**	-0.054	0.090	-3.776***
	(0.135)	(1.254)	(0.213)	(0.092)	(1.335)
Asylum Seekers					
× East	1.666***	-3.516	1.454	2.165***	-0.009
	(0.363)	(12.055)	(1.211)	(0.523)	(13.936)
× Share of natives		2.931**			3.922***
		(1.394)			(1.395)
× Share of natives × East		5.138			1.735
		(12.403)			(14.096)
× Unemployment			0.007		0.010
			(0.006)		(0.007)
× Unemployment × East			0.001		0.000
			(0.024)		(0.024)
× Attacks90s				0.378***	0.361***
				(0.108)	(0.106)
× Attacks90s × East				-0.772	-0.750
				(0.554)	(0.601)
AME[Asylum Seekers]		0.523***	0.469***	0.598***	0.629***
		(0.123)	(0.139)	(0.128)	(0.123)
AME[Asylum Seekers] if East=0		0.229**	0.177	0.312***	0.430***
		(0.113)	(0.135)	(0.112)	(0.127)
AME[Asylum Seekers] if East=1		1.509**	1.672***	2.012***	1.576*
		(0.639)	(0.503)	(0.371)	(0.824)
Spatially lagged outcome by jump distance	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.43	0.43	0.43	0.44	0.44
N	804	804	804	804	804

Note: The table shows the first-difference regression results of hate crime against asylum seekers per 1 million residents on assigned asylum seekers per 1,000 residents, either interacted with the share of Germans living in the county in 2013 (Defended Neighborhoods), the number of unemployed persons per 1,000 residents in 2013 (Economic Hardship), or the dummy variable *Attacks90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the county between 1991 and 1993 and 0 otherwise (Legacy of Hate Crimes). Triple interactions involve the dummy variable *East*, which takes on the value of 1 if the county belongs to the former territory of the German Democratic Republic and 0 otherwise. For the covariates see Table 3. Standard errors are clustered at the county level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

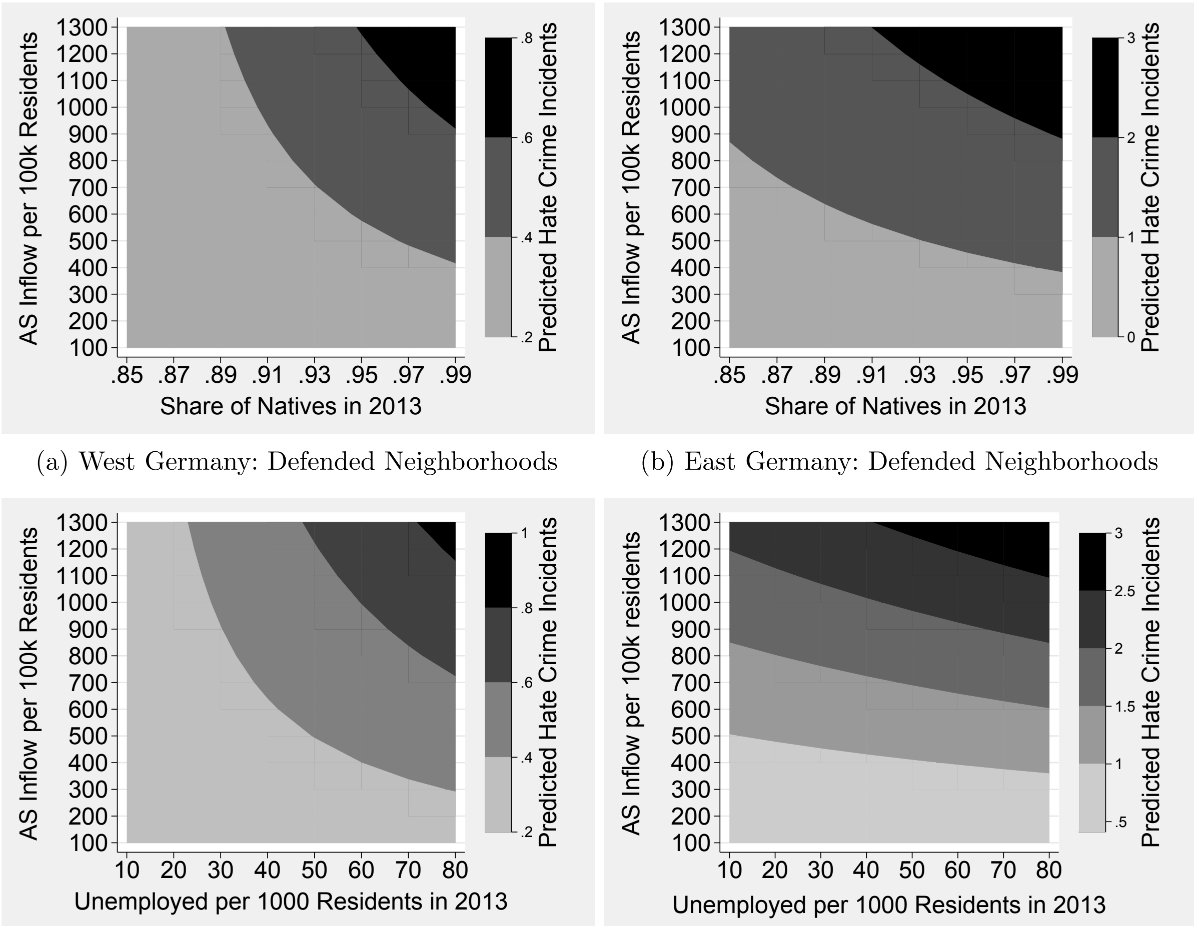
A.2 Figures

Figure A1: Type of hate crime against asylum seekers in 2014 and 2015



Note: Left panel shows non-violent hate crimes against asylum seekers whereas the right panel depicts violent hate crimes against asylum seekers. Data comes from the Federal Criminal Police Office (see section 3). Own depiction.

Figure A2: Predicted Hate Crime Incidents against Asylum Seekers per 100,000 Residents



(a) West Germany: Defended Neighborhoods

(b) East Germany: Defended Neighborhoods

(c) West Germany: Economic Hardship

(d) East Germany: Economic Hardship

Note: The Figure displays the number of predicted hate crime events against asylum seekers for combinations of the size of asylum seeker inflows per 100,000 residents and with either the share of German-born residents in 2013 (defended neighborhood hypothesis) or the number of unemployed persons per 1,000 residents in 2013 (economic hardship hypothesis).

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