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Refugees welcome? Understanding the regional heterogeneity of anti-refugee hate crime☆

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ABSTRACT

In this article, we examine anti-refugee hate crime in the wake of the large influx of refugees to Germany in 2014 and 2015. By exploiting institutional features of the assignment of refugees to German regions, we estimate the impact of unexpected and sudden large-scale immigration on hate crime against refugees. Results indicate that it is not simply the size of local refugee inflows which drives the increase in hate crime, but rather the combination of refugee arrivals and latent anti-refugee sentiment. We show that ethnically homogeneous areas, areas which experienced hate crimes in the 1990s, and areas with high support for the Nazi party in the Weimar Republic, are more prone to respond to the arrival of refugees with incidents of hate crime against this group. Our results highlight the importance of regional anti-immigration sentiment in the analysis of the incumbent population's reaction to immigration.

1. Introduction

International refugee migration has increased dramatically in recent years. The United Nations High Commissioner for Refugees (UNHCR) has estimated that as of 2018, over 25.9 million individuals sought refuge in a country other than their country of origin—a more than twofold increase with respect to 2008 (UNHCR, 2019). Within this period, European states have been increasingly chosen as destination countries for international refugees. In 2015 alone, more than one million persons sought refuge in Europe (Eurostat, 2016).

This large inflow of migrants has dominated the public and political debate on migration in Europe in recent years. While governments of European countries have struggled to find a joint strategy to cope with the inflow, the citizens of European countries have become increasingly concerned about immigration and its consequences. Harnessing these elevated concerns, populist, anti-immigration parties have won greater electoral support (e.g., Eichengreen, 2018). As well as a general shift to the (extreme) right in terms of voting, host countries have also witnessed increasing levels of hate crime targeting immigrants. The phenomenon of violent, openly expressed anti-immigrant sentiment has become more and more salient in many European countries (see for instance Corcoran et al., 2015; Bundesministerium des Innern, 2016a; Commission Nationale Consultative des Droits de l'Homme, 2018, for the UK, Germany, and France, respectively). As hate crime can be seen as the most severe form of openly expressed anti-foreigner hatred, it carries severe economic and social costs and is therefore relevant for policy makers. Such crimes affect immigrants' safety, their integration efforts, and inhibit social cohesion, not only between the native population and immigrants, but also within the native population itself (Gould and Klor, 2016; Steinhardt, 2018; Deole, 2019).

Despite the severity, salience, and relevance of these incidents, limited (causal) empirical evidence exists on the causes of hate crimes (Green and Spry, 2014). In this article, we investigate the regional

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causes for crime against minorities in a quasi-experimental setting. Specifically, we analyze the determinants of regional differences in hate crime victimization of newly arrived refugees in Germany in the wake of the refugee immigration episode to Europe in 2015.

In our empirical analysis, we make use of a quasi-experimental design and detailed panel data at the level of German districts.[1] Specifically, we estimate how local conditions shape the relationship between refugee arrivals and hate crime incidents against this group. In order for such an analysis to deliver credible estimates, we implement two empirical designs that rely on a refugee dispersal policy. As refugees are allocated to German regions following a quota-based system, regional assignments of refugees are not distorted by the usual problem of regional sorting of migrants. We rely on these quota-based assignments as our main variable to explain the upsurge in hate crime in a first-difference model and an instrumental variable (IV) approach. We either use the quota-based assignments directly and estimate intention-to-treat (ITT) effects on refugee arrivals on hate crime incidents or we use the assignments as IV to instrument the actual, likely endogenous allocation of refugees. Furthermore, we interact measures of regional conditions that are pre-determined to the influx of refugees with the quota-based assignments to investigate regional differences in hate crime victimization of refugees.

We inspect several dimensions of local conditions that may influence the relationship of refugee arrivals and hate crime incidents. The focus of this analysis is on local latent hostility against foreigners. Using proxies for latent anti-foreigner sentiment, we investigate the role of these potentially deeply rooted attitudes for the upsurge of hate crimes across Germany. We hypothesize that the local predominance of a homogeneous incumbent population increases the probability of hate crimes against newly-arriving refugees. This is in line with the idea of Green et al. (1998), who argue that hate crimes against newcomers are the result of 'threatened' incumbents opposing ethnic change in their neighborhoods. We proxy ethnic homogeneity on a regional level using the share of German-born residents in the district. In addition, we investigate the regional persistence of anti-foreigner sentiment, i.e. whether a high number of incidents of hate crime in the past, is reflected in a high number of incidents today. Employing information on anti-foreigner hate crime incidents in the early 1990s, we test whether recent refugee arrivals trigger hate crimes against this group in the same areas today. Furthermore, as recent studies convincingly demonstrate the (long-term) persistence of anti-minority sentiment in Germany (e.g., Voigtländer and Voth, 2012; Cantoni et al., 2017), we analyze whether present-day hate crime events occur more often in areas with large refugee arrivals and a historical strong support for the Nazi party (NSDAP).

Our results provide no evidence of a simple, homogeneous effect of refugee assignments on the emergence of hate crime in Germany. Instead, we confirm that the specific areas in which refugees are placed are a critical factor of whether their arrival will result in an increase in hate crime. Our first-difference ITT and IV estimates show that refugee arrivals trigger significantly more hate crimes in areas that are ethnically homogeneous, in areas which witnessed anti-foreigner hate crime incidents in the early 1990s, and in areas in which there was strong support for the NSDAP in the Weimar Republic. In addition, we confirm large structural differences in hate crimes between East and West Germany. That is, refugee arrivals are associated with increases in hate crime in East but not in West Germany. The influence of our measures of latent local hostility, however, are not driven by East-West German differences and, thus, their relevance for the upsurge of hate crime hold for both parts of Germany. We do not find evidence for the hypothesis that local economic conditions are important for the emergence of hate crime. Once we explicitly incorporate East-West German differences, economic conditions do not play an important role for the upsurge in hate crime against refugees.

Furthermore, our findings are robust to several sensitivity analysis that address concerns about the reporting of hate crimes, the chosen estimation models, or a potential omitted variable bias. Specifically, we investigate the robustness of our main results by looking at the subset of violent hate crimes, applying count data estimations models, and controlling for police effectiveness in clearing crimes as well as for spatial spillovers in criminal activity.

Germany constitutes an ideal case for the analysis of our research question for at least three reasons. First, Germany has been a primary host country for international refugees in Europe at that time. In 2015, Germany registered 890,000 incoming refugees (Bundesministerium des Innern, 2016b)—this constitutes a rise of more than one percent in the population size. Moreover, the large-scale immigration of ethnically diverse migrants, primarily from Middle Eastern and African countries, to German regions provides a unique example in which refugees are hosted by regions that were previously unpopular and generally avoided by immigrants. This natural experiment allows us to study the otherwise latent, intangible anti-foreigner sentiment of the incumbent local population. Second, the German Federal Police Office (BKA) officially documents hate crimes against refugees. Relying on official hate crime statistics allows for a credible analysis of the phenomenon of hate crime, which is often times clouded by unofficial reports of civic society organizations. Finally, refugees are subject to a dispersal policy. We utilize this institutional feature to circumvent endogenous regional sorting of refugees as well as potential actions of regions to influence refugee reception.

This article contributes to three strands of the literature on anti-immigrant sentiment. First, it contributes to the literature on (refugee) immigration and attitudes towards immigrants by focusing on hateful criminal actions of the host society. Previous studies in this area investigate predominantly voting patterns (e.g., Dustmann et al., 2018; Dinas et al., 2019; Bratti et al., 2020; Steinmayr, 2021) or attitudinal responses (e.g., Card et al., 2012; Hangartner et al., 2018; Deiss-Helbig and Remer, 2021). We supply new evidence about the impact of refugee arrivals on the emergence of hate crime—and thereby concentrate on real criminal actions as opposed to expressing sentiments in surveys or at the ballot box.

Second, our study contributes to the emerging literature on hate crime and xenophobia. Recent studies focus on social media usage (Bursztyn et al., 2019; Müller and Schwarz, 2021), political events or propagation of xenophobic views (Edwards and Rushin, 2018; Bursztyn et al., 2020; Romarri, 2020; Colussi et al., 2021), as well as terrorist attacks (Hanes and Machin, 2014; Gould and Klor, 2016; Ivandic et al., 2019) as reasons for the emergence of hate crime. Notably, hate crime has become a major research topic in relation to Brexit (Albornoz et al., 2020; Carr et al., 2020; Devine, 2020). In contrast, our contribution to this literature is the focus on regional determinants of hate crimes following large-scale immigration. Specifically, we document evidence for the importance of regional conditions in the emergence of hate crimes—in particular (long-run) latent local hostility.

A few studies have been conducted that focus also on regional determinants of hate crime incidents. These studies usually focus on the impact of economic conditions and yield mixed evidence (Krueger and Pischke, 1997; Falk et al., 2011; Dustmann et al., 2011). While Falk et al. (2011) find a significant link between unemployment as a measure of economic conditions and right-wing hate crime, Krueger and Pischke (1997) do not find a significant relationship between anti-foreigner hate crime and economic variables. Our results corroborate the findings of Krueger and Pischke (1997) that economic conditions do not seem to be associated with the emergence of hate crime. Furthermore, our results on the importance of residential homogeneity are consistent with previous studies that focus on changes in the ethnic

[1] German districts correspond to the NUTS 3 level of the Nomenclature of Territorial Units for Statistics of the European Union and are, with on average 200,000 inhabitants, comparable to U.S. counties.

composition of residents for rising hate crime (Green et al., 1998; Grattet, 2009; Stacey et al., 2011).

More recently, Jäckle and König (2017), Jäckle and König (2018), and Ziller and Goodman (2020) analyze hate crimes against refugees in Germany with respect to political party agitation, crime committed by the refugees and islamic terrorist attacks, as well as local government efficiency as drivers of anti-refugee violence, respectively. These papers advance our understanding of these particular determinants of hate crime formation. However, they are limited by their focus on the early onset of the immigration period and rely on incomplete hate crime data from civic society organizations. It may be very likely that this measurement error correlates with local conditions that lead to biased estimates. On the contrary, our study employs official hate crime statistics that are arguably much more reliant.

Finally, this study contributes to the economic literature that documents a strong regional persistence of attitudes. Recent studies convincingly demonstrate the importance of historic events for modern-day attitudes and behavior (e.g. Voigtländer and Voth, 2012; Grosjean, 2014; Couttenier et al., 2017). Accordingly, the extremist period of the Nazi regime in Germany seems to have had a lasting legacy on present-day outcomes. Voigtländer and Voth (2015), for instance, show that there is a high probability that Germans who grew up in areas with strong anti-Semitic beliefs in the beginning of the 20th century, still hold such views in reunified Germany. Similarly, Cantoni et al. (2017) demonstrate that areas with higher support for the Nazi party during the Weimar Republic continue to show higher levels of support for anti-immigration parties today. It thus seems that regional out-group bias has remained rather persistent throughout German history. We corroborate this finding by presenting evidence that refugee arrivals in areas with strong support for the Nazi party in the Weimar Republic and with incidents of hate crimes against foreigners in the 1990s are more likely to trigger hate crimes today compared to areas without such a legacy.

The remainder of this article is organized as follows. The next section provides information on the phenomenon of hate crime and the latest episode of refugee immigration to Germany. We introduce our data on hate crimes, refugee assignments, and the latent measures of anti-foreigner sentiment in Section 3. We then describe the German refugee dispersal policy and our identification strategy in Section 4. Section 5 presents the main estimation results and Section 6, the additional sensitivity analyses. In Section 7, we discuss the relevance of our findings and provide our conclusions.

2. Hate crime and immigration

The important difference between hate crime and the majority of crimes is the restricted motivation of offenders. Hate crime offenders are motivated by prejudice towards minorities of a different race, religion, or sexual orientation. Incidents of hate crime are widespread in many industrialized countries and immigrants are generally at a particularly high risk of victimization. In 2014/15, the British Home Office for example, reported an increase of 15 percent in racially motivated hate crimes across England and Wales compared to 2013/14 (Corcoran et al., 2015). According to the U.S. Department of Justice (2018), the majority of hate crime victims in the United States perceived that the offender was motivated by bias against their ethnicity, race, or ancestry (59.6 percent). Van Kesteren (2016) analyzed survey data on hate crime victimization from 14 Western European countries, and notes that in all countries, immigrants are disproportionately targeted in hate crimes.

Given the emergent importance of hate crime, this topic has been studied in various scientific disciplines, and theoretical explanations are manifold.[2] 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 hold negative views of 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 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.

We interpret the latest large-scale influx of refugees to Germany as a salient event which activated potentially deeply rooted, anti-foreigner out-group bias. In 2014 and 2015, more than one million refugees, primarily from the Middle East, entered Germany to seek asylum. The largest proportion of immigrants came from countries affected by civil war such as Syria (36.9%), Afghanistan (17.6%), and Iraq (13.3%). Refugees were mostly aged under 30 years (73.8%) and male (65.7%) (BAMF, 2017). The sharp increase in net migration to Germany thus consists largely of refugees of different ethnic origins. Fig. 1 depicts the net foreign migration to Germany and hate crimes perpetrated against refugees from 2011 to 2015 on the left and right axes respectively (see Section 3 on data). While hate crime against refugees was almost absent in 2011, it increased in the following years, jumping sharply in 2015. In parallel to the high net migration in 2015, hate crime against refugees peaked in 2015 with 925 incidents that year. These figures clearly show that hate crime is increasing in Germany, and that this trend strongly correlates with the recent inflow of refugees to the country.

3. Data and descriptive statistics

3.1. Hate crime statistics

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

Following a xenophobic incident at an refugee accommodation, the local police administration notes the event as hate crime against refugees. 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 includes information on the time, place, and type of hate crime. We collected this data using the responses of the Federal Government to several parliamentary inquiries made by DIE LINKE party in relation to the period between 2013 and 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, 2021), we employ official hate crime records. A major advantage of these administrative records is that they are less prone to under-reporting. For example, our data set includes 50 percent more entries than the data set used by Jäckle and König (2017), who employ data on attacks against refugees taken from newspaper reports collected

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

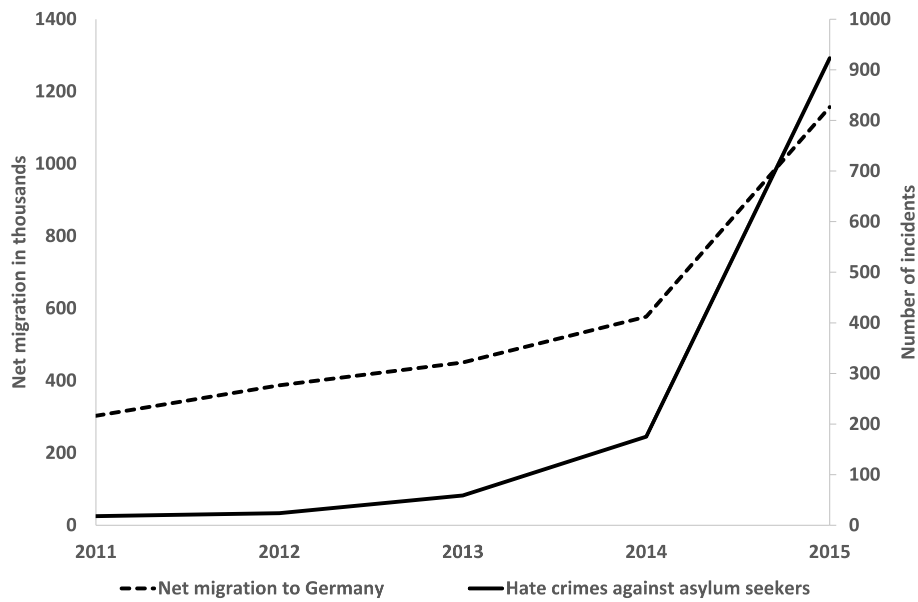

Fig. 1. Foreign Net Migration and Hate Crime in Germany from 2011 to 2015.
Note: Data on foreign net migration is from the Federal Statistical Office. Foreign net migration is defined as the number of non-native immigrants minus the number of non-native emigrants at the domestic level. Data on hate crime against refugees is from the Federal Criminal Police Office. See Section 3.1 for a detailed description of the hate crime statistics. Own depiction.

by the Amadeu Antonio Foundation in 2015.[3] By using administrative data, we avoid shortcomings such as selective media attention whereby only shocking incidents of anti-foreigner hate crime are reported. This type of under-reporting could be particularly problematic in regions where negative attitudes against foreigners are dominant, thus biasing the regional documentation of hate crimes. Strict regulations in police reporting ensure that this bias in administrative police records is unlikely.

Our analysis includes all incidents labeled as being right-wing extremist. In doing this, we exclude the possibility of picking-up intra-refugee community hate crimes. As a robustness check in Section 6, we restrict the analysis to violent hate crimes including only arsons 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 undertaken with the aim of threatening, insulting, or defaming refugees. Examples of non-violent hate crime include swastika graffiti at refugee accommodations, or threatening refugees at gunpoint. Ultimately, we identify 1155 incidents for the whole of Germany from 2013 to 2015. In 2014, 171 cases of hate crime against refugees were recorded. When asylum immigration to Germany spiked in 2015, hate crime incidents peaked at 925, of which 74 were arson attacks and 63 assaults. Figure A3 in the online appendix illustrates the number of hate crime incidents by type and year.

Panel (a) and (b) in Figure A1 in the online appendix depicts the distribution of hate crimes against refugees per 100,000 residents. Almost 72 percent of the German districts experienced at least one hate crime incident against refugees, and almost one quarter encountered a minimum of one violent attack. In 2015, after adjusting for population size, all regions which experienced the highest levels of hate crimes against refugees were located in East 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 districts of Uckermark and Saale with 8.24 and 7.99 attacks per 100,000 residents respectively.

3.2. *Refugee data*

Our source of refugee data is Gehrsitz and Ungerer (2022), who collected data on the assignment of refugees to districts from the State Ministries of Interior. Their data provides information on the number of refugees assigned to subordinate districts by the State Ministries of Interior in 2014 and 2015. We use this data for two reasons. First, using the number of assigned refugees alleviates concerns regarding the potential endogeneity of refugees' location choices or about districts' efforts to influence the actual number of refugees hosted. We are therefore able to estimate causal ITT effects in relation to the increase in hate crime against refugees (see Section 4). Second, to date, only imperfect accounts of refugee stock data that stretches over several years have been available (Gehrsitz and Ungerer, 2022; Statistisches Bundesamt, 2017). Nevertheless, to complement our findings, i.e. by applying an instrumental variable strategy, we retrieve data on the annual end-of-year stock of refugees from the Federal Statistical Office (Statistisches Bundesamt). This database should include all foreigners and their residence status, enabling the isolation of those who migrated to Germany via applying for asylum. Unfortunately, these numbers seem to reflect some imprecision, especially during the influx of refugees in 2015 (Statistisches Bundesamt, 2017). We therefore will use this data solely as an approximation for the observed distribution of refugees that will be instrumented in our IV approach.[4]

[3] Figure A2 presents an overview of hate crime cases from Jäckle and König (2017) and our data for 2015. Newspaper-based data from the Amadeu Antonio Foundation (AAS) used by Jäckle and König (2017) contain almost 100 more cases of arsons and assaults than the BKA data used by us. This discrepancy may be the result of miscategorization by AAS (or by newspapers) that report a fire in a refugee accommodation directly as a right-wing hate crime before the investigation is concluded. With respect to non-violent hate crime against refugees, the BKA data are much more extensive than the ASS data and cover more than twice as many incidents (788 v. 363). In total, the BKA data include 50 percent more entries than the AAS data used by Jäckle and König (2017).

[4] Furthermore, information on refugee stocks is not available for all 402 districts in Germany. In some areas, there is only one office for foreigners that operates in several districts, and therefore, reports only joint immigration numbers. Therefore, the number of districts in the IV estimation reduces to 390.

We also use information on the presence of a state-run refugee reception center (Erstaufnahmeeinrichtung, EAE) from Gehrsitz and Ungerer (2022). Districts in which there is such a reception center usually receive a deduction on their quota. Therefore, we control for the presence of these centers in our analysis. The map in Panel (c) in Figure A1 presents the assignment of refugees to districts per 100,000 residents in 2014 and 2015. Darker areas indicate a larger number of assignments per 100,000 residents. The black dots mark whether an EAE is present in the district. The number of newly assigned refugees ranges from zero to almost 7500 refugees per 100,000 residents.[5]

3.3. Regional measures of anti-foreigner sentiment

In order to explain the regional variation in hate crime incidents we interact the inflow of refugees with district-level information on latent hostility against foreigners. We focus on three measures which proxy or correlate with latent anti-refugee sentiment at a regional level.

First, we utilize the share of German-born residents in 2013 as a proxy for regional ethnic homogeneity. This should capture a potential preference for German neighbors. Residents of regions with only limited previous experience of immigration, may have a more extreme reaction to the arrival of refugees, than those living in regions with a historically high proportion of migrants in the population. Numbers of German and foreign residents come from the Federal Statistical Office.

Second, we employ information on the location in which incidents of hate crime took place in the 1990s. This is when the last well documented episode of violence against foreigners occurred in reunified Germany. While the prominent pogrom-like attacks against refugees in Hoyerswerda in 1991, and Rostock-Lichtenhagen in 1992, led to worldwide dismay, these were only two examples within a much more widespread phenomenon. During this period, the upsurge of anti-foreigner violence was linked to the large-scale immigration of ethnic Germans from former USSR countries and refugees fleeing the Yugoslavian civil war. Using data from Krueger and Pischke (1997), who investigated the high and rising rate of anti-foreigner hate crimes during the early 1990s, we test whether past patterns of hate crime are reflected in patterns of increased aggression towards refugees today. Their account of hate crime incidents is based on newspaper reports and spans from January 1991 to June 1993. We construct a dummy variable which has the value of one if at least one hate crime event was documented in their database, and zero otherwise.

Third, we exploit regional variation in the support for the Nazi party (NSDAP). We rely on the work of Falter and Hänisch (1990) who provide the results of all elections in the Weimar Republic at the municipality level. In order not to depend solely on one election, we construct an average support for the NSDAP between 1928 and 1933, i.e. before the Weimar Republic came to an end. We use the elections in May 1928, September 1930, and March 1933, for which data quality is best, in order to reduce the number of missing observations. Regional electoral results are converted to today's district classification using the geographical link described in Cantoni et al. (2017).

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

3.4. Regional characteristics by occurrence of hate crime

Table 1 presents a descriptive comparison between districts in which anti-refugee hate crimes have and have not been observed. It contains the mean and standard deviation for several socio-demographic and economic indicators (i) for all districts in Germany, (ii) for districts that experienced at least one hate crime in 2014 or 2015, and (iii) for districts without a single recorded incident in these years. The last column reports the differences in means between districts in which attacks against refugees were, and were not seen. Asterisks highlight statistically significant differences. Panel A shows the average number of attacks per district and Panel B shows general demographic statistics. Panel C to E give first impressions on how potential explanations for anti-foreigner hate crime are distributed across districts in which attacks have, and have not been seen.

Data at the district level for 2013 to 2015 are supplied by the Federal Statistical Office of Germany, Federal Returning Officer (Bundeswahlleiter), and the BKA. With the exception of variables only available for a certain period (e.g. election outcomes), all district 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 hate crimes occurred per district, of which 0.20 were registered as violent hate crimes. When normalizing the number of hate crimes by population size, the respective frequencies are 0.67 and 0.08 incidents per 100,000 residents. These figures indicate that hate crimes against refugees are not frequent, but rather, fairly rare and extreme cases of anti-foreigner hatred.

Regarding the demographics in Panel B, the number of residents of districts in which attacks did and did not occur, differs greatly, but only marginally in terms of population density. Districts in which no hate crime was seen have fewer residents, but a higher density of residents. Hate crimes against refugees occur disproportionately often in districts belonging to the former territory of the German Democratic Republic in East Germany. Among all districts that experienced at least one incident, about one quarter are located in the East (the share of eastern districts among all districts is 18.88 percent). In comparison, of the 118 districts in which no hate crime was observed, only 4 (or 3.38 percent) are located in East Germany. Internal migration of German residents does not seem to differ between districts in which hate crimes are, and are not recorded during our estimation period. According to Willems et al. (1993), perpetrators of hate crime are predominantly young males with low educational achievement. Thus, we report the share of males of less than 35 years of age, as well as the share of school dropouts amongst the number of students finishing school. P-values of the tests of equality of means suggest that on average, districts in which more hate crimes are committed, are generally home to a higher number of school dropouts, but to a lower share of males of less than 35 years of age.

Panel C reports that districts with hate crimes against refugees have a statistically significant higher share of citizens with German nationality compared to districts with no hate crimes. This supports the notion that immigrants usually bypass areas in which they expect to be subject to hostility by the resident population. When comparing the number of assignments to the difference in the stock of refugees, we observe that the difference in stock of refugees is slightly smaller than the number of assignments. Recall, however, that the stock of refugees is likely to contain measurement error and also comprises outflows of refugees. Notably, there is no statistically significant difference in the number of assigned refugees nor for the observed number of refugees. This may indicate that the quota-based assignments were not undermined by hate crimes against refugees. In addition, among districts in which hate crimes were observed, and districts in which hate crimes were not observed, there is approximately the same share of districts hosting a refugee reception center. Interestingly, the share of districts which experienced anti-foreigner hate crime incidents in the 1990s, is

Table 1
Summary statistics by districts with and without hate crime incidents.

	Total		Hate crime		No hate crime		Diff.
	mean	sd	mean	sd	mean	sd	
Panel A: Attacks on Refugees							
Number of Hate Crimes	1.36	3.08	1.93	3.52	–	–	–
Number of Violent Hate Crimes	0.20	0.71	0.28	0.83	–	–	–
Hate Crimes per 100,000 Residents	0.67	1.17	0.94	1.29	–	–	–
Violent Hate Crimes per 100,000 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*
Cities over 100,000 Residents in %	16.54	37.18	16.20	36.87	17.37	37.97	−1.18
Districts in the East in %	18.91	39.18	25.35	43.54	3.39	18.14	21.96***
Net Internal Migration of Natives %	−2.78	29.42	−2.23	29.47	−4.09	29.34	1.86
Males under 35 in %	18.48	1.79	18.27	1.84	18.98	1.57	−0.72***
School Dropouts in %	5.69	2.27	5.93	2.38	5.13	1.88	0.79***
Vacant Private Housing in %	5.60	2.95	5.90	3.08	4.89	2.48	1.00***
Panel C: Immigration							
German-born Residents in %	91.72	4.82	92.36	4.62	90.20	4.95	2.16***
Assigned Refugees per 100,000 Residents	546.62	455.29	553.80	386.27	529.32	589.82	24.48
Δ Refugees per 100,000 Residents	412.83[a]	424.74	405.93[b]	320.04	429.35[c]	606.41	−23.42
Districts with Refugee Reception Center in 2015 in %	36.82	48.26	35.92	48.02	38.98	48.87	−3.07
Districts with Hate Crime Incidents between 1991–1993 in %	0.62	0.48	0.70	0.46	0.44	0.50	0.26***
Non-German Crime Suspects in %	25.62	11.58	24.34	11.45	28.70	11.33	−4.36***
Panel D: Economy							
GDP per Capita in 1,000 Euro	34.11	14.56	32.80	14.26	37.28	14.80	−4.48***
Average Household Income in 1,000 Euro	21.25	2.61	21.06	2.78	21.72	2.10	−0.66***
Unemployed Persons per 1,000 Residents	32.51	14.33	33.93	14.60	29.09	13.07	4.84***
Panel E: Voting							
Voter Turnout at the 2013 Federal Election in %	70.71	4.26	70.86	4.14	70.34	4.53	0.52
Extreme Right Vote Shares at the 2013 Federal Election in %	1.62	0.90	1.68	0.99	1.46	0.62	0.22***
Average NSDAP Vote Share between 1928 and 1933 in %	23.22[d]	7.49	23.08[e]	7.50	23.57[f]	7.47	−0.49
N	402		284		118		402

Note: The table shows the summary statistics by districts with and without hate crime incidents. The first six columns show the mean and standard deviation (sd) of regional variables for all German districts, for districts with at least one recorded hate crime against refugees in 2014 or 2015, and for districts without any such incident. Column seven displays the difference in means between columns five and three. Statistical significant differences are indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a]: $N = 390$. [b]: $N = 275$. [c]: $N = 115$. [d]: $N = 394$. [e]: $N = 278$. [f]: $N = 116$.

statistically significantly higher in districts with hate crime today. Note that the share of foreign-born crime suspects is considerably higher in districts without attacks.

Panel D suggests that economic conditions do play some role in determining whether hate crimes are perpetrated. In regions in which hate crimes have not taken place, GDP per capita and the average household income is higher. In addition, unemployment figures are lower in those regions.

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 refugees began. The immigration of refugees was not on the top of the political agenda, and did not mobilize a large body of voters. Districts in which there were attacks against refugees do not statistically differ from districts in which no attack took place in terms of voter turnout. However, voters living in districts with hate crimes against refugees cast slightly more votes for extreme-right wing parties.[6] When studying support for the NSDAP, there seems to be no unconditional difference between districts in which incidents of hate crime did, and did not, occur.

Table 1 reveals strong differences between districts with and without hate crimes against refugees in terms of economic conditions, demographics, and ethnic composition. However, there is no statistically significant difference in the presence of refugees. The unconditional descriptive comparison in terms of the share of native residents, hate crime in the 1990s, and the NSADP vote share indicates already stark differences among the former two regional measures between districts in which hate crimes did, and did not occur.

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

4. Dispersal policy and empirical strategy

In order to attach a causal interpretation to our estimates of local refugee inflows and regional conditions on the increasing incidence of hate crime, we rely on the exogeneity of the assignment of refugees with respect to regional characteristics influencing hate crime. For this exogeneity assumption to hold, it is required that the *assignments* of refugees to areas are not undermined by regional factors that are not reflected in the allocation quotas. We explicitly do not rely on the much more stricter assumption that the *actual* allocation of refugees is orthogonal to regional conditions and a potential regional sorting of refugees. As we are going to demonstrate in the this section, refugee assignments indeed seem to be unaffected by regional factors, while the actual allocation is not.

4.1. *Refugee dispersal policy in Germany*

Based on the federal system in Germany, refugees are assigned to different locations in a two or three-stage procedure. In the first stage, newly arriving refugees are assigned to a state. Then, within a state, they are either assigned to a district and then to a municipality, or directly to a municipality.[7]

In the following, we describe the typical progression of an refugee through the German assignment scheme during the large influx of refugees (see also BAMF, 2016). When refugees crossed the German border, they were picked up by police officers and taken to register at

[7] Since we use the district-level aggregate assignment of refugees in our approach, it does not matter whether states first assign refugees to districts and then to municipalities, or directly to municipalities.

the closest reception center that incorporates a local branch of the Federal Office for Migration and Refugees (Bundesamt für Migration und Flüchtlinge, BAMF). At these centers, refugees are assigned to one of the German states on the basis of 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 size of the state. A computer program called EASY (Erstverteilung der Asylbegehrenden) assigns refugees to reception centers in a particular state in accordance with this quota.

In the second step, refugees are assigned either to districts, or directly to municipalities within the state.[9] Since each state has its own laws determining the way in which refugees are further allocated, this second step can vary from state to state. The majority of states first assign refugees to districts and then to municipalities within the district (see Wendel, 2014). State-to-district or state-to-municipality assignments are primarily based on the population size of districts and municipalities. This is directly stated in the respective state law, or implicitly demonstrated by the rules implemented on the basis of the population size of the subordinate level.[10] Furthermore, some states directly allow for the possibility to deviate from the original quota because of a lack of local housing. That is, authorities usually assign more refugees to rural areas, i.e. into areas with less tight housing markets. Thus, both population sizes and the availability of suitable accommodations govern the assignment of refugees.

In 2015, the sheer mass of incoming refugees put the entire distribution system under pressure. Although the quota-based assignments remained in place, refugees were most often sent to *any* place where the authorities were able to host them (Gehrsitz and Ungerer, 2022). It is therefore quite likely that the actual distribution of refugees is distorted by unknown factors that may relate to the attractiveness of certain regions or by districts that did not cooperate with the authorities. This conjecture is corroborated by Table A1 in the online appendix. It presents OLS regression results of the actual allocation of refugees in 2015 on pre-determined local anti-foreigner sentiment statistics and regional economic indicators. Table A1 indeed suggests that the actual allocation of refugees is distorted by regional sorting of refugees in urban areas. That is why we will focus on the quota-based assignments of refugees in our empirical analysis.

In addition, refugees are legally obliged to stay at their assigned location until a final decision has been reached regarding their application for asylum. The process of reaching a decision following submission of an asylum application took an average of 7.9 months in 2015 (BAMF, 2016). Moreover, newly arrived asylum seekers were required to wait for an average of 4.5 months before being able to submit their application (Deutscher Bundestag, 2017). Non-compliance with this residence obligation is sanctioned with a fine and, if repeatedly disobeyed, with a prison sentence of up to one year. More importantly, refugees receive monetary benefits and free housing at their assigned location. As most refugees depend on these benefits, non-compliance is highly unlikely. Since this study focuses on the immediate reaction of the incumbent population to refugee arrivals, a potential regional sorting of refugees after the lengthy application process is completed does not affect the estimation strategy.

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

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

[10] Two states have additional criteria. North Rhine-Westphalia assigns refugees 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 of these allocation schemes by state is provided by Geis and Orth (2016).

4.2. Empirical strategy

We wish to explore whether the recent local influx of refugees has led to a significant increase in the incidence of hate crime against this group. In order to do so, we leverage the quota-based assignments of refugees to German districts. Specifically, we implement two complementary approaches: an Intention-to-Treat (ITT) and an Instrumental Variable (IV) estimation strategy. Both approaches have different advantages and drawbacks that are discussed in the following subsections.

4.2.1. Intention-to-treat approach

In general, we are interested in identifying a parameter that gives us the impact of the number of newly-arrived refugees on anti-refugee hate crime in Germany. To interpret such a parameter as revealing a causal relationship, we implement a first-difference estimation equation in order to eliminate time-constant unobserved heterogeneity between districts. This is important because districts are subject to long-lasting structural attributes, which are not perfectly covered by socio-demographic and socio-economic control variables. Moreover, the nature of the unexpected large-scale immigration of refugees suggests a natural foundation of a first-difference specification. The estimation equation takes the following form:

$$\Delta hate\ crime_{ct} = \beta assigned\ refugees_{ct} + \Delta X_{ct}\gamma + \Delta\theta_t + \Delta\theta_s + \Delta u_{ct}\,, \tag{1}$$

where we use the annual difference between the periods 2013–2015, resulting in a panel of $T = 2$, $t = 2014, 2015$ with all $n = 402$ districts in Germany. The outcome variable $hate\ crime_{ct}$ is measured as the total number of attacks against refugees in district c in year t normalized by 100,000 residents in 2013. The main explanatory variable $assigned\ refugees_{ct}$ reflects the annual district-level assignments and is normalized by 100,000 residents in 2013. X_{ct} constitutes a vector of time-varying covariates, including the share of German-born residents, unemployed persons per 1000 residents, GDP per capita, as well as the net internal migration of German citizens and share of foreign-born alleged offenders of violent crimes. Since the literature on the perpetrators of hate crime suggests that young male adults or adolescents with low educational achievement commit the majority of hate crimes (Willems et al., 1993), X_{ct} also includes the share of males aged below 35 years, and the share of school dropouts in each district. In order to account for omitted regressors that correlate with our main explanatory variable, we also control for the share of vacant housing and the presence of state-run reception centers.[11] Furthermore, we include a dummy variable for the year 2015 (θ_t), we control for state fixed effects (θ_s), and cluster standard errors at the district level. As states are responsible for the assignment of refugees as well as the administration of the police, controlling for potential differences in state trends strengthens the causal interpretation of our estimates.

In addition, we wish to investigate why some regions are more prone to hate crime against refugees than others. The analysis considers several channels of influence by interacting the district-level assignments of refugees with district characteristics (CC). Our second estimation equation reads as follows:

$$\begin{aligned}\Delta hate\ crime_{ct} = {} & \beta assigned\ refugees_{ct} + \delta assigned\ refugees_{ct} \times CC_c \\ & + \Delta X_{ct}\gamma + \Delta\theta_t + \Delta\theta_s + \Delta u_{ct}\,,\end{aligned} \tag{2}$$

where CC_c denotes the potential district-level characteristic of interest, which will differ according to the respective hypothesis under consideration. The parameters β and δ are the main coefficients of interest used to evaluate the influence of refugees and district-level characteristics on

[11] As potentially some of the control variables may be affected by the inflow of refugees, we perform our main analysis also without including control variables. We present these findings, that are very close to our main results, in Table A5 in the Online Appendix.

the incidence of anti-foreigner hate crime in Germany. For the analysis of district-level characteristics, we use explanatory variables for 2013 or earlier, i.e. the time prior to the primary inflow of refugees, to avoid any endogenous changes in regional characteristics in response to the immigration shock. Yet, one might raise the concern that district characteristics are correlated with the assignments. We argue that this is quite unlikely given the rules that determine the quota-based assignments. In Table A2 we show that correlations are indeed rather weak and statistically indistinguishable from zero, particularly after controlling for vacant housing.

Due to our first-difference specification, the identifying variation comes from *within* district differences in the administrative assignments. Therefore, we take the first stage of the assignment process – from the federal to state level – as given. The differences in assignments arise due to authorities not being able to balance assignments within each year, but trying to accomplish an even distribution of refugees over time. A threat to our identification strategy would arise if past xenophobic incidents affect the assignments. The rationale here is that regions which previously experienced incidents of anti-refugee hatred might be able to argue in favor of receiving (relatively) fewer refugees. Even though such a behavior is quite unlikely given the regulations to which the assignments must adhere by law, a correlation between previous incidents of anti-foreigner crime and assignments may occur by chance. We are able to formally test this proposition by regressing the local assignment of refugees per 100,000 residents on hate crime against refugees in 2012 and 2013, i.e. before the recent large influx. In addition, we use the vote shares for extreme-right wing parties at the federal election of 2013 as a measure of the political power of anti-immigration parties at the local level. Column (1) in Table 2 presents the results of a linear regression including these measures. 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 also positive, indicating that, if anything, more votes for extremist right wing parties would be associated with hosting more refugees in a region. This suggests that pre-existing local hostility against refugees did not drive nor influence their assignment.

The result holds when controlling for other factors that might have influenced the assignment of refugees (Table 2, column (3)). Notably, economic local conditions – such as unemployment – seem to be unrelated to refugee assignments. As discussed previously, the availability of housing capacity is one factor in explaining variations in refugee assignments. Furthermore, cities with a population of more than 100,000 residents were on average assigned around 200–300 refugees less per 100,000 residents than other districts. Since housing is relatively scarce in big cities, this again reflects the importance of the availability of accommodations for the assignment of refugees. Thus, we conclude that the evidence provided in Table 2 supports the assumption regarding the orthogonality of the assignment of refugees to district characteristics prior to the influx. Relying on this assumption and by conditioning on the factors determining the assignment, we are able to estimate and identify a causal Intention-to-Treat (ITT) effect of refugee inflows on the increase in hate crimes.

The ITT effect has two major advantages in our setting. First, it is very informative, as it directly captures policy makers' influence. The assignment of refugees are governed by the quotas, thus, modifying the quotas in order to reduce the likelihood for hate crimes could be a potential policy reaction. Second, estimating the ITT allows under the stated assumptions to derive causal estimates. As the actual distribution of refugees is likely to be confounded, the ITT effect is much more likely to come close to the true effect of refugee immigration on hate crime formation.

4.2.2. Instrumental variable approach

Complementary to estimating an ITT effect, we also apply an instrumental variable approach. Because the actual distribution of refugees might be influenced by unobserved district characteristics leading to non-compliant behavior of municipalities or refugees, we will instrument the actual distribution of refugees by the assignments. By using the arguably exogenous assignments as an instrumental variable, we employ a (governmentally enforced) "encouragement design" (Holland, 1986; Angrist et al., 1996). That is, we use the number of locally assigned refugees as an instrumental variable for the number of actual refugees in German districts. Technically, we implement the IV on variants of Eqs. (1) and (2), in which we substitute the assignment by the actual inflow of refugees and subsequently instrument the actual inflow with the assignments.

By using a continuous instrument, our 2SLS estimates can be interpreted as a weighted average of local average treatment effects. In order to assess the relevance of our instrument, we provide the common F-test statistics. When instrumenting only one endogenous variable, we present Kleibergen–Paap F-test statistics as we always cluster the standard errors at the district level. If we instrument more than one endogenous variable, i.e. due to the inclusion of interaction terms, we provide Sanderson and Windmeijer (2016) F-test statistics of weak instruments tests.

The IV approach depends on the exclusion restriction, i.e. that assignments only influence the rise in hate crime via the resident refugee population. This assumption is quite intuitive as the assignment process is an abstract administrative process, in which state officials assign head counts of refugees to districts based on pre-defined quotas. Nevertheless, recall that also the availability of housing influenced assignments (see Table 2), which may limit the validity of the IV estimates. In our IV analysis, we will therefore always control for the share of vacant housing at the district level, in order to mitigate this concern. Notwithstanding, we will be cautions in interpreting the IV estimates and favor the arguably more reliable ITT estimates introduced in the previous subsection.

5. Results

5.1. Hate crime and refugee inflows

We first present the results of regressing hate crimes on refugee inflows without explicitly considering differences in regional conditions. We do this in order to isolate the victim supply effect, namely the effect whereby a mere increase in the number of refugees in a particular district would increase the incidence of hate crime against refugees. Generally, we would expect that a higher supply of potential victims per capita should lead to a proportional increase in the number of observed acts of hate crime against this group. Panel A of Table 3 provides the results of this regression in column (1). We estimate the ITT effect, which informs us about the effect of refugee inflows when these (strictly) follow administrative assignments. Conditional on district characteristics, a 2015 year dummy, and state fixed effects, we estimate a statistically insignificant coefficient of 0.00032 of refugee inflows on hate crime. Besides the statistical insignificance, this result would suggest that the arrival of 3000 additional refugees per 100,000 residents would lead to approximately one additional hate crime per 100,000 residents. Given an average inflow of 546 refugees per 100,000 residents in 2014 and 2015, the increase in refugees would have to be substantial to trigger an additional hate crime.

Panel B of Table 3 presents the IV estimates.[12] The IV estimate in column (1) is of similar size and also statistically indistinguishable from zero. Given that we cannot rule out that the true effect may very well be not different from zero, we conclude that the link between the size of refugee inflows and hate crime attacks seems, at least on average, to be subordinate.

An alternative explanation could be that a certain threshold of incoming refugees must be exceeded before potential perpetrators turn

[12] The corresponding first stage regressions are summarized in Table A3.

Table 2
Determinants of refugee assignment.

Dependent Variable: Assigned Refugees per 100,000 Residents	(1)	(2)	(3)	(4)
Extreme-Right Vote Share$_{2013}$ (%)	37.112		25.869	−16.933
	(35.071)		(41.782)	(36.085)
Hate Crimes per 100,000 Residents$_{2013}$		−43.393	−23.480	−32.550
		(78.271)	(70.948)	(74.828)
Unemployment per 1,000 Residents$_{2015}$			2.805	0.545
			(2.880)	(2.706)
Mean Income per Capita$_{2015}$ in 1,000 EUR			−15.944	−11.307
			(14.864)	(13.384)
GDP per Capita$_{2015}$ in 1,000 EUR			9.612	10.374
			(6.813)	(6.909)
City over 100,000 Residents			−280.567***	−187.518**
			(99.464)	(84.707)
Vacant Housing$_{2015}$ (%)				42.339***
				(13.023)
Constant	12.290***	12.561***	12.451***	10.639***
	(0.936)	(0.944)	(2.863)	(2.757)
State Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.09	0.09	0.13	0.15
N	402	402	402	402

Note: Columns one to three show the OLS estimates of the determinants of refugee assignments to districts in 2014 and 2015. Regional variables are based in 2013 or 2015 and explained in detail in Section 3. Standard errors are clustered at the district level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

against newcomers, i.e. analogous to the idea of tipping-point models (see Card et al., 2008). To investigate this idea, we focus on districts with very high inflows of refugees. The models in columns (2) and (3) of Table 3 show the estimated coefficients for refugee inflows and the interaction effect of refugee inflows with dummy variable D, which takes on the value of one if the district is located in the upper half or upper quartile of refugee assignments, and zero otherwise, respectively. For these specifications, we find statistically insignificant interaction terms for both, ITT and IV estimations. It thus seems that districts in the upper end of the refugee distribution do not experience more attacks against refugees than those with less refugees per capita.

These results may suggest that it is not mainly about the size of the inflows, but *where* authorities place refugees. The regression results in column (4) support this idea. Here, we interact refugee inflows with a dummy variable which is one if a district lies in the East of Germany, and zero otherwise. The interaction term is positive, sizable, and statistically significant for both, ITT and IV. The estimated ITT effect can be interpreted as 1000 additional refugee per 100,000 residents would result in 1.85 new hate crimes per 100,000 residents in East Germany, while the same increase in hate crime occurs in West Germany only after the arrival of 10,000 additional refugees.

We conclude from these regression results that the size of the inflow of refugees does not automatically translate into higher numbers of attacks against this group. However, it seems to be crucial to which region refugees are allocated to. Since East and West Germany differ to a large extent in terms of their regional conditions, it is vital to study the interplay of the magnitude of an influx of asylum seeks with regional measures of latent xenophobia. As will be clarified in subsequent sections, even a small number of refugees in responsive regions might have larger effects than very large inflows to regions with lower levels of pre-existing anti-foreigner sentiment.

5.2. Hate crime and regional accounts of latent anti-refugee sentiment

In this section, we analyze whether the effect of refugee inflows on hate crime is magnified when accounting for the local ethnic composition or the historical existence of out-group bias. We consider the share of German-born residents, hate crime incidents in the 1990s, and support for the NSDAP between 1928 and 1933.

Panel A of Table 4 presents the estimation results of Eq. (2) for the ITT effect. The estimated models in column (1) to (3) include interaction terms of refugee inflows with one of the regional measures for anti-foreigner sentiment. In order to proxy (a preference for) local ethnic homogeneity, we use the share of Germans in 2013 as an interaction term. Column (1) indicates a statistically significant negative coefficient estimate of refugee inflows and a statistically significant positive estimate of the interaction with the pre-existing share of native residents. This implies that newly assigned refugees trigger more hate crime against this group in regions with relatively larger shares of native residents, and less hate crimes in regions with an already relatively large share of foreigners. Furthermore, the average marginal effect (AME) is positive and exceeds the corresponding value of the baseline regression without interactions in column (1) of Table 3 (0.00046 instead of 0.00032). Figure A4 in the online appendix visualizes the interplay of refugee inflows and the share of natives in Panel (a), based on the ITT estimates. The contour plot presents the predicted number of incidents of hate crime for every observed combination of refugee inflows and the share of native residents. For instance, areas with a share of German incumbent residents of a minimum of 97 percent that are at the same time subject to at least 900 assigned refugees per 100,000 residents witness about one perpetrated hate crime on average. Evidently, what matters is not purely the absolute size of incoming refugees, but the encounter of unaccustomed native residents to inflows of (ethnically different) foreigners.

Furthermore, we investigate whether past incidents of anti-foreigner hate crime predict hate crimes against refugees today. In order to do this, we interact the inflow of refugees with a dummy variable, which takes on the value of one if incidents of hate crime were documented in the early 1990s in the district, and zero otherwise. Column (2) in Table 4 confirms that refugees assigned to regions in which anti-foreigner crimes occurred around 25 years ago, face significantly more attacks than those assigned to areas without such a legacy. In Panel A, the AME substantially increases from 0.00032 in Table 3 to 0.00050 after considering past regional patterns of hate crime. A similar pattern is visible for the IV results (an increase in the AME from 0.00042 to 0.00081). This important finding shows that the current upsurge in hate crime is not only related to the contemporary factors of ethnic composition, but also rooted in longer term xenophobic attitudes that persist in affected regions.

Table 3
Refugees arrivals and hate crime.

Dependent Variable: Δ Hate Crimes per 100,000 Residents	(1)	(2)	(3)	(4)
Panel A: ITT				
Assigned Refugees	0.00032	0.00035	0.00057*	0.00018
	(0.00020)	(0.00034)	(0.00031)	(0.00013)
Assigned Refugees				
× D[Inflow > 50th percentile]		−0.00002		
		(0.00019)		
× D[Inflow > 75th percentile]			−0.00022	
			(0.00020)	
× East				0.00167***
				(0.00036)
2015 Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj. R^2	0.37	0.37	0.37	0.43
N	804	804	804	804
Panel B: IV				
Δ Refugees	0.00042	0.00047	0.00066	0.00030
	(0.00036)	(0.00052)	(0.00052)	(0.00027)
Δ Refugees				
× D[Inflow > 50th percentile]		−0.00004		
		(0.00025)		
× D[Inflow > 75th percentile]			−0.00019	
			(0.00029)	
× East				0.00295***
				(0.00068)
2015 Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Kleibergen–Paap *F-stat*	12.32			
Sanderson–Windmeijer *F-stats*		105.59	70.41	15.04
		210.12	138.61	168.57
Adj. R^2	0.37	0.36	0.36	0.30
N	780	780	780	780

Note: The table shows the first-difference regression results of hate crime against refugees per 100,000 residents on either the assigned number of refugees per 100,000 residents (Panel A) or the first-difference of refugees per 100,000 residents (Panel B). Refugee measures are interacted with dummy variables *D*, which either take on the value of 1 if the district is above the median or within the fourth quartile of refugees assignments and 0 otherwise, or with the dummy variable *East*, which takes the value of 1 if the district belongs to East Germany and 0 otherwise. Panel A refers to the ITT, while Panel B estimates the IV approach. Control variables 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. Standard errors are clustered at the district level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

It may well be that this persistence stretches back over a much longer period of time. Employing vote shares of the NSDAP between 1928 and 1933, we investigate whether regional differences in the support for the Nazi party bears some relation to the number of hate crimes committed against refugees today. The interaction term in column (3) of Table 4 is positive and statistically significant different from zero, both for the ITT in Panel A as well as for the IV in Panel B. It seems that areas with higher support for the Nazi party in the 20th century are more hostile to incoming refugees than areas with lower support for the NSDAP. Again, the AME of refugee inflows is substantially magnified compared to the baseline estimate in column (1) of Table 3. This result suggests that it is not simply anti-foreigner sentiment, but the broader concept of out-group biases which persists over almost a century. Based on the ITT estimation, Panel (b) of Figure A4 in the online appendix visualizes the number of predicted hate crimes for combinations of refugee inflows and electoral support for the NSDAP. On average, one hate crime is perpetrated if areas receive about 1100 refugees per 100,000 residents and have a historical average vote share of about 37 percent for the NSDAP.

When simultaneously assessing the influence of all measures in a unified model in column (4), the coefficient of the NSDAP vote share loses its statistical significance in Panel A as well as in Panel B. The contemporary degree of ethnic homogeneity and more recent incidents of hate crime against foreigners sustain their predictive power. These measures prove to be more important for predicting increases in hate crime as a reaction to unexpected immigration today.

In general, the IV estimates presented in Panel B of Table 4 always confirm the results obtained from the ITT approach.[13] The IV estimates are larger in size than the ITT estimates, but generally reproduce the same relationships presented in Panel A.

5.3. The special case of East Germany

The previous section documents that refugee inflows trigger hate crime in areas with a low share of foreigners and a history of xenophobic attacks and attitudes. In addition, column (4) of Table 3, that presented our baseline results, showed that refugee inflows are associated with hate crimes in districts in East Germany, but not in West Germany. As our measures of local latent hostility against foreigners are know to be particularly pronounced in East Germany (see for instance Krueger and Pischke, 1997; Lange, 2021), it could be the case that our results are purely driven by differences between East and West Germany. Recall, that we already control for different time trends of the states in our empirical analysis. Nonetheless, there could be general East-West differences that are not picked up by the inclusion of state

[13] The corresponding first stage regressions are summarized in Table A4.

Table 4
Measures of regional xenophobia and hate crime.

Dependent Variable: Δ Hate Crimes per 100,00 Residents	(1)	(2)	(3)	(4)
Panel A: ITT				
Assigned Refugees	-0.00618^{***}	0.00021	−0.00006	-0.00583^{***}
	(0.00145)	(0.00014)	(0.00026)	(0.00141)
Assigned Refugees				
× Share of Natives 2013	0.00714^{***}			0.00637^{***}
	(0.00163)			(0.00162)
× Hate Crime 90s		0.00046^{***}		0.00044^{***}
		(0.00013)		(0.00012)
× Mean NSDAP Vote Share			0.00182^{**}	0.00119
			(0.00080)	(0.00079)
AME[Refugees]	0.00046^{***}	0.00050^{***}	0.00036^{**}	0.00064^{***}
	(0.00013)	(0.00015)	(0.00018)	(0.00013)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.40	0.39	0.41
N	804	804	788	788
Panel B: IV				
Δ Refugees	-0.01174^{***}	0.00036	−0.00026	-0.01148^{***}
	(0.00272)	(0.00030)	(0.00044)	(0.00274)
Δ Refugees				
× Share of Natives 2013	0.01353^{***}			0.01274^{***}
	(0.00312)			(0.00320)
× Hate Crime 90s		0.00073^{***}		0.00062^{***}
		(0.00021)		(0.00020)
× Mean NSDAP Vote Share			0.00331^{***}	0.00200
			(0.00125)	(0.00126)
AME[Refugees]	0.00083^{***}	0.00081^{***}	0.00051	0.00120^{***}
	(0.00026)	(0.00031)	(0.00032)	(0.00027)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Sanderson–Windmeijer *F-stats*	551.62	27.04	531.82	502.83
	486.35			431.67
		406.13		530.37
			771.51	755.47
Adj. R^2	0.36	0.35	0.36	0.33
N	780	780	762	762

Note: The table shows the first-difference regression results of hate crime against refugees per 100,000 residents on either the assigned number of refugees per 100,000 residents (Panel A) or the first-difference of refugees per 100,000 residents (Panel B). Refugees measures are interacted either with the share of Germans living in the district in 2013, a dummy variable *Hate Crime 90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the district between 1991 and 1993, and 0 otherwise, or the average share of votes cast for the NSDAP between 1928 and 1933. Column (4) presents the results of a model that includes all interaction. Panel A refers to the ITT, while Panel B estimates the IV approach. Control variables are the same as in Table 3. Standard errors are clustered at the district level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

fixed effects. We investigate this issue explicitly in this section by estimating the specific East Germany effect of refugee inflows on the rise in hate crimes. To do so, we repeat our analysis of the previous section but augment our regression models by an interaction effect of an East Germany dummy variable with the assigned number of refugees (i.e. as done in column (4) of Table 3).

Table 5 presents the extended results by the inclusion of an East Germany interaction effect. In each of the regression models in Table 5 the *East* coefficient is statistically significantly different from zero and sizable, hinting consistently at level differences between East and West Germany in the likelihood of increases in hate crime as a result of refugee inflows. A comparison of these estimates to the baseline effect for East Germany in column (4) of Table 3 suggests that the differential effect for East Germany is not notably affected by the inclusion of measures of latent hostility against foreigners. In turn, the estimated interaction effects of our measures of latent hostility against foreigners do decrease in size, but are at the same time more precisely estimated as indicated by uniformly lower standard errors.

These estimates show that indeed East-West differences play a role in the influence of latent local hostility on the rise of hate crime. Nevertheless, the measures of latent local hostility remain statistically significantly different from zero and continue to be important factors in explaining the rise in hate crime as a result of the influx of refugees.

5.4. Further regional influences and hypotheses

The previous sections documented that latent local hostility is an important driver for the emergence of hate crimes against newly arrived refugees. Nonetheless, there may exist further regional factors that may influence the rise in hate crime. For instance, the public debate on hate crime in Germany revolves around the roles of economic deprivation and extremist right-wing attitudes as potential sources of frustration and anti-foreigner crime. Indeed, deprivation seems to be related to the formation of hate groups and extremist parties, as has been shown by Dustmann et al. (2011) and Adamczyk et al. (2014). Hate crimes might also be perpetrated as a form of retaliation. Evidence that suggests this link has been provided by Hanes and Machin (2014) and Ivandic et al. (2019). We thus investigate the importance of the vote shares of right-wing extremist parties, the share of foreign-born suspects of violent crimes, as well as unemployment, and the average household income as further potential explanations for the upsurge in

Table 5
Measures of regional xenophobia, East Germany, and hate crime.

Dependent Variable: Δ Hate Crimes per 100,00 Residents	(1)	(2)	(3)	(4)
Panel A: ITT				
Assigned Refugees	−0.00267*	0.00012	−0.00013	−0.00252*
	(0.00136)	(0.00010)	(0.00020)	(0.00132)
Assigned Refugees				
× East	0.00150***	0.00156***	0.00166***	0.00139***
	(0.00037)	(0.00035)	(0.00036)	(0.00037)
× Share of Natives 2013	0.00315**			0.00262*
	(0.00151)			(0.00150)
× Hate Crime 90s		0.00030***		0.00031***
		(0.00011)		(0.00011)
× Mean NSDAP Vote Share			0.00142*	0.00125*
			(0.00075)	(0.00074)
AME[Refugees]	0.00054***	0.00060***	0.00053***	0.00066***
	(0.00012)	(0.00013)	(0.00013)	(0.00012)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj. R^2	0.44	0.44	0.43	0.44
N	804	804	788	788
Panel B: IV				
Δ Refugees	−0.00600**	0.00027	−0.00031	−0.00607**
	(0.00237)	(0.00025)	(0.00036)	(0.00240)
Δ Refugees				
× East	0.00250***	0.00274***	0.00290***	0.00227***
	(0.00069)	(0.00068)	(0.00068)	(0.00070)
× Share of Natives 2013	0.00703***			0.00654**
	(0.00271)			(0.00280)
× Hate Crime 90s		0.00045**		0.00044**
		(0.00020)		(0.00019)
× Mean NSDAP Vote Share			0.00293**	0.00237*
			(0.00120)	(0.00121)
AME[Refugees]	0.00100***	0.00107***	0.00093***	0.00126***
	(0.00027)	(0.00030)	(0.00028)	(0.00028)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Sanderson–Windmeijer *F-stats*	563.21	27.76	540.81	453.81
	349.31	211.93	181.92	354.06
	499.69			387.60
		382.62		487.28
			800.42	761.46
Adj. R^2	0.30	0.29	0.30	0.28
N	780	780	762	762

Note: The table shows the first-difference regression results of hate crime against refugees per 100,000 residents on either the assigned number of refugees per 100,000 residents (Panel A) or the first-difference of refugees per 100,000 residents (Panel B). Refugee measures are interacted with the dummy variable *East*, which takes the value of 1 if the district belongs to East Germany and 0 otherwise with either the share of Germans living in the district in 2013, a dummy variable *Hate Crime 90s*, which takes on the value of 1 if hate crimes against foreigners occurred in the district between 1991 and 1993, and 0 otherwise, or the average share of votes cast for the NSDAP between 1928 and 1933. Column (4) presents the results of a model that includes all interaction. Panel A refers to the ITT, while Panel B estimates the IV approach. Control variables are the same as in Table 3. Standard errors are clustered at the district level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

anti-refugee hate crimes. We do so by employing the previous regression framework, including the East Germany interaction to explicitly control for East-West differences with respect to asylum immigration.

First and foremost, a high vote share for extremist right-wing parties can be seen as a measure for contemporary latent anti-foreigner sentiment and should be a complementary measure to our preferred proxies for latent local hostility against immigrants. We expect to observe more hate crimes against refugees 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.[14] Column (1) of Table 6 presents the regression results including an interaction term of extremist right-wing parties' vote share with refugee inflows. Contrary to expectations, the coefficients of extreme right-wing parties' vote shares are statistically insignificant in Panel A and B. This outcome is the result of the considerable difference between East and West Germany in regard to extremist right-wing parties' vote shares.[15] While these parties usually receive very few votes in West Germany, they tend to be much more popular with voters in East Germany. Pure East-West differences are,

[14] We deliberately refrain from using AfD vote shares as a measure of latent xenophobia as this party shifted its focus from a eurosceptic to an anti-immigration party, after the large influx of refugees began. The results for this party at the federal election in 2013 would thus not pick-up latent hostility against immigrants.

[15] Estimating our empirical model without the East Germany interaction effect indeed delivers a positive association between extremist right-wing parties' vote shares and the rise in hate crime. Regression results are available upon request.

Table 6
Further regional conditions and hate crime.

Dependent Variable: Δ Hate Crimes per 100,00 Residents	(1)	(2)	(3)	(4)
Panel A: ITT				
Assigned Refugees	0.00031	0.00058**	−0.00006	0.00060
	(0.00026)	(0.00023)	(0.00027)	(0.00050)
Assigned Refugees				
× East	0.00182***	0.00145***	0.00149***	0.00160***
	(0.00042)	(0.00036)	(0.00034)	(0.00036)
× Extremist Right Vote Share 2013	−0.00009			
	(0.00015)			
× Share of Foreign-Born Suspects 2013		−0.00002**		
		(0.00001)		
× Unemployment 2013			0.00001	
			(0.00001)	
× Income per Capita 2013				−0.00002
				(0.00002)
AME[Refugees]	0.00052***	0.00053***	0.00048***	0.00048***
	(0.00014)	(0.00012)	(0.00014)	(0.00014)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Adj. R^2	0.43	0.44	0.43	0.43
N	804	804	804	804
Panel B: IV				
Δ Refugees	0.00053	0.00137***	−0.00021	0.00046
	(0.00050)	(0.00052)	(0.00048)	(0.00072)
Δ Refugees				
× East	0.00319***	0.00238***	0.00255***	0.00292***
	(0.00081)	(0.00066)	(0.00066)	(0.00069)
× Extremist Right Vote Share 2013	−0.00014			
	(0.00025)			
× Share of Foreign-Born Suspects 2013		−0.00004**		
		(0.00002)		
× Unemployment 2013			0.00002	
			(0.00001)	
× Income per Capita 2013				−0.00001
				(0.00003)
AME[Refugees]	0.00091***	0.00100***	0.00080***	0.00084***
	(0.00032)	(0.00028)	(0.00031)	(0.00031)
Year Dummy	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Sanderson–Windmeijer *F-stats*	295.97	354.60	515.43	270.85
	104.08	205.42	118.81	179.82
	485.96	489.45	504.02	203.42
Adj. R^2	0.30	0.32	0.31	0.31
N	780	780	780	780

Note: The table shows the first-difference regression results of hate crime against refugees per 100,000 residents on either the assigned number of refugees per 100,000 residents (Panel A) or the first-difference of refugees per 100,000 residents (Panel B). Refugee measures are interacted with the dummy variable *East*, which takes the value of 1 if the district belongs to East Germany and 0 otherwise, and with either the share of votes cast for extremist right-wing parties in 2013, the share of foreign-born criminal suspects in 2013, the number of unemployed persons per 1,000 residents in 2013, or the average household income per capita in 1,000 Euros in 2013. Panel A refers to the ITT, while Panel B estimates the IV approach. Control variables are the same as in Table 3. Standard errors are clustered at the district level and displayed in parentheses. Statistical significance is indicated by asterisks according to: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

however, already captured by the interaction term *East*, such that little variation is left to identify the influence of extremist right-wing parties.

An alternative explanation for the upsurge in hate crime could be that perpetrators use these crimes as a form of retaliation. Since refugees might be involved in criminal activity in Germany, it is possible that hate crime against this group would be enacted as a form of retaliation—a tit-for-tat strategy at the local level. This motive might be especially strong when there are many victims in the majority population. Unfortunately, we cannot directly test this hypothesis, because we do not have information on victim-offender relations at the district level. In addition, we lack information indicating whether the perpetrators of anti-foreigner hate crime had previously been victim to crimes perpetrated by refugees. However, the literature on the victim-offender overlap (Haidt, 2003; Jacobs and Wright, 2010) suggests that retaliation is not necessarily targeted directly against the perpetrator. Through random redirection of hate, any available person of the out-group may be victimized, leading to a general climate of violence and fear. Moreover, the motive of retaliation may 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[16] from the German Police Statistics (Polizeiliche Kriminalstatistik, PKS) with our existing district-level database. We focus on the share of foreign-born suspects among all suspects involved in a violent crime—these crimes are most likely to provoke retaliatory behavior.

[16] A suspect is the outcome of the police investigation of a crime. Suspects can be viewed as alleged criminals, as they are not charged nor convicted (yet). However, from the perspective of the police, they are very likely to have committed the crime under consideration.

In column (2) in Table 6, we display the ITT and IV estimates of interactions with the share of foreign-born suspects of violent crimes. The parameter estimates of the interactions with foreign-born suspects are negative and statistically significant. The effect of refugee inflows seems to be higher in regions with relatively small shares of foreign-born crime suspects. Thus, the hypothesis of retaliation cannot be confirmed with the data to hand. Initially at least, this negative outcome seems counterintuitive. However, note that a relatively small share of crimes committed by foreigners are observed when the proportion of foreigners in the population is relatively small and the share of native residents is high. This outcome is in accordance with the result of ethnic homogeneity: High shares of incumbent inhabitants are associated with higher rates of hate crime against newcomers.

Thus far, we have considered measures of out-group biases at the regional level as the main explanation for the upsurge in hate crimes against refugees. An alternative explanation for such an increase, might be economic inequalities between regions. We thus consider the number of unemployed persons per 1000 residents, as well as the average household income, as regional economic measures. We expect that in regions with poor labor market conditions, refugees are considered as competitors for jobs and welfare benefits. A sense of competition may be particularly apparent amongst members of the local population who depend on low-skilled work, or who are unemployed. In order to ensure that we cover the economic situation at the time prior to the massive inflow of refugees, we use unemployment figures from 2013. Because registered unemployment rates depend on the size of the labor force, which depends in turn on the participation rate, we instead use the number of unemployed individuals per 1000 residents as our interaction variable.[17]

Column (3) and (4) in Table 6 report the ITT and IV estimates of refugee inflows and the economic variables. In both models, the interaction terms are statistically not significantly different from zero. We therefore confirm the result of Krueger and Pischke (1997), who found economic variables to be unimportant for hate crime against foreigners in the 1990s. Thus, economic conditions might not play a great role in explaining the rise in hate crime seen today.

6. Sensitivity analysis

In Section 5, we confirmed that regional measures of latent local anti-foreigner sentiment are important indicators in explaining the rise in hate crime against refugees. We now explore the robustness of these findings by considering different estimation models, focusing on the subset of violent hate crime, controlling for additional potentially confounding variables, and examine spatial correlation in standard errors. The regression tables for these analyses can be found in the online appendix.

Fixed effect and count data estimation

Thus far, we estimated first-difference models in the empirical analysis. An alternative way to deal with time-invariant unobserved heterogeneity is to estimate fixed effects models. In Table A6, we re-estimate our main results from Table 5 using a two-way fixed effects approach, including all variables in levels. The results shown in Table A6 corroborate our findings obtained by first-differencing.

Since hate crime events are the most extreme expression of anti-foreigner sentiment, their frequency is low. Therefore, as an alternative approach to analyzing the upsurge in hate crime, these events can be treated as count data. In Table A7, we report the results of a Poisson pseudo-maximum likelihood (PPML) regression using the number of hate crime incidents as the dependent variable instead of the first-differenced population normalized hate crime statistics used thus far (Correia et al., 2020). Instead of first-differencing, we now control directly for district fixed effects. The results in Table A7 corroborate our previous results. Only the coefficient of the interaction term with hate crimes in the 1990ies loses its statistical significance. In the model including all interaction terms, we cannot conclude that the interaction of refugee arrivals and the share of natives differs statistically significantly from zero.

Violent hate crimes

Our measure of hate crime comprises all types of hate-related criminal incidents directed against refugee accommodations and their inhabitants. As the inclination of violent perpetrators to express hatred against foreigners can be expected to be greater than it is for the perpetrators of non-violent hate crime, we examine whether our results also hold for violent hate crimes such as arson and assault. Committing a violent hate crime involves crossing the threshold from an aggressive attitude, to an aggressive action. As such, 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 A8 provides the results of the previous ITT and IV specifications containing exclusively violent hate crimes in 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 a dummy variable for areas in East Germany. Again, as in the analysis comprising all hate crime incidents, refugee inflows have a stronger effect in East Germany than they do in West Germany. Columns (2) to (4) show the regression estimates and average marginal effects for the regional measures of anti-foreigner sentiment. Only the coefficient estimate of the share of native residents 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 refugee inflows and the share of native residents in the incumbent population is highly predictive not only of the rise in overall hate crime against refugees, but also of purely violent attacks.

Police effectiveness and spatial spillovers

We also provide evidence that the results obtained thus far are not driven by an omitted variable bias. In the regression analyses presented in Tables A9, A10, and A11, we control for potentially confounding variables.

Table A9 includes the local crime clearance rates of all crimes and violent crimes as a measure of local police force efficiency. The results are fairly similar to the main results presented in Table 5. Following Zenou (2003) and Piopiunik and Ruhose (2017), we also include spatial lags of hate crime as control variables to capture potential spatial spillovers of hate crime. More specifically, we construct spatially lagged outcome variables as the sum of first-differenced hate crimes per one million residents weighted either by travel time by car (Table A10), or jump distance (Table A11) between district centroids. The augmented specifications do not notable deviate from the main regression results in Table 5.

In addition, we provide evidence that inference is not driven by spatial autocorrelation. In Table A12, we again report our estimates from Table 5, but now also present heteroskedastic and autocorrelation-corrected standard errors (HAC) according to Conley (1999) and Colella et al. (2019). The size and statistical significance of standard errors remains almost unaffected.

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

Mid run influence of refugee arrivals on hate crime

Finally, we elucidate the question of whether the increase in refugee immigration around 2015 also explains hate crime against refugees in later years. As we only have information on refugee assignments for the years 2014/2015, we cannot extend the timeframe of our original analysis from Section 4.2 to later years. Instead, we resort to a cross-sectional analysis by regressing changes in hate crime against refugees from 2013 to 2016 and to 2017 on the cumulative assignment of refugees in the years 2014 and 2015.[18] Put differently, this analysis tests whether refugee arrivals and local latent factors of anti-foreigner hatred are still predictive for the occurrence of hate crimes in later years. The results of this analysis hinge on several aspects, such as whether the assignment in 2014/2015 remained stable in the following years, whether refugees who have been assigned in later years do not substantially alter the regional distribution of refugees, and whether there has not been any variation (such as policy responses) that affected assignments and hate crime incidents in later years.

Table A13 presents the results of this cross-sectional analysis. Panel A shows the correlation between the cumulated refugee assignments and the change in hate crimes from 2013 to 2016. While the results remain fairly stable with respect to the influence of refugee assignments and the share of natives on hate crime, the interaction terms of hate crimes in the 1990s and the vote share of the NSDAP with refugee assignments seem no longer predictive of hate crimes. Panel B mirrors the analysis in Panel A, but further extends the time period of the dependent variable to the change in hate crimes from 2013 to 2017. The estimates in Panel B suggest that refugee inflows and regional measures of latent anti-foreigner hatred are not predictive of hate crime incidents over this extended period.

The finding that the influence of refugee assignments on hate crime incidents is rather contemporary and perhaps transitional fits the aggregate data. Refugee arrivals were substantially reduced after 2015, resulting in only a moderate inflow of approximately 280,000 individuals in 2016, and 186,644 individuals in 2017 (Bundesministerium des Innern, 2018). At the same time, hate crimes against refugees have decreased more sluggishly. While 919 offenses were registered in 2016, only about 271 were registered in 2017, according to the definition of hate crimes against refugees formulated in Section 3.1. Reduced inflows of refugees may have also slowed the occurrence of hate crime incidents after the large inflow in 2015. However, as refugee shelters have been closed after refugees moved on after their arrival, these statistics may underreport the true extent to which refugees keep being exposed to hate crime. The findings based on later years should thus be treated with caution and might only be indicative of how refugee settlement and hate crime interact after immediate arrival.

7. Conclusion

Germany's enthusiasm, exemplified in the motto "refugees welcome", sits in stark contrast to the attacks seen against refugee shelters throughout the country. These two phenomena indicate the two faces of Germany's response to Europe's escalating experience of refugee immigration. In this article, we analyze the association between the size of the inflow of refugees and the spatial upsurge in attacks against this group. We employ three measures of latent anti-foreigner sentiment to explain the large regional heterogeneity in the increase in hate crime. Specifically, this study focuses on the importance of contemporary ethnic homogeneity, past hate crime events, and the legacy of Nazi Germany.

In order to identify the relevance of the size of refugee arrivals for the upsurge in hate crime, we make use of a quota system in Germany, according to which refugees are assigned across German regions. We employ data on these administrative assignments to estimate intention-to-treat and instrumental variable effects of refugee arrivals on the rise in anti-refugee hate crime in Germany.

Our results reveal that there is no homogeneous link between refugee intake and hate crime. We find that the size of the inflow does not automatically translate into a higher number of attacks against refugees. The regional dimension in refugee reception, i.e. in which areas refugees are hosted, is a considerably more important consideration in predicting potential increases in hate crime. Inflows of refugees seem to trigger a rise in hate crime when refugees are accommodated in ethnically homogeneous areas, places in which hate crimes have occurred in the past, or areas in which there was strong support for the Nazi party in the Weimar Republic. Although we detect a strong regional persistence of out-group biases, the sensitivity analyses solely uniformly emphasize the importance of high shares of native residents.

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. Our tested hypotheses hold for both parts of Germany. However, despite the large regional differences between East and West Germany, we did not find any consistent explanation for the large gap in hate crime intensity.

In addition to our main analysis, we examine further regional channels through which hate crime might evolve. When considering economic conditions, we could not reject the statistical unimportance of unemployment rates and differences in household income for the rise in hate crime. We further consider retaliation motives and study the correlation between hate crime and extreme right-wing voting behavior. None of these convincingly explain the rise in hate crime, once we control explicitly for East-West German differences.

Our findings at the regional level can be rationalized by a severe out-group bias at the individual level. Grattet (2009) points 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 et al. (2012) similarly argue (economically) that a loss of compositional amenities reduces support for immigration. Policy makers might consider the results of our study by raising awareness and levels of compassion when assigning refugees 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 provides three explanations for the regional variation in increases in extreme anti-foreigner attitudes against newly arrived refugees. As our data and empirical analyses are conducted 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 empirical evidence from this study significantly contributes to understanding the rise in hate crime.

CRediT authorship contribution statement

Horst Entorf: Conceptualization, Methodology, Investigation, Writing, Supervision. **Martin Lange:** Conceptualization, Methodology, Investigation, Data curation, Writing, Visualization.

Declaration of competing interest

Martin Lange declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The same is true for Horst Entorf, who unexpectedly and terribly to early deceased on February 16, 2020.

[18] In order to remain consistent with the previous analyses, we use the same categorization of hate crimes as described in Section 3.1 but now extend our statistics to the years 2016 and 2017.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2023.103913.

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