DISCUSSION PAPER

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The 2015 Refugee Inflow and Concerns Over Immigration

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The 2015 refugee inflow and concerns over immigration

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Abstract

How did the large asylum-seeker inflow to Germany in 2015 affect concerns about immigration? Using individual-level panel data for the years 2012–2018, I show that after 2015 concerns about immigration increased by about 21 pp. and support for extreme right-wing parties by about 1.7 pp. These trends show considerable heterogeneity for different demographic groups. Using a policy that allocates asylum-seekers to districts I identify the effect of exposure to asylum-seekers. In line with the contact hypothesis, living in a high refugee migration district reduced concerns about immigration by 3 pp. The effect appears larger for right-leaning respondents but is otherwise similar across demographic groups.

Keywords: immigration, refugees, attitudes, concerns about immigration
JEL Codes: J15, D72, P16, R23

1 Introduction

In the second half of 2015, around 868,000 refugees arrived—either by sea or land—to Europe. This number was almost six times larger than the arrivals during the first half of 2015 (approx. 147,000 refugees) (UNHCR, 2018). This large increase in only a few months depicts the rapid escalation of forced migration due to civil conflicts. Germany alone received about half a million first-time asylum applications in 2015, representing 35.2% of all applications in the European Union (Eurostat, 2016). Refugee migration was not only a topic highly present in the media but also in the political arena. During this time, support for the Alternative for Germany (AfD)—the largest right-wing populist (RWP) party in Germany—increased rapidly in the polls and in regional elections (see figure 1). This leads to the question of what role the arrivals of asylum-seekers has played in shaping political attitudes and concerns over immigration from the German population.

The recent literature studying the refugee crisis of 2015 (Bredtmann, 2020; Dinas et al., 2019; Gehrsitz & Ungerer, 2018; Schaub et al., 2020; Steinmayr, 2021; Tomberg et al., 2021)[1] has mainly focused on electoral outcomes using aggregate data at the district or municipality level, which does not allow for the identification of changing individual preferences and how this change is shaped by individual characteristics. These studies describe two types of effects. First, at the macro-level, all citizens are exposed to the information that refugees are coming (via the media, political rhetoric, etc.). Second, at the micro level, citizens are exposed to asylum-seekers[2] and might have direct contact with them (e.g. in their neighbourhood) which might change individual attitudes—as described by the contact hypothesis (Allport, 1954).

I analyse both effects using individual level panel data for the years 2012–2018 from the German Socio-Economic Panel (Wagner et al., 2008) which I merge with the inflow of asylum-seekers to Germany in 2015. This large and unexpected inflow together with the rules governing the allocation of asylum-seekers, which entails national and state quotas, provides a one-time shock with geographical variation. Since the share of allocated asylum-seekers varies across districts, this allows me to compare how their presence affects individual concerns over immigration and party affinity. For identification I use the dispersal policy that assigned asylum-seekers to districts together with the panel structure of my data. As stressed by Gehrsitz and Ungerer (2018), since the state quotas depend on tax revenues and population, the allocation of refugees is not completely random but does not allow for self-selection. However, given that shortage of accommodation was a major issue in 2015, one concern is selection on the receiving districts side: available accommodation might not be equally distributed across districts. Likewise, more welcoming districts could have created additional space for receiving asylum-seekers while the opposite might be true for districts in which residents were more reluctant to host asylum-seekers. To control for these unobservable characteristics, I estimate a dynamic difference-in-differences model (event-study) with individual fixed effects. I argue that conditional on the individual fixed-effects the allocation of asylum-seekers was as good as random.

The general time trend suggests that after the large inflow of asylum-seekers to Germany (2016-2018) there was an increase in concerns over immigration by 21 percentage points (pp.) at the national level. Yet, concerns over immigration were almost 3 pp. lower among respondents living in high refugee migration districts relative to those living in low refugee migration districts. This exposure

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[1]See Cools et al. (2021) for a systematic review.
[2]For the purpose of this paper I use the terms *refugees* and *asylum-seekers* interchangeably.

effect is in line with the contact hypothesis (Allport, 1954). Similarly, Cools et al. (2021) hypothesise that immigration at the national level might be more important than local exposure to immigrants, which is in line with my findings. Support for extreme right-wing parties increased by 1.7 pp. after the arrival of asylum-seekers at the national level (time trend). Yet, the individual exposure—to the arrival of asylum-seekers in one's districts of residence—did not contribute to this increase. Furthermore, heterogeneity analysis shows that the reductions in concerns over immigration were larger among right-leaning individuals, comparable to the findings from Steinmayr (2021) and Bansak et al. (2016). Apart from this, I find that the reduction in concerns over immigration due to exposure to asylum-seekers in the district of residence were overall similar across subgroups (sex, age, education, urban/rural, East/West Germany), akin to Bansak et al. (2016). Nonetheless, the point estimates suggest that the dynamics of the response might differ across subgroups, although these differences are not statistically different from each other. For example, exposure to asylum-seekers saw larger reductions in concern for female respondents, older individuals (above age 45), those with tertiary education, and those living in a high income household. In addition, respondents living in West German and urban districts had larger and more persistent reductions in concerns until two years after the inflow. By the third year, the trend seems to reverse for respondents living in rural districts. Moreover, among respondents living in a low unemployment district the reduction in concerns over immigration is larger, showing that socio-economic context variables matter (Arzheimer, 2009; Tomberg et al., 2021). Notwithstanding, I do not find a significant effect of exposure to asylum-seekers on individual economic concerns such as the own economic situation and job security. I find a significant reduction in concerns over crime. The relation between concerns over immigration and crime has been well-described in the literature (Dehos, 2021). It is reassuring for my results to find that the exposure effects for both concerns are similar in terms of direction and size.

My paper contributes to the literature in several ways. First, to the best of my knowledge, it is the first study that uses individual level panel data for analysing exposure to asylum-seekers in the district of residence. Until now, papers studying the refugee inflow of 2015 for Germany have only used aggregate data to analyse how voting outcomes react to the share of asylum-seekers in a municipality/district (Bredtmann, 2020; Gehrsitz & Ungerer, 2018). Hence, focusing only on the micro-level effect. An advantage of my data is that I can also approximate the macro-level effect with year dummies that capture trends in concerns. I find that the macro-level effect (time trend) is larger than the micro-level exposure effect. The former result is close to the one found in Sola (2018) who shows that respondents from the 2015-wave of the German Socio-Economic Panel (SOEP) who were interviewed after June 2015 experienced an increase in concerns over immigration of 6 pp. Although at the micro level exposure to a higher share of refugees favours the contact hypothesis, by reducing concerns over immigration, I do not find a statistically significant effect of the share of allocated refugees on support for RWP parties. This is in line with Gehrsitz and Ungerer (2018) who do not find an effect of either refugee inflows or reception centre capacities on support for the AfD in the 2017 elections using district-level data. Instead, when using municipality-level data for the state of North Rhine-Westphalia, they find a small negative effect of the number of asylum-seekers on AfD's vote share. Similarly, Bredtmann (2020) find that in municipalities with zero inflows of refugees, the vote-share for RWP increased more than in municipalities with small but positive inflows of refugees. My findings are also in line with Steinmayr (2021) who studies the Austrian case and Dustmann et al. (2019) who study refugee migration to Denmark in the 1990s. Both studies find evidence supporting the contact hypothesis, although the latter only in urban municipalities.

Second, I describe effect heterogeneities based on individual and district characteristics. Until now, only two studies for Germany have performed a similar analysis (Schaub et al., 2020; Tomberg et al., 2021). Schaub et al. (2020) conduct an own survey in East German municipalities in 2018, where some municipalities received almost no refugees. They report null effects of exposure on right-wing support and find that younger respondents react more negatively to exposure. Finally, Tomberg et al. (2021) find that the inflow of asylum-seekers during 1998–2017 together with economic downturns (e.g. districts with high unemployment) increases voting for RWP. This paper complements both approaches.

Third, I test whether the inflow of asylum-seekers also had an effect on other economic and social concerns. Many studies have investigated the determinants of attitudes towards immigration. I identify two large groups: studies that describe political-economy models favouring motives of economic self-interest (Facchini & Mayda, 2008; Hanson et al., 2007; Mayda, 2006; Mayda & Rodrik, 2005; O'Rourke & Sinnott, 2006) and another branch that argues individuals are not predominantly motivated by self-interest, but by other cultural and social beliefs (Card et al., 2005; Hainmueller & Hiscox, 2010; Hainmueller & Hopkins, 2014; Hopkins, 2010). I do not find evidence in favour of the former: economic concerns are not affected by the inflow of asylum-seekers in the respondent's district of residence. I interpret the reductions in concerns over immigration and crime due to a higher exposure of asylum-seekers as support for the contact hypothesis, which falls into the latter branch of the aforementioned literature.

Fourth, I study the effects of asylum-seekers rather than economic migrants, where the latter has been the focus of much of the previous literature. Refugee migrants differ from economic migrants not only in the motives for migration, but in how they can economically and socially integrate into the host country (Brell et al., 2020). The impact of (economic) immigration (immigrants as a share of the population) has been broadly studied in the literature, mostly focusing on labour market outcomes, crime rates, and most recently on voting outcomes of RWP parties. In general, immigration poses an empirical challenge due to its endogeneity: migrants self-select in terms of destination. The economic literature thus far has made use of quasi-random variation (Dinas et al., 2019; Dustmann et al., 2019; Hangartner et al., 2019) and shift-share IV approaches (Barone et al., 2016; Halla et al., 2017; Mayda et al., 2018; Otto & Steinhardt, 2014) to estimate the true effect of immigration on electoral outcomes. Edo et al. (2019) provide a literature overview of 13 papers that study the impact of immigration on voting behaviour. These studies mostly find a positive effect on support for RWP/anti-immigration parties (effect sizes ranging between 0–3 pp.). My findings, on the other hand, support the contact hypothesis as in Steinmayr (2021) and Dustmann et al. (2019). Steinmayr (2021) states that it is important to note that these findings do not necessarily contradict those from the migration literature: likely the specific context under consideration (refugee migration) drives the difference in findings since more humanitarian concerns are taken into account, as suggested by Bansak et al. (2016).

The following eight sections are organised as follows. Section 2 provides some theoretical considerations on attitudes and preference formation. Section 3 briefly describes the refugee crisis of 2015 and the German asylum system. Section 4 describes the data sources and presents descriptive statistics. Section 5 describes the empirical strategy, identification and treatment. Section 6 presents the main results. Section 7 describes the heterogeneity analysis by subgroups. Section 8 presents sensitivity checks and section 9 concludes.

2 Theoretical considerations

The sociological and political science literature has broadly described which individual and macro characteristics shape preferences for RWP parties/negative attitudes towards immigrants. Below I provide a summary of these characteristics:

- *Social background characteristics:* generally less educated people, manual workers, unemployed persons, non-religious people, youths and men tend to vote for RWP/anti-immigration parties (Alabrese et al., 2019; Arzheimer, 2009, 2017; Becker et al., 2017; Goodwin & Heath, 2016; Lubbers, 2001).
- *Contextual (macro) variables:* Immigration figures, unemployment and growth rates, charismatic leaders, media coverage (Arzheimer, 2009, 2017), and a lack of access to (West German) television (Hornuf et al., 2017) might increase support for RWP parties.

Furthermore, the economic literature describes two possible mechanisms through which preferences might be shaped:

- *Economic (self) interest:* as supported by the political economy literature studying preferences over immigration via fiscal concerns (Hanson et al., 2007) and labour market competition (Mayda & Rodrik, 2005), or fear of losing one's job (Geishecker & Siedler, 2012).
- *Non-economic concerns/cultural traits:* e.g. personal traits, bitterness in life[3] (Poutvaara & Steinhardt, 2018), intergenerational associations from preferences (parents-children) (Avdeenko & Siedler, 2017), partisanship/ideology, isolationism/tolerance (Hanson et al., 2007), psychological/sociological theories (realistic group conflict theory, social identity theory, intergroup contact theory) (Card et al., 2005), compositional amenities (Card et al., 2012).

In terms of the psychological/sociological theories, one that has found more support among the recent literature (Bredtmann, 2020; Dustmann et al., 2019; Hornuf et al., 2017; Steinmayr, 2021) is the contact hypothesis (Allport, 1954). This theory comes from the social psychology literature and has developed into what is now known as the intergroup contact theory (Dovidio et al., 2005). Allport (1954) mentioned that under certain conditions (equal status, common goals, no intergroup competition, and authority sanction) interaction between opposing groups could reduce prejudice. Pettigrew et al. (2011) conduct a meta-analysis with over 500 studies that test the contact hypothesis, finding that the optimal contact conditions facilitated the decrease of prejudice but were not essential. Furthermore, intergroup friendship plays a major role. However, negative contact can occur, boosted by involuntary contact and the feeling of being threatened (Dinas et al., 2019; Hangartner et al., 2019; Steinmayr, 2021).

3 Background

3.1 The German asylum system until early 2016

According to the Federal Office for Migration and Refugees (Seedorf, 2014) as soon as all asylum-seekers reached the German border, they had to report their willingness to seek asylum to the border

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[3]People who feel that they have not got what they deserve in life.

authority. They could also do so thereafter—within the country—by reporting to a security authority. The respective authority would then send the asylum-seekers to the closest *Erstaufnahmeeinrichtung* (EAEs, by its initials in German, or initial reception centres) where basic personal information would be entered into the EASY-system[4] for the posterior re-assignment of the asylum-seekers via a quota system: asylum-seekers are distributed according to the "Königsteiner Schlüssel" across federal states.[5] Hence, asylum-seekers might be assigned to an EAE in a different state to the one in which they arrived. At the assigned initial reception centre asylum-seekers were given accommodation and food and were told to register at the Central Immigration Authority. They needed to wait for an appointment from the Federal Office for Migration and Refugees (BAMF, by its initials in German) in order to submit their asylum application.[6] After submitting their application, asylum-seekers were given a temporary residence permit and their status changed from asylum-seekers to asylum applicants.

The initial reception centre to which asylum-seekers are assigned may be responsible for both temporary and longer-term accommodation. The allocation to a specific reception facility depends on current capacities as well as the BAMF branch offices' competence by country of origin. Not all BAMF branch offices are responsible for processing asylum applications from all nationalities. Asylum-seekers may stay at the reception facilities for up to six months or until a decision is made regarding their application; during this period they are not allowed to work. Only after this period are they assigned to follow-up accommodations, typically run by the districts in the federal state. The allocation to a particular district depends on the federal state's regulation, that assigns quotas while taking into account the population size of a district, among other factors.[7] However, during the peak of the refugee crisis the share of refugees allocated to districts differed slightly from the state assigned quotas due to capacity constraints from the facilities (Bredtmann, 2020; Gehrsitz & Ungerer, 2018), which created additional variation in the allocation across districts (see figure A.2).

Furthermore, asylum-seekers are entitled to asylum benefits as soon as they state their desire to apply for asylum.[8] Hence, data on recipients of asylum benefits might be more reliable than records from the Central Register of Foreign Nationals (*Ausländerzentralregister*, AZR)—at least for 2015—given that there was a lag in registration of asylum-applications in that year (see figure 1).

3.2 The unfolding of the refugee crisis in Germany

In early September 2015 Hungary was unable to register any more asylum-seekers, and the decision was made to send them to the Austrian Border. Germany and Austria agreed on opening their borders to allow asylum-seekers entry without being subject to border controls. Several days prior, on August 31, Chancellor Angela Merkel stated at the Federal Press Conference *"Wir schaffen das!"* (We can do it!), since Germany had temporarily abandoned the Dublin Regulation, i.e. allowing asylum-

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[4]An IT-system for the allocation of asylum-seekers to the Federal States. EASY stands for *Erstverteilung der Asylbegehrenden* (Initial Distribution of Asylum-Seekers).

[5]Defined on the previous year, according to the state's tax revenues (two thirds) and population (one third). This quota is assigned to each state annually to ensure an even spread of social burdens, in this case of asylum-seekers in particular. See table A.1 for the 2015 state quotas.

[6]During 2016 processes were initiated to integrate the asylum-seeking procedures to have all responsible agencies under one roof and avoid long waiting periods (Federal Office for Migration and Refugees, 2016a).

[7]Some states, such as North-Rhine-Westphalia and Brandenburg, also take into account the area of a district or the number of employees subject to social security contributions, but these criteria are only given a weight of 10%. The overall quotas to the districts very much resemble a pure allocation by population.

[8]See Appendix B for further description.

seekers to fill-in applications in Germany even though it was not their EU country of entry.[9] From September 5 onwards, refugees arrived faster than expected and by September 13 all border controls with Austria were temporarily re-established. But it was only until early 2016 that this high influx of refugees ceased. Austria and the Balkan countries started to close their borders, and on March 2016 the European Union and Turkey came to an agreement that Turkey would retain the refugees and prevent onward migration to EU countries in exchange for 6 billion Euro in humanitarian aid for the refugees.

Figure 1: Number of asylum-seekers' arrivals and first-time applications in Germany (2014-2016), AfD vote shares in state parliament elections and voting intention.
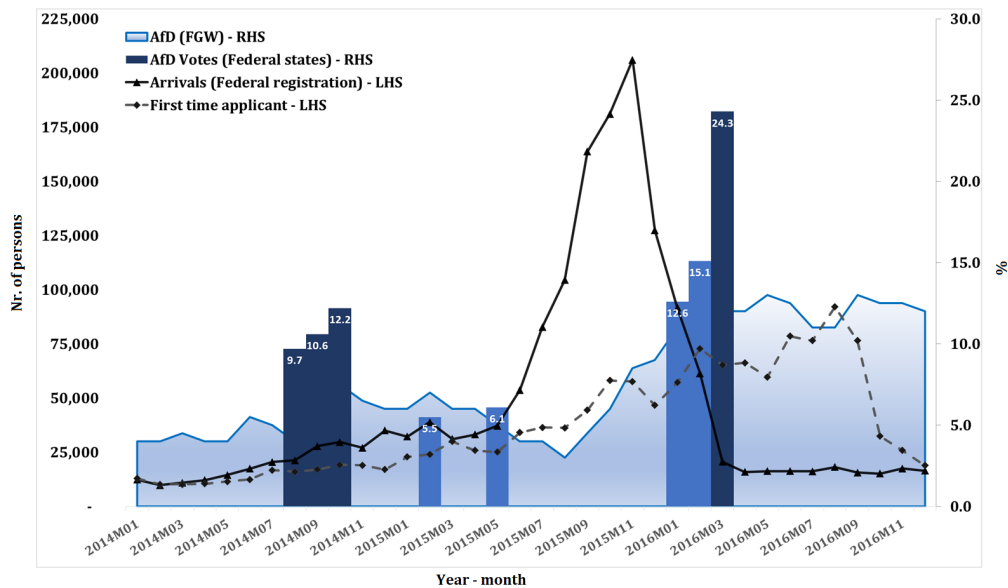
Source: Der Bundeswahlleiter (2017); Eurostat (2018); Federal Ministry of the Interior, Building and Community (2017); Zicht and Cantow (2015)
Notes: In 2015 1,091,984 asylum-seekers were registered in the EASY-system and 441,800 first-time applicants submitted an asylum request. However, since no personal data was registered in the EASY system, it was not possible to exclude false and double entries. Furthermore, many asylum-seekers continued their journey (to other EU Member States). "Only with completion of the re-registrations until September 2016, it became clear that the number of entries in 2015 had actually been around 890,000 people" (Federal Office for Migration and Refugees, 2016a). The solid line shows the arrivals to Germany and the dashed line the number of first-time applications. Both are depicted in the left-hand axis. The bars show election results for the AfD in regional parliament elections (*Landtagswahlen*) that took place during the plotted period. Dark-blue bars show East-German states, and light-blue ones West-German states. The shaded area show the evolution of voting intention for the AfD (polling results from the *Forschungsgruppe Wahlen e.V. (FGW)*). The bars and shaded area are depicted in the right-hand axis.

The solid line in figure 1 displays the registration of asylum-seekers (EASY-system) and the dashed-line shows the number of first-time applicants. The bump in applications has a lag with respect to the arrivals given the waiting time for receiving an appointment for registering applications. Shortly before the large influx of asylum-seekers, some states had regional parliament elections while some occurred shortly after. The bars show the results for the AfD (RWP party) in these elections. In order of appearance in figure 1 these states are: Saxony, Thuringia, Brandenburg, Hamburg, Bremen, Rhineland-Palatine, Baden Württemberg and Saxony-Anhalt. For comparison, East German

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[9]The Dublin Regulation stipulates which country is responsible for the asylum procedure in the European Union (EU). It is often the first EU country in which the asylum-seeker arrived, which back in 2015 posed a big burden for border states such as Greece, Italy and Hungary. The most common route was to enter via the Balkan countries through Turkey or the Mediterranean Sea, but many immigrants try to reach richer countries than their port of entry. In this sense, in 2015 Germany was the country receiving the highest amount of asylum applications (476,508) followed by Hungary (177,134), Sweden (162,451), Austria (88,159), Italy (83,540) and France (76,163) (UNHCR, 2018).

states are depicted in dark-blue while West German states are depicted in light-blue. Although the AfD vote shares were already higher in East German states prior to these arrivals when compared to West Germany, their vote shares sharply increased in both East and West German state elections.

4 Data

4.1 German Socio-Economic Panel (SOEP)

The SOEP is a longitudinal survey of private households in Germany and has been carried out since 1984 by the German Institute for Economic Research (DIW, Berlin). I use data until 2018 (wave N° 35), containing information for around 22,000 households and 35,000 adults. This dataset contains information on household composition and characteristics across all 16 German federal states, as well as information on all household members (employment, education, perceptions, etc.). The standard dataset identifies only the federal states, although access to further spatial disaggregation (e.g. at district level) is possible through the SOEPremote (on-line access) (Liebig et al., 2019; Wagner et al., 2008). This paper uses the SOEP data to evaluate changes in concerns about immigration and the support to political parties across time (during 2012–2018), exploiting the panel structure of the dataset. The following questions are relevant for constructing the variables of interest:

1. Many people in Germany lean towards one party in the long term, even if they occasionally vote for another party. Do you lean towards a particular party? (Yes/No)
2. (If Yes) Which party do you lean toward?
3. (Since 1999) How concerned are you about the following issues? (The economy in general, your own economic situation, your own retirement pension, your health, environmental protection, the impacts of climate change, maintaining peace, crime in Germany, social cohesion in society, immigration to Germany, hostility towards foreigners or minorities in Germany, (if employed) your job security)

Figure A.1 in Appendix A displays the relationship between German federal elections outcomes (y-axis) and the declared party affinity for the respective parties from the SOEP (x-axis). Their correlations are positive and significant at the 1% level, validating the use of the SOEP dataset for studying political outcomes. I group the political parties as follows: right-wing parties (NPD, REP, DVU, and AfD since 2013), centre-right parties (CDU/CSU, FDP), centre-left parties (SPD, Gruene/Buendnis90), and left-wing parties (Die Linke). I create dummies for these four groups of parties that equal one if the respondents lean toward any of the above mentioned parties and zero otherwise. If the respondent does not have a party preference, I code it as missing.

The answer options for the third question (about concerns) are: *very concerned, somewhat concerned, and not concerned at all*. I recode these answers to a dummy that equals one if the respondent is "very concerned" about an issue. Furthermore, the SOEP question is about "immigration to Germany" not specifically "refugee migration". Hence, for the years prior to the refugee crisis respondents might have had in mind their "standard" concerns on immigration (as stated by the literature, economic self-interest concerns, fiscal concerns, etc.), but during the refugee crisis they might have had different considerations, e.g. humanitarian concerns, deservingness, etc. (Bansak et al., 2016). Therefore, I restrict the sample to years after 2011 when refugee migration started to receive more attention in terms of public debate.

4.2 Administrative data at the district level

I merge socio-demographic characteristics and the number of asylum-seekers (*Schutzsuchende*) by district.[10] Regional covariates (such as population by gender, youth quota, educational attainment, unemployment rates and per capita GDP) are extracted from INKAR (BBSR, 2018). Data on asylum-seekers by district was obtained from the Research Data Centre (RDC) from the Federal Statistical Office (RDC, 2015), who report statistics on recipients of asylum-seekers' benefits (*Statistik der Empfänger von Asylbewerberregelleistungen*). These data are reported for December 31 of each year at the district (*Kreise*) and municipality (*Gemeinde*) level. Hence, there is coverage for the period in which the large inflow of refugees occurred, in 2015. Furthermore, to better measure this inflow, I restrict the data to those asylum-seekers that started receiving benefits in 2015 (approximately 82% of the sample in 2015, or 803,225 asylum seekers). Since asylum-seekers must stay in their designated place of residence for at least 3 months, these data best reflect the inflow of refugees that arrived to Germany during the peak of the refugee crisis, from mid-2015 until the beginning of 2016 as shown in figure 1.

4.3 Descriptive statistics

Table A.2 in Appendix A presents descriptive statistics by treatment status and their differences. The top panel shows the outcome variables that will be analysed in the next section while the remained are covariates. In the pre-treatment period (average over the years 2012–2014) people living in low refugee migration districts had less concerns about immigration to Germany compared to those living in high refugee migration districts (3 pp. less). Post-treatment this difference has reduced to almost zero. Although an increase in concerns over immigration can be observed for both groups: pre-treatment only 22.1% of respondents were very concerned about immigration, while post-treatment this share increased to 39.7%. Around 48% of the interviewees did support a political party in the pre-treatment period, while in the post period this percentage reduced to 46% in both groups. Pre-treatment support for a political party was 3.6 pp. lower in low refugee migration districts (46.4% vs. 50% in high refugee migration districts) but post-treatment this difference reduced to 1.8 pp. (45% vs. 46.8%).

Support for RWP parties increased in the post period for both groups, from 0.7% to 2.6%. This increase was 0.4 pp. higher in low migration districts, and statistically significant at the 1% level. Support for centre-right and centre-left parties decreased in the post-treatment period, while support for the left remained the same. Support for centre-left and left parties is significantly lower for individuals living in low refugee migration districts. Furthermore, the sample differs in age (slightly younger interviewees in low refugee migration districts), share of employed individuals (higher in low refugee migration districts), log household income (higher in low refugee migration districts), and the share of unemployed and retired people (both are lower in low refugee migration districts). In the pre-treatment period respondents in low refugee migration districts were more satisfied with their lives (0.03 points more), while in the post period this difference doubled (0.06 points more). Overall, interviewees in low refugee migration districts had fewer concerns over immigration to Germany pre-treatment, reported less support for centre-left and left parties, are slightly younger, live in wealthier households, are more satisfied with their lives, and are less frequently unemployed.

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[10]There are 401 districts (*Kreise*) in Germany. Equivalent to the NUTS-3 level of the European classification. On average, districts have 200,000 inhabitants.

Looking at district-level characteristics (bottom panel), low refugee migration districts have a smaller population, are slightly younger on average, have a higher share of foreigners, a lower unemployment rate, and a slightly higher per capita GDP than high refugee migration districts. Moreover, low refugee migration districts are more rural and are less frequently located in East Germany.

I control for these individual and district characteristics in the estimations shown in section 6.

5   Methodology

Using the allocation of asylum-seekers per 100,000 inhabitants to each district in 2015, I define low and high refugee migration districts (based on their 2013 population). Those districts who are above the median of the weighted distribution of refugee inflow (which is 875 allocated refugees per 100,000 inhabitants) are defined "high refugee migration districts", while districts below the median are labelled "low refugee migration districts". I estimate whether respondents who lived in high/low refugee migration districts in 2015 significantly change their preferences over immigration and party affinity due to a higher exposure to refugees. I fix the treatment to the district where respondents resided in 2015 and follow their outcomes over time. For this, I use a difference-in-differences strategy following equation 1 with individual fixed-effects to exploit the panel structure of the dataset. In the main specification, I estimate the following event study equation, where 2014 is the reference year:

$$
y_{idt} = \alpha + \sum_{t=2012}^{2013} \beta_t HighRef_{d2015} * Year_t + \sum_{t=2016}^{2018} \beta_t HighRef_{d2015} * Year_t
$$
$$
+ \pi_t Year_t + \gamma_1 X_{it} + \gamma_2 X_{dt} + \tau_i + \epsilon_{idt}
$$

(1)

where y_{ict} measures the outcome variables (concerns over immigration or preferences toward a particular group of parties) for person i in district d at period t (2012–2018). $HighRef_{d2015}$ is a dummy equal to one if the individual lives in a high refugee migration district (defined by their location in 2015). The β_t coefficients will measure the "exposure effect". $Year_t$ is equal one if the observation corresponds to the post treatment years (2016–2018) and zero otherwise.[11] X_{it} are individual characteristics and X_{dt} are district characteristics (measured at the end of the year prior to the interview).

Given that individuals might have unobserved time-invariant characteristics (e.g. intergenerational transmitted preferences), the use of fixed-effects — represented by τ_i in equation 1— will help to control for any unobserved heterogeneity arising at the individual level.

Furthermore, a possible threat to identification is that the deviations from the allocation quotas were not random, i.e. the fact that asylum-seekers were sent to places where housing was available could reflect poor economic conditions or positive attitudes toward migrants (e.g. room was offered in more friendly areas). In figure A.3 in Appendix A, I estimate the determinants of the 2015 allocation. The best predictor is having an initial reception centre in 2014 in the district. The economic and socio-demographic variables do not predict the allocation of asylum-seekers. Moreover, I argue that asylum-seekers are as good as randomly assigned conditional on individual fixed effects and time-varying covariates (Angrist & Pischke, 2008). Hence, even in the case that asylum-seekers were sent to "more friendly districts", this would be absorbed by the individual fixed-effects.

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[11]Alternatively, I replace the year dummies with a $Post_t$ dummy to perform a standard DiD estimation.

The specification of equation 1 also allows me to test whether pre-trends were parallel. Parallel pre-trends lend credibility to the parallel trends assumption, i.e. that in absence of the treatment individuals in high and low refugee migration districts would have followed the same trends in concerns. If the leads are not statistically different than zero, then there is evidence in favour of the parallel trends assumption.

The outcome variables are concerns about immigration (dummy equal one if an individual is very concerned about immigration to Germany, zero otherwise) and party preferences (dummies for the support towards the major political groups described in section 4). I restrict the sample to those individuals aged 18 and above, who were interviewed in 2015 (for assigning treatment). Their first interview had to be before 2015 (for observing pre-treatment outcomes) and the last one after 2015. Even though I assign treatment based on the district of residence in 2015, I drop the observations from that year. As shown in figure 1, asylum-seekers' arrivals peaked in the second half of 2015 but most of the interviews are carried-out in the first half of the year. In 2015, 81.3% of the respondents were interviewed before July. Therefore, most of the 2015 respondents had not been treated by the time of the interview since the large inflow of late 2015 was not yet fully realised. Given that the SOEP broadly asks about "concerns over immigration" and not "refugee migration", I only focus on the 2012–2018 period when the refugee topic was more salient in the media and the public debate. I normalise the year 2014 to zero (base year) and I do not consider the most recent migration samples (special top-up samples from the SOEP to oversample migrants carried-out since 2013). This yields an unbalanced panel with 45,513 observations for the pre-treatment period and 51,817 for the post-treatment period.

6   Results

Table 1 presents the results for all outcomes of interest (concerns about immigration to Germany and party support) with a standard DiD setting (Panel B). For comparison, the upper panel (Panel A) shows the results of a pooled OLS estimation (without individual FE). In all specifications standard errors are clustered at district-level, based on district of residence in 2015.

In column (1) the results for "concerns about immigration" show similar results in terms of magnitude and significance for both FE and pooled OLS estimations. On average, concerns over immigration increased by about 21–23 pp. in the post treatment period ($Post$ dummy). However, this increase was lower in high refugee migration districts by around 2–3 pp. These findings are in line with the contact hypothesis as in Steinmayr (2021) and Dustmann et al. (2019), i.e. hosting more refugees probably decreases prejudices towards them, hence leading to a reduction in concerns. On the other hand, a high inflow of asylum-seekers to a district does not seem to affect political preferences, as shown by the non-significance of the $High\ ref.\ dist.*Post$ in both panels. When controlling for individual fixed-effects, the point estimates for centre-right and left wing support are significant at the 10% level: support for the centre-right decreased by 1 pp. in high refugee migration districts, while it increased by 0.7 pp. for the left-wing. The $Post$ dummy has a negative coefficient for centre-right preferences (-4.7 pp.) and a positive one for right-wing parties (4.6 pp.) in the OLS specifications (both significant at the 1% level). When using individual fixed-effects, only the positive coefficient for right-wing preferences remains: a 1.7 pp. increase in the post inflow period for both high and low refugee migration districts. However, there is now a negative and significant point estimate for left-wing preferences (-1.4 pp.). This would suggest that there was a shift in preferences towards

right-wing parties in the post treatment period in both treatment and control groups. Yet, there is no statistically significant difference between respondents in high and low refugee migration districts, i.e.the exposure effect is close to zero and not significant.

Table 1: Regression results: High vs. low refugee migration districts, concerns about immigration and party affinity

	(1) Concerns Immigration	(2) Centre right	(3) Centre left	(4) Left wing	(5) Right wing
Panel A: OLS					
High ref. dist.*Post	-0.026 **	0.002	0.001	0.006	-0.009
	(0.011)	(0.009)	(0.009)	(0.004)	(0.005)
Post dummy	0.213 ***	-0.047 ***	-0.001	0.003	0.046 ***
	(0.010)	(0.010)	(0.010)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.094	0.066	0.056	0.106	0.064
Obs.	97,330	45,636	45,636	45,636	45,636
N	19,686	13,215	13,215	13,215	13,215
Panel B: Individual FE					
High ref. dist.*Post	-0.020 **	-0.010 *	0.001	0.007 *	-0.003
	(0.010)	(0.005)	(0.005)	(0.003)	(0.004)
Post dummy	0.232 ***	-0.004	-0.006	-0.014 ***	0.017 ***
	(0.010)	(0.006)	(0.006)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
R^2 -within	0.087	0.004	0.007	0.007	0.022
Obs.	97,330	45,636	45,636	45,636	45,636
N	19,686	13,215	13,215	13,215	13,215

Notes: This table shows the results for a standard DiD equation using $HighRef_{d2015} * Post_t$ instead of yearly interactions. Panel A uses an OLS specification while Panel B includes individual FE. The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. The colums (1)-(5) show the different outcomes: concerns about immigration or support for a particular group of parties. These variables are coded as dummies. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2. Controls at the individual level: age and age^2 in the OLS specification, age groups in the FE specification (ref. cat: $age <= 24$), sex (omitted in FE), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), disability status, migration background (omitted in FE), log net household income, number of children in the household. Controls at the district level: urban, average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All specifications include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

To disentangle the dynamics of the exposure effect (*High ref. dist.*Post* coefficient) for concerns about immigration, I interact the *High ref. dist.* dummy with year dummies as in equation 1. Figure 2(a) shows the trend in concerns among all respondents in both groups (high and low refugee migration districts). A peak is evident in 2016, but the trend returns to pre-inflow values thereafter. Figure 2(b) shows the treatment effects. Only the coefficients for the interactions post-2015 are significant at the 5% level (decrease in concerns by about 3 pp.). It is reassuring for validity of the parallel trends assumption to see a flat pre-trend before 2015: all pre-treatment leads are not statistically different from zero. Figure 2(b) further shows a persistent effect in the medium-run with a slight upward trend in the last year, suggesting that the effect could decrease in the following years. Together, both panels of figure 2 show that there was an overall increase in concerns over immigration following the large

and unexpected inflow of 2015 (figure 2(a)), but that this increase was smaller for individuals living in districts that hosted more asylum-seekers (figure 2(b)). I interpret the year dummies as reflecting the macro-level effect and the interaction terms as the micro-level exposure effect. Hence, if anything, respondents living in districts that hosted more asylum-seekers had a reduction in concerns over immigration.

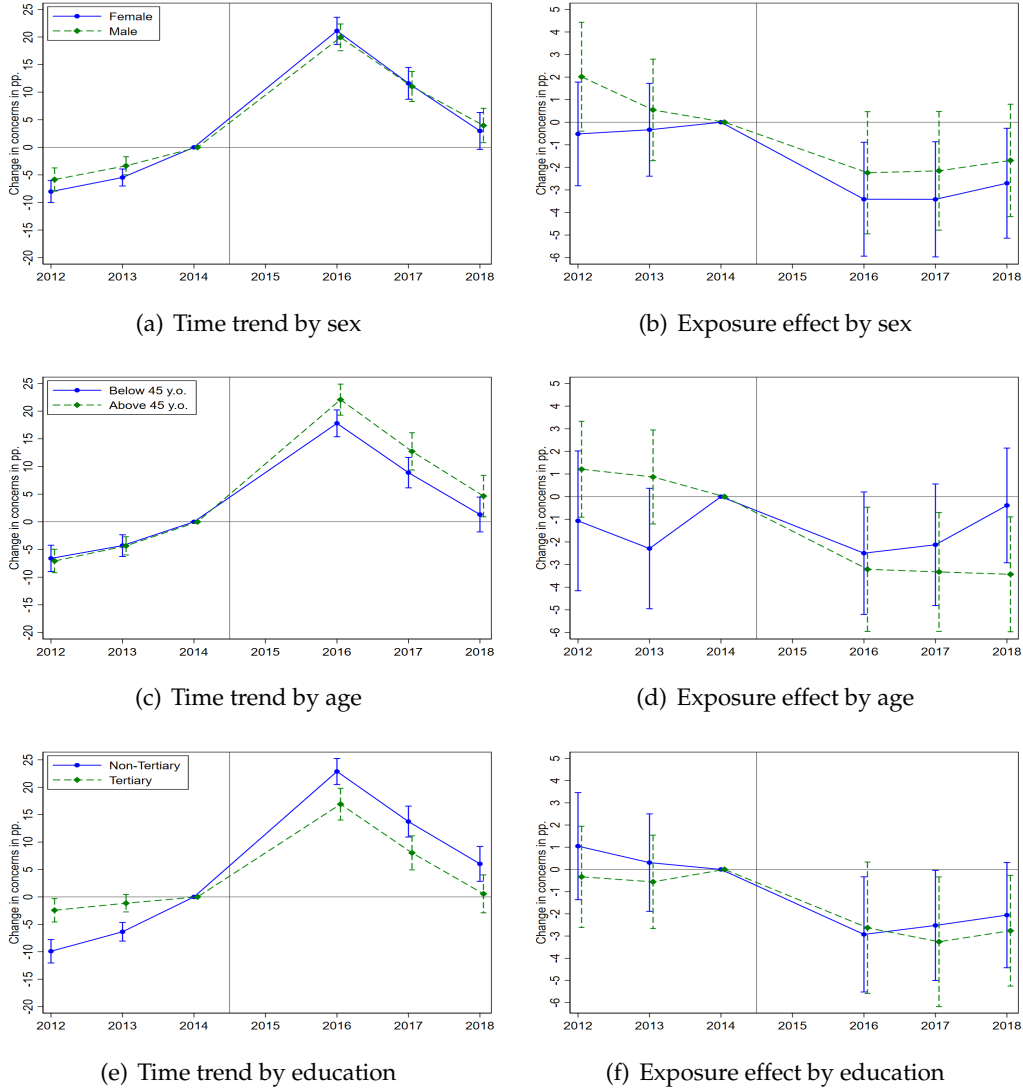Figure 2: Concerns over immigration over time and exposure effect

| (a) Time trend | (b) Exposure effect |
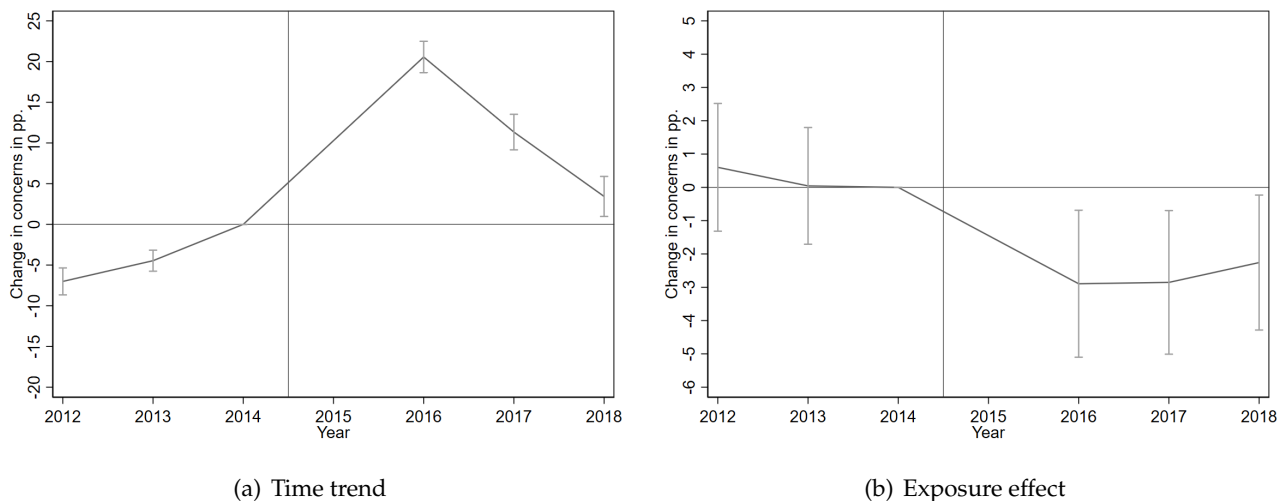
Notes: Figure (a) shows the π_t coefficients for $Year_t$ in equation 1. Figure (b) shows the β_t coefficients from the interaction $HighRef_{d2015} * Year_t$ of the same equation. This coefficients are multiplied by 100 to be directly interpretable as percentage points. The estimations are performed on the 2012–2018 unbalanced sample, where the observations for 2015 have been dropped and 2014 is set as base year. All regressions include the covariates described in table A.2, month of interview and state fixed effects. The continuous line joins the point estimates. The bars display the 95% confidence intervals. *Source:* SOEP v35. Own graph.

7 Effect heterogeneity

To investigate whether my results are driven by individual and/or district characteristics, I perform the analysis on different subgroups. Overall, I find similar reactions across subgroups since the confidence intervals mostly overlap. However, some patterns can be described. Figure 3 shows on the left-hand side the overall evolution of concerns (time trend) and on the right-hand side the exposure effect (treatment effects). The first row depicts results by sex: the trend in concerns is almost identical for both male and female respondents. However, the significance at the 1% level of the exposure effect remain only for female respondents (see figure 3(b)). For male respondents the coefficients remain negative, but are not statistically significant at conventional levels. When looking at individuals older and younger than 45 years of age, the former have an overall larger increase in concerns. Furthermore, the treatment effects remain significant and stable for older individuals aged 45 and above (see figure 3(d)). The treatment effects for younger respondents (below age 45) are negative and seem to return to pre-treatment levels three years after the inflow, but lack statistical significance. By education levels, the trend in concerns exhibits a larger increase for non-tertiary educated individuals than for those with tertiary education. Nonetheless, the exposure effect is only statistically significant at the 5% level for individuals with tertiary education.

Figure 4 shows further heterogeneities by household income and political preferences. Overall

Figure 3: Heterogeneities by individual characteristics

(a) Time trend by sex

(b) Exposure effect by sex

(c) Time trend by age

(d) Exposure effect by age

(e) Time trend by education

(f) Exposure effect by education

Notes: The left-hand graphs show the π_t coefficients for $Year_t$ in equation 1 (time trend). The right-hand graphs show the β_t coefficients from the interaction $HighRef_{d2015} * Year_t$ of the same equation. The estimations are performed on the 2012–2018 unbalanced sample, where the observations for 2015 have been dropped and 2014 is set as the base year. All regressions include the covariates described in table A.2, month of interview and state fixed effects, with the exception of the covariate for which the sample split is performed. I fix the covariates to their 2015 value for performing the heterogeneity analysis. Tertiary equals 1 if the respondent had completed tertiary education in 2015. The graphs show the coefficients multiplied by 100 so that they can directly be interpreted as percentage points. The continuous line joins the point estimates. The vertical bars display the 95% confidence intervals. *Source:* SOEP v35. Own graph.

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Figure 4: Heterogeneities by individual characteristics (cont.)
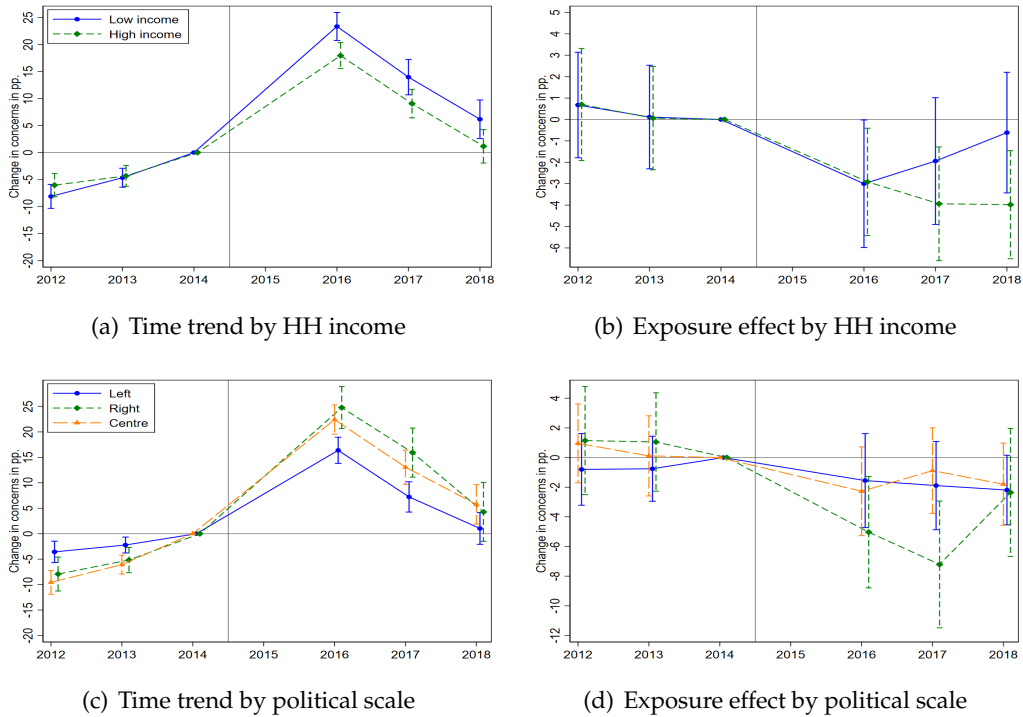
(a) Time trend by HH income

(b) Exposure effect by HH income

(c) Time trend by political scale

(d) Exposure effect by political scale

Notes: The left-hand graphs show the π_t coefficients for $Year_t$ in equation 1 (time trend). The right-hand graphs show the β_t coefficients from the interaction $HighRef_{d2015} * Year_t$ of the same equation. The estimations are performed on the 2012–2018 unbalanced sample, where the observations for 2015 have been dropped and 2014 is set as the base year. All regressions include the covariates described in table A.2, month of interview and state fixed effects, with the exception of the covariate for which the sample split is performed. I fix the covariates to their 2015 value for performing the heterogeneity analysis. High income equals 1 if in 2015 the respondent lived in a household with a log household income above the median (=7.94). Since the political scale was only asked in 2014, I fix its value to this year. Left equals 1 if the response in the scale was below 5, centre equals 1 if the response was equal to 5 and right equals 1 if the response was above 5. The graphs show the coefficients multiplied by 100 so that they can directly be interpreted as percentage points. The continuous line joins the point estimates. The bars display the 95% confidence intervals. *Source:* SOEP v35. Own graph.
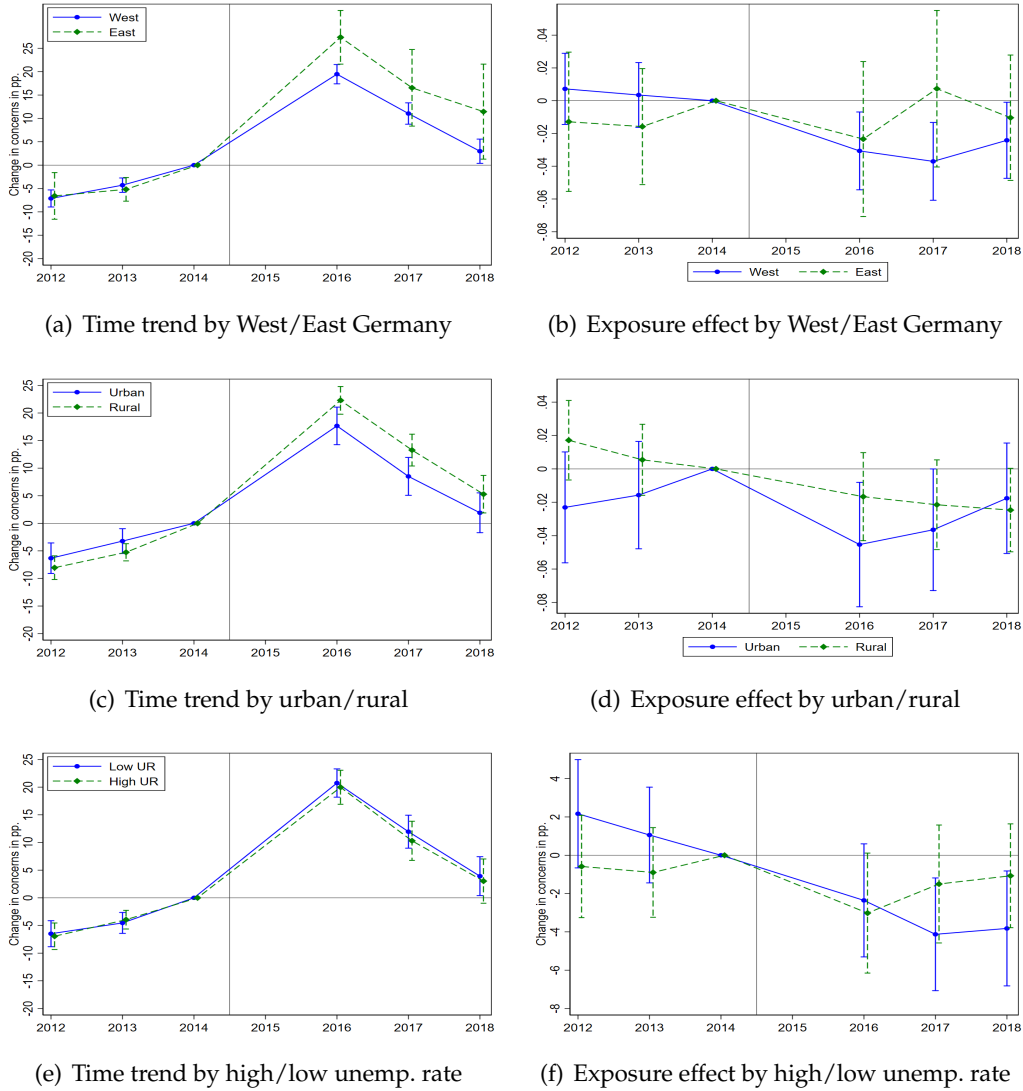
concerns increased slightly more for respondents from low-income households. A drop in concerns in 2016 is immediately evident for both below and above median household income respondents.

However, there is a striking divide after 2016: for individuals with high household income the reduction in concerns remain, for those with low household income this seem to vanish from 2017 onward. Finally, I split respondents into three groups based on their stated political preferences measured on an 11-point scale: left (<5), centre ($=5$) and right (>5).[12] The overall increase in concerns over immigration was very similar for right and centre-leaning individuals and somewhat lower for left-leaning respondents. On the other hand, the reduction in concerns for centre and left-leaning individuals appears to follow the same pattern and is similar in terms of magnitude (approx. 2 pp.). However, the largest reduction occurs for right-leaning individuals, where the reduction in concerns for 2016–2017 is about 6 pp. on average and is the only reduction that is significant at the 5% level. In 2018, although the point estimates are still negative, they are similar in magnitude for all individuals regardless of their political preferences. This is in line with the findings of Bansak et al. (2016) who show that although left-leaning respondents show stronger humanitarian concerns and weaker anti-Muslim bias, they also exhibit a greater penalty for asylum-seekers that migrate seeking economic opportunities than individuals on the right side of the scale do. As shown in Schaub et al. (2020) the presence of refugees appears to make right-leaning individuals less negative in their attitudes and behaviour toward foreigners. They interpret their results by a way of a "reality check" (p. 24): "while the actual presence of refugees might contrast the heated rhetoric that surrounds their arrival, eventually replacing the alarmism of the right as well as the sanguine views of the left with a more realistic and middle of the road experience". The full set of results by individual characteristics are shown in tables A.3 and A.4 in Appendix A. Finally, figure 5 shows that overall concerns over immigration increased more in the East and in rural districts. These concerns were higher by almost 8 pp. in 2016 for East relative to West Germans, showing the classical East-West German divide. Similarly, the reduction in concerns is similar and statistically significant at the 5% level for respondents living in West Germany and urban districts. One interesting pattern is that concerns over immigration decrease more over time in rural areas. This would reflect that perhaps sceptical at first, respondents in rural areas might have closer interactions with refugees in the medium run. Schmidt et al. (2020) mention that in 2018 almost 60% of refugees in rural areas had frequent contact with Germans in their circle of friends. In urban areas this was only 40%. Moreover, the exposure effect is larger in magnitude and significance (for the years 2017 and 2018) for people living in low unemployment districts compared to those living in high unemployment districts. The time trend, however, is similar for respondents in both high and low unemployment districts. This is in line with the findings by Dustmann et al. (2019), who show that in urban municipalities the unemployment rate exacerbated the increase in support for anti-immigration parties.

The full set of results are shown in table A.5 in Appendix A. Another possible mechanism is that people living in areas with a higher share of foreigners are already more open and therefore have more positive views toward migrants. In column (1) of table A.5, I show the results for respondents living in districts with foreign share above the median while column (2) shows the results for districts with below-median shares. The overall increase in concerns was larger for respondents living in districts with a lower share of foreigners. Although the exposure effect is similar in sign, the coefficients are larger in magnitude and are only significant at the 5% level for respondents living in a

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[12]In 2014 an 11-point left-right scale was asked in the SOEP: "In politics people often talk about "left" and "right" when it comes to characterize different political attitudes. If you think about your own political views: Where would you place yours?". In the 11-point scale, zero equals "completely left" and 10 equals "completely right".

Figure 5: Heterogeneities by district characteristics

(a) Time trend by West/East Germany

(b) Exposure effect by West/East Germany

(c) Time trend by urban/rural

(d) Exposure effect by urban/rural

(e) Time trend by high/low unemp. rate

(f) Exposure effect by high/low unemp. rate

Notes: The left-hand graphs show the π_t coefficients for $Year_t$ in equation 1 (time trend). The right-hand graphs show the β_t coefficients from the interaction $HighRef_{d2015} * Year_t$ of the same equation. The estimations are performed on the 2012–2018 unbalanced sample, where the observations for 2015 have been dropped and 2014 is set as the base year. All regressions include the covariates described in table A.2, month of interview and state fixed effects, with the exception of the covariate for which the sample split is performed. I fix the covariates to their 2015 value for performing the heterogeneity analysis. West equals 1 if the district of residence in 2015 was in West Germany. Urban equals 1 if the district of residence in 2015 was classified as "Urban" *(Kreisfreie Stadt)* by the Federal Office for Building and Regional Planning (BBR). The graphs show the coefficients multiplied by 100 so that they can directly be interpreted as percentage points. The bars display the 95% confidence intervals. *Source:* SOEP v35. Own graph.

district with "high foreigner share" for the years 2016–2017. Comparing districts with high and low GDP per capita, the results are very similar and are statistically significant at the 10% level for the exposure effect in 2016. In 2017, the point estimate is larger and significant at the 5% level for high GDP per capita districts. Finally, I compare individuals that lived in a district which hosted an EAE (initial reception centre) in 2014—pre-treatment—with those who did not.[13] Although the standard errors are quite large due to the smaller sample of individuals living in a district with an EAE, the trend in concerns over immigration evolved similarly for respondents in both types of district. But there was only a reduction in concerns for those who lived in districts without an EAE. This is in line with the findings by Bredtmann (2020) who shows that the increase in right-wing support for the state of Rhineland-Palatine in 2016 was only driven by municipalities that hosted a reception centre.

Although there is some indication that different subgroups might have reacted differently in the short-run, and may also have different time dynamics, none of the coefficients are statistically different from the other coefficients. Therefore, I conclude that the reduction in concerns was quite similar across subgroups. This is in line with the findings by Bansak et al. (2016) who show that preferences toward refugees are homogeneous across respondents from different subgroups.

8 Sensitivity analysis

8.1 Other sample restrictions

In column (1) of table A.6, I report the full set of results depicted in figure 2 for comparison. Column (2) shows the same results without covariates, which do not drastically vary from my main specification. In column (3) I drop outliers in the inflow of asylum-seekers, i.e. districts which in 2015 received below or equal to the first percentile (0.25%) and above or equal to the ninety-ninth percentile (4.3%) of the asylum-seekers distribution.[14] Column (4) only considers individuals of working age, who were at least 18 and at most 65 in 2015, i.e. those that could feel threatened by migrants entering the labour market. Column (5) shows results excluding the five largest districts in Germany (Berlin, Hamburg, Hanover, Cologne and Munich. All have a population of more than 1 million inhabitants) to address concerns that these large districts might be driving the results. Column (6) considers only a balanced panel, i.e. individuals who were interviewed throughout 2012–2018, although this drastically reduces the sample size by more than half. Finally, column (7) only considers respondents without a migration background (i.e. "natives"), to address potential concerns that these respondents might in general have more positive attitudes toward new migrants. In all specifications, the main results remain similar in magnitude and significance, i.e. there was an overall increase in concerns in 2016 (by about 21 pp.) which was lower in districts that received a larger inflow of asylum-seekers in 2015 (by about 2–3 pp.). My results are in line with the ones found in the literature: Steinmayr (2021) finds that the presence of asylum-seekers in a municipality reduces the vote share for RWP parties by about 3.86 pp. in Austria, while Dustmann et al. (2019) finds a reduction of about 3.8 pp. for the 5% largest municipalities in Denmark.

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[13]In 2014 only 36 out of 401 districts in Germany hosted an EAE. In 2015, 148 districts hosted either an initial reception centre or some kind of collective group accommodation.

[14]The district with the highest reported inflow of asylum-seekers in 2015 received 10,672 asylum-seekers per 100,000 inhabitants, while the one with the lowest inflow only 3. These extreme values might reflect some reporting errors and introduce large variations.

8.2 Other concerns

As in Poutvaara and Steinhardt (2018) and Sola (2018), I also test the treatment on other concerns as shown in figure 6 (for the complete results see table A.7). The $Post$ dummy is positive and significant for many of the other concerns (crime in Germany, hostility towards foreigners, maintaining peace and economic development).

Figure 6: Exposure effect on other outcomes
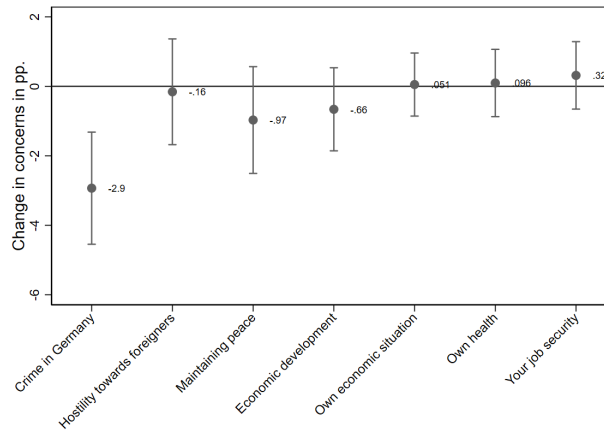
Notes: Coefficient plots from standard DiD regressions using $HighRef_{d2015} * Post_t$ instead of yearly interactions. The graph shows the coefficients multiplied by 100 so that they can directly be interpreted as percentage points. The outcomes measure concerns about different topics: crime to Germany, hostility towards foreigners or minorities in Germany, maintaining peace, the economy in general, own economic situation, own health, own job security. They are all coded as dummies equal to 1 if the respondent is "very concerned". *Source:* SOEP v35. Own graph.

The interaction *High ref.district*Post* is significant and negative at the 1% level only for those very concerned about crime in Germany. Hence, even though concerns increased in the post treatment period, having a higher allocation of refugees in a district reduced concerns about crime in Germany by about 2.9 pp. One of the largest events related to refugees and crime was New Year's Eve 2015/16. Sexual assaults and thefts were reported in Cologne and some other major cities in Germany that were attributed to foreign men, almost half of them asylum-seekers. This event could have influenced the response toward some of these additional outcomes, i.e. concerns about crime. Since these debates happened at the national level, they might be captured in the $Post$ dummy. In any case, the reduction in concerns about crime would also support the contact hypothesis if this is related to the reduction in concerns about immigration. Furthermore, it is important to notice that other concerns such as "own economic situation" and "job security" all have point estimates close to zero and are not statistically significant. Hence, this indicates that the "economic concerns" might not be the mechanism through which immigration shapes attitudes.

Given that concerns over immigration and crime are both affected by the inflow of asylum-seekers to a district, I test whether they are also related to political preferences. As seen in table 1 the exposure effect was not significant for any of the party preferences, only the $Post$ dummy was significant for leaning towards right-wing parties. In table A.8 in Appendix A, I test whether being "very concerned about immigration to Germany" and "very concerned about crime to Germany" could be possible mediators of the treatment. These results have no causal interpretation. Being very concerned about immigration is negatively correlated with preferences toward centre-left and left-wing parties (decrease by about 0.06 pp.), while being positively correlated with leaning toward

right-wing parties (by about 1.5 pp., significant at the 1% level). Furthermore, being very concerned about crime only increases the probability of leaning toward right-wing parties by about 0.07 pp. (half the magnitude of "concerns about immigration"). These results suggest that the treatment (living in a high refugee migration district) could have an indirect impact on political preferences via concerns about immigration and crime, where the former effect is stronger than the latter.

8.3   Alternative treatment specification: Using the actual share

As an additional robustness check I define as an alternative treatment the refugee allocation in 2015 as a share of the total district population.

Figure 7: Exposure effect for concerns over immigration - continuous treatment
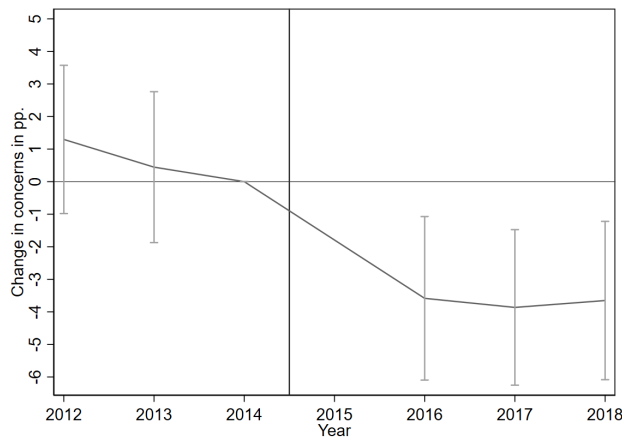
Notes: The figure shows the β_t coefficients from the interaction $HighRef_{d2015} * Year_t$ in equation 1, where $HighRef_{d2015}$ is replaced by the actual share of allocated refugees (continuous treatment) instead of the treatment dummy. All regressions include the covariates described in table A.2, month of interview and state fixed effects. The continuous line joins the point estimates. The bars display the 95% confidence intervals. *Source:* SOEP v35. Own graph.

Figure 7 presents the results on concerns about immigration to Germany. The figure follows the same pattern as the one displayed in figure 2. These results are for the restricted sample, without outliers in asylum-seeker reporting (i.e. I take out those districts that are below or equal the first and above or equal the ninety-ninth percentile of the allocation distribution).[15] The interaction between the share of allocated refugees and the year dummies 2016–2018 are significant at the 5% level. In 2016, a 1 pp. increase in the share of allocated refugees led to a decrease in concerns about immigration by about 3.6 pp. in line with the estimates using the extensive margin (high/low refugee migration districts).

9   Conclusion

By exploiting regional distribution and timing of arrival of the largest wave of asylum-seekers to Germany since World War II, I investigate how concerns over immigration and party preferences at the individual level reacted to this inflow. I show that respondents living in districts that experienced a large inflow of asylum-seekers had a reduction in concerns by about 2–3pp.

My results are in line with the literature studying refugee migration (Bredtmann, 2020; Dustmann et al., 2019; Gehrsitz & Ungerer, 2018; Schaub et al., 2020; Sola, 2018; Steinmayr, 2021). At the macro

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[15]In the results using the full sample, only the interaction with the year 2016 is statistically significant at the 1% level.

level, there was an increase in concerns about immigration by about 21 pp. and a smaller increase in support for RWP parties (1.7 pp.). However, this was not driven by the exposure to asylum-seekers in the district of residence.

On the contrary, at the micro level, the allocated share of asylum-seekers reduced concerns about immigration by about 3 pp. in 2016, or alternatively a 1 pp. increase in the share of allocated refugees reduced concerns by about 3.6 pp. These results are in line with the contact hypothesis and remain negative and significant even three years after the 2015 inflow of asylum seekers. Finally, my analysis shows different dynamics for the treatment effects by individual and district-level characteristics. However, these are not statistically different from each other for the different subgroups, thus I conclude the reduction in concerns was homogeneous across subgroups.

Putting all of these pieces together, it seems that the macro-level effect plays a major role when shaping attitudes towards immigration and support for RWP parties compared to the micro-level exposure. This result is in line with what has been found by Steinmayr (2021) and with the review by Cools et al. (2021). What is particularly interesting, is that the effects I find at the micro-level (reduction in the concerns over immigration) persist over time whereas the macro-level effect reverts to the pre-treatment mean by the third year after the asylum-seekers' arrival. Further research is needed on the conditions that make this reduction in concerns sustainable in order to derive policy implications.

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A Additional figures and tables

Table A.1: Koenigsteiner Key vs. actual allocation shares

	(1) Königsteiner Key	(2) Refugees' allocation	(3) Difference (1) - (2)
Baden-Wuerttemberg	12.86%	12.34%	0.52%
Bayern	15.52%	12.79%	2.73%
Berlin	5.05%	4.45%	0.60%
Brandenburg	3.06%	3.10%	-0.04%
Bremen	0.96%	1.18%	-0.22%
Hamburg	2.53%	2.11%	0.42%
Hesse	7.36%	6.55%	0.81%
Mecklenburg-Vorpommern	2.03%	2.09%	-0.06%
Niedersachsen	9.53%	10.47%	-0.94%
North Rhine-Westphalia	21.21%	23.92%	-2.71%
Rhineland-Palatinate	4.84%	5.08%	-0.24%
Saarland	1.22%	1.22%	0.00%
Saxony	5.08%	4.76%	0.32%
Saxony-Anhalt	2.83%	3.04%	-0.21%
Schleswig-Holstein	3.40%	3.78%	-0.38%
Thuringia	2.72%	3.11%	-0.39%

Notes: Königsteiner Key for 2015 was obtained from Bundesministerium der Justiz und für Verbraucherschutz (2014). Data on refugee allocation for 2015 is from the RDC (2015).

Table A.2: Descriptive statistics (SOEP)

	Pre-treatment (2012-2014)				Post-treatment (2016-2018)			
	All	Low refugee	High refugee	Diff	All	Low refugee	High refugee	Diff
Very concerned about immigration	0.221	0.206	0.237	-0.031 ***	0.397	0.395	0.399	-0.004
Political support (Yes)	0.481	0.464	0.500	-0.036 ***	0.459	0.450	0.468	-0.018 ***
Party afil: right	0.007	0.007	0.007	0.000	0.026	0.028	0.024	0.004 ***
Party afil: centre-right	0.205	0.205	0.206	-0.001	0.190	0.193	0.187	0.006
Party afil: centre-left	0.217	0.203	0.232	-0.029 ***	0.190	0.180	0.200	-0.020 ***
Party afil: left	0.031	0.026	0.035	-0.009 ***	0.032	0.027	0.037	-0.010 ***
Age	51.963	51.726	52.212	-0.486 ***	52.988	52.828	53.157	-0.329 **
Age $\leq$ 24	0.061	0.062	0.060	0.002	0.050	0.052	0.047	0.005 **
Age 25-34	0.111	0.109	0.113	-0.004	0.096	0.094	0.097	-0.003
Age 35-44	0.165	0.170	0.159	0.011 ***	0.176	0.176	0.177	-0.001
Age 45-54	0.218	0.222	0.215	0.007	0.231	0.237	0.226	0.011 ***
Age 55-64	0.188	0.186	0.189	-0.003	0.177	0.176	0.178	-0.002
Age 65+	0.257	0.251	0.264	-0.013 ***	0.270	0.265	0.275	-0.010 **
Male	0.460	0.460	0.460	0.000	0.451	0.451	0.451	0.000
Primary	0.021	0.020	0.023	-0.003 **	0.013	0.011	0.015	-0.004 ***
Secondary Education	0.667	0.671	0.661	0.010 **	0.665	0.667	0.663	0.004
Tertiary Education	0.312	0.309	0.315	-0.006	0.322	0.322	0.322	0.000
Married	0.637	0.636	0.638	-0.002	0.641	0.641	0.640	0.001
Divorced	0.095	0.096	0.093	0.003	0.102	0.103	0.102	0.001
Single	0.201	0.202	0.201	0.001	0.189	0.190	0.189	0.001
Widowed	0.067	0.066	0.068	-0.002	0.068	0.067	0.069	-0.002
Employed	0.594	0.606	0.582	0.024 ***	0.620	0.628	0.611	0.017 ***
Retired	0.217	0.212	0.223	-0.011 ***	0.230	0.226	0.235	-0.009 **
Maternityleave	0.015	0.015	0.015	0.000	0.013	0.013	0.013	0.000
Unemployed	0.039	0.032	0.046	-0.014 ***	0.034	0.029	0.039	-0.010 ***
Non Working	0.082	0.081	0.082	-0.001	0.069	0.069	0.069	0.000
In Education	0.023	0.023	0.024	-0.001	0.015	0.015	0.016	-0.001
Other Non Working	0.029	0.030	0.028	0.002 *	0.018	0.019	0.018	0.001
Disability status	0.128	0.122	0.136	-0.014 ***	0.128	0.123	0.133	-0.010 ***
Ln(Net HH Income)	7.865	7.893	7.836	0.057 ***	7.965	7.992	7.936	0.056 ***
Migration Background	0.121	0.123	0.118	0.005 *	0.133	0.131	0.134	-0.003
Number of children (mean)	0.534	0.550	0.516	0.034 ***	0.662	0.662	0.661	0.001
Life satisfaction (mean)	7.221	7.234	7.207	0.027 *	7.305	7.333	7.275	0.058 ***
Asylumseekers per 100k (2015)				-	998.099	711	1301	-590.229 ***
Total county population	437,582	315,796	565,936	-250,140 ***	446,177	324,150	575,105	-250,955 ***
Average age	43.848	43.780	43.919	-0.139 ***	44.174	44.091	44.262	-0.171 ***
Foreigner share (in %)	7.747	8.148	7.325	0.823 ***	10.351	10.734	9.946	0.788 ***
Youth quota (in %)	19.954	20.119	19.780	0.339 ***	20.393	20.504	20.275	0.229 ***
Female share (in %)	51.078	51.077	51.079	-0.002	50.682	50.665	50.701	-0.036 ***
Unemployment rate (in %)	7.208	6.415	8.044	-1.629 ***	6.243	5.554	6.970	-1.416 ***
Housing vacancies (in %)	4.989	5.093	4.881	0.212 ***	5.194	5.145	5.246	-0.101 ***
Ln(GDP per cap in 1,000€)	3.439	3.463	3.415	0.048 ***	3.546	3.574	3.515	0.059 ***
Urban	0.305	0.272	0.341	-0.069 ***	0.299	0.266	0.333	-0.067 ***
East	0.226	0.213	0.238	-0.025 ***	0.216	0.203	0.230	-0.027 ***
Obs.	45513	23354	22159		51,817	26,621	25,196	

Notes: The table displays the sample means for outcomes and covariates for the pre and post-treatment periods, by low and high refugee migration districts. The upper panel presents the outcome variables, which are all dummy variables; the middle panel presents all the covariates; and the bottom panel presents district characteristics obtained from INKAR that were merged into the SOEP dataset. Age is measured in years, age brackets are dummies (for the FE estimations). Education variables are classified according to the "International Standard Classification of Education (ISCED)" of 2011 and are dummies. Marital status and employment variables are also dummies. Life satisfaction is measured on an 11 point scale (being 0 completely dissatisfied and 10 completely satisfied). GDP is measured in 1.000 euro per inhabitant. District characteristics are as of the end of the previous year (i.e. for 2016, the reported values for 2015 are considered). Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.3: Sensitivity analysis: effect heterogeneity - individual characteristics

	(1) Male	(2) Female	(3) Below 45 yo.	(4) Above 45 yo.	(5) Married	(6) Not married
High ref. dist*Y2018	-0.017	-0.027 **	-0.004	-0.034 ***	-0.036 ***	0.000
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.014)
High ref. dist*Y2017	-0.022	-0.034 ***	-0.021	-0.033 **	-0.031 **	-0.024
	(0.013)	(0.013)	(0.014)	(0.013)	(0.012)	(0.015)
High ref. dist*Y2016	-0.022	-0.034 ***	-0.025 *	-0.032 **	-0.026 **	-0.034 **
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.015)
High ref. dist*Y2014	.	.	.	.	.	.
	.	.	.	.	.	.
High ref. dist*Y2013	0.005	-0.003	-0.023	0.009	-0.001	0.005
	(0.011)	(0.010)	(0.014)	(0.011)	(0.011)	(0.013)
High ref. dist*Y2012	0.020	-0.005	-0.011	0.012	0.013	-0.005
	(0.012)	(0.012)	(0.016)	(0.011)	(0.011)	(0.015)
Y2018	0.040 **	0.030 *	0.013	0.047 **	0.046 **	0.010
	(0.016)	(0.017)	(0.016)	(0.019)	(0.018)	(0.016)
Y2017	0.110 ***	0.116 ***	0.089 ***	0.127 ***	0.128 ***	0.086 ***
	(0.014)	(0.015)	(0.014)	(0.017)	(0.015)	(0.016)
Y2016	0.199 ***	0.211 ***	0.178 ***	0.221 ***	0.215 ***	0.188 ***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.013)
Y2014	.	.	.	.	.	.
	.	.	.	.	.	.
Y2013	-0.033 ***	-0.055 ***	-0.043 ***	-0.043 **	-0.042 ***	-0.052 ***
	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.010)
Y2012	-0.058 ***	-0.080 ***	-0.066 ***	-0.071 ***	-0.080 ***	-0.056 ***
	(0.011)	(0.010)	(0.012)	(0.011)	(0.010)	(0.013)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	44,308	53,022	34,656	62,674	62,053	35,277
N	8,912	10,774	7,850	11,836	12,274	7,412

Notes: This table shows the results for equation 1 (exposure effects and time trends). The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. The columns (1)-(6) show the different subgroups for which the results are estimated. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2, with the exception of the covariate for which the sample split is performed. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.4: Sensitivity analysis: effect heterogeneity - individual characteristics

	(1) Tertiary	(2) Non-Tertiary	(3) Employed	(4) Not-employed	(5) Low income	(6) High income	(7) Left (<5)	(8) Centre(=5)	(9) Right (>5)
High ref. dist*Y2018	-0.028 **	-0.021 *	-0.026 **	-0.016	-0.006	-0.040 ***	-0.022 *	-0.018	-0.024
	(0.013)	(0.012)	(0.011)	(0.016)	(0.014)	(0.013)	(0.012)	(0.014)	(0.022)
High ref. dist*Y2017	-0.033 **	-0.025 **	-0.036 ***	-0.019	-0.019	-0.039 ***	-0.019	-0.009	-0.072 ***
	(0.015)	(0.013)	(0.011)	(0.017)	(0.015)	(0.014)	(0.015)	(0.015)	(0.022)
High ref. dist*Y2016	-0.026 *	-0.029 **	-0.031 **	-0.027 *	-0.030 **	-0.029 **	-0.016	-0.023	-0.050 ***
	(0.015)	(0.013)	(0.012)	(0.016)	(0.015)	(0.013)	(0.016)	(0.015)	(0.019)
High ref. dist*Y2014	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
High ref. dist*Y2013	-0.006	0.003	-0.008	0.013	0.001	0.001	-0.008	0.001	0.010
	(0.011)	(0.011)	(0.011)	(0.013)	(0.012)	(0.012)	(0.011)	(0.014)	(0.017)
High ref. dist*Y2012	-0.003	0.010	-0.002	0.019	0.007	0.007	-0.008	0.010	0.011
	(0.012)	(0.012)	(0.011)	(0.013)	(0.013)	(0.013)	(0.012)	(0.014)	(0.019)
Y2018	0.006	0.060 ***	0.009	0.069 ***	0.062 ***	0.012	0.010	0.058 ***	0.043
	(0.018)	(0.016)	(0.013)	(0.022)	(0.018)	(0.016)	(0.016)	(0.020)	(0.029)
Y2017	0.080 ***	0.137 ***	0.088 ***	0.152 ***	0.140 ***	0.091 ***	0.072 ***	0.131 ***	0.159 ***
	(0.016)	(0.014)	(0.011)	(0.019)	(0.017)	(0.013)	(0.015)	(0.017)	(0.025)
Y2016	0.169 ***	0.229 ***	0.185 ***	0.236 ***	0.233 ***	0.179 ***	0.164 ***	0.224 ***	0.248 ***
	(0.015)	(0.012)	(0.010)	(0.016)	(0.013)	(0.012)	(0.013)	(0.015)	(0.021)
Y2014	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.
Y2013	-0.011	-0.064 ***	-0.048 ***	-0.042 ***	-0.047 ***	-0.043 ***	-0.022 ***	-0.061 ***	-0.052 ***
	(0.008)	(0.009)	(0.008)	(0.010)	(0.009)	(0.010)	(0.008)	(0.009)	(0.013)
Y2012	-0.024 **	-0.099 ***	-0.067 ***	-0.077 ***	-0.081 ***	-0.060 ***	-0.036 ***	-0.096 ***	-0.079 ***
	(0.011)	(0.011)	(0.010)	(0.013)	(0.011)	(0.011)	(0.011)	(0.012)	(0.017)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	30,812	66,078	58,527	39,502	49,244	48,086	32,019	39,654	23,298
N	5,997	13,485	12,040	7,877	9,892	9,794	6,299	7,866	4,645

Notes: This table shows the results for equation 1 (exposure effects and time trends). The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. The columns (1)-(9) show the different subgroups for which the results are estimated. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2, with the exception of the covariate for which the sample split is performed. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.5: Sensitivity analysis: effect heterogeneity - district characteristics

	(1) Low foreig.	(2) High foreig.	(3) Low GDPpc	(4) High GDPpc	(5) Low unempl.	(6) High unempl.	(7) West	(8) East	(9) Urban	(10) Rural	(11) EAE 14	(12) No EAE 14
High ref. dist*Y2018	-0.028 **	-0.012	-0.022	-0.024 *	-0.038 **	-0.011	-0.024 **	-0.010	-0.018	-0.025 *	0.015	-0.029 **
	(0.013)	(0.017)	(0.015)	(0.013)	(0.015)	(0.014)	(0.012)	(0.019)	(0.017)	(0.013)	(0.025)	(0.012)
High ref. dist*Y2017	-0.020	-0.036 **	-0.025	-0.033 **	-0.041 ***	-0.015	-0.037 ***	0.007	-0.036 **	-0.021	0.010	-0.035 ***
	(0.015)	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.012)	(0.024)	(0.018)	(0.014)	(0.023)	(0.013)
High ref. dist*Y2016	-0.016	-0.045 ***	-0.027 *	-0.030 *	-0.024	-0.030 *	-0.031 **	-0.023	-0.045 **	-0.017	-0.019	-0.028 **
	(0.014)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.012)	(0.024)	(0.019)	(0.013)	(0.029)	(0.013)
High ref. dist*Y2014	.	.	.	.	.	.	.	.	.	.	.	.
High ref. dist*Y2013	0.003	-0.003	-0.001	0.001	0.011	-0.009	0.003	-0.016	-0.016	0.005	0.000	-0.003
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.010)	(0.018)	(0.016)	(0.011)	(0.016)	(0.010)
High ref. dist*Y2012	0.020	-0.019	0.013	-0.004	0.022	-0.006	0.007	-0.013	-0.023	0.017	-0.020	0.007
	(0.014)	(0.013)	(0.015)	(0.012)	(0.014)	(0.014)	(0.011)	(0.021)	(0.017)	(0.012)	(0.023)	(0.011)
Y2018	0.074 ***	0.024 *	0.055 **	0.030 **	0.039 **	0.030	0.030 **	0.115 **	0.019	0.053 ***	-0.007	0.039 ***
	(0.021)	(0.014)	(0.022)	(0.014)	(0.018)	(0.020)	(0.013)	(0.051)	(0.018)	(0.017)	(0.029)	(0.014)
Y2017	0.143 ***	0.105 ***	0.135 ***	0.102 ***	0.120 ***	0.103 ***	0.110 ***	0.165 ***	0.085 ***	0.133 ***	0.074 **	0.119 ***
	(0.018)	(0.013)	(0.018)	(0.014)	(0.015)	(0.018)	(0.012)	(0.041)	(0.017)	(0.015)	(0.027)	(0.012)
Y2016	0.234 ***	0.188 ***	0.225 ***	0.192 ***	0.207 ***	0.200 ***	0.195 ***	0.274 ***	0.177 ***	0.223 ***	0.180 ***	0.209 ***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.013)	(0.016)	(0.010)	(0.029)	(0.017)	(0.013)	(0.033)	(0.011)
Y2014	.	.	.	.	.	.	.	.	.	.	.	.
Y2013	-0.057 ***	-0.035 ***	-0.051 ***	-0.040 ***	-0.045 ***	-0.039 ***	-0.043 ***	-0.052 ***	-0.032 ***	-0.053 ***	-0.030 **	-0.047 ***
	(0.010)	(0.008)	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)	(0.013)	(0.011)	(0.008)	(0.014)	(0.007)
Y2012	-0.084 ***	-0.063 ***	-0.082 ***	-0.065 ***	-0.065 ***	-0.069 ***	-0.071 ***	-0.066 **	-0.063 ***	-0.080 ***	-0.045 **	-0.074 ***
	(0.013)	(0.010)	(0.014)	(0.010)	(0.012)	(0.012)	(0.009)	(0.025)	(0.014)	(0.011)	(0.020)	(0.009)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	54,459	42,871	52,767	44,563	47,090	50,240	75,923	21,407	29,362	67,968	17,147	80,183
N	11,015	8,671	10,633	9,053	9,671	10,015	15,492	4,194	5,871	13,815	3,419	16,267

Notes: This table shows the results for equation 1 (exposure effects and time trends). The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. The columns (1)-(12) show the different subgroups for which the results are estimated. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2, with the exception of the covariate for which the sample split is performed. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.6: Sensitivity analysis: different sample restrictions

	(1) FE-main	(2) FE w/o covars	(3) FE no extremes	(4) FE<=65	(5) FE<p99 pop	(6) Balanced	(7) No migback
High ref. dist*Y2018	-0.023 **	-0.019 *	-0.024 **	-0.019 *	-0.021 *	-0.024 *	-0.027 **
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)	(0.011)
High ref. dist*Y2017	-0.029 ***	-0.026 **	-0.030 ***	-0.029 **	-0.025 **	-0.026 *	-0.028 **
	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.014)	(0.012)
High ref. dist*Y2016	-0.029 ***	-0.027 **	-0.029 ***	-0.025 **	-0.022 *	-0.034 **	-0.028 **
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.011)
High ref. dist*Y2014	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
High ref. dist*Y2013	0.000	-0.001	0.000	-0.007	-0.002	-0.001	0.001
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)	(0.009)
High ref. dist*Y2012	0.006	0.004	0.005	0.004	0.008	0.001	0.006
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
Y2018	0.034 ***	0.087 ***	0.032 **	0.026 **	0.044 ***	0.043 ***	0.038 ***
	(0.013)	(0.007)	(0.012)	(0.013)	(0.014)	(0.016)	(0.013)
Y2017	0.113 ***	0.153 ***	0.112 ***	0.101 ***	0.120 ***	0.129 ***	0.112 ***
	(0.011)	(0.007)	(0.011)	(0.011)	(0.012)	(0.014)	(0.012)
Y2016	0.206 ***	0.230 ***	0.204 ***	0.191 ***	0.211 ***	0.230 ***	0.207 ***
	(0.010)	(0.007)	(0.010)	(0.010)	(0.011)	(0.013)	(0.010)
Y2014	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
Y2013	-0.045 ***	-0.054 ***	-0.045 ***	-0.050 ***	-0.046 ***	-0.032 ***	-0.044 ***
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
Y2012	-0.070 ***	-0.089 ***	-0.071 ***	-0.074 ***	-0.076 ***	-0.058 ***	-0.069 ***
	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
Covariates	Yes	No	Yes	Yes	Yes	Yes	Yes
Obs.	97,330	97,330	95,096	71,569	88,334	58,512	84,972
N	19,686	19,686	19,239	15,018	17,896	9,752	16,969

Notes: This table shows the results for equation 1 (exposure effects and time trends). The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. The columns (1)-(7) show the different specifications for the robustness checks. Column (1) shows the result of equation 1. Column (2) does the same but without including any individual or district covariates. Column (3) exclude districts were the reported inflow of asylum-seekers was too low (below the first percentile) or too high (above the ninety-ninth percentile). Column (4) only considers individuals aged 18-65 (in working age). Column (5) excludes respondents in the 5 largest cities (Berlin, Hamburg, Hanover, Cologne, Munich). Column (6) uses only a balanced panel. Column (7) considers only respondents without a migration background. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications—except column (2)—include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.7: Robustness check: High-low refugee migration districts and other concerns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Very concerned about			
	Crime in Germany	Hostility towards foreigners or minorities in Germany	Maintaining peace	Economic development	Own economic situation	Own health	Your job security
High ref. dist*Post	-0.029 ***	-0.002	-0.010	-0.007	0.001	0.001	0.003
	(0.008)	(0.008)	(0.008)	(0.006)	(0.005)	(0.005)	(0.005)
Post	0.196 ***	0.327 ***	0.238 ***	0.066 ***	0.011 **	0.016 ***	-0.002
	(0.009)	(0.011)	(0.009)	(0.007)	(0.006)	(0.005)	(0.006)
R^2 -within	0.055	0.098	0.082	0.011	0.034	0.023	0.018
Obs.	97,252	97,099	97,225	97,164	97,213	97,254	58,833
N	19,686	19,685	19,686	19,683	19,684	19,686	14,570
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the results for a standard DiD equation using $HighRef_{d2015} * Post_t$ instead of yearly interactions, using as outcome the concerns mentioned in columns (1)-(7). The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications include month of interview and state fixed effects. Statistically significant at $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.8: Concerns about immigration, crime and political preferences

	(1)	(2)	(3)	(4)
		Lean towards		
	Centre-right	Centre-left	Left-wing	Right-wing
High ref. dist*Post	-0.009*	0.001	0.007*	-0.004
	(0.005)	(0.005)	(0.003)	(0.004)
Very concerned about immigration	-0.004	-0.007*	-0.006***	0.015***
	(0.004)	(0.004)	(0.002)	(0.002)
Very concerned about crime	-0.001	-0.002	-0.002	0.007***
	(0.004)	(0.004)	(0.002)	(0.002)
R^2 -within	0.004	0.008	0.008	0.026
Obs.	45,473	45,473	45,473	45,473
N	13,205	13,205	13,205	13,205
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month of int. FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes

Notes: This table shows the results for a standard DiD equation using $HighRef_{d2015} * Post_t$ instead of yearly interactions, where the outcomes are preferences toward the group of parties mentioned in columns (1)-(4). The main regressors are $HighRef_{d2015} * Post_t$, a dummy that equals one if the respondent is very concerned about immigration, and a dummy that equals one if the respondent is very concerned about crime in Germany. The results are estimated using the 2012–2018 unbalanced sample, where observations for 2015 are dropped. Standard errors are clustered at the level of the district of residence in 2015. All regressions include the covariates described in table A.2. Controls at the individual level: age groups (ref. cat: $age <= 24$), education level (ref. cat: primary), marital status (ref. cat: married), employment status (ref. cat: employed), log net household income, number of children in the household. Controls at the district level: average age, % of foreigners, dependency ratio, total population, % of female, unemployment rate, log GDP per capita, % of empty housing. All covariates are as of the year previous to the interview. All specifications include month of interview and state fixed effects. Statistically significant at ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Figure A.1: Official votes at the German federal elections and declared party identification at the federal states level
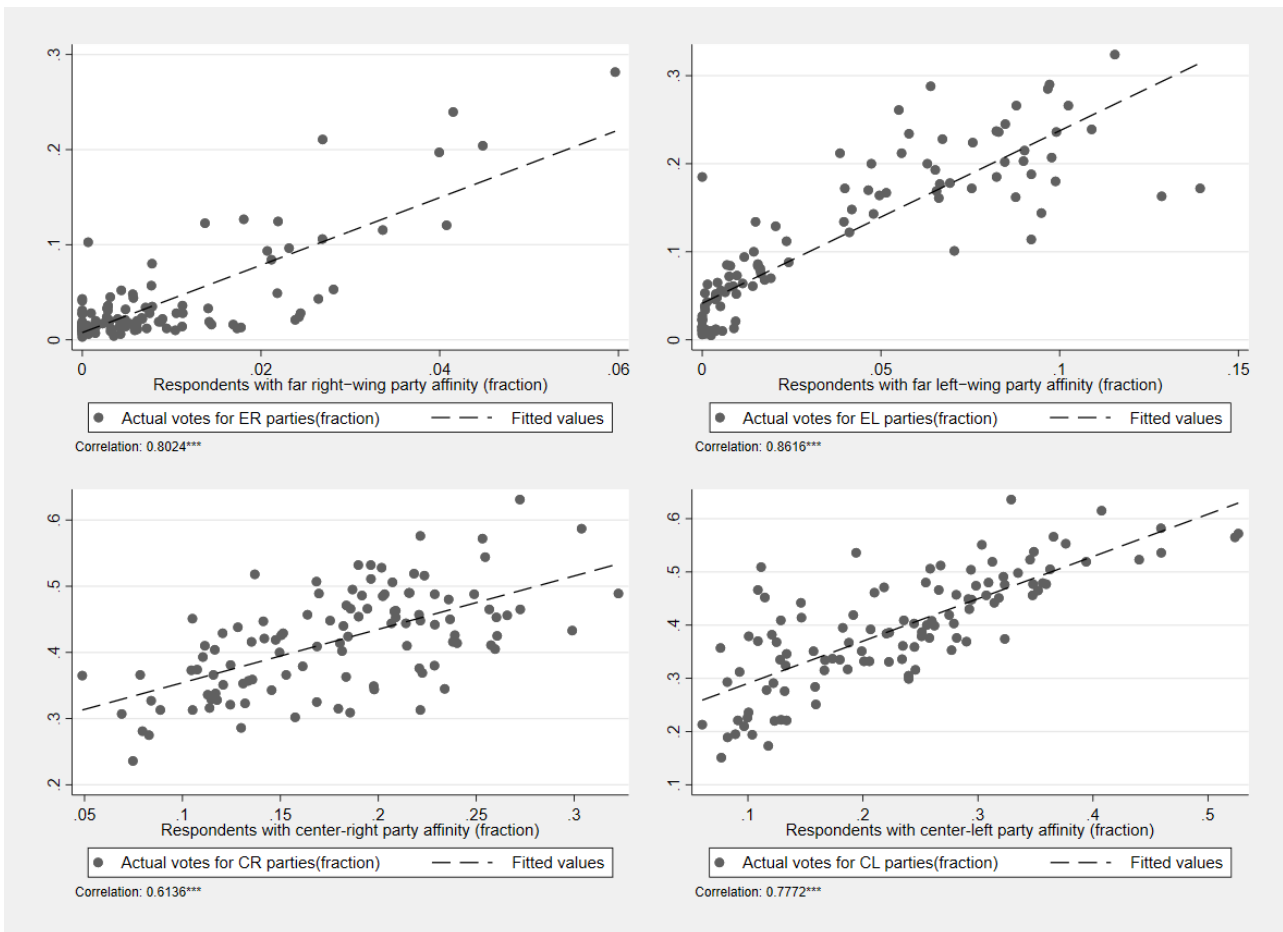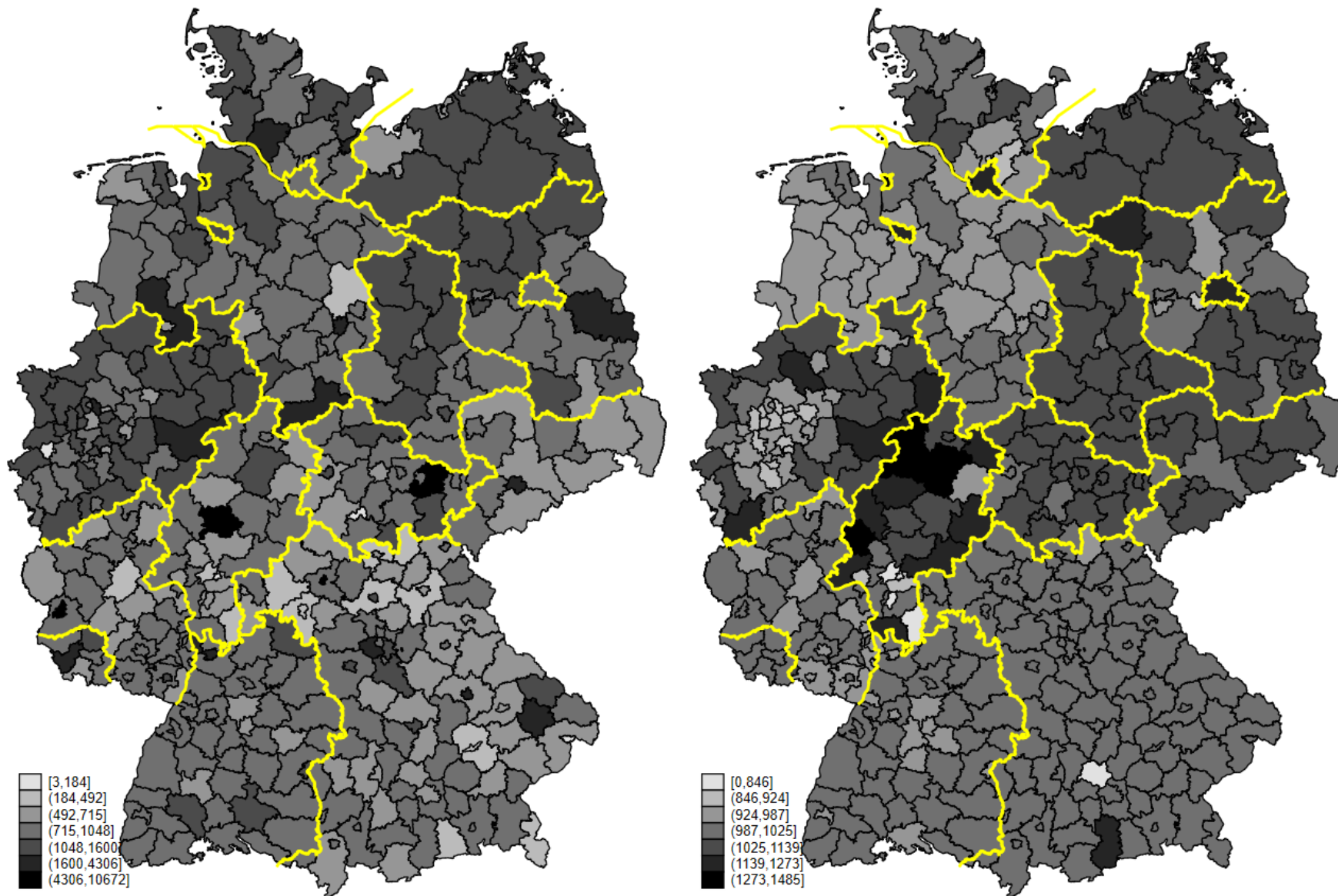
Notes: The figure displays the proportion of votes for right-wing parties (NPD, REP, DVU, and AfD since 2013), centre-right parties (CDU/CSU, FDP), centre-left parties (SPD, Gruene/Buendnis90), and left-wing parties (Die Linke) at seven federal elections (1994, 1998, 2002, 2005, 2009, 2013 and 2017) at the state level; with the proportion of party preferences from SOEP respondents for the respective years.

Figure A.2: Actual vs. theoretical allocation of asylum seekers per 100,000 inhabitants

[3,184]		[0,846]
(184,492]		(846,924]
(492,715]		(924,987]
(715,1048]		(987,1025]
(1048,1600]		(1025,1139]
(1600,4306]		(1139,1273]
(4306,10672]		(1273,1485]

(a) Actual allocation of asylum-seekers   (b) Theoretical allocation

Source: RDC (2015)

Notes: The maps show the actual vs. the theoretical allocation of asylum-seekers in 2015. The theoretical allocation is based on the established quotas by the states to the districts. The yellow lines represent state borders.

Figure A.3: Determinants of asylum-seekers allocation in 2015 (standardise beta coefficients)
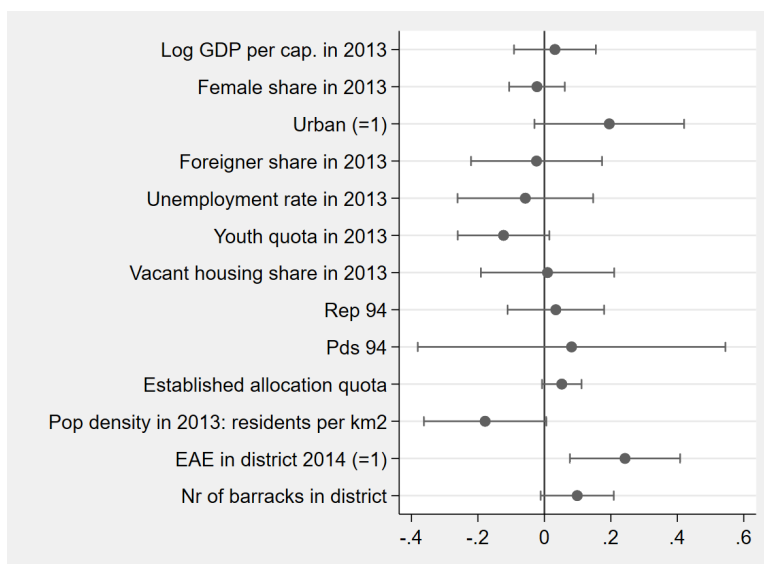
B   Asylum-seekers' data

The data used in this paper for asylum-seekers comes from Research Data Centre from the German (RDC) (RDC, 2015) (*Asylstatistiken*). This dataset contains information on the recipients of asylum-seeker benefits under the Asylum Seekers Benefits Act (AsylbLG). These statistics are reported annually (as of December 31 of each year) and comprise comprehensive information on the asylum-seekers (date on which they started receiving benefits, country of origin, gender, employment status, type of benefit received, etc.). Data access has to be requested and paid for, access is only possible at the venues of the RDC.

Since I want to analyse the impact of the refugee inflow of 2015, and given the mobility restrictions during the first 6 months in Germany, I consider this dataset to provide a comprehensive and reliable measure of this inflow. Given that the major inflow occurred in the second half of 2015, the new asylum-seekers must be reported on the *Asylstatistiken* of 2015.

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