From Crisis to Controversy: Refugees and the Rise of the Far Right in Bavaria

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Abstract

This paper investigates the causal impact of the 2015 refugee crisis on the electoral performance of the far-right *Alternative für Deutschland* (AfD) party in Bavaria. To address concerns about endogeneity in refugee allocation, we construct a novel proxy for exposure to asylum seekers using exogenous, pre-crisis municipal characteristics and machine learning techniques (XGBoost with SHAP values), followed by a logistic regression. This proxy estimates the likelihood of hosting a refugee center and serves as the key explanatory variable in a two-way fixed effects model. Contrary to our hypothesis, which align with the Threat Theory framework, we find that greater proxied exposure to refugees is associated with a statistically significant *decrease* in AfD vote share, with stronger effects in smaller municipalities. We also find no evidence that exposure significantly affected voter turnout. These findings partially align with Intergroup Contact Theory, suggesting that close interaction with refugees can mitigate prejudice and negative attitudes, leading to diminished support for radical right-wing parties. Our study contributes to the literature by challenging the assumption that localized refugee presence fuels far-right support and by offering a new approach to modeling refugee exposure using exogenous, infrastructural variables.

1 Introduction

The 2015 refugee crisis was a major test of Europe's ability to respond to humanitarian emergencies. Germany, led by Chancellor Angela Merkel, took a central role. Her phrase "Wir schaffen das" ("We can manage") captured the government's welcoming stance but also triggered strong backlash, often linked to the rise of the right-wing Altenrative für Deutschland (Alternative for Germany) party (AfD) (Delcker, 2016).

The refugee crisis deeply polarized public opinion in Germany. In many communities it heightened anxieties about competition for housing, employment, and access to public services, as well as fears of cultural displacement. These concerns were frequently amplified by media narratives and political discourse. Empirical evidence from Czymara and Dochow (2018), based on survey data, demonstrates that increased media coverage of migration issues was significantly associated with rising public concern about immigration, especially in conservative and rural contexts. At the same time, however, numerous communities responded with acts of solidarity: civil society organizations, churches, and individual citizens actively mobilized to support and assist incoming refugees.

These reactions can be understood through two influential theories in intergroup relations. Threat Theory emphasizes that negative attitudes often arise from perceived threats—whether to material resources or to group identity (Blumer, 1958). De Coninck et al. (2021) find that symbolic threats to national identity have a greater impact on attitudes towards refugees than the frequency of direct contact. In contrast, Intergroup Contact Theory (ICT) posits that positive interactions between different groups can reduce prejudice by altering how group boundaries are perceived (Pettigrew, 1998).

Attitudes toward refugees strongly shape voting behavior. Research shows that anti-refugee sentiment boosts support for far-right parties, while pro-refugee attitudes align with green or progressive ones. Indelicato et al. (2023) find this pattern across several European countries. In Germany, over the past 10 years, the AfD has gained traction by leveraging on anti-refugee sentiment using fear-based narratives focused on cultural and economic threats (Arzheimer & Berning, 2019).

Because the 2015 crisis had a lasting impact on people's attitudes towards refugees—and these attitudes appear to influence voting—it's important to understand how the crisis may have reshaped the political landscape.

This paper examines whether the refugee crisis acted as a catalyst for the rise of the AfD, with a particular focus on Bavaria—a federal state that faced considerable strain due to its location along the so-called Balkan Route, which brought a large influx of refugees through its territory. Our central research question is: To what extent did the 2015 refugee crisis contribute to the increase in the AfD votes in Bavaria? To address this question, we build on the approach of Stecker and Debus (2019) by developing a proxy for their binary exposure measure. Specifically, we treat their exposure variable—which equals 1 if a municipality hosts a refugee center—as the dependent variable in a binary logistic regression model. The independent variables consist of politically exogenous municipal-level predictors selected using an XGBoost machine learning algorithm. This strategy enables us to estimate the probability of intergroup interactions between refugees and local residents based on a politically exogenous measure. This proxy is interacted with a post-2015 refugee crisis dummy in a linear model, alongside relevant controls and municipal and time fixed effects, to estimate its impact on AfD vote share in the Bundestag elections in Bavarian municipalities in 2017. Drawing on the Threat Theory framework, we hypothesize that the localized presence of refugee centers may have amplified perceptions of both realistic and symbolic threats among residents. We also hypothesize that this heightened sense of threat is likely to have translated into increased support for far-right parties, therefore we expect our proxy to have a positive effect on the AfD voteshare.

This paper also examines whether exposure to the 2015 refugee crisis influenced voter turnout in the 2017 elections. Since electoral outcomes depend both on participation and preferences, it is important to assess if turnout itself was shaped by the refugee crisis. We apply the same model used for AfD vote share, replacing the dependent variable with the turnout rate. Existing evidence on the relationship between refugee exposure and turnout is mixed: Barone et al. (2016) report a negative effect of refugee exposure on turnout, Rozo and Vargas (2020) find a positive association. We hypothesize that the significant increase in the salience of migration in public discourse due to the crisis, in the historically conservative Bavarian context might have exacerbated feelings of threat among voters. As a result, these heightened perceptions may have driven greater electoral participation, as individuals sought to express their concerns at the ballot box.

Our research contributes to the existing literature by offering a new perspective on the analysis of the link between exposure to asylum seekers and the rise in far-right voting. To the best of our knowledge, we are the first to address potential endogeneity in the allocation of asylum seekers in Bavaria by employing proxy measure based on various pre-crisis politically exogenous predictors.

Contrary to our hypothesis, we find that greater exposure—proxied by the likelihood of hosting a refugee center—is associated with a decrease in AfD vote share, partially consistent with ICT. This effect is stronger in smaller municipalities, suggesting that exposure has a greater impact where local contact with refugees is more likely or more salient. We also find that proxied exposure has only an exiguous effect on turnout, suggesting that while the localized presence of refugees may influence party preferences, it does not substantially alter overall political engagement.

The remainder of the paper is structured as follows. In the section 2, we review relevant literature and expand on the necessary theoretical framework. We then provide an overview of Germany's political system, its major political parties, and the asylum allocation process in section 3. In section 4, we describe the data collected for our analysis, followed by an explanation of the methods applied both for our benchmark analysis and our principal model (see section 5). Finally, we interpret the obtained results in section 6 and conclude with a discussion of their implications in section 7.

2 Literature review

To clarify the structure of the upcoming literature review, it will be organized into two main thematic strands. The first strand explores the underlying mechanisms that regulate how everyday exposure to refugees shapes attitudes toward refugees. The second strand examines the literature that focuses on the effects of sudden shifts in refugee populations caused by the 2015 refugee crisis on political outcomes.

We start by analyzing how exposure to refugee presence may impact attitudes towards refugees of the local inhabitants. We extend our analysis to migration flows in a more general sense, as the refugee crisis was a migratory phenomenon.

According to Allport's *The Nature of Prejudice* (Allport, 1954), intergroup contact reduces prejudice when four key conditions are met: equal status, common goals, cooperation, and institutional support. During the 2015 refugee crisis, however, these conditions were not fully in place. Most asylum seekers faced significant economic hardship and language barriers, reinforcing their position of unequal status. Holzberg et al. (2018) finds that German media frequently portrayed refugees as threats, whether economic, security-related, or related to gender relations, through a dehumanizing "us vs. them" narrative. This portrayal undermined perceptions of shared goals between refugees and the host society. Although a surge of civil cooperative initiatives emerged in mid-2015 to compensate for governmental shortcomings (Schmid & Green, 2017), the lack of official support eventually led to feelings of neglect and discouragement, weakening the initial wave of civic engagement.

According to Allport's ICT, the situation described above could result in negative intergroup interactions due to deviations from ideal conditions. Even from a more contemporary perspective, Lowe (2021)'s study—examining the random allocation of men from different socio-economic backgrounds into cricket teams—highlights how the nature of intergroup interaction shapes outcomes. By comparing collaborative and adversarial settings, the study shows that adversarial competition tends to intensify negative attitudes between groups. In the German context, as previously discussed, media narratives contributed to the perception that refugees and locals did not share common goals. As a result, the conditions necessary for positive intergroup contact appear to have been largely absent.

On the other hand, differences in social status and limited government support may contribute to feelings of uncertainty or perceived threat among host populations. Within the framework of Threat Theory, these factors can influence public attitudes, potentially leading to a shift from neutral or positive perceptions to more negative ones.

These mechanisms—ranging from suboptimal intergroup conditions to perceived symbolic threats—do not operate in a vacuum. They can translate into tangible political consequences. As Indelicato et al. (2023) demonstrates, in areas where refugees are perceived or portrayed as threatening outsiders, these perceptions can catalyze broader patterns of political realignment, particularly by increasing electoral support for far-right parties (p. 13).

Germany has seen a marked shift toward right-wing parties, with AfD rising from 4.2% in 2013 to 12.4% in 2017, and in the 2025 elections received above 20% of votes (Grün & Zeier, 2025). Given the literature on how refugee attitudes can shift due to contact-related mechanisms and how these attitudes influence voting, it is worth investigating whether the 2015 crisis served as a catalyst for AfD's rise.

A thorough review of the literature on migration's political impact reveals a strong focus on the link between immigration and far-right party support (Schaub et al., 2021, Pettrachin et al., 2023, Dinas et al., 2019, Steinmayr, 2021, Stecker and Debus, 2019, Jäckle et al., 2018, Barilari et al., 2025), particularly in response to major migratory shocks like the 2015 refugee crisis. Relevant studies fall into two main categories: national-level analyses (Dustmann et al., 2019, Fisunoğlu and Sert, 2019, Sola, 2018, Schaub et al., 2021) and localized analyses of regional or municipal trends (Pettrachin et al., 2023, Stecker and Debus, 2019, Jäckle et al., 2018, Steinmayr, 2021).

Several of these works (Dustmann et al., 2019, Fisunoğlu and Sert, 2019, Schaub et al., 2021, Stecker and Debus, 2019, Pettrachin et al., 2023) exploit quasi-random refugee allocation to identify causal effects of exposure on political outcomes within affected regions. The results from these analyses differ significantly, Pettrachin et al. (2023) and Schaub et al. (2021) find a negative effect of refugee exposure on AfD voteshare, while Stecker and Debus (2019) finds a positive effect.

These analyses rely on aggregated data, as high-quality individual-level voting information is unavailable. Given this data limitation, exposure to refugees is typically proxied through spatial measures—most often the proximity of municipalities (or other units) to refugee housing facilities—as a way to estimate the likelihood of interaction.

The work of Stecker and Debus (2019) provides a baseline for the analysis of the impact of refugee housing placement on electoral support for the AfD in Bavaria. The authors build their exposure measure by identifying the locations of refugee housing facilities (refugee centers) and employs dummy variables to indicate whether a municipality hosts such a facility or if one is present in a neighboring municipality. These dummy variables, along with a set of control variables, are used as explanatory factors. The difference in vote shares obtained in the 2013 and 2017 elections at the municipal level are employed as dependent variables. The authors argue that the allocation of refugee centers is quasi-random across municipalities. Additionally, they aim to establish a causal relationship between the proxied exposure to refugees and increased support for the AfD. However, this approach is subject to several important methodological shortcomings. Most notably, the assumption of exogeneity in the placement of refugee centers—central to the causal claims made in the paper—is inadequately defended. The authors attempt to address this concern by conducting a basic endogeneity check: they regress the binary exposure measure on historical electoral support for far-right parties (specifically, the Republicans and the National Democratic Party of Germany (NPD)). This test is problematic on several grounds.

First, the logic behind the test seems to rely on the idea that if past political preferences do not significantly predict the later placement of refugee centers, then the exposure variable can be treated as exogenous. However, a lack of statistical association between past political outcomes and later exposure does not necessarily rule out the possibility of endogeneity. There may still be other factors—such as omitted variables or concurrent influences—that affects both refugee placement and political outcomes but are not accounted for in the test.

Second, the choice of lag structure in the test raises concerns. The authors use electoral data from 2013 to test for endogeneity in refugee allocations made around 2015–2016. This implicitly assumes that any endogeneity would manifest itself with a two-to-three-year lag, overlooking the possibility of contemporaneous endogeneity. In fact, as mentioned later in this section, there is evidence of refugees being reallocated in response to local tensions—a dynamic that clearly suggests that endogeneity could occur at the time of placement or even after initial placement.

Third, the test uses past outcomes for far-right parties that are ideologically adjacent to the AfD but not identical in their voter base. While there is likely overlap between the electorates of the NPD/Republicans and the AfD, the assumption that their local support can serve as a precise proxy for attitudes toward the AfD introduces further measurement error into the endogeneity test.

We posit that local attitudes toward refugees may have influenced these allocation decisions. To investigate this concern, we examined the decision-making process behind the placement of asylum centers in specific municipalities. More on this is reported in subsection 3.4.

As an alternative proxy for refugee exposure, Jäckle et al. (2018) use the distance of Bavarian municipalities from the Austrian and Czech borders to explain AfD support. They find that, controlling for other factors, municipalities closer to the borders show higher support for the anti-immigration party. However, due to confounding factors—such as cross-border commuting from the Czech Republic—it remains unclear whether this effect is driven by proximity to the Balkan route (i.e., greater exposure to refugee inflows) or by other border-related dynamics.

While the literature offers valuable insights, key gaps remain in analyzing the 2015 refugee crisis' political impact in Bavaria. Most analyzed studies assume quasi-random refugee allocation to identify causal effects. However, although this assumption is more plausible when allocation decisions are well-documented, it does not appear to be adequately justified in the case of Bavaria. In contrast, our paper avoids this assumption entirely, using pre-crisis exogenous variables to proxy exposure. Additionally, many existing models face identification challenges; we address this by employing fixed effects to better isolate the impact of exposure on voting outcomes.

Concerning the relationship between migration and voter turnout, results reported in the literature are mixed. All studies reviewed use Instrumental Variable (IV) strategies based on historical migrant settlement patterns to address endogeneity from migrants selfselecting into politically favorable areas. Barone et al. (2016) find that in Italy, higher immigrant shares reduce turnout and increase blank or invalid votes, interpreted as disillusionment among center-left voters. In contrast, Halla et al. (2017), studying Austria, show that immigration boosts support for the FPÖ but does not affect overall turnout. Rozo and Vargas (2020) find that Venezuelan refugee inflows in Colombia increase turnout and shift votes toward right-wing candidates. These findings suggest that immigration's effect on turnout is highly context-dependent: it may lead to disengagement where mainstream representation fails (Barone et al., 2016), or mobilization when perceived threats dominate (Rozo & Vargas, 2020).

In this context, our paper introduces a novel approach to estimating the effect of refugee exposure on voter turnout. By using exogenous municipal-level variables collected shortly before the crisis, we construct a more contemporaneous proxy—less prone to distortions from long time lags—which may benefit from reduced measurement error and improved alignment with actual exposure to refugees.

3 Overview of German Political Landscape and Asylum Procedures

In this section, we provide an overview of the German political system and the major national political parties between 2013 and 2017. We also present the results of the parties and further analyze the asylum seeker allocation process; in this sense, we also investigate possible endogeneity in the allocation of refugee centers with respect to support for the AfD. Germany, officially the Federal Republic of Germany, is a federal parliamentary republic composed of sixteen constituent states. It is home to approximately 82 million inhabitants and, during the refugee crisis, hosted around one million refugees (Albarosa & Elsner, 2022).

3.1 Electoral system

German federal elections determine the composition of the Bundestag, the national parliament. Voters cast two votes: the first for a direct candidate in their constituency, and the second for a party list (Federal Ministry of the Interior, Building and Community, 2021).

Held every four years, elections follow a mixed-member proportional system. Of roughly 600 seats, 299 are direct mandates, elected by plurality in single-member constituencies.

Each direct win reduces a party's proportional seat count (Federal Election Commissioner, 2025a; The Editors of Encyclopaedia Britannica, 2025).

The second vote plays a larger role in determining the Bundestag's overall composition. Parties that pass the 5% threshold or win at least three constituencies qualify for proportional seat allocation using the Sainte-Laguë/Schepers method (Federal Election Commissioner, 2025b, 2025d; Federal Ministry of the Interior, Building and Community, 2021).

Though the system aims for proportionality, slight deviations can occur due to overhang and leveling seats, which are designed to compensate smaller parties (Federal Election Commissioner, 2025c). Since the second ballot vote reflects party support across all levels, it represents the overall vote share that a given party received in the election. In our research, we assume that voters use their second ballot to vote for the party that most closely aligns with their political views, regardless of their choice on the first ballot. This assumption leads us to focus our analysis on the party vote in greater detail.

3.2 Party overview

Germany's major political parties span a wide ideological spectrum. **CDU/CSU**, the center-right alliance of the CDU (nationwide) and CSU (Bavaria), is rooted in Christian-democratic and conservative values, though internal tensions arose during the 2015 refugee crisis (Knight, Ben, 2018). **SPD**, the traditional center-left party, advocates for democratic socialism and progressive policies, balancing leftist ideals with moderate views on migration (Bierbach, 2017; Social Democratic Party of Germany, 2007). **Die Linke**, formed in 2007, represents the far-left, with anti-capitalist and anti-military views and a broad leftist base (Bierbach, 2017; Duitsland Instituut, 2025). **Bündnis 90/Die Grünen** promote green politics and social liberalism, positioning themselves as centrist among left-leaning parties with moderate immigration stances (Bierbach, 2017; Bundeszentrale für politische Bildung, 2025; Knight, 2021). The **FDP**, a classical liberal party, advocates economic liberalism and immigration reform from a center-right perspective (Bierbach, 2017; Galpin, 2017; Green et al., 2004). Lastly, the **AfD**, founded in 2013, has evolved from a Eurosceptic, conservative party into a far-right nationalist movement, known for its strong opposition to immigration and Islam (Alternative für Deutschland, 2021; Bierbach, 2017; Havertz, 2021).

3.3 German Election result in Bavaria 2013 and 2017

The table below summarizes the election results for the six major parties in Bavaria between 2013 and 2017. It is evident that, during this period, the two dominant parties lost voters, while the smaller parties gained support. Additionally, the AfD nearly tripled its share of the vote. We can also see that the turnout of voters was higher in 2017.

Year	**CSU**	**SPD**	**DIE LINKE**	**GRÜNE**	**FDP**	**AfD**	**Others**	**Turnout**
2013	49.3	20.0	3.8	8.4	5.1	4.2	9.2	70.0
2017	38.8	15.3	6.1	9.8	10.2	12.4	7.5	78.1

Table 1: Bundestag election results and turnout in Bavaria in 2013 and 2017 at the federal state level

At the national level, no party secured an absolute majority of seats. As a result of coalition negotiations, so-called grand coalition was formed in 2013 between the CDU/CSU and the SPD, with Die Linke and the Grüne forming the opposition (Staff, 2013).

3.4 Asylum Seekers Allocation Process

Germany's asylum seeker procedure is specified in the Asylum Act, which was passed into law in 2008 (Federal Ministry of the Interior, 2016). It confirms the continuation of the EASY (Initial Distribution Of Asylum Seekers, Erstverteilung Asylbegehrende) procedure, which has been in use since 1998 (Federal Office for Migration and Refugees (BAMF), 2022). EASY creates an allocation quota for each of the sixteen German federal states (Länder) using the Königsteiner Schlüssel, a distribution formula that takes into account each state's tax revenue and population size to determine its share of asylum seekers. At the district level, quotas are set by the Landesbeauftragter, who operates under the authority of the State Ministry for Labor and Social Affairs, Family and Integration (Staatsministerium für Arbeit und Soziales, Familie und Integration) (Fachinger et al., 2024)

At the municipal level, decisions are made by the local district authority (administrative regions' governments or counties' and independent cities' governments, depending on type of accommodation)[1] and it is plausible that these authorities consider matters of public order and local sentiment when assigning refugee centers. To explore this, we began by

[1]Please refer to Appendix A for an explanation of the different types of asylum seeker housing

examining the "centralized part" of the allocation process and the key officials responsible for it in 2015: Dr. Frank-J. Weise (Federal Office for Migration and Refugees) and Werner Staritz (Landesbeauftragter Bayern). Our research uncovered no readily available evidence suggesting that political incentives influenced their decisions. A review of tabloids, journals, and major newspapers yielded no indication of political bias in their actions.

We also analyzed local reactions to the selection of municipalities for refugee center placements. Numerous protests led by the right-wing PEGIDA movement were documented throughout 2015 (Schulze, 2015). Moreover, we identified anti-immigrant incidents such as the arson attack in Wallerstein, where a fire was set near accommodations for refugees (Deutsche Welle, 2015). These events underscore local opposition. A notable case of refugees being relocated due to public resistance occurred in Mainstockheim in July 2015 (Diestelmann, 2015).

Therefore, it is possible that local attitudes toward refugees, which are closely linked to political preferences (Indelicato et al., 2023), may influence where refugee centers are placed. This raises a potential endogeneity issue in our analysis.

In the upcoming subsection, we will describe the practical aspects of an asylum application from the asylum seeker's standpoint.

3.4.1 Asylum Application

The "Asylum Act" (n.d.) outlines three main scenarios in which asylum seekers may apply for protection in Germany. As stipulated in §18 of the Act, the asylum procedure may begin at the border. Upon interception by border patrols, these have the responsibility to evaluate the acuteness of the case and have the choice of rejecting entry to the country based on reasons such as criminal record, arrival from a safe third country or starting the procedure in another EU country, or of accepting the claim for humanitarian protection, in which case the foreigner is directed to the closest centralized arrival centre unless a particular one has already been identified (they are transported to an initial reception centre for registration and the initiation of the asylum process). Similarly, §18a of "Asylum Act" (n.d.) applies to individuals arriving by air. If an applicant enters Germany via an airport without a valid visa or the required documentation, they may submit their asylum application at the airport's border control. ("Asylum Act", n.d.) In such cases, they are held in the airport transit zone while the Federal Office for Migration and Refugees (BAMF) conducts a fast-track assessment of their claim. If the application is accepted, the individual is transferred to an initial reception centre for further processing. Lastly, individuals already present in Germany—either due to irregular entry or a change in circumstances in their country of origin—may apply for asylum at a local police station or directly at a branch of the Federal Office for Migration and Refugees. (§19 "Asylum Act", n.d.)

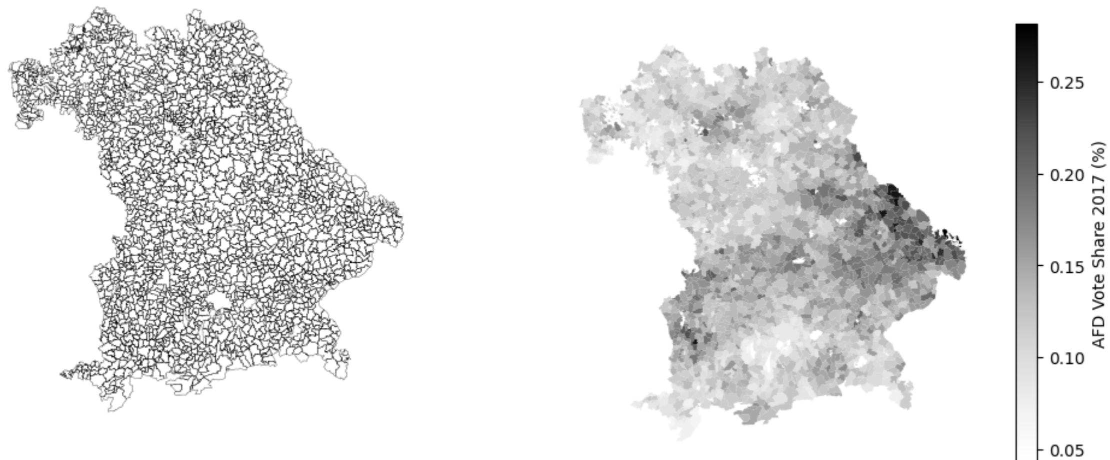
3.4.2 Asylum Centers

Each Asylum Seeker is first sent to the Initial Reception Center (Erstaufnahmeeinrichtungen) based on the EASY system and federal quotas. There, they spend a time ranging from 6 weeks to 6 months (§47, "Asylum Act", n.d.). During that time, their application is processed and the required documentation is collected. Then, given that their application proceeds, they are moved into the communal housing within the federal Land where they were housed (§53, "Asylum Act", n.d.). There, they would wait for the finalization of their application. If approved, they will be moved to individual housing, if rejected, they would be required to leave the country.

4 Data

In this section, we analyze the collected data, outline its key characteristics, and highlight its relevance in addressing our research question concerning the refugee crisis and its impact on voting patterns.

Ideally, we would have employed individual level data about voting outcomes, attitudes towards refugees, socio-economic and demographic variables to carry out our analysis, however such data in Bavaria is not available at the moment, therefore we turned to the most granular aggregate level within our reach, the municipal level. Bavaria, located in the southeast of Germany, is one of the country's sixteen federal states and comprises 2,056 municipalities, including independent cities such as Munich. Figure 1(a) displays a map of Bavaria, clearly indicating the municipal boundaries.



((a)) Bavaria with the borders of municipalities

((b)) AfD Support in 2017 national Elections

Figure 1: Spatial Overview: Borders of municipalities and AfD support in 2017

First, we present descriptive statistics of our dependent variable, the AfD second vote share at the municipal level during the 2013 and 2017 national elections, in Table 2. This data is obtained from the national statistical office (Statistisches Bundesamt (Destatis), 2025) and it is reported percentage points of total valid votes in the respective municipality. As shown, the average AfD vote share in Bavaria increased significantly, from 4.95% in 2013 to 12.61% in 2017. Notably, the 2017 vote share data presents large variability at the municipal-level, ranging from 1.1% to 27.90%. We illustrate these election results using a gray-scale gradient map of the municipalities, as shown in Figure 1(b).[2]

Table 2: Descriptive Statistics for AfD Vote Share (%) in 2013 and 2017

Year	**N**	**Mean**	**SD**	**Min**	**Max**
AfD Share 2013	2056	4.95	2.53	0.10	15.00
AfD Share 2017	2056	12.61	3.64	1.10	27.90

As discussed in section 2, our goal is to proxy the potential contact with asylum seekers using variables that are exogenous with respect to political outcomes. Information about likelihood of contact due to the existence of refugee centers, which we will use to construct

[2] A full comparison between the electoral outcome maps for AfD in Bavaria in 2013, 2017 and the resulting difference can be found in the Appendix panel of Figure 4.

the dependent variable in the proxy constructing part of the paper, is sourced from a parliamentary inquiry. This inquiry is dated January 1, 2016 and it lists the locations and capacities of active refugee centers (Rinderspacher, 2015). The data, summarized in Table 10, includes 466 refugee centers across Bavaria, with a combined capacity exceeding 66,000 individuals. While we do not differentiate between types of accommodation in our main analysis, the definitions of each category can be found in Appendix A.

In Table 3, we also present the characteristics of municipalities that form the set of independent variables of the proxy constructing process. [3]We focus on municipal infrastructure, particularly facilities that provide access to fundamental rights such as education and sports. These are typically built in response to population needs, independent of local political orientation. We also include data on land use within municipalities and residential infrastructures; here, exogeneity arises from the fact that residential and commercial zoning has developed over decades due to economic and demographic factors, rather than political influence. Finally, the presence of military facilities reflects strategic considerations and is not politically motivated. This selection arises from a consideration of all publicly available exogenous variables, that are then reduced to a subset containing inter-variable correlations of less than 0.8 (see Figure 3 in Appendix B the correlation matrix).

The municipality characteristics follow distinct formats, reflecting their descriptive roles. Variables such as *Trade and Services*, *Leisure Facilities*, *Industry and Commerce*, *Sports Facilities*, and *Residential Area* are expressed as fractions of the municipality's total area that is employed for such activities. Information on the number of *Apartments*, *Schools*, *Churches* and *Residential Square Meters* is reported per 1000 inhabitants; in the subsequent sections, we denote variables reported in this way with the suffix *(cont)*. We also introduce a variable indicating the number of active *Military Facilities* in each municipality, based on data from Bundeswehr (2013). Church locations are identified using the Google Maps API (Google, 2025). All other variables are retrieved from the internet direction of Bayerisches Landesamt für Statistik (2025). Given the structural heterogeneity of the dataset—including fractional, binary, and continuous variables—we standardize all variables by subtracting the sample mean and dividing by the sample standard deviation. In the following sections, standardized variables are marked with the suffix *(std)*. All descriptive statics of the standardized variables are presented in Table 3.

In Table 3 we also present the number of *Unemployed* people over 1000 inhabitants

[3]For non-standarized descriptive statistcs of the variables please see Appendix B

for the years 2013 and 2017 (denoted by *_13, _17*, respectively), which will be used as a confounder in our final model specification.[4] In our analysis, any missing values (NA) are systematically replaced with zeros to maintain consistency across all variables and ensure a complete dataset for pre-processing and estimation.

Table 3: Descriptive Statistics for Standardized and Control Variables

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
Military Facilities_std	2056	0.000	1.000	-1.240	16.874
Residential Area_std	2056	0.000	1.000	-9.004	12.517
Industry and Commerce_std	2056	0.000	1.000	-0.669	12.141
Trade and Services_std	2056	0.000	1.000	-5.563	11.236
Sports Facilities_std	2056	0.000	1.000	-6.556	10.483
Leisure Facilities_std	2056	0.000	1.000	-3.076	2.472
Schools_cont_std	2056	0.000	1.000	-1.289	5.900
Apartments_cont_std	2056	0.000	1.000	-3.067	8.094
Residential Square Meters_cont_std	2056	0.000	1.000	-4.417	6.656
Churches_cont_std	2056	0.000	1.000	-7.047	9.819
unemployed_13_cont	2056	15.221	5.670	3.714	47.921
unemployed_17_cont	2056	13.186	4.712	2.714	37.473

For our replication efforts, we draw once again on the parliamentary enquiry mentioned above on refugee centers. Stecker and Debus report five additional centers, increasing the total capacity by 50 beds. These minor discrepancies stem from the undocumented aspects of their data collection process, which, according to their paper, included supplemental information from media sources and newspaper articles that are not cited. We provide a side-by-side summary of all refugee centers identified by our research and those reported by Stecker and Debus in Appendix B.

[4]Data for *Unemployment* can be found in Bayerisches Landesamt für Statistik (2025).

5 Methodology

The exact inner workings of the proposed model are to be discussed in this section, starting by replicating the Benchmark model estimation proposed by Stecker and Debus (2019). We then use the tree-based XGBoost algorithm to select exogenous variables that best predict whether a municipality hosted refugee centers during the 2015 crisis. This procedure is preferred over theory-based variable selection, as the field remains largely unexplored. Thereafter, we proceed with down-flow binary logit regression with the selected variables to construct an exogenous proxy for Stecker and Debus (2019) exposure measure. Once the exogenous proxy is computed, we make use of it in our final model specification to understand how exposure to refugees impacted support for AfD at the municipal level.[5]

5.1 Benchmark Model

As our analysis overlaps both in scope, level of aggregation, and employed exposure measure with the work of Stecker and Debus (2019), we start by replicating the benchmark model proposed in said paper. This model attempts to measure the effect of exposure to refugees on AfD voting patterns in small municipalities; it is specified in Equation 1 and is to be estimated via OLS.[6]

$$AfD\_win_d = \alpha + \beta \cdot RefCent_d + \varepsilon_d \tag{1}$$

AfD_win_d describes the change in AfD vote shares from the election year 2013 to the election year 2017 for municipality d in percentage points. This shift is regressed on $RefCent_d$, the binary exposure measure that proxies contacts with refugees, which takes value 1 if municipality d hosts at least one refugee center as of January 2016 and 0 otherwise.

A further replication attempt for the entire model is not deemed necessary at this point, as we propose to use an alternative model that specifically targets the shortcomings of this model as described in section 2. Therefore, instead of using the proposed controls, we present the specification given in Equation 9.

Similar to the paper of reference, we estimate the effect of the exposure to immigrants on AfD voting patterns for a range of different municipality sizes using this full model.

[5]Throughout our analysis, we use the commonly adopted random seed value of 42.

[6]By small municipalities all those municipalities are included that have less than six electoral precincts, with each precinct bearing no more than 2500 eligible voters.

5.2 Variable Selection Technique

To identify features that best predict whether a municipality hosts a refugee center, we use **eXtreme Gradient Boosting (XGBoost)**—a robust, high-performance machine learning algorithm that is particularly well-suited to our data. XGBoost is resilient to multicollinearity, handles missing values, and automatically learns nonlinearities and interactions.[7] The dataset is imbalanced, noisy, and features potential multicollinearity, all of which reduce the reliability of traditional linear models.[8] XGBoost addresses these challenges through its ensemble structure, regularization techniques, and flexibility in modeling complex patterns.

The tree-based model minimizes the following regularized loss function:

$$\mathcal{L} = \sum_{d=1}^{n} \ell(y_d, \hat{y}_d) + \sum_{k=1}^{K} \Omega(f_k), \tag{2}$$

where ℓ is the binary logistic loss (cross-entropy) as given in Equation 3, and Ω is a regularization term that penalizes the complexity of each tree f_k to prevent overfitting (see Equation 4).

$$\ell(y_d, \hat{y}_d) = -\left[y_d \log(\hat{y}_d) + (1 - y_d)\log(1 - \hat{y}_d)\right] \tag{3}$$

The logistic loss function is the negative log-likelihood of observing the true label given the model's predicted probability. It measures how well the predicted probability $\hat{y}_d$ aligns with the actual binary outcome $y_d \in \{0, 1\}$. When the prediction is close to the true label, the loss is small; when it is far off, the loss increases sharply.

$$\Omega(f_k) = \gamma T_k + \frac{1}{2}\lambda \sum_{j=1}^{T_k} w_{kj}^2 + \alpha \sum_{j=1}^{T_k} |w_{kj}| \tag{4}$$

The additional penalization term is closely related with the more standard Elastic Net penalization terms (Lasso and Ridge). It aims at reducing overfitting as well as multicollinearity while inducing sparsity. The first term (γT_k) reduces the number of leafs T in tree k. The second term is a modified Ridge term that targets excessive variance in the

[7]A full description of the algorithm is provided in Chen and Guestrin (2016), from which a brief summary is presented in Appendix C.

[8]Data imbalance refers to the unequal distribution of classes, with the proportion of positive to negative cases deviating substantially from 0.5. Noise is introduced by the inclusion of many non-exhaustive variables that may be measured with error.

weight distribution between different leafs j within the same tree k (w_{kj}^2). The last term is the Lasso based penalty ensuring the magnitude of the weight attributed to each leaf j within tree k to be kept at a minimum. α and λ are commonly known as the L1 and L2 regularization parameter respectively.[9]

To evaluate the performance of the binary classification model, we use the *Receiver Operating Characteristic – Area Under the Curve* (ROC AUC), which measures the model's ability to distinguish between classes. Intuitively, it represents the probability that a randomly selected positive instance is assigned a higher score than a randomly selected negative one. This makes it especially robust to class imbalance. ROC AUC is formally defined as:

$$\text{AUC} = \mathbb{P}\left(s(x^+) > s(x^-)\right), \tag{5}$$

where $s(x)$ is the model's scoring function, $x^+ \sim P_1$ is a randomly drawn positive instance, and $x^- \sim P_0$ is a randomly drawn negative instance.[10]

To tune model hyperparameters, we perform a grid search with cross-validation, optimizing for ROC AUC.

For feature selection, we employ **SHAP values**, as defined by Marcilio-Jr and Eler (2021), to decompose each prediction into additive, feature-level contributions. The SHAP framework attributes the prediction difference between the model output and a baseline to each input feature by computing its marginal contribution across all possible feature subsets. Mathematically, for a feature j, its SHAP value ϕ_j is defined as:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(p - |S| - 1)!}{p!} \left[f_{S \cup \{j\}}(\mathbf{x}_{S \cup \{j\}}) - f_S(\mathbf{x}_S) \right], \tag{6}$$

where $N = \{1, 2, \ldots, p\}$ is the set of all features, S is a subset excluding feature j, and $f_S(\mathbf{x}_S)$ denotes the model prediction based only on the features in S. The expression inside the summation represents the marginal contribution of j to S, while the weighting term accounts for all permutations of feature subsets. Although computing exact SHAP values is generally computationally expensive with complexity $O(2^p)$, we take advantage of the **TreeSHAP** algorithm, which efficiently computes exact SHAP values for tree-based models like XGBoost in polynomial time, specifically $O(T \cdot L \cdot D^2)$, where T is the number of

[9] Leaf weights in a binary XGBoost classifier are the optimal prediction scores assigned to each terminal leaf of a decision tree. For more information please refer to the Leaf Weight Formula paragraph in Appendix C.

[10] ROC AUC is threshold-independent. A further (mathematical) definition is provided in Appendix C.

trees, L is the maximum number of leaves, and D is the maximum tree depth. TreeSHAP leverages the model's structure to avoid exhaustive enumeration of feature subsets.

To interpret SHAP values, a positive ϕ_j indicates that feature j increases the prediction's log-odds ratio (i.e., increases the likelihood of a municipality hosting a refugee center), whereas a negative ϕ_j implies a decreasing effect. The absolute value $|\phi_j|$ reflects the strength of this influence. We rank features based on the average magnitude of their SHAP values and select the top k for further analysis in a downstream binary logit model. The optimal number of features k is determined through 5-fold cross-validation by maximizing the average ROC AUC score.[11]

5.3 Exposure Measurment Proxy

After filtering for the most explanatory features, we construct a binary logistic regression model to ensure interpretability. The dependent variable is the same binary indicator used during variable selection, indicating whether a municipality hosts at least one refugee center. The resulting estimated probability of a municipality hosting a center is shown in Equation 7. This model is estimated by means of maximum likelihood.

$$\hat{\mathbb{P}}(Y_d = 1|X_d) = \frac{1}{1 + exp(-X_d\hat{\beta})} \tag{7}$$

where we define $Y_d = 1$ as the municipality d that has the asylum center through the refugee crisis, and the $(n \times k)$ matrix X consists of the municipality's characteristics. Here, n is the total number of observations and k is the selected amount of features.

From now on *Proxy for Exposure* is defined as follows:

$$EM_d = \hat{\mathbb{P}}(Y_d = 1 \mid X_d) \tag{8}$$

5.4 Model Specification

To answer our research question, we specify the following model to investigate the potential causal relationship between the refugee crisis and electoral outcomes:

$$VS_{d,t} = \beta_0 + \beta_1 X_{d,t} + \beta_2 C_{d,t} + \alpha_d + \gamma_t + \epsilon_{d,t} \tag{9}$$

[11] 5-fold cross-validation partitions the data into five equally sized folds, training the model on four folds and validating on the fifth. This process is repeated across all folds, and the final score is averaged to ensure stability and generalizability of model performance.

We examine two election years, $t \in \{2013, 2017\}$, corresponding to the German federal elections. The dependent variable, $VS_{d,t}$, represents the AfD vote share in second votes in municipality d at time t.

The main explanatory variables are incorporated in the vector $X_{d,t}$, the main variable of interest is the *Proxy for Exposure* EM_d. To assess the post-crisis effect, we interact EM_d with a post-treatment indicator $Post_t$, equal to 1 in 2017 and 0 in 2013.

We also account for the spillover effects of refugee exposure by incorporating the mean values for EM_d of neighboring municipalities, $EMNeigh_d$, into the covariate vector $X_{d,t}$. When we operationalize this variable we interact it with the post-treatment dummy. The resulting interaction terms are labeled as EMP_d and as $EMNeighP_d$, respectively. The vector $C_{d,t}$ includes time- and municipality-specific control variables. Municipality fixed effects α_d capture time-invariant characteristics, while time fixed effects γ_t account for common temporal shocks. $\epsilon_{d,t}$ denotes the error term. The model is ultimately estimated using OLS to obtain the coefficients estimates, while it's error terms are estimated by means of wild bootstrapping, as explained in subsection 5.5.

Furthermore, we aim to assess whether the effect of the exposure varies across municipalities of different sizes. To this end, we group municipalities based on the number of electoral precincts, as each precinct is expected to encompass a comparable number of voters. By creating bins with a similar number of observations, we can better identify potential differences. We will then estimate the model within each group to examine possible variations in the effect of the exposure measure.

5.4.1 Turnout Analysis

As voters turnout is a decisive factor for election results, The initial decision to vote, can, in itself, be motivated by the political analysis of the individual. We wish to assess whether the exposure to asylum seekers was one of the causes of an increase of voter turnout in the 2017 elections compared to 2013. We will evaluate it via the equation:

$$T_{d,t} = \beta_0 + \beta_1 X_{d,t} + \beta_2 C_{d,t} + \alpha_d + \gamma_t + \epsilon_{d,t} \tag{10}$$

Where $T_{d,t}$ stands for Voters' turnout rate in municipality d in election year t. The equation follows the similar specification as the model to determine the AfD support in subsection 5.4.

The estimation of the regressions 10 and 9 is done using the Ordinary Least Squares method.

5.5 Bootstrap

Given the use of proxy variables and potential spatial heterogeneity in voting patterns, standard regression assumptions such as homoskedasticity and independence may not hold. While robust or clustered standard errors could address some of these violations, the use of estimated exposure measures introduces additional sampling uncertainty that cannot be fully captured by standard inferential procedures. To ensure valid inference under these conditions, we employ the wild bootstrapping resampling method to estimate standard errors. This method is particularly well-suited for models with generated regressors, heteroskedastic or spatially dependent errors, and measurement error, offering robust inference without relying on restrictive distributional assumptions (Davidson & MacKinnon, 2010).

6 Results

6.1 Benchmark Model

The regression outcome described in subsection 5.1 is shown in Table 6.1. This table presents the estimation results for our dataset in column (1) and the results reported by Stecker and Debus (2019) in column (2). As expected, due to minor differences in our dataset and the use of different software (Python in our case versus R in theirs) slight differences in parameter estimates and standard errors are observable. Nevertheless, the results demonstrate that our data successfully reproduces the findings of the original paper. For illustration, we also replicate the map showing the percentage point increase in AfD vote share between the 2013 and 2017 federal elections (see Figure 6.1).

Table 6.1: OLS Regression Predicting AfD Vote Share

Variable	**(1)**	**(2)**
(Intercept)	9.2632***	9.250***
	(0.109)	(0.109)
Refugee center	1.8855***	1.928***
	(0.542)	(0.526)
Observations	1,216	1,215
R-squared	0.010	0.011
F-statistic	12.10	13.453
Prob(F)	0.0005	0.000

Note. Standard errors in parentheses.
$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$
Model (1) uses our data; Model (2) replicates Stecker and Debus (2019).

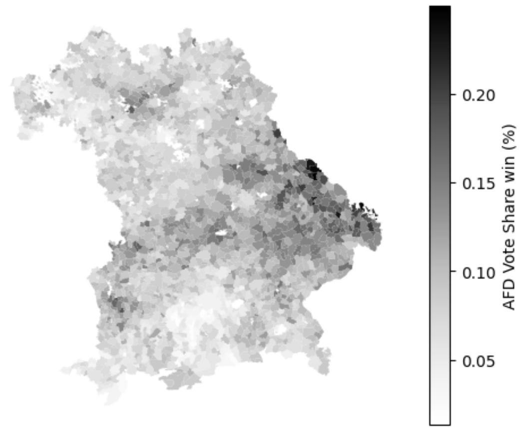


Figure 6.1: AfD vote share gain, 2013–2017

6.2 Variable Selection

After tuning[12] and training the XGBoost on the full set of variables, we obtain the feature importance ranking as presented in Table 4 through the TreeSHAP algorithm. The table contains the SHAP values for ten variables ranked by explanatory power. The values shown in this table correspond with the mean magnitude of the SHAP values for each feature, e.g., the impact that the standardized apartments per 1000 inhabitants measure has on the log-odds ratio is on average 0.5687 in magnitude. Since the log-odds ratio is the logarithm of the probability of hosting a refugee center over the probability of not hosting a refugee center, these measures are not bound by an upper bound, and can therefore not be used for significance testing.

[12]The exact tuning procedure and its resulting parameter values are reported in Appendix D.

Table 4: All 10 Features Ranked by SHAP Importance

Feature	**Mean SHAP Value**
Apartments_cont_std	0.5687
Trade and Services_std	0.5211
Industry and Commerce_std	0.4524
Residential Square Meters_cont_std	0.3713
Schools_cont_std	0.2763
Residential Area_std	0.2003
Churches_cont_std	0.1637
Leisure Facilities_std	0.1420
Sports Facilities_std	0.1350
Military Facilities_std	0.0045

The resulting 5-fold cross-validation run on the down-stream binary logit model is summarized in Figure 2. It shows the average ROC AUC values plotted against the number of features included according to the rankings provided as shown in the tables above.

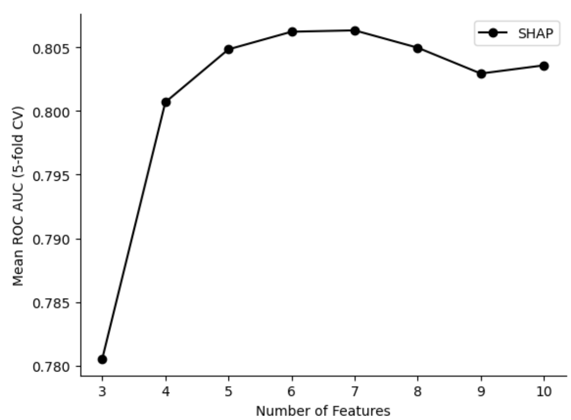


Figure 2: Cross-validation results in terms of mean ROC AUC scores for different subsets of variables included in the binary logit model

By the given ROC AUC scores, the set of the first seven features results in the highest obtainable ROC AUC value of 0.8063. Hence, selecting the best seven features will result in the model with the highest predictive power for any given threshold. This is why we include the first seven variables of the list above (Table 4).

6.3 Exposure Measurement (EM)

In this section, we interpret the binary logistic model in which the dependent variable indicates the presence of a refugee center in a municipality, and the predictors are standardized exposure measures selected in subsection 6.2. The logistic regression results are summarized in Table 5. Notably, among the explanatory variables, only *Trade and Services* and *Residential Area* are statistically insignificant even at the 10% level.

We interpret the model in terms of the sign and magnitude of coefficients. In particular a positive coefficient means that an increase in the corresponding variable leads to a higher probability of presence of a refugee center. While there is no straightforward interpretation of the magnitude, as the marginal effect depends on the value of the variable. Coefficients with larger magnitudes tend to induce greater changes in the predicted probability, as they exert a stronger influence on the log-odds.

The variable *Apartments* exhibits the largest significant positive coefficient, indicating that a one standard deviation increase in this variable is associated with the greatest rise in the predicted probability. This variable can be interpreted as a proxy for unused housing capacity, which may be available for accommodating refugees. Accordingly, it is intuitive that higher values increase the likelihood of a municipality hosting a refugee center. Furthermore, the observation that apartments are more typically encountered in cities rather than smaller villages can hint at the fact that it is more likely to encounter a refugee center in an urban hub.

Additionally, the variables *Schools* and *Industry and Commerce* have very similar significant positive estimates. This implies that a one standard deviation increase in the number of schools per 1,000 inhabitants, or in the share of land used for industrial and commercial purposes, is associated with a comparable increase in the predicted probability of hosting a refugee center. These variables may serve as proxies for local infrastructure and economic capacity, suggesting that municipalities with better-developed services and economic activity are more likely to be selected for refugee accommodation. This can be driven back to both the resulting larger abundance of economic means needed to sustain refugee centers, and the larger physical capacity available to host these centers.

The variables *Residential Square Meters* and *Churches* exhibit significant negative coefficients. Among them, a one standard deviation increase in residential square meters per 1,000 inhabitants appears to be associated with a larger decrease in the predicted probability than a similar increase in the number of churches. Higher values of residential space per capita are often indicative of more rural settings, where households tend to have more living space compared to denser urban areas. These findings are in line with the earlier hypothesis that asylum centers may have been more commonly located in larger or medium-sized cities, where average residential space per inhabitant is lower. Similarly, the number of churches per 1000 inhabitants is also negatively correlated with city size in terms of inhabitants. Thus a similar logic applies.

Table 5: Binary Logistic Regression Predicting Refugee Center Presence

Feature	**Coefficient (SE)**
Intercept	-2.4276^{***}
	(0.0921)
Apartments_cont_std	0.8789^{***}
	(0.0819)
Trade and Services_std	0.0627
	(0.0841)
Industry and Commerce_std	0.2197^{**}
	(0.0722)
Residential Square Meters_cont_std	-0.7786^{***}
	(0.0915)
Schools_cont_std	0.2498^{**}
	(0.0804)
Residential Area_std	-0.1172
	(0.0943)
Churches_cont_std	-0.2229^{*}
	(0.1055)

Note. Standard errors in parentheses.
$^{\cdot}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

6.4 Model Specification

We now analyse the effects estimated in our main model, as described in subsection 5.4. The results are presented in Table 6, which summarizes the findings for each of the four selected specifications. All standard errors are wild bootstrap estimates based on 1,000 iterations.

The results consistently indicate a negative effect of proxied exposure to asylum seekers on the AfD's vote share. Since our proxy of the exposure measure reflects the percentage-point probability of a municipality hosting a refugee center, a one percentage point increase in this probability is associated with an approximate -0.0342 percentage point decrease in AfD vote share in 2017. When we control for unemployment in the municipality, this effect becomes even stronger, with an estimated change of -0.0358 percentage points per one percentage point increase in exposure probability.

Furthermore, we analyze the potential spillover effects from neighboring municipalities. Here too, we observe a negative relationship with AfD support. Notably, the magnitude of the spillover effect is larger than the within-municipality effect, with estimates of -0.0921 compared to -0.0081. This suggests that residents may respond more strongly to developments in the broader local area than to conditions within their own municipality alone. A similar pattern holds when controlling for unemployment, confirming the significance of the spillover effect.

Table 6: Two-Way Fixed Effects Regression of AfD share

Feature	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	9.2425^{***}	8.7862^{***}	10.2582^{***}	9.7935^{***}
	(0.0407)	(0.0333)	(0.2537)	(0.2626)
EMP	-0.0081^{**}	-0.0342^{***}	-0.0099^{**}	-0.0358^{***}
	(0.0032)	(0.0031)	(0.0033)	(0.0033)
EMNeighP	-0.0921^{***}		-0.0921^{***}	
	(0.0051)		(0.0054)	
Unemployed			-0.0707^{***}	-0.0703^{***}
			(0.0176)	(0.0180)

Note. Wild bootstrap standard errors in parentheses, calculated with 1000 iterations
$^{\cdot}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

The stronger effect of neighboring exposure may be attributed to both social and methodological factors. Socially, individuals might be more responsive to broader regional dynamics and public sentiment than to direct, personal contact with refugees. Methodologically, the neighboring exposure variable, calculated as an average across adjacent municipalities—tends to be more stable and less prone to random variation, which can lead to a more robust association with voting patterns.

On another note, we analyze whether the effect of our proxy for exposure varies with the size of a municipality. The results of the urban vs. non-urban comparison, as well as a comparison with the findings of Stecker and Debus (2019), are presented in the Appendix subsection D.2. For this analysis, municipalities were grouped by the number of electoral precincts, which serves as a proxy for municipality size. The corresponding regression results are shown in Table 7.

We find that as the number of precincts increases, the effect of exposure to asylum seekers on AfD support decreases, while remaining statistically significant. This pattern may be explained by the fact that in smaller municipalities, the presence of a refugee center has a more noticeable impact on residents' daily lives, increasing the likelihood of direct contact. According to the Intergroup Contact Theory (ICT), such interactions can foster more positive attitudes toward refugees, ultimately reducing support for radical anti-immigrant parties. In contrast, in larger municipalities, individuals may be less likely to encounter asylum seekers due to greater physical and social distance—for example, if asylum seekers are concentrated in specific neighborhoods. The size of the negative effect diminishes with increasing municipality size, reaching a -0.0214 percentage point decrease in AfD support per 1% increase in exposure likelihood in the largest bin.

Table 7: Regression Results by Binned Values of the Effect of Exposure Measure on AfD Support

Statistic	**Bin 0**	**Bin 1**	**Bin 2**	**Bin 3**	**Bin 4**	**Bin 5**
EMP	-0.0815^{***}	-0.0608^{**}	-0.0511^{***}	-0.0353^{**}	-0.0392^{***}	-0.0214^{***}
(SE)	(0.0155)	(0.0206)	(0.0142)	(0.0122)	(0.0090)	(0.0048)
Observations	776	738	560	846	548	644
Bin Edges	[1.0, 2.0]	(2.0, 3.0]	(3.0, 4.0]	(4.0, 7.0]	(7.0, 11.0]	(11.0, 942.0]

Note. Wild bootstrap standard errors in parentheses calculated with 1000 iterations
$^{\cdot}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

6.4.1 Turnout Analysis

Similarly, we present the results of the analysis of voter turnout in Table 8. The proxy for exposure does not appear to have a statistically significant effect on the willingness to vote. Moreover, the magnitude of the coefficient is notably small: even at the maximum possible level of exposure (i.e., 100%), the predicted increase in turnout would amount to only 0.13 percentage points.

Additionally, we find that higher levels of unemployment within a municipality are associated with a statistically significant decrease in voter turnout. However, the size of the effect remains modest, with a one percentage point increase in unemployment corresponding to a -0.0525 percentage point change in turnout.

Taken together, these results suggest that any potential effect of exposure to asylum seekers on voter turnout is marginal. The observed variation in participation is more likely driven by other underlying factors. Further analysis of voter turnout is provided in the Appendix subsection D.3.

Table 8: Comparison of Turnout Regressions (Wild Bootstrap SE)

Variable	Model 1	Model 2
Intercept	75.984***	76.7365***
	(0.0214)	(0.1709)
EMP	0.0025	0.0013
	(0.0019)	(0.0019)
Unemployed	—	−0.0525***
		(0.0118)

Note. Wild bootstrap standard errors in parentheses calculated with 1000 iterations.
˙p < .1, *p < .05, **p < .01, ***p < .001

7 Discussion

Our findings contradict our initial hypotheses regarding both political outcomes and voter turnout. Specifically, the consistently negative effect of our proxy for refugee exposure on AfD vote share challenges expectations derived from Threat Theory. Instead, our results partially align with Intergroup Contact Theory: while Allport's ideal conditions for positive contact are likely not met during the 2015 crisis, exposure appears to foster familiarity rather than fear.

This effect is most pronounced in smaller municipalities, where contact is likely more frequent and visible, supporting the notion that local context shapes how exposure translates into political behavior.

Empirically, our results are consistent with studies such as Pettrachin et al. (2023) and Schaub et al. (2021), who also find a dampening effect of refugee presence on far-right support. Unlike Stecker and Debus (2019), who rely on potentially endogenous refugee placement, our approach uses pre-crisis exogenous characteristics. This key difference, together with other methodological discrepancies, likely explains their contrasting finding of a positive effect on AfD vote share.

Taken together, our findings suggest that the rise of the far right during the refugee crisis was not primarily driven by direct local exposure to asylum seekers. Instead, voter behavior appears to have been more strongly shaped by broader influences—such as national narratives and overarching socio-economic concerns. As highlighted in the literature, refugees were often portrayed as a threat in mainstream media, which may have influenced public attitudes even in municipalities with minimal or no direct contact.

While our findings offer valuable insights, several limitations affect the generalizability and reliability of our results.

First, we lack access to comprehensive data on refugee centers. Our dataset only captures facilities operational at the start of 2016, missing dynamic information from the rapidly evolving situation in 2015—including duration of the operations and actual occupancy over time. Additionally, many refugees are housed in private or other decentralized accommodations not included in our data. As a result, our exposure proxy remains incomplete, and the omission of certain centers likely weakens its validity.

Building on this, although our dataset includes information on center capacities, we are unable to construct a reliable continuous exposure proxy. While incorporating total capacity would allow for a more precise measure of exposure, the predictive strength of our exogenous variables is insufficient to support this approach.

Methodologically, our model does not disentangle the mechanisms behind voting changes. It does not distinguish between protest voting, changes in turnout, or vote switching across parties. This limits our ability to interpret the political pathways through which exposure affects outcomes.

We also face class imbalance in our data: most municipalities do not host a refugee center. This causes both XGBoost and the binary logit model to over-estimate the majority class, leading to unstable out-of-sample predictions. As a result, we rely on in-sample performance to select the exogenous variables that hold the highest explanatory power when building our proxy, limiting external validation.

Moreover, the modeling choice we make to build our proxy involves trade-offs. While a non-linear logit model offers higher predictive accuracy, it reduces interpretability. For clarity, we ultimately opt for a linear specification.

Future research can address these limitations by using richer infrastructural data and more detailed information on refugee center presence, capacity, and operation. A strong proxy for a continuous exposure measure could improve precision. Additionally, modeling voting behavior as a two-stage process—first the decision to vote, then the choice of party—could help uncover the distinct channels through which refugee exposure influences electoral outcomes.

Despite these limitations, the methods we develop for constructing an exogenous proxy for exposure to the refugee crisis can potentially be generalized beyond Bavaria. Similar analyses can be conducted in other regions or applied at a larger scale—such as contrasting eastern and western Germany—provided the political systems and contextual factors are sufficiently comparable.

8 Conclusion

In this paper, we set out to investigate the relationship between the 2015 refugee crisis and the rise of the right-wing party, *Alternative für Deutschland* (AfD), in Bavaria. Our research question asks: *To what extent does the 2015 refugee crisis contribute to the increase in AfD votes in Bavaria?*

To address this, we construct a novel, exogenous proxy for refugee exposure, defined as the estimated probability of interaction with asylum seekers. This estimated probability is based on pre-crisis municipal characteristics, particularly infrastructural variables. We estimate this proxy by first using an XGBoost classifier to select the most relevant infrastructural variables, followed by a binary logistic regression to model the probability of hosting a refugee center using the selected variables.

Our main empirical strategy employs a linear model comprising two types of fixed effects, controls for unemployment, and interacts our proxy with a post-crisis dummy to estimate its effect on two electoral outcomes: AfD vote share and voter turnout. Contrary to our initial hypothesis, which anticipates a positive relationship based on Threat Theory, we find that greater exposure to asylum seekers is associated with a statistically significant **decrease** in AfD vote share. This effect persists even when accounting for neighboring municipalities' exposure, where we observe an even stronger negative spillover effect.

Furthermore, we find no meaningful relationship between exposure and voter turnout, suggesting that the refugee crisis does not significantly mobilize or demobilize voters overall.

Moreover, we explore heterogeneous effects based on municipality size. The negative effect of exposure is strongest in the smallest municipalities and diminishes in magnitude as size increases. We posit that in smaller communities, where interactions with refugees are more likely and salient, contact may play a greater role in reducing prejudice and support for radical right-wing parties. This is likely rooted in the closer day to day contact experienced by inhabitants of those smaller communities.

Our findings partially align with the Contact Theory framework and contradict widespread assumptions that refugee presence necessarily fuels far-right support. The rise of the AfD in Bavaria appears to reflect broader national political trends rather than localized reactions to refugee placements.

In conclusion, while the 2015 refugee crisis undoubtedly reshapes the political landscape, our analysis suggests that local exposure to asylum seekers dampens, rather than fuels, support for the AfD. Future research can build on our approach by incorporating richer infrastructural data and more detailed records on refugee center capacity and operations, enabling the construction of a proxy for a continuous exposure measure. Moreover, adopting a two-stage modeling framework can help clarify the mechanisms through which refugee exposure influences electoral outcomes—whether by affecting voter turnout, party preferences, or both.

AI Use Statement

Generative artificial intelligence (AI) was utilized in the preparation of this scientific work. All data have been processed in accordance with the regulations of the Seminar Econometrics for Health and Society. As the authors, we take full responsibility for the content, claims, and references presented in this document. A detailed overview of how generative AI was employed is provided below:

- The text was revised using AI tools to enhance readability and ensure consistency in tone and style.
- AI was used to enhance efficiency in the Python/R code necessary for the data analysis.
- AI systems assisted in brainstorming and identifying potential papers, ideas and statistical techniques relevant for our research.

References

Albarosa, E., & Elsner, B. (2022, January). *Forced migration, social cohesion and conflict: The 2015 refugee inflow in germany* (Policy Research Working Paper No. 9913). World Bank. https://documents1.worldbank.org/curated/en/830181643248457941/pdf/Forced-Migration-Social-Cohesion-and-Conflict-The-2015-Refugee-Inflow-in-Germany.pdf

Allport, G. W. (1954). *The nature of prejudice*. Addison-Wesley.

Alternative für Deutschland. (2021). AfD – Die Partei [[Online; accessed 7-April-2025]]. https://web.archive.org/web/20211029212613/https://www.afd.de/partei/

Arzheimer, K., & Berning, C. C. (2019). How the alternative for germany (afd) and their voters veered to the radical right, 2013–2017. *Electoral Studies*, *60*, 102040.

Asylum act [Accessed: 7 April 2025]. (n.d.).

Barilari, F., Bellucci, D., Conzo, P., & Zotti, R. (2025). The political effects of (mis)perceived immigration. *Journal of Economic Geography*, 1–21. https://doi.org/10.1093/jeg/lbaf003

Barone, G., D'Ignazio, A., De Blasio, G., & Naticchioni, P. (2016). Mr. rossi, mr. hu and politics. the role of immigration in shaping natives' voting behavior. *Journal of Public Economics*, *136*, 1–13.

Bayerisches Landesamt für Statistik. (2025). Genesis-online: Bayerisches landesamt für statistik [Accessed April 14, 2025].

Bierbach, M. (2017). Afd, cdu, spd: Where do german parties stand on refugees, asylum, and immigration? [[Online; accessed 7-April-2025]]. https://www.dw.com/en/afd-cdu-spd-where-do-german-parties-stand-on-refugees-asylum-and-immigration/a-40610988

Blumer, H. (1958). Race prejudice as a sense of group position. *Pacific sociological review*, *1*(1), 3–7.

Bundeswehr. (2013). Bundeswehr official information portal (archived version) [Accessed April 14, 2025]. https://web.archive.org/web/20130608160720/https://www.bundeswehr.de/portal/a/bwde/!ut/p/c4/HYtBDoAgDATf4gfo3Zu_UC-m6IoNpBoo-n3R7GEymSzN1KZ8S2CTUznRSNMqvX-cfza4YhliMTN2g1PUgGKcrGpo7f8I8mfK67H4qhtKYjRkpS

Bundeszentrale für politische Bildung. (2025). Bündnis 90/Die Grünen [[Online; accessed 7-April-2025]]. https://www.bpb.de/themen/parteien/wer-steht-zur-wahl/baden-wuerttemberg-2021/326189/buendnis-90-die-gruenen/

Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16)*, 785–794. https://doi.org/10.1145/2939672.2939785

Czymara, C. S., & Dochow, S. (2018). Mass media and concerns about immigration in germany in the 21st century: Individual-level evidence over 15 years. *European Sociological Review*, *34*(4), 381–401.

Davidson, R., & MacKinnon, J. G. (2010). Wild bootstrap tests for iv regression. *Journal of Business & Economic Statistics*, *28*(1), 128–144.

De Coninck, D., Rodríguez-de-Dios, I., & d'Haenens, L. (2021). The contact hypothesis during the european refugee crisis: Relating quality and quantity of (in) direct intergroup contact to attitudes towards refugees. *Group Processes & Intergroup Relations*, *24*(6), 881–901.

Delcker, J. (2016, August). The phrase that haunts angela merkel [Accessed: 2025-04-11]. https://www.politico.eu/article/the-phrase-that-haunts-angela-merkel/

Deutsche Welle. (2015). German police investigate anti-foreigner motive in bavaria fire. *Deutsche Welle*. https://www.dw.com/en/german-police-investigate-anti-foreigner-motive-in-bavaria-fire/a-18941130

Diestelmann, E. (2015, July 27). *Mainstockheim: Flüchtlingsunterkunft in Bayern wird geräumt*. Retrieved April 11, 2025, from https://www.zeit.de/gesellschaft/zeitgeschehen/2015-07/mainstockheim-fluechtlingsunterkunft-geraeumt

Dinas, E., Matakos, K., Xefteris, D., & Hangartner, D. (2019). Waking up the golden dawn: Does exposure to the refugee crisis increase support for extreme-right parties? *Political analysis*, *27*(2), 244–254.

Duitsland Instituut. (2025). Die Linke [[Online; accessed 7-April-2025]]. https://duitslandinstituut.nl/naslagwerk/192/die-linke

Dustmann, C., Vasiljeva, K., & Piil Damm, A. (2019). Refugee migration and electoral outcomes. *The Review of Economic Studies*, *86*(5), 2035–2091.

Fachinger, T., Hoffmeyer-Zlotnik, P., & Stiller, M. (2024). Freedom of movement [Accessed: 2025-04-06]. https://asylumineurope.org/reports/country/germany/reception-conditions/access-and-forms-reception-conditions/freedom-movement/

Federal Election Commissioner. (2025a). Erststimme (First Vote) [[Online; accessed 7-April-2025]]. https://www.bundeswahlleiterin.de/en/service/glossar/e/erststimme.html

Federal Election Commissioner. (2025b). Sainte-Laguë/Schepers [[Online; accessed 7-April-2025]]. https://www.bundeswahlleiterin.de/en/service/glossar/s/sainte-lague-schepers.html

Federal Election Commissioner. (2025c). Überhangmandate (Overhang Seats) [[Online; accessed 7-April-2025]]. https://www.bundeswahlleiterin.de/en/service/glossar/u/ueberhangmandate.html

Federal Election Commissioner. (2025d). Zweitstimme (Second Vote) [[Online; accessed 7-April-2025]]. https://www.bundeswahlleiterin.de/en/service/glossar/z/zweitstimme.html

Federal Ministry of the Interior, G. (2016). Asylum act (asylgesetz) [Translation provided by the Language Service of the Federal Ministry of the Interior. Version includes amendments up to Article 2 of the Act of 11 March 2016 (Federal Law Gazette I, p. 394).]. https://www.gesetze-im-internet.de/englisch_asylvfg/englisch_asylvfg.html

Federal Ministry of the Interior, Building and Community. (2021). Federal Elections Act (Bundeswahlgesetz) [[Online; accessed 7-April-2025]]. https://www.bundeswahlleiterin.de/en/dam/jcr/4ff317c1-041f-4ba7-bbbf-1e5dc45097b3/bundeswahlgesetz_engl.pdf

Federal Office for Migration and Refugees (BAMF). (2022). Initial distribution of asylum seekers (easy) [Accessed: 2025-04-06]. https://www.bamf.de/EN/Themen/AsylFluechtlingsschutz/AblaufAsylverfahrens/Erstverteilung/erstverteilung-node.html

Fisunoğlu, A., & Sert, D. Ş. (2019). Refugees and elections: The effects of syrians on voting behavior in turkey. *International Migration*, *57*(2), 298–312.

Galpin, C. (2017). *The euro crisis and european identities: Political and media discourse in germany, ireland and poland*. Springer.

Google. (2025). *Google maps platform* [Accessed: April 7, 2025]. https://developers.google.com/maps

Green, D. P., Palmquist, B., & Schickler, E. (2004). *Partisan hearts and minds: Political parties and the social identities of voters*. Yale University Press.

Grün, G.-C., & Zeier, K. (2025, February). *German election results explained in graphics* [Accessed: 2025-04-21]. https://www.dw.com/en/german-election-results-explained-in-graphics/a-71724186

Halla, M., Wagner, A. F., & Zweimüller, J. (2017). Immigration and voting for the far right. *Journal of the European economic association*, *15*(6), 1341–1385.

Havertz, R. (2021). *Radical right populism in germany: Afd, pegida, and the identitarian movement*. Routledge.

Holzberg, B., Kolbe, K., & Zaborowski, R. (2018). Figures of crisis: The delineation of (un) deserving refugees in the german media. *Sociology*, *52*(3), 534–550.

Indelicato, A., Martín, J. C., & Scuderi, R. (2023). A comparison of attitudes towards immigrants from the perspective of the political party vote. *Heliyon*, *9*(3).

Jäckle, S., Wagschal, U., & Kattler, A. (2018). Distanz zur grenze als indikator für den erfolg der afd bei der bundestagswahl 2017 in bayern? *Zeitschrift für Vergleichende Politikwissenschaft: Comparative Governance and Politics*, *12*(3), 539–566.

Knight, B. (2021). Germany's green party and the fdp: Two kingmakers poles apart [[Online; accessed 7-April-2025]]. *DW News*. https://www.dw.com/en/germanys-green-party-and-the-fdp-two-kingmakers-poles-apart/a-59329828

Knight, Ben. (2018). Germany's political crisis over asylum: What happens now? [[Online; accessed 7-April-2025]]. https://www.dw.com/en/germanys-political-crisis-over-asylum-what-happens-now/a-44242973

Lowe, M. (2021). Types of contact: A field experiment on collaborative and adversarial caste integration. *American Economic Review*, *111*(6), 1807–1844.

Marcilio-Jr, W. E., & Eler, D. M. (2021). From explanations to feature selection: Assessing shap values as feature selection mechanism [Available at: https://github.com/wilsonjr/SHAP-FSelection]. *Proceedings of the 30th International Conference on Artificial Neural Networks (ICANN)*.

Pettigrew, T. F. (1998). Intergroup contact theory. *Annual review of psychology*, *49*(1), 65–85.

Pettrachin, A., Gabrielli, L., Kim, J., Ludwig-Dehm, S., & Pötzschke, S. (2023). Did exposure to asylum seeking migration affect the electoral outcome of the 'alternative für deutschland'in berlin? evidence from the 2019 european elections. *Journal of Ethnic and Migration Studies*, *49*(2), 576–600.

Rinderspacher, M. (2015, November 26). Schriftliche Anfrage: Flüchtlingsunterbringung in bayerischen Gemeinden, Landkreisen und Bezirken [Bayerischer Landtag, 17. Wahlperiode, Drucksache 17/9998]. https://www.bayern.landtag.de

Rozo, S., & Vargas, J. F. (2020). The effect of venezuelan migration on educational outcomes in colombia.

Schaub, M., Gereke, J., & Baldassarri, D. (2021). Strangers in hostile lands: Exposure to refugees and right-wing support in germany's eastern regions. *Comparative Political Studies*, *54*(3-4), 686–717.

Schmid, A., & Green, M. (2017). Case study 6: Civil society and the refugee crisis in germany 2015/16. In S. L. Greer, M. Wismar, G. Pastorino, & M. Kosinska (Eds.), *Civil society and health: Contributions and potential* (pp. 156–180). World Health Organization, Regional Office for Europe. https://www.researchgate.net/publication/320056805_Civil_Society_and_the_Refugee_Crisis_in_Germany_201516

Schulze, K. (2015, October). Schriftliche anfrage der abgeordneten katharina schulze bündnis 90/die grünen vom 19.10.2015: Rechtsextreme prägung von pegida münchen. https://www1.bayern.landtag.de/www/ElanTextAblage_WP17/Drucksachen/Schriftliche%20Anfragen/17_0009185.pdf

Social Democratic Party of Germany. (2007). Hamburg Programme [[Online; accessed 7-April-2025]]. https://www.spd.de/fileadmin/Dokumente/Beschluesse/Grundsatzprogramme/hamburger_programm_englisch.pdf

Sola, A. (2018). The 2015 refugee crisis in germany: Concerns about immigration and populism.

Staff, C. (2013). Germany coalition: Angela merkel agrees to form government after talks [[Online; accessed 8-April-2025]]. https://edition.cnn.com/2013/11/27/world/europe/germany-coalition/index.html

Statistisches Bundesamt (Destatis). (2025). GENESIS-Online regional database [Accessed April 11, 2025]. https://www.regionalstatistik.de/genesis/online

Stecker, C., & Debus, M. (2019). Refugees welcome? zum einfluss der flüchtlingsunterbringung auf den wahlerfolg der afd bei der bundestagswahl 2017 in bayern. *Politische Vierteljahresschrift*, *60*(2), 299–323. https://doi.org/10.1007/s11615-019-00151-3

Steinmayr, A. (2021). Contact versus exposure: Refugee presence and voting for the far right. *Review of Economics and Statistics*, *103*(2), 310–327.

The Editors of Encyclopaedia Britannica. (2025). Plurality system [[Online; accessed 7-April-2025]]. https://www.britannica.com/topic/plurality-system

A Literature Review Appendix

Types of refugee centers and their functions summarized:

AE **Reception Center (Aufnahmeeinrichtung)** – The first place of accommodation for asylum seekers, where registration and initial processing take place.

ÜAE **Transitional Reception Center (Übergangsaufnahmeeinrichtung)** – Temporary housing for asylum seekers after initial registration, before they are assigned to longer-term facilities.

ARE **Reception and Return Center (Aufnahme- und Rückführungseinrichtung)** – Facilities for accelerated asylum procedures, often used for people from safe countries of origin, with preparation for potential return.

DP **Satellite Facility (Dependance)** – An annex or external branch of a main reception center, used to increase capacity or decentralize accommodation.

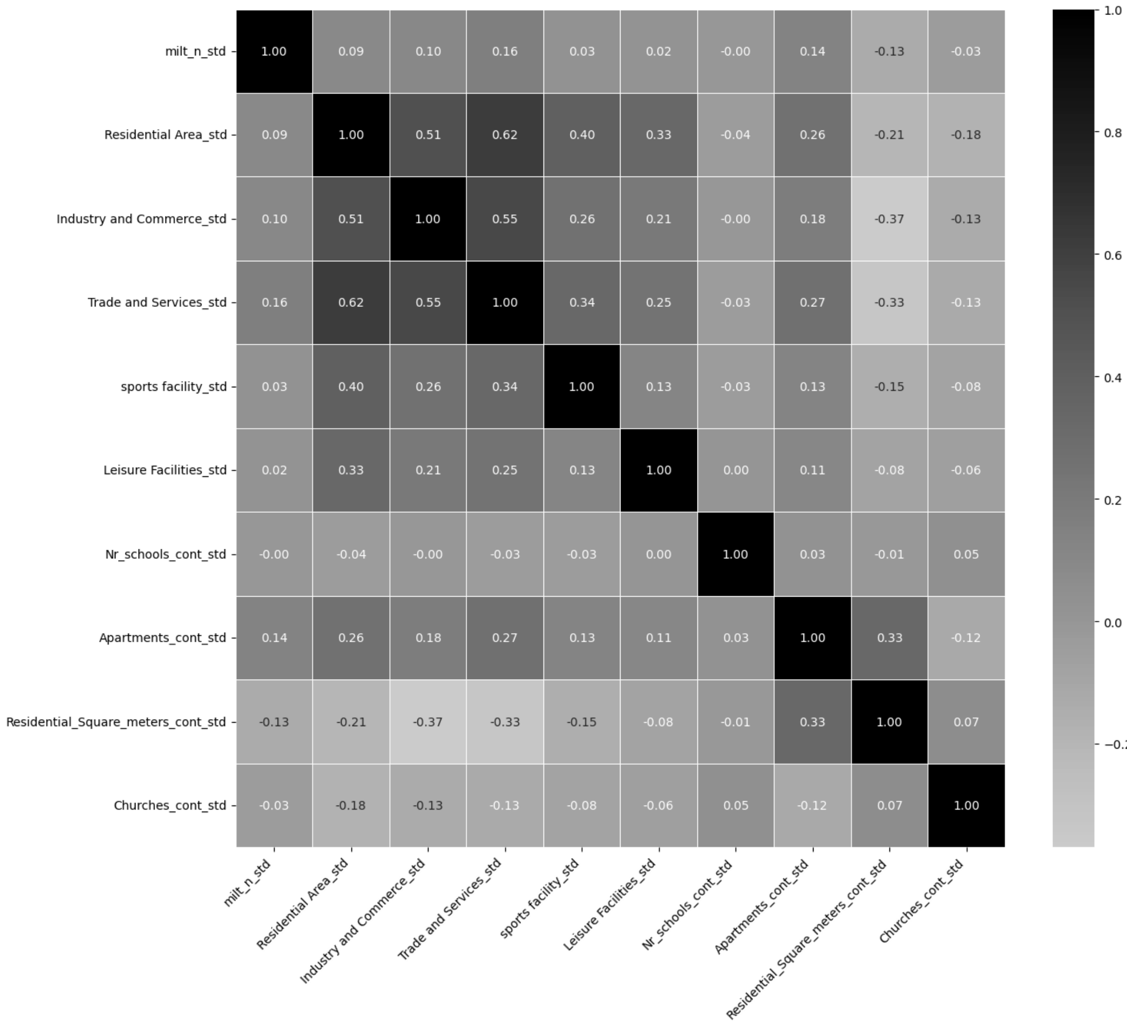
NAE **Emergency Reception Center (Notaufnahmeeinrichtung)** – Quickly established housing used during capacity shortages, often in temporary structures.

GU **Collective Accommodation (Gemeinschaftsunterkunft)** – Shared housing where multiple asylum seekers live together during the asylum process, usually after the initial phase.

TGU **Decentralized Collective Housing (Dezentrale Gemeinschaftsunterkunft)** – Smaller, more integrated forms of group housing, often in apartments or repurposed buildings.

ZAE **Central Reception Center (Zentrale Aufnahmeeinrichtung)** – A larger state-run center used for centralized intake and distribution of asylum seekers.

B Data Appendix



	milt_n_std	Residential Area_std	Industry and Commerce_std	Trade and Services_std	sports facility_std	Leisure Facilities_std	Nr_schools_cont_std	Apartments_cont_std	Residential_Square_meters_cont_std	Churches_cont_std
milt_n_std	1.00	0.09	0.10	0.16	0.03	0.02	-0.00	0.14	-0.13	-0.03
Residential Area_std	0.09	1.00	0.51	0.62	0.40	0.33	-0.04	0.26	-0.21	-0.18
Industry and Commerce_std	0.10	0.51	1.00	0.55	0.26	0.21	-0.00	0.18	-0.37	-0.13
Trade and Services_std	0.16	0.62	0.55	1.00	0.34	0.25	-0.03	0.27	-0.33	-0.13
sports facility_std	0.03	0.40	0.26	0.34	1.00	0.13	-0.03	0.13	-0.15	-0.08
Leisure Facilities_std	0.02	0.33	0.21	0.25	0.13	1.00	0.00	0.11	-0.08	-0.06
Nr_schools_cont_std	-0.00	-0.04	-0.00	-0.03	-0.03	0.00	1.00	0.03	-0.01	0.05
Apartments_cont_std	0.14	0.26	0.18	0.27	0.13	0.11	0.03	1.00	0.33	-0.12
Residential_Square_meters_cont_std	-0.13	-0.21	-0.37	-0.33	-0.15	-0.08	-0.01	0.33	1.00	0.07
Churches_cont_std	-0.03	-0.18	-0.13	-0.13	-0.08	-0.06	0.05	-0.12	0.07	1.00

Figure 3: Correlation matrix of all considered variables prior to feature selection (color coded in gray scale)

Table 9: Descriptive Statistics for Key Variables

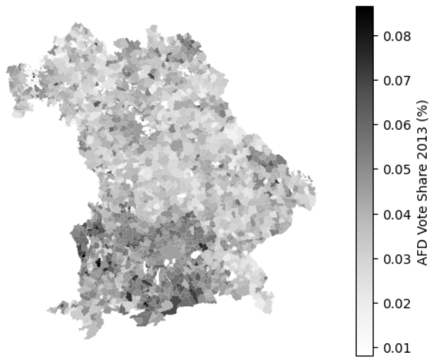
Variable	**N**	**Mean**	**SD**	**Min**	**Max**
Military Facilities	38	1.184	0.563	1.000	3.000
Schools	1582	2.908	10.003	1.000	339.000
Apartments	2056	3020.54	18907.80	98.000	772878.00
Residential Square Meters	2056	293249.2	1387977.0	11134.0	55715110.0
Churches	1216	1.807	2.480	1.000	58.000
Industry and Commerce	2056	0.690	1.039	0.000	13.306
Leisure Facilities	2056	0.048	0.156	0.000	3.897
Sports Facilities	2056	0.404	0.616	0.000	6.863
Residential Area	2056	3.546	3.785	0.138	50.920
Trade and Services	2056	0.323	0.580	0.000	6.845
Total Area	2056	3319.77	2553.21	138.910	31070.58
Total population	2056	6172.94	34969.51	225.000	1429584.0
unemployed_13	2056	128.70	1040.90	3.000	39778.00
unemployed_17	2056	112.53	914.78	2.000	35718.00

Note. The surface in use for *Industry and Commerce*, *Leisure Facilities*, *Sports Facilities*, *Residential Area*, and *Total Area* are all given in hectares (ha).

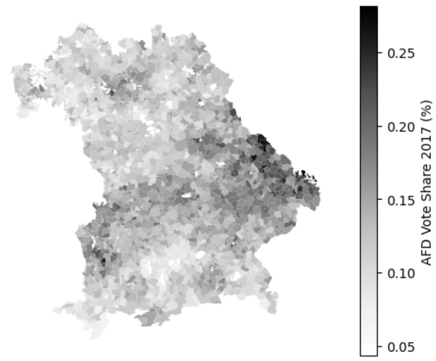
Table 10: Comparison of our data on refugee centers per type as of January 2016 as compared to Stecker and Debus (2019)

Category	**Count 1**	**Capacity 1**	**Count 2**	**Capacity 2**
Collective Accommodation	231	21,413	232	21,266
Satellite Facility	49	12,821	50	13,006
Emergency Reception Center	111	20,314	111	20,314
Decentralized Collective Housing	62	2,847	65	2,859
Reception Center	7	5,611	7	5,611
Reception and Return Center	4	2,750	4	2,750
Central Reception Center	1	650	1	650
Transitional Reception Center	1	250	1	250
Total	**466**	**66,656**	**471**	**66,706**

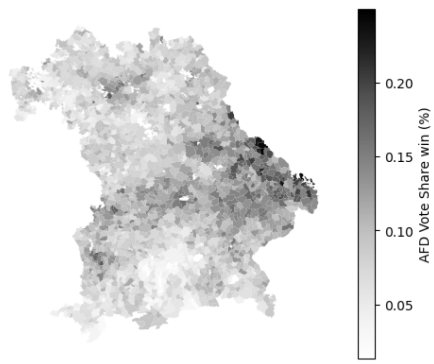
Note. Number 1 indicates our count and number 2 indicates Stecker's count



((a)) AfD election outcomes in Bavaria at a municipal level in 2013



((b)) AfD election outcomes in Bavaria at a municipal level in 2017



((c)) AfD vote share difference between 2013 and 2017

Figure 4: These maps summarize the geographic AfD voting patterns for the federal elections of 2013 and 2017

C Methodology Appendix

C.1 Variable Selection Technique

Mathematical Framework of the XGBoost Classifier (Binary Logistic)

The XGBoost classifier with `objective='binary:logistic'` is a tree-based ensemble method that outputs a probability $\hat{y}_d \in (0, 1)$, representing the likelihood that an municipality d belongs to class 1. The model is trained using regularized gradient boosting with a logistic loss function.

1. Model Structure XGBoost builds an additive model of K regression trees. Each tree's contribution is scaled by a learning rate $\eta \in (0, 1]$:

$$f(\mathbf{x}_d) = \sum_{k=1}^{K} \eta \cdot f_k(\mathbf{x}_d), \quad f_k \in \mathcal{F}$$

- η: the **learning rate** (also known as shrinkage); reduces the impact of each tree to prevent overfitting
- $f_k(\cdot)$: the k-th decision tree
- $\mathcal{F}$: the space of all possible regression trees
- K: number of boosting rounds (trees)

The predicted class probability is given by:

$$\hat{y}_d = \sigma(f(\mathbf{x}_d)) = \frac{1}{1 + e^{-f(\mathbf{x}_d)}}$$

where $\sigma(\cdot)$ is the logistic sigmoid function.

2. Training Objective The overall objective function combines the empirical loss with a regularization term:

$$\mathcal{L} = \sum_{d=1}^{n} \ell(y_d, \hat{y}_d) + \sum_{k=1}^{K} \Omega(f_k)$$

- $\ell(y_d, \hat{y}_d)$: binary logistic loss (cross-entropy)
- $\Omega(f_k)$: regularization term for tree f_k

3. Binary Logistic Loss The binary log-loss for a single instance is:

$$\ell(y_d, \hat{y}_d) = -\left[y_d \log(\hat{y}_d) + (1 - y_d) \log(1 - \hat{y}_d)\right]$$

4. Regularization Term Each tree is penalized to control model complexity. The regularization term includes both L1 and L2 penalties on leaf weights:

$$\Omega(f_k) = \gamma T_k + \frac{1}{2}\lambda \sum_{j=1}^{T_k} w_{kj}^2 + \alpha \sum_{j=1}^{T_k} |w_{kj}|$$

- T_k: number of leaves in tree k
- w_{kj}: weight of leaf j in tree k
- γ: penalty for each leaf (controls tree size)
- λ: L2 regularization parameter (shrinks weights smoothly)
- α: L1 regularization parameter (drives weights toward zero, induces sparsity)

5. Optimization via Gradient Boosting At each boosting round t, a new tree f_t is added to minimize the following second-order Taylor expansion of the loss:

$$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} \left[g_d f_t(\mathbf{x}_d) + \frac{1}{2} h_i f_t(\mathbf{x}_d)^2\right] + \Omega(f_t)$$

- $g_d = \frac{\partial \ell(y_d, \hat{y}_d)}{\partial f(\mathbf{x}_d)} = \hat{y}_d - y_d$: gradient
- $h_d = \frac{\partial^2 \ell(y_d, \hat{y}_d)}{\partial f(\mathbf{x}_d)^2} = \hat{y}_d(1 - \hat{y}_d)$: Hessian

6. Leaf Weight Formula The optimal weight for a leaf j is:

$$w_j^* = -\frac{\sum_{i \in I_j} g_d}{\sum_{d \in I_j} h_d + \lambda}$$

And the contribution to the objective from this leaf is:

$$\mathcal{L}_{\text{leaf}} = -\frac{1}{2} \cdot \frac{\left(\sum_{d \in I_j} g_d\right)^2}{\sum_{d \in I_j} h_d + \lambda} + \gamma$$

Where I_j is the set of training instances (municipalities) assigned to leaf j.

With both λ and α, there is no closed-form solution for optimal weights w_j^* as in the purely L2 case. Instead, the optimal leaf weight is found via the **soft-thresholding function**:

$$w_j^* = \begin{cases} -\frac{\sum_{d\in I_j} g_d - \alpha}{\sum_{d\in I_j} h_d + \lambda} & \text{if } \sum_{d\in I_j} g_d > \alpha \\ -\frac{\sum_{d\in I_j} g_d + \alpha}{\sum_{d\in I_j} h_d + \lambda} & \text{if } \sum_{d\in I_j} g_d < -\alpha \\ 0 & \text{otherwise} \end{cases}$$

This is equivalent to applying an L1 shrinkage penalty to the gradient sum at each leaf. Small gradients are "zeroed out", promoting sparsity in the model.

7. Tunable Hyperparameters and Their Roles (Expanded)

- *learning_rate* (η): shrinks the contribution of each tree ($\eta \cdot f_k(\mathbf{x})$), improving generalization
- *n_estimators* (K): total number of trees (boosting rounds)
- *max_depth*: maximum tree depth, controls interaction complexity
- *subsample*: row subsampling fraction for each boosting round
- *colsample_bytree*: column (feature) subsampling per tree
- *lambda* (λ): L2 regularization term on leaf weights
- *alpha* (α): L1 regularization term (for sparsity)
- *gamma* (γ): minimum loss reduction required for a split
- *scale_pos_weight*: adjusts the gradient for imbalanced classification

For highly imbalanced datasets, *scale_pos_weight* rescales the gradient term:

$$g_d = \hat{y}_d - y_i \quad \Rightarrow \quad g_d^{\text{scaled}} = \begin{cases} \textit{scale\_pos\_weight} \cdot (\hat{y}_d - y_d) & \text{if } y_d = d \\ \hat{y}_d - y_d & \text{if } y_d = 0 \end{cases}$$

This increases the gradient impact of positive-class examples, effectively making the model more sensitive to underrepresented labels.

8. Final Prediction and Classification (with Learning Rate) The final model output is the sum of weighted tree predictions, transformed into a probability:

$$f(\mathbf{x}_d) = \sum_{k=1}^{K} \eta \cdot f_k(\mathbf{x}_d) \quad \Rightarrow \quad \hat{y}_d = \frac{1}{1 + e^{-f(\mathbf{x}_d)}}$$

Classification is done by thresholding the probability:

$$\tilde{y}_d = \begin{cases} 1 & \text{if } \hat{y}_d > \tau \\ 0 & \text{otherwise} \end{cases} \quad (\text{usually } \tau = 0.5)$$

C.1.1 SHAP Values

1. SHAP Axioms SHAP values satisfy four key axioms that make them unique among feature attribution methods:

- **Efficiency (Additivity)**:

  $$\sum_{j=1}^{p} \phi_j = f(\mathbf{x}) - E[f(\mathbf{x})]$$

  The total contribution from all features equals the difference between the actual prediction and the expected prediction.

- **Symmetry (Equal Treatment)**:

  $$\text{If } f_{S \cup \{d\}} = f_{S \cup \{j\}} \text{ for all } S, \text{ then } \phi_d = \phi_j$$

  Features that contribute equally in all subsets receive equal attribution.

- **Dummy (Missingness)**:

  $$\text{If } f_{S \cup \{j\}} = f_S \text{ for all } S, \text{ then } \phi_j = 0$$

  If a feature does not affect the model in any subset, it gets zero attribution.

- **Linearity (Additivity of Models)**:

  $$\phi_j^{f+g} = \phi_j^f + \phi_j^g$$

If two models are added, SHAP values add accordingly for each feature.

4. TreeSHAP: Efficient SHAP Computation for Tree Models The original SHAP formula is computationally expensive with time complexity $O(2^p)$. TreeSHAP is a specialized algorithm for decision trees and ensembles (e.g., XGBoost) that computes exact SHAP values in polynomial time:

$$\text{Complexity: } O(T \cdot L \cdot D^2)$$

- T: number of trees in the ensemble
- L: maximum number of leaves per tree
- D: maximum depth of a tree

TreeSHAP leverages the internal structure of tree models to efficiently compute the expected contribution of each feature, without explicitly enumerating all subsets.

5. Interpretation

- $\phi_j > 0$: feature j increases the model prediction
- $\phi_j < 0$: feature j decreases the model prediction
- The magnitude $|\phi_j|$ indicates the strength of influence

C.1.2 ROC AUC

Receiver Operating Characteristic – Area Under the Curve (ROC AUC) is a metric used to evaluate binary choice models. It can be though of as the the probability that a randomly chosen positive instance is ranked higher than a randomly chosen negative one. It makes it threshold-independent and robust to imbalanced classes. It is defined as shown in Equation 11

$$\text{AUC} = \mathbb{P}\left(s(x^+) > s(x^-)\right), \tag{11}$$

where $s(x)$ is the model's scoring function, $x^+ \sim P_1$ is a randomly drawn positive instance, and $x^- \sim P_0$ is a randomly drawn negative instance. Another possible definition of the this metric is given in Equation 12 and is to be interpreted as the area under the ROC curve described by plotting the true positives rate (Recall/Sensitivity) ($\frac{TP}{TP+FN}$) against the false positive rate ($\frac{FP}{FP+TN}$) for each possible threshold:

$$\mathrm{ROC} = \{(\mathrm{FPR}(\tau), \mathrm{TPR}(\tau)) \mid \tau \in [0,1]\}$$

$$\mathrm{AUC} = \int_0^1 \mathrm{TPR}(\mathrm{FPR})\, d(\mathrm{FPR}), \tag{12}$$

D Result Appendix

D.1 Variable Selection Technique

To optimize model performance, a hyperparameter search is conducted using *Randomized-SearchCV* on an XGBoost classifier. The tuning process samples 50 random combinations from predefined distributions over key hyperparameters, including tree depth, learning rate, regularization parameters, and subsampling rates. Each combination is evaluated using 5-fold cross-validation and the area under the ROC curve (AUC) as the scoring metric. The data is randomly split into a training and test set (70/30), and class imbalance is addressed through the *scale_pos_weight* parameter, calculated as the inverse of the class ratio. The final model is selected based on the best cross-validated AUC score. The resulting parameters are given in Table 11.

Table 11: Tuned Hyperparameter Values for XGBoost Classifier

Parameter	**Selected Value**
n_estimators	243
max_depth	4
learning_rate	0.0195
subsample	0.6635
colsample_bytree	0.8628
gamma	0.4357
alpha (L1)	0.5167
lambda (L2)	3.6502

D.2 Model specification

Comparison of the results of the model between Urban and Rural Areas as classified by the Bavarian Federal State.

Table 12: Two-Way Fixed Effects Regression of `AFD_share` in Urban and Rural Areas

Feature	**Urban Areas**	**Rural Areas**
Intercept	10.0804^{*}	10.2644^{***}
	(4.3277)	(0.2519)
EM_post	-0.0139	-0.0090^{**}
	(0.0181)	(0.0042)
Neighbor_EM_post	-0.1363^{***}	-0.0918^{***}
	(0.0336)	(0.0054)
Unemployed	0.0065	-0.0730^{***}
	(0.1420)	(0.0175)

Note. Wild bootstrap standard errors in parentheses calculated with 1000 iterations.
$^{\cdot}p < .1$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

Furthermore, the results of the municipalities with 6 or less electoral precincts as suggested by Stecker and Debus (2019) are presented below

Table 13: Two-Way Fixed Effects Regression of `AFD_share` (1216 Observations, Fewer than Six Precincts)

Feature	Model 1: Full	Model 2: EM & Unemployment Only
Intercept	10.4307^{***}	10.0920^{***}
	(0.2830)	(0.2754)
EM_post	-0.0129	-0.0702^{***}
	(0.0103)	(0.0086)
Neighbor_EM_post	-0.0911^{***}	—
	(0.0090)	
Unemployed	-0.0945^{***}	-0.0942^{***}
	(0.0209)	(0.0204)

Note. Wild bootstrap standard errors in parentheses calculated with 1000 iterations.
$^{\cdot}$p < .1, *p < .05, **p < .01, ***p < .001

D.3 Turnout analysis

While we acknowledge that turnout may also influence voting behavior, incorporating it directly into our final model could introduce several issues, mainly related to multicollinearity.

To additionally analyse the effect that the voter participation had on the vote share of the parties, we apply the following models:

$$VS_{d,p} = \alpha_p + \beta_p \Delta T_d + \epsilon_{d,p} \tag{13}$$

$$\Delta VS_{d,p} = \alpha_p + \beta_p T_d + \epsilon_{d,p} \tag{14}$$

$$VS_{d,p} = \alpha_p + \beta_p T_d + \epsilon_{d,p} \tag{15}$$

$$\Delta VS_{d,p} = \alpha_p + \beta_p \Delta T_d + \epsilon_{d,p} \tag{16}$$

As shown in Table 14, AfD benefited most from increases in voter turnout. Changes in turnout had the strongest positive effect on the AfD's vote share. Interestingly, the party also performed better in municipalities with relatively low overall turnout. These results suggest that a significant portion of the AfD's electoral gains came from mobilizing previous non-voters.

Table 14: Effect of Turnout and Change in Turnout on Party Vote Share and Its Change

Party	Model 1 $VS_{d,p} \sim \Delta T_d$	Model 2 $\Delta VS_{d,p} \sim T_i$	Model 3 $VS_{d,p} \sim T_i$	Model 4 $\Delta VS_{d,p} \sim \Delta T_d$
AfD	0.811*** (0.030)	-0.402*** (0.016)	-0.405*** (0.016)	0.787*** (0.031)
CDU/CSU	-0.352*** (0.054)	0.243*** (0.020)	0.291*** (0.028)	-0.586*** (0.037)
FDP	-0.179*** (0.024)	0.069*** (0.008)	0.131*** (0.012)	-0.067*** (0.016)
SPD	-0.052 (0.046)	-0.002 (0.011)	-0.158*** (0.024)	0.094*** (0.021)
Grüne	-0.387*** (0.028)	0.057*** (0.006)	0.231*** (0.014)	-0.113*** (0.011)
Linke	-0.036** (0.013)	0.014* (0.005)	-0.041*** (0.007)	-0.042*** (0.010)
Other	0.195*** (0.021)	0.020* (0.009)	-0.049*** (0.011)	-0.072*** (0.016)

Note. Each cell shows the estimate and standard error. *p < .05, **p < .01, ***p < .001.

Given the strong relationship between turnout and the AfD vote share, we also examine whether our exposure measure influenced turnout itself.

$$AFD\_share_{dt} = \beta_1 \cdot \text{Turnout}_{dt} + \gamma_d + \delta_t + \varepsilon_{dt} \tag{17}$$

The regression results in Table 15 indicate that higher exposure has a small but statistically significant positive effect on turnout. In contrast, exposure in neighbouring municipalities has a somewhat larger—though still modest—negative effect. Although these findings highlight the importance of turnout in shaping vote shares, particularly for the AfD, incorporating turnout into our final model requires further investigation and it is a possible field of expansion for future research. Therefore, we leave this extension outside the scope of the present paper. More detailed information, comprising the estimated models' formulations, can be found in the appendix.

Nevertheless, we believe that a further analysis of the voter turnout is needed to obtain a plausible causation relation.

These two regressions are for understanding what effect turnout has on the AFD shares, and what connection our Exposure Measure has with turnout.

Table 15: Regression Summary: AFD Vote Share regressed on Turnout

	AFD Share
$Turnout_{dt}$	0.787^{***}
	(0.040)
Num. Obs.	4,112
R^2	0.916

Note. Both measures are given in percentage points. Standard errors in parentheses. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.