ERASMUS UNIVERSTY ROTTERDAM

Erasmus School of Economics

Master Thesis Economics of Markets and Organisations

From Crisis to Ballot: Analyzing the Effect of Ukrainian Refugees on Anti-Immigration Sentiment in Dutch Elections

Name student: Robina Sediqi

Student ID number: 557549

Supervisor: prof. dr. O.H. Swank

Second assessor: prof. dr. R.A.J. Dur

Date final version: 09-07-2024

Abstract

This paper examines the effect of contact with Ukrainian refugees on anti-immigration sentiment in Dutch municipalities. Motivated by the rise of anti-immigration parties amid increasing refugee numbers, the study seeks to answer how the presence of Ukrainian refugees influences local voting behavior for anti-imigration parties. Using a Difference-in-Difference method with data from the 2012-2023 Dutch elections and refugee registrations, the study finds no statistically significant impact of Ukrainian refugees on votes for anti-immigration parties or voter turnout. This suggests that the predominantly white and culturally similar Ukrainian refugees did not provoke a political backlash, contrasting with previous non-European refugee crises.

Table of Contents

1. Introduction

It was not only big news in the Netherlands (NOS, 2023), but also across Europe (BBC, 2023), and even worldwide (CNN, 2023; Al Jazeera, 2023); Wilders' right-wing populist Freedom Party (Partij Voor de Vrijheid or PVV) won the 2023 General Elections. With statements such as proposing policies like a complete asylum stop and a ban on dual nationalities (PVV 2023), PVV secured 37 out of the 150 seats. The Netherlands has long been considered one of the most tolerant countries in Europe (Tilburg University, 2019); recent election results suggest a shift in this perception. This is also evident from the results of the 2017 House of Representatives elections, where PVV became the second-largest party (Kiesraad, 2017). This happened two years after one of the largest refugee influxes in Dutch history, as a result of wars and tensions in the Middle East. This refugee crisis led to criticism from citizens, and in some municipalities, there were even protests against asylum seekers' centers (NOS, 2016; NOS, 2022). However, there were also citizens who wanted to support the refugees, with a significant number of volunteers registering with RefugeeHelp by the end of 2015 (NRC, 2016).

It is safe to say that the Netherlands has experienced many refugee influxes; from the fall of the Iron Curtain in Eastern Europe to the wars in Syria, Iraq, and Afghanistan, to the most recent arrival of Ukrainian refugees. This influx began in February 2022 in response to the Russian invasion of Ukraine on February 24, 2022. Since then, more than 100,000 Ukrainian refugees have sought refuge in the Netherlands (Government of the Netherlands, 2024). The initial reaction of Dutch citizens was overwhelmingly positive. EenVandaag (2022) found that 72% of their sample wanted to help Ukrainian refugees, 89% believed Ukrainian refugees were welcome in their municipality, 56% were willing to donate money, and 8% were even willing to consider housing Ukrainian refugees themselves. In fact, less than a month after the start of the war, more than 30,000 Dutch people had registered to host Ukrainian refugees in their homes (Nieuwsuur, 2022). However, this acceptance and willingness to help seemed to decrease as the war continued. In 2024, the shelter in Utrecht started denying Ukrainian men shelter, perceiving them as migrant workers. A petition against a shelter in Purmerend was created and signed by thousands in 2023 (NH Nieuws, 2023), and in April 2024, inhabitants of Elp expressed concerns about the number of Ukrainian refugees being accommodated in their area (RTV Drenthe, 2024).

One major difference between this refugee influx and previous ones is the demographic. In the past, refugees primarily came from countries such as Egypt, Syria, or Ethiopia. Ukrainian refugees, however, are predominantly white. Some observers believe this war exposed underlying biases against non-Europeans, which they base on statements from various people in the media (Euro-Med, 2022). For example, French journalist Phillipe Corbé remarked about Ukraine: "We're not talking about Syrians

fleeing the bombing of the Syrian regime backed by Putin. We're talking about Europeans leaving in cars that look like ours to save their lives" (The Guardian, 2022).

Previous research has extensively studied the effect of refugees on voting behavior, primarily focusing on the 2015 refugee crisis, which involved refugees predominantly from the Middle East entering Europe. Most researchers find that this influx led to an increase in far-right votes at the country level (Jasny & Becker, 2020; Fremerey et al., 2024; Steinmayr, 2016; Enos, 2023; Rickardsson, 2023; Campo, 2020). In the case of Ukrainian refugees, the fact that they are predominantly white may present a different dynamic. Indeed, using survey data from Hungary, Pepinsky et al. (2024) find that the influx of Ukrainian refugees was met with a significant rise in tolerance for refugees. Currently, however, no further research exists regarding the effect of Ukrainian refugees on support for anti-immigration parties. Additionally, this topic has not yet been studied in the Netherlands. By using General Election data specific to the Netherlands, this study aims to fill this gap in research on Ukrainian refugees.

This research aims to determine how the increased presence of Ukrainian refugees influences local voting behavior, specifically the rise in support for anti-immigration parties in the 2023 General Elections. Thus, I will try to answer the following research question:

What is the effect of contact with Ukrainian refugees on support for Dutch anti-immigration parties at the municipal level?

By highlighting the electoral consequences of refugee presence in Dutch municipalities, this research aims to provide actionable insights for Dutch policymakers seeking to foster inclusive communities and enhance social harmony. Additionally, political strategists can use these findings to align their policies with evolving public sentiments, thereby promoting democratic responsiveness and stability. This study also seeks to raise awareness among the public regarding their collective response to Ukrainian refugees, offering a comparative perspective with the 2015 refugee crisis.

To determine the effect of contact with Ukrainian refugees on local voting behavior, I will, among other things, make use of data from the 2012, 2017, 2021, and 2023 Dutch General Elections, as well as the number of registered Ukrainian refugees per municipality in 2023. The data will be used to conduct Difference-in-Difference and placebo analyses with.

In my research on the effect of Ukrainian refugees on anti-immigration sentiment in Dutch elections, the results did not yield statistically nor economically significant findings. The robustness checks reinforce these findings. Thus, no substantial impact of Ukrainian refugee presence on the vote share for anti-immigration parties or voter turnout was observed. This could suggest that the influx of

Ukrainian refugees, a predominantly white demographic, did not elicit the same political reaction as previous refugee crises involving non-European groups.

However, I cannot, with certainty, state that Ukrainian refugees have no effect on voter sentiment, due to selection effects and possibly, reverse causality. As will be explained in detail later, in contrast to previous refugee influxes, EU regulations allowed Ukrainian refugees to register in the municipalities of their choice. Moreover, while there were shelters available, these refugees were allowed to find regular housing as well. Therefore, it is likely that a portion of these refugees moved to homes in municipalities where they already know some people, or believe they will be more accepted, leading to non-random assignment of refugees to municipalities. While I tried to control for this by obtaining data on the number of available spots in shelters per municipality, the organization with this data was not able to provide me with it.

In order to answer the research question, existing theories and studies will be reviewed, and hypotheses will be formulated in the theoretical framework. Next, data collection will be discussed. Then, the perfect method will be outlined. Subsequently, my method of testing the hypotheses will be explained. This section will also include a more detailed discussion of self-selection. After, the results will be presented and explained. The robustness of the results is then analyzed. Following the robustness checks, findings will be discussed, the research question will be answered, and the limitations and suggestions for further research will be given in the conclusion and discussion.

2. Theoretical framework

2.1. Intergroup contact theory

The intergroup contact theory, also known as the contact theory, states that intergroup contact between two ethnic groups can reduce prejudice (Allport, 1954). Consequently, individuals that have contact with immigrants should have more positive attitudes towards them than individuals that do not have contact with these groups (Abrams et al., 2018). According to Allport (1954), this positive effect is only present when the contact is optimal, which is characterized by four conditions. Firstly, both groups should expect and perceive an equal status within the situation. Secondly, the groups need to have common goals. Thirdly, intergroup cooperation is important to reach their common goal. Lastly, support from authority, law, or custom is needed, as the explicit support of intergroup contact is shown to improve attitudes, e.g. in the military (Pettigrew, 1998). Generally, these conditions are not met in 'transit countries', i.e. countries refugees move away from as soon as possible.

This theory has been the subject of extensive empirical research. In the United Kingdom, direct contact with African American soldiers led to less implicit bias and prejudice towards against African Americans (Schindler & Wescott, 2020). Additionally, they found that at locations in which more African American soldiers were posted, there was less support for the UK's leading far-right party. In the Netherlands, Achard et al. (2022) find that individuals living close to refugee facilities, which were mainly being used by Middle Eastern refugees, became less inclined to vote for anti-immigration parties. According to Steinmayr (2016), this may be because direct contact with refugees has a positive impact on the in-group, making them more optimistic that the refugees' integration can be managed. Steinmayr (2020) also finds that in Austria, the arrival of refugees caused significant anxiety in the settlements, though it reduced after they had lived there for some time. And in Hungary, which was more of a transit country during the 2015 refugee crisis, people in settlements through which refugees traveled voted substantially more anti-immigration on a referendum than people from other areas in the country (Gessler et al., 2021). Furthermore, as a result of Turkey's open-door policy, Turkey has received millions of Syrian refugees. This led to a decrease in votes for the leading government party in Turkey and an increase in votes for Turkey's biggest nationalist party (Usta, 2022; Karacuka, 2019).

Other researchers study the effect of non-economic factors behind prejudice of the in- and out-group. Dustmann and Preston (2007) use British survey data and find that high concentrations of ethnic minorities can lead to more hostile attitudes of the in-group. Furthermore, the education level of people in the in-group also has an impact on the amount of prejudice towards the out-group (Card et al., 2012). Hainmueller and Hiscox (2007) find that more educated people are less racist, care more about cultural diversity and are more likely to believe migration is good for the host country, compared to people with lower education levels. According to Sinclair et al. (2023), the perception of cultural distance also plays a significant role in shaping attitudes towards refugees. Namely, they find that British participants were less willing to assist culturally distant Yemeni refugees compared to other refugees.

Pepinsky et al. (2022) have studied the effect of the Ukrainian refugee influx on public opinion in Hungary. They find that this influx came with a substantial increase in tolerance for refugees, which is remarkable, as previous research finds that the 2015 refugee crisis did not have such an effect in Hungary (Gessler et al., 2021). Pepinsky et al. (2022) find that the distinguishing characteristic of the 2022 refugee crisis is the fact that Ukrainian refugees are predominantly white European Christians. Hence, I expect votes for anti-immigration parties in the 2023 elections to decrease in municipalities with a higher proportion of Ukrainian refugees, compared to municipalities with an average proportion of Ukrainian refugees:

H1: Municipalities with a higher proportion of Ukrainian refugees will show a significant decrease in votes for anti-immigration parties in the 2023 elections, compared to municipalities with an average proportion of Ukrainian refugees.

2.2. Group threat theory

A theory that contrasts from the intergroup contact theory is the group threat theory. According to this theory, there is a perceived threat between the two groups, and intergroup contact can then promote conflicts (Blumer, 1958). Regardless of whether the threats are real, or whether there is direct contact between the groups, the (perceived) threat can still have very real consequences for the groups involved (Stephan et al., 2009). A distinction can be made between realistic and symbolic threats (Stephan et al., 2009). Realistic threats relate to crime or economics and can make the in-group view the out-group as competitors, which can enforce prejudice. Furthermore, von Hermanni and Neumann (2009) find that economic and fiscal concerns, as well as crime, negatively affect individuals' acceptance of refugees seeking asylum. This effect is bigger among individuals with a low socioeconomic status (Fetzer, 2012; Lancee & Pardos-Prado, 2013). On the other hand, symbolic threats refer to the fear that immigrants will challenge the in-group's culture of religion, i.e. their values, beliefs, or worldview. The (perceived) threat this can cause is bigger when the out-group has largely different from the in-group in terms of religion or culture and can therefore lead to higher levels of prejudice (Ha, 2010). Schleuter and Wagner (2008) also find that the size of the group of immigrant matters; the threat and subsequent prejudice is larger if the group of immigrants is larger. At the same time, there seems to be a spill-over effect; cities with large local immigrant populations show lower levels of prejudice than people from cities with a small or nonexistent local immigrant population (Dirksmeier, 2014; Jolly & DiGiusto, 2014; Semyonov & Glikman, 2009; Wagner et al., 2016; Moise et al., 2024). This may also be related to the intergroup contact hypothesis, as cities that receive many immigrants tend to be bigger and thus, experience more intergroup contact (Dirksmeier, 2014).

Furthermore, Hopkins et al. (2019) investigate whether misconceptions among Americans regarding the share of the population that is foreign-born has an effect on Americans' perception of immigrants. They find that many Americans overestimate the number of immigrants in the country. After being corrected, however, their stance on immigration did not change. This suggests that misconceptions of the size of the foreign-born population is not the cause of attitudes towards them, but rather a consequence. Therefore, citizens who are skeptical about immigration may perceive the refugee crisis as more threatening (Gessler et al., 2021). Hence, I expect support for anti-immigration parties due to Ukrainian refugee presence to me moderated by historical support for these parties, i.e. in municipalities with historically high support for anti-immigration parties, the influx of more Ukrainian refugees will be associated with an increase in support for these parties:

H2: The effect of the number of Ukrainian refugees on the vote share for anti-immigration parties is moderated by historical support for anti-immigration parties. Specifically, in municipalities with historically high support for anti-immigration parties, the presence of more Ukrainian refugees will be associated with an increase in votes for anti-immigration parties.

Moreover, Bratti et al. (2020) have studied the relationship between geographical proximity to refugee reception centers and voter turnout. More specifically, they look for differences in voter turnout of Italian municipalities during the 2013 and 2018 general elections, as well as the Constitutional referendum that took place in 2016. In all three cases, they find that the closer the municipality is to a refugee reception center, the higher voter turnout is. Additionally, they find that the closer the municipality is to a refugee reception center, the more votes go to the Italian populist party. Furthermore, they find that being close to a refugee reception center is associated with less support for center-leftist parties. Hence, I expect voter turnout in the 2023 elections to increase in municipalities with a higher proportion of Ukrainian refugees, compared to municipalities with an average proportion of Ukrainian refugees:

H3: *Municipalities with a higher proportion of Ukrainian refugees will show a significant increase in turnout in the 2023 elections, compared to municipalities with an average proportion of Ukrainian refugees.*

2.3. Municipalities and the hosting of Ukrainian refugees

Ukrainian refugees' choices regarding which Dutch municipality to live in are influenced by a combination of factors related to existing ethnic networks, public financial support, living conditions, economic factors, employment opportunities, and administrative policies. Firstly, established ethnic networks play a critical role in settlement decisions. Refugees often gravitate towards areas where there are pre-existing communities of their compatriots, providing a sense of familiarity and support. For example, this trend is evident in Germany, where Ukrainian refugees tend to settle in regions with high numbers of previous Ukrainian migrants, highlighting the importance of social connections in their relocation process (Sauer et al., 2023).

Public financial support and living conditions are also significant determinants. Refugees show a higher willingness to remain in locations that offer better living conditions and substantial financial support. For instance, a study comparing Ukrainian refugees in Kraków and Vienna finds that the latter, with its more favorable living conditions and financial assistance, was more attractive to refugees (Kohlenberger et al., 2023). This indicates that the quality of life in the host location is a major factor influencing their decision to stay or move. Furthermore, they also find that the further Ukrainians move

to the West, the more self-selected they are in terms of educational levels, previous work experience and intent to return.

Economic factors such as affordable housing and lower rents are equally important. In Germany, these economic considerations significantly influenced where Ukrainian refugees chose to settle. Affordable housing and lower living costs made certain regions more appealing, suggesting that financial viability is a key concern for refugees when selecting a place to live (Sauer et al., 2023). Moreover, employment opportunities play a crucial role in the decision-making process. This factor is especially important due to the Temporary Protection Directive (TPD), which gives Ukrainian refugees the right to housing, education and healthcare in all EU Member States until 2025. Urban areas with plentiful job prospects attract more refugees, as seen in the Czech Republic, where many refugees settled in cities that offered better employment opportunities (Molikevych, 2022). Moreover, it may be the case that municipalities with an excess labor demand offer more attractive living conditions to Ukrainian refugees, although this has not been researched yet.

Finally, administrative policies and integration efforts by host countries significantly affect refugees' settlement choices. For example, Denmark's implementation of special laws to facilitate the resettlement and integration of Ukrainian refugees has positively impacted their adaptation and quality of life (Castaner et al., 2023). Such effective policies that support refugees' integration into the host society may make certain municipalities more attractive.

3. Data

To analyze the impact of Ukrainian refugee presence on voting behavior in parliamentary elections, two primary data sources will be utilized. Firstly, data on the (12 September) 2012, (15 March) 2017, (17 March) 2021 and (22 November) 2023 Dutch parliamentary elections will be used, obtained from the Electoral Council (*Kiesraad*). The Russia-Ukraine war and consequent influx of Ukrainian refugees started in 2022, which means I have three election years of pre-treatment data, and one election year of post-treatment data. Thus, I will create a post-treatment dummy variable that equals 1 if the data is on the 2023 elections, and 0 otherwise. Furthermore, I will create three pre-treatment dummy variables; for 2012, 2017 and 2021 respectively, each taking a value of 1 if the observation is from that election year, and 0 otherwise.

The datasets from 2017 and 2021 contain information on the number of votes per political party, on a municipal level. The 2012 and 2023 datasets include the number of votes per person, per party and per municipality, which I aggregated to obtain the number of votes per party per municipality, similar to

the available data from 2027 and 2021. Between 2012 and 2023, the number of municipalities decreased by 63, due to 36 municipal reorganizations and the termination of four municipalities (see Table A1), complicating the panel analyses. Therefore, I decided to merge all the datasets into the municipal classification of 2023. Furthermore, seven municipalities have been deleted from the dataset (Ameland, Baarle-Nassau, Renswoude, Rozendaal, Schiermonnikoog, Terschelling and Vlieland) due to missing data, and the municipalities in the Dutch Caribbean (Bonaire, Saba and Sint Eustatius) have also been removed, as they are not relevant for this study.

Furthermore, to establish which political parties are anti-immigration, I looked at all parties' election manifestos. Whether a party falls into the anti-immigration category is based on if its election manifesto includes statements in favor of a full asylum stop, comments about immigrants being a threat to Dutch culture and wanting to, for a large part, stop hosting international students, and the like. I created a dummy variable that equals 1 if the party is anti-immigration. The anti-immigration parties per election year can be found in Table A2. All other parties fall into the other category of parties that are not strictly anti-immigration. I aggregated the number of votes for anti-immigration parties per municipality for each round of elections, and calculated the share of votes for anti-immigration parties, in percentages, per municipality and per election year:

$$Share\ of\ votes\ for\ anti-immigration\ parties_{it}(\%) = \frac{Votes\ for\ anti-immigration\ parties_{it}}{Number\ of\ valid\ votes_{it}} * 100$$

Additionally, the average share of votes for anti-immigration parties over 2012-2021 will be calculated for each municipality. This will then be used to create a historical support dummy, which equals 1 if the municipality belongs to the top 25% in terms of historical support, and 0 otherwise. Furthermore, the datasets include data on the number of eligible voters and total number of votes per municipality. I use those variables to calculate the voter turnout, as a percentage, per municipality and per election year:

$$Voter\ turnout_{it}(\%) = \frac{Total\ number\ of\ votes_{it}}{Number\ of\ eligible\ voters_{it}} * 100$$

Additionally, I obtained data from Statistics Netherlands (*Centraal Bureau voor de Statistiek*) on the number of registered Ukrainian refugees per municipality since 24 February 2022, measured on 1 November 2023. It also includes the population size per municipality, as well as the number of Ukrainian refugees per 1,000 inhabitants on a municipal and country level. I will categorize the municipalities into five quintiles based on the proportion of Ukrainian refugees: 0-20%, 21-40%, 41-60%, 61-80%, and 81-100% of the observations.[1] Table A3 contains a list of municipalities per quintile.

---

[1] The decision to split the municipalities into quintiles rather than using the raw variables directly is based on several methodological considerations. It allows for a clearer comparison between groups with differing levels of exposure to Ukrainian refugees, facilitating the interpretation of the treatment effects. Furthermore, by using quintiles, I can better

The reference group will be the municipalities in the third quintile (41-60%). This categorization allows for a detailed analysis of the effects of varying levels of Ukrainian refugees on the voting results for anti-immigration parties. Statistics Netherlands was also used to obtain data on the total number of inhabitants per municipality in 2012, 2017, 2021 and 2023.

Moreover, I obtained data on the standardized median income levels per municipality for 2012, 2017, 2021 and 2022 from Statistics Netherlands. At the time of doing the research, data on income from 2023 has not been made available yet. However, it is very unlikely that changes in income from 2022 to 2023 differ significantly among municipalities. Rather, income levels are likely to have changed relatively equally throughout the country. Therefore, I believe the 2022 mean income data serves as a suitable proxy for 2023 median income per municipality.

Due to the presence of selection effects that will be elaborated on in section 4.2.2, I tried to obtain data on what type of housing or shelters municipalities offered Ukrainian refugees. More specifically, I wanted to have data on which municipalities had set up shelters or made homes available specifically for Ukrainian refugees, and how many refugees would fit in these facilities. That way, I would be able to distinguish Ukrainian refugees in shelters from ones who live independently. I requested this data from RefugeeHelp, a Dutch NGO that helps Ukrainian refugees with things such as healthcare, education and shelter, from the moment of entry. While they have this data, they unfortunately were not able to share it with me. It is important to note that therefore, I do not have comprehensive data on which specific Dutch municipalities offered housing or shelters for Ukrainian refugees, and in what ways, which poses a challenge in fully understanding and controlling for the settlement patterns and support systems in place for these refugees.

The overall descriptive statistics of the variables used can be found in Table 1. Firstly, it shows that the proportion of Ukrainian refugees per 1,000 inhabitants across the 334 municipalities has a mean of 6.13, with a median of 5.4, indicating a slightly right-skewed distribution. Furthermore, the lowest number of Ukrainian refugees per 1,000 inhabitants registered in a municipality is 0.8, while the maximum is 28.7. Additionally, the mean support for anti-immigration parties stands at 18.54%, with a median of 17.20%. Moreover, the median income ranges from €24,000 to €52,700 with a mean of €34,242.93, indicating some economic diversity across the municipalities. Additionally, Tables A4.1-A4.5 present the descriptive statistics per quintile. The tables show that in the first quartile, the range in proportions

---

capture potential non-linear effects and provide a more nuanced understanding of the impact across different levels of refugee presence. Although it is possible to perform a Difference-in-Differences (DiD) analysis using the raw continuous variables, the complexity of interpreting interaction effects and potential non-linearities may reduce the clarity and robustness of the results.

of registered Ukrainian refugees per 1,000 people in municipalities is 0.8-3.9 (Table A4.1). In the second, third, fourth and fifth quartiles, these ranges are 4.0-4.9, 5.0-6.1, 6.2-7.8 and 7.8-28.7 respectfully. However, the descriptive statistics per quintile (Tables A4.1-A4.5) do not differ substantially from the overall numbers in Table 1.

Table 1   Descriptive statistics of all municipalities

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	334	6.13	5.4	3.32	0.8	28.7
Anti-immigration support (%)	334	18.54	17.20	8.36	4.02	56.83
Turnout (%)	334	80.19	80.74	4.85	62.63	98.26
Population	334	50364.52	31950	71538.74	7200	874100
Median income (€)	334	34242.93	34600	5074.10	24000	52700
Historical support	334	0.25	0	0.43	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the data set. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Ameland, Baarle-Nassau, Renswoude, Rozendaal, Schiermonnikoog, Terschelling, and Vlieland have been removed due to missing data. Source: Dutch Electoral Council and Statistics Netherlands.

4. Method

4.1.   Perfect method

The aim of this study is to investigate the causal effect of contact with Ukrainian refugees on anti-immigration voting behavior in Dutch municipalities. To achieve this, I would ideally utilize a randomized controlled trial design with municipalities as the unit of analysis. This approach ensures that any observed differences in voting behavior can be attributed to the presence of refugees, thereby providing strong causal inference.

First, the Netherlands would be divided into its existing municipalities. Using a computer algorithm, municipalities would be randomly assigned to either the treatment or control group. Municipalities in the treatment group receive a proportionally high number of Ukrainian refugees, while municipalities in the control group receive no Ukrainian refugees. This random assignment ensures that each municipality has an equal probability of being assigned to either group, thereby eliminating selection bias and ensuring that both observed and unobserved confounders are equally distributed between the treatment and control groups. In an ideal situation, people do not interact with people from other municipalities to ensure there are no spillover effects.

For data collection, three key areas would be focused on: voting behavior, socio-economic and demographic variables, and refugee integration. To measure voting behavior, data would be collected on the share of votes for anti-immigration parties in each municipality during general elections. The pre-treatment periods included the elections in 2012, 2017, and 2021, while the post-treatment period included the election in 2023. Furthermore, data on the voter turnout per year per municipality would be collected. This data was sourced from official election results provided by the Dutch Electoral Council (*Kiesraad*).

To understand the level and nature of contact between Ukrainian refugees and local inhabitants, I would conduct surveys and collect data on refugee integration. This data includes information on participation in local activities, employment, education, and housing. By examining these factors, I aim to gain insights into how the presence of refugees might influence local residents' attitudes and behaviors.

The analytical approach for this study would involve conducting a balance test to ensure that the random assignment of municipalities to the treatment and control groups was successful in creating comparable groups. This would be followed by a simple comparison of voting behavior and turnout between the municipalities with and without refugees. This approach allows for perfect random assignment and perfectly balanced treatment and contrl groups. As a result, a straightforward analysis and interpretation of the impact of refugee presence suffices, without the need for more complex methods like Difference-in-Differences (DiD).

In reality, however, this method of research is not feasible due to several factors. Firstly, the refugee influx has already started, so Ukrainian refugees have already settled in municipalities in the Netherlands. Secondly, the Temporary Protection Directive (TRD) allowed Ukrainian refugees to register and live in the municipalities of their choice, rather than having to live in allocated shelters or specific municipalities. Thirdly, in the real world, inhabitants of municipalities cannot be restricted from going to other municipalities or interacting with people from other municipalities, making it impossible to prevent spillover effects. Fourthly, data on topics such as municipal education levels, employment rates, and housing are not always available and thus, cannot be controlled for. These are all factors I considered when designing my own method.

4.2. Utilized method

For my main analyses, I plan on using the Difference-in-Difference (DiD) method with multiple treatment groups. I will categorize municipalities into five quintiles based on the proportion of Ukrainian refugees: 0-20%, 21-40%, 41-60%, 61-80%, and 81-100% of the observations. The reference group will be the municipalities in the 41-60% quintile. I will use DiD to firstly examine whether the

influx of Ukrainian refugees starting in February 2022 causes a significant decrease in the share of votes for anti-immigration parties, and whether the size of the proportion of Ukrainian refugees affects the magnitude of this change. I will first run the base DiD regression, without any control variables. Then, I will run a model in which I control for population sizes, median income levels of municipalities and voter turnout, to help ensure that changes in vote shares are not simply due to changes in the number of people voting. Before conducting the DiD analyses, I will check whether the Parallel Trends Assumption (PTA) holds for all models. The pre-treatment period will consist of the elections in 2012, 2017, and 2021, while the post-treatment period will consist of the 2023 election. The full DiD formula will look as follows:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 (Post_t * Treatment_i) + \gamma X_{it} + \epsilon_{it}$$

Where:

- Y_{it} is the share of votes for anti-immigration parties in municipality i at time t;
- $Post_t$ is a dummy variable that equals 1 for the year 2023 (post-treatment period) and 0 otherwise;
- $Treatment_i$ is a categorical variable that represents the treatment group (quintile);
- $Post_t * Treatment_i$ is an interaction term between the post-treatment period and treatment group
- β_3 is the DiD estimator, representing the differential effect of having a higher proportion of Ukrainian refugees on the voting behavior regarding anti-immigration parties;
- X_{it} is a vector of control variables, which includes population, median income and voter turnout in municipality i at time t.

My second hypothesis states that effect of the number of Ukrainian refugees on the vote share for anti-immigration parties is moderated by historical support for anti-immigration parties. Specifically, in municipalities with historically high support for anti-immigration parties, the presence of more Ukrainian refugees will be associated with an increase in votes for anti-immigration parties. To test this hypothesis, a moderator variable will be added to the previous DiD regression, while keeping all else the same. The moderator variable will be historical support for anti-immigration parties, which equals 1 when the average share of votes for these parties in previous elections (2012, 2017 and 2021) is in the fourth quartile (76-100%). Additionally, I will interact this moderator variable with the refugee proportion quintiles and the post-treatment period to capture the differential effect of historical support across different levels of Ukrainian refugee presence. The full DiD formula will look as follows:

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 HistSupport_i + \beta_4 (Post_t * Treatment_i) \\ + \beta_5 (HistSupport_i * Treatment_i) + \beta_5 (Post_t * HistSupport_i * Treatment_i) \\ + \gamma X_{it} + \epsilon_{it} \end{aligned}$$

Where:

- Y_{it} is the share of votes for anti-immigration parties in municipality i at time t;
- $HistSupport_i$ is a dummy variable that equals 1 when municipality i belongs to the top 25% in terms of average share of votes for anti-immigration parties in previous elections, and 0 otherwise;
- X_{it} is a vector of control variables, which includes population, median income and voter turnout in municipality i at time t.

To test my third hypothesis, which states that municipalities with a higher proportion of Ukrainian refugees will experience significantly higher voter turnout in the 2023 elections compared to municipalities with fewer refugees, I will run a base-model DiD regression and one with control variables. The dependent variable will now be the share of voter turnout per municipality. The treatment groups will remain the proportion of Ukrainian refugees, with the third quintile as the reference group. In the second regression, population as well as median income will be controlled for. This DiD formula will now be the following:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 (Post_t * Treatment_i) + \gamma X_{it} + \epsilon_{it}$$

Where:

- Y_{it} is the voter turnout in municipality i at time t;
- $Post_t * Treatment_i$ is an interaction term between the post-treatment period and treatment groups, and its coefficient β_3 measures the DiD estimate of the refugee impact on voter turnout;
- X_{it} is a vector of control variables, that includes population and median income in municipality i at time t.

4.2.1. Parallel Trends Assumption

For the DiD analyses to be valid, the Parallel Trends Assumption (PTA), or common trends assumption, must hold. The parallel trends assumption states that, in the absence of the 2022 refugee influx, the average change in the outcome variable for the treated group would have been the same as the average change in the outcome variable for the control group over time. Essentially, it means that the groups of municipalities with a higher proportion of Ukrainian refugees since 2022, and the groups with a low proportion would follow parallel paths in their outcome trajectories if there had been no refugee influx in 2022. I test whether this assumption holds for each hypothesis separately, using two different methods. The first one utilizes robust Ordinary Least Squares (OLS) regressions. OLS provides a statistically formal test and only includes data from the pre-treatment period. Including interaction terms between time and the treatment groups makes it possible to test whether there are statistically significant differences in pre-treatment trends between the groups. Like before, the group of municipalities in the 41-60% range will be the reference category. The PTA will be tested for the base models, as well as the

models with additional variables. The PTA holds when all interaction terms are statistically insignificant, i.e. the p-value exceeds 0.1. The general OLS formula will look as follows:

$$Y_{it} = \beta_0 + \beta_1 year_{2012} + \beta_2 year_{2017} + \beta_2 year_{2021} + \beta_3 Treatment_i$$
$$+ \beta_5 (year_{2012} * Treatment_i) + \beta_6 (year_{2017} * Treatment_i)$$
$$+ \beta_7 (year_{2021} * Treatment_i) + \gamma X_{it} + \epsilon_{it}$$

The second method of checking whether the PTA holds involves the use of line graphs. By plotting the means of the outcome variable over time for the treatment groups, I can visually assess whether the pre-treatment trends appear to be similar. Furthermore, line graphs can reveal patterns or outliers that may not be immediately evident in OLS results. I will use means of the raw data for my base models, while using means of the predicted values for the models with additional variables. That is because using average predicted values helps to better isolate and understand the effect of the treatment while accounting for the control variables. These predicted averages will be calculated over the OLS regression values used in the formal test.

For DiD to be valid for Hypothesis 1, it must hold that before the refugee influx, the treatment groups follow the same trend in terms of the shares of votes for anti-immigration parties. Column 2 of Table B1 contains the regression results with control variables, which shows that all the interaction terms are statistically insignificant. Additionally, the line graph analysis is displayed in Figure 1.1, which shows that the pre-treatment trends are very similar. Thus, from the regression and visual test, I can deduce that the PTA with control variables is very likely to hold. The same can be said about the base model (Table B1 Column 1; Figure B1).
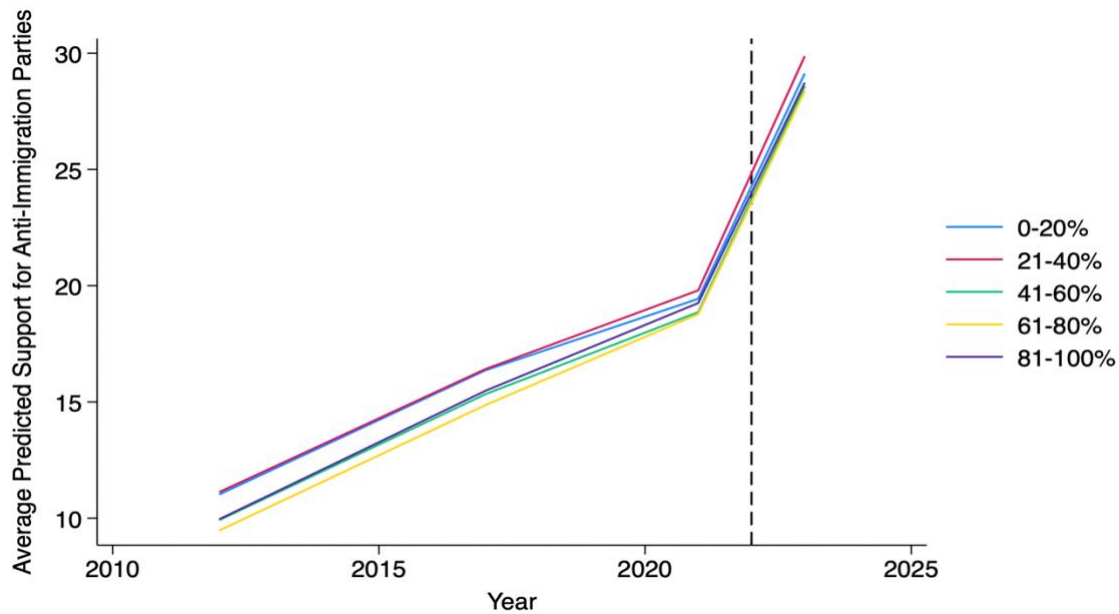
Figure 1.1   Visual PTA test: the effect of Ukrainian refugees on votes, with controls
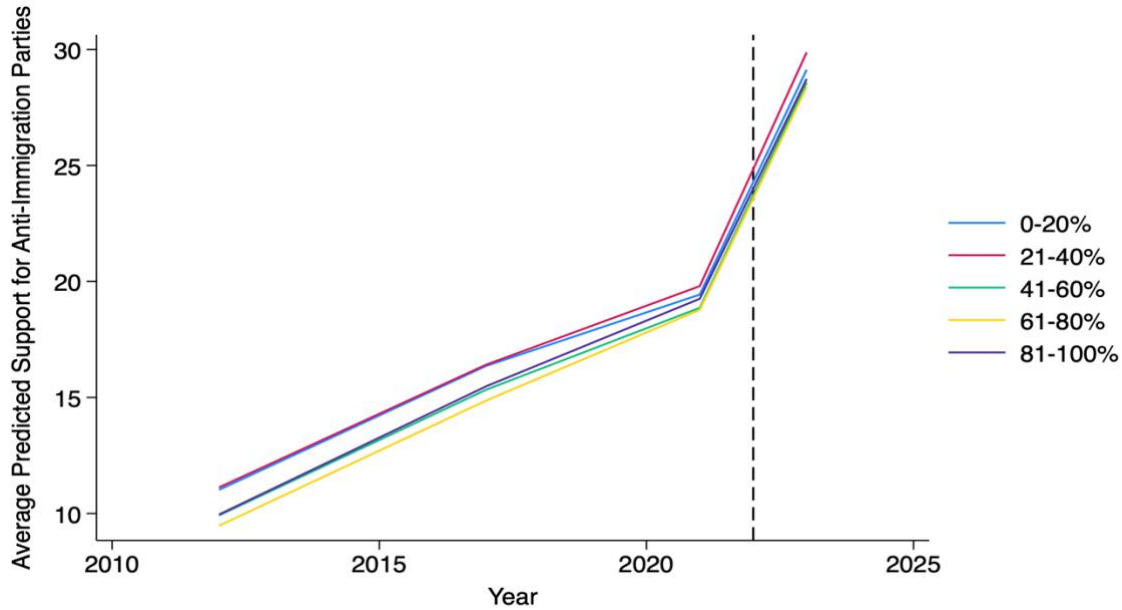
Note. Visual representation of the PTA test. The dependent variable is the average predicted support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The vertical dashed line represents the start of the Russia-Ukraine war and the consequent refugee influx in February 2022. Median income, population and voter turnout have been included as controls.

For the PTA to hold in the context of Hypothesis 2, any observed differences in the post-treatment period can be attributed to the presence of refugees and not to pre-existing trends in voting behavior between municipalities with historically higher and lower support for anti-immigration parties. Table B2 contains the regression results when historical support is included as a moderator, using interaction terms. The coefficient for historical support is significantly positive, while all interaction terms between the years and quintiles, quintiles and historical support, and all three interacted, are statistically insignificant, indicating that the PTA holds. Furthermore, the line graph can be seen in Figure 1.2. The graph looks very similar to the one in Figure 1.1 and once again, the pre-trends are very similar, so I can deduce that the PTA most likely holds here too.

Figure 1.2   Visual PTA test: the effect of Ukrainian refugees on votes, with controls and historical support as moderator

Note. Visual representation of the PTA test. The dependent variable is the average predicted support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The vertical dashed line represents the start of the Russia-Ukraine war and the consequent refugee influx in February 2022. Median income, population and voter turnout have been included as controls. Historical support has been included as a moderator using interaction terms.

For DiD to be valid for Hypothesis 3, it must hold that before the refugee influx, the treatment and control group follow the same trend in terms of voter turnout. Table B3 contains the regression results of the base model (Column 1) and the model with control variables (Column 2), which shows that all interaction terms are statistically significant, indicating that the PTA likely holds. The line graph of the base model (Figure B2) and model with controls (Figure 2) offer decent support, so I can conclude the PTA most likely holds here as well.

Figure 2   Visual PTA test: the effect of Ukrainian refugees on voter turnout, with controls
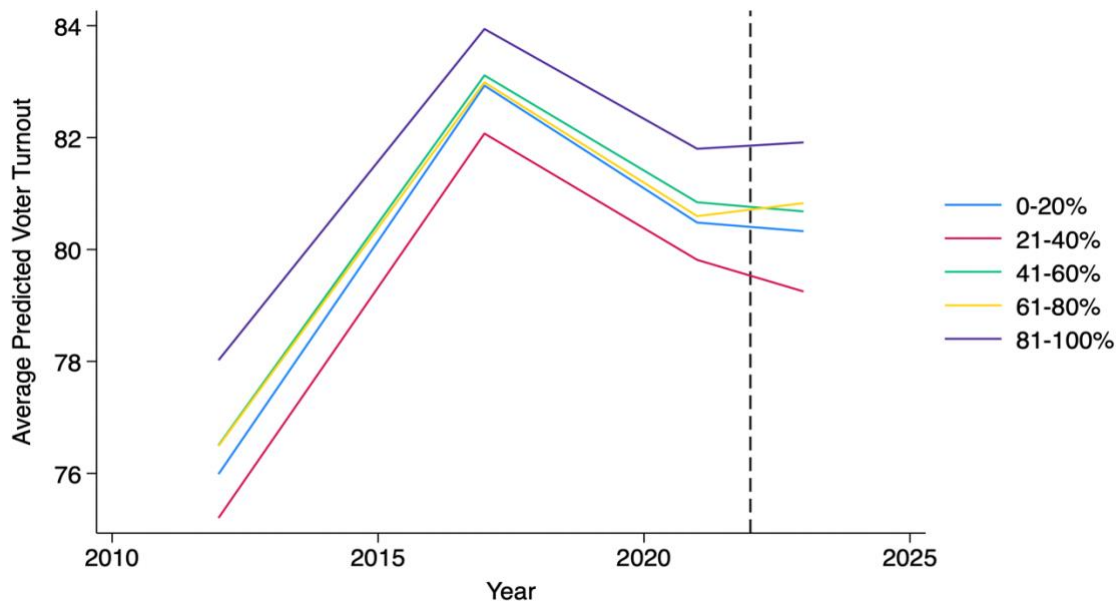
Note. Visual representation of the PTA test. The dependent variable is the average predicted voter turnout, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The vertical dashed line represents the start of the Russia-Ukraine war and the consequent refugee influx in February 2022. Median income and population and voter turnout have been included as controls.

4.2.2. Possible self-selection

When researching the effect of contact with Ukrainian refugees (measured by the proportion of Ukrainians per 1,000 people for each municipality) on voting patterns for anti-immigration parties, self-selection can introduce significant biases into a Difference-in-Difference (DiD) analysis. This issue arises because the municipalities with higher proportion of Ukrainian refugees might systematically differ from those with lower proportion in ways that are related to the voting outcomes of interest, independent of the presence of refugees.

Municipalities that attract more Ukrainian refugees might have certain characteristics that make them more welcoming or supportive of immigrants, such as friends or family, better social services, more liberal political climates, or stronger economic conditions. Conversely, municipalities with fewer refugees might be those with fewer resources, more conservative political views, or higher levels of economic distress. These pre-existing differences can affect voting patterns, making it challenging to isolate the causal impact of refugee presence on support for anti-immigration parties. It may also be the case that refugees who already know which municipality they want to register in are more likely to stay in a house, rather than a shelter. However, as mentioned in section 3, I unfortunately was not able to obtain data to control for this possible self-selection effect.

The parallel trends assumption, which is crucial for the validity of DiD estimations, posits that in the absence of the treatment (the influx of Ukrainian refugees), the treatment and control groups would have followed similar trajectories over time. However, self-selection into municipalities means that this assumption might not hold. If the treatment group (municipalities with non-average proportions of Ukrainian refugees) was already on a different trajectory compared to the control group (municipalities with an average proportion of Ukrainian refugees) before the arrival of refugees, any observed changes in voting patterns could be attributed to these pre-existing differences rather than the effect of refugee contact.

Fortunately, given that there is sufficient evidence to prove that the PTA does hold, I believe the self-selection will have a minimal impact on my results. Yet, it is still important to acknowledge the possibility of the results being biases due to this self-selection of Ukrainian refugees into Dutch municipalities.

4.2.3. Possible reverse causality

The PTA ensures that trends are parallel pre-trreatment. However, it does not control for pre-existing differences that could affect both refugee distribution and voting patterns, non-random treatment assignments, or residual confounding variables. As a result, reverse cauality could still arise in my research. For example, pre-existing political sentiments in municipalities with strong anti-immigration views might deter Ukrainian refugees from settling there, falsely suggesting that higher Ukrainian refugee presence has no effect on anti-immigration sentiment or turnout. Tables A4.1-A4.5 show that while historical voting for anto-immigraiton parties is higher in municipalities with low proportions of Ukrainian refugees, the difference is stilll quite small. Economic factors like unemployment rates and housing availability can also attract or repel refugees and influence voting behavior simultaneously, which the PTA does not account for and neither fo my models, due to the lack of available data. Additionally, self-selection of refugees into municipalities where they feel welcome or have pre-existing networks can bias the observed relationship between refugee presence and anti-immigration votes. However, since I was not able to obtain data on the housing of Ukrainians per municipality, this also is something my analyses do not account for.

5. Results

The first hypothesis states that municipalities with a higher proportion of Ukrainian refugees will show a significant decrease in votes for anti-immigration parties in the 2023 elections compared to municipalities with an average proportion of Ukrainian refugees. Table 2 presents the results from the Difference-in-Differences (DiD) regression analysis, which is used to test this hypothesis. Column 1

displays the base model, while the model in Column 2 controls for yearly population size per municipality, as well as yearly median income per municipality. The interaction terms for the year 2023 and the proportion categories (in quintiles) provide the basis for this hypothesis.

Table 2   DiD regression results of the effect of Ukrainian refugees on votes for anti-immigration parties

Variables	(1) Share votes for anti-immigration parties	(2) Share votes for anti-immigration parties
2023	13.876***	9.084***
	(0.813)	(0.741)
Q1 (0-20%)	0.901	0.227
	(0.567)	(0.451)
Q2 (21-40%)	1.075*	0.318
	(0.583)	(0.461)
Q4 (61-80%)	-0.332	-0.202
	(0.513)	(0.401)
Q5 (81-100%)	0.192	0.352
	(0.542)	(0.437)
2023*0-20%	-0.353	-0.461
	(1.258)	(1.126)
2023*21-40%	0.222	0.0570
	(1.281)	(1.133)
2023*61-80%	0.138	0.338
	(1.069)	(0.970)
2023*81-100%	-0.0396	0.0185
	(1.168)	(1.092)
Median income		0.000739***
		(4.47e-05)
Population		-1.59e-05***
		(2.12e-06)
Voter turnout		-0.623***
		(0.0359)
Constant	14.70***	41.59***
	(0.377)	(2.672)
Observations	1,336	1,336
R-squared	0.521	0.653

Note. Results of the DiD regression. The dependent variable is the support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In Model 1 (Table 2 Column 1), the coefficient for the year 2023, 13.876, is positive and statistically significant at 1%, indicating an overall increase in support for anti-immigration parties in 2023 across all municipalities. However, the interaction terms (e.g., 2023*0-20%, 2023*21-40%, etc.) are not statistically significant at 10%, suggesting that the change in votes for anti-immigration parties in 2023 does not significantly differ by the proportion of Ukrainian refugees present in the municipalities.

Column 2 of Table 2 presents the results of Model 2, where median income, population, and voter turnout are included as controls, the results are similar. The 2023 coefficient (9.084) remains positive and statistically significant, although it does decrease in magnitude. Furthermore, the interaction terms remain statistically insignificant. This suggests that while there is a general increase in votes for anti-immigration parties in 2023, this increase does not appear to be significantly related to the proportion. Of Ukrainian refugee sin the municipalities. Additionally, while the controls are statistically significant at 1%, they are economically insignificant given their very small magnitudes. Thus, while my results do not show an increase in tolerance for refugees as a result of Ukrainian refugees' presence, there also is no evidence to suggest backlash.

The second hypothesis suggests that the effect of the number of Ukrainian refugees on the vote share for anti-immigration parties is moderated by historical support for these parties. Specifically, it posits that in municipalities with historically high support for anti-immigration parties, the presence of more Ukrainian refugees will be associated with an increase in votes for anti-immigration parties. The results of this DiD regression are depicted in Table 3.

Table 3   DiD regression results of the effect of Ukrainian refugees on votes for anti-immigration parties, with historical support as moderator

Variables	(1) Share votes for anti-immigration parties
2023	9.186***
	(0.696)
0-20%	-0.221
	(0.355)
21-40%	0.0127
	(0.413)
41-60%	0.261
	(0.341)
81-100%	-0.0767
	(0.396)
Historical support	6.456***
	(0.680)
2023*0-20%	-0.563
	(1.024)
2023*21-40%	-0.105
	(1.155)
2023*41-60%	0.216
	(0.909)
2023*81-100%	-0.144
	(1.108)
0-20%*Historical support	1.754*
	(1.020)
21-40%*Historical support	0.709
	(0.985)
41-60%*Historical support	-1.162
	(0.889)
81-100%*Historical support	-0.235
	(0.876)
2023*0-20%*Historical support	0.0882
	(2.355)
2023*21-40%*Historical support	0.165
	(2.230)
2023*41-60%*Historical support	0.380
	(1.929)
2023*81-100%*Historical support	-0.0363
	(1.998)
Median income	0.000608***
	(3.86e-05)
Population	-6.29e-06***
	(2.07e-06)
Voter turnout	-0.205***
	(0.0323)
Constant	10.39***
	(2.366)
Observations	1,336
R-squared	0.763

Note. Results of the DiD regression. The dependent variable is the support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Historical support is a dummy variable that takes on the value of 1 when the municipality belongs to the top 25% in terms of average share of votes for anti-immigration parties in 2012-2021. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Model 3 (Table 3) includes an interaction term for historical support for anti-immigration parties. The historical support variable has a magnitude of 6.456 and is significantly positive at 1%, indicating that municipalities with higher historical support for anti-immigration parties tend to have higher support in 2023 as well. This suggests a persistence in voting patterns. It also shows that municipalities in the lowest quantile vote significantly more for anti-immigration parties if support for these parties was high in the past. However, at 10%, the interaction terms between the year 2023, the quintiles, and historical support do not show significant effects, indicating that the historical support does not significantly moderate the impact of Ukrainian refugees on voting behavior. This means that the increase in votes for anti-immigration parties in 2023 is not significantly different in municipalities with varying levels of historical support as a result of the presence of Ukrainian refugees.

Overall, the DiD regression analysis indicates that while there is a general increase in support for anti-immigration parties in 2023, this increase is not significantly influenced by the proportion of Ukrainian refugees in the municipalities. Additionally, historical support for anti-immigration parties does not appear to significantly moderate this relationship. Consequently, these models do not provide conclusive evidence to support or refute Hypotheses 1 and 2.

Table 4 presents the results from the Difference-in-Differences (DiD) regression analysis, which tests the impact of the proportion of Ukrainian refugees on voter turnout in the 2023 elections. This analysis aims to investigate the third hypothesis, which states that municipalities with a higher proportion of Ukrainian refugees will show a significant increase in turnout in the 2023 elections compared to municipalities with an average proportion of Ukrainian refugees.

Table 4   DiD regression results of the effect of Ukrainian refugees on voter turnout

Variables	(1) Voter turnout	(2) Voter turnout
2023	0.527	-3.173***
	(0.668)	(0.572)
Q1 (0-20%)	-0.315	-0.725*
	(0.477)	(0.385)
Q2 (21-40%)	-1.123**	-1.179***
	(0.487)	(0.407)
Q4 (61-80%)	-0.104	-0.0295
	(0.463)	(0.395)
Q5 (81-100%)	1.101**	0.559
	(0.482)	(0.408)
2023*0-20%	-0.0386	-0.104
	(0.942)	(0.749)
2023*21-40%	-0.307	-0.291
	(0.946)	(0.784)
2023*61-80%	0.251	0.280
	(0.921)	(0.770)
2023*81-100%	0.133	0.109
	(0.949)	(0.801)
Median income		0.000536***
		(2.63e-05)
Population		-1.74e-05***
		(2.30e-06)
Constant	80.15***	63.79***
	(0.327)	(0.923)
Observations	1,336	1,336
R-squared	0.026	0.309

Note. Results of the DiD regression. The dependent variable is voter turnout, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The first column of Table 4 shows the baseline regression without control variables. The variable for the year 2023 has a coefficient of 0.527, which is positive but not statistically significant at 10%, suggesting that there is no overall increase in voter turnout in 2023 across all municipalities when not controlling for other factors. The coefficients for the quintiles show mixed results. The 21-40% category has a significantly negative coefficient (-1.123), indicating that municipalities with from the second quintile have lower voter turnout compared to the reference group (third quintile). The 81-100% category shows a positive and statistically significant coefficient of 1.101, suggesting that municipalities with the highest proportion of Ukrainian refugees have higher voter turnout.

However, at 10%, the interaction terms between the year 2023 and the quintiles are not statistically significant in this first model. This indicates that the presence of Ukrainian refugees does not significantly influence voter turnout in 2023 relative to the pre-treatment period for the different proportion categories.

Model 2 is presented in Column 2 of Table 4, which includes controls for median income and population size. The coefficient for the year 2023 becomes negative (-3.173), but does become statistically significant at 1%, suggesting an overall decrease in voter turnout in 2023 when controlling for socio-economic factors. The proportion categories continue to show mixed results. The 0-20% category has a significantly negative coefficient (-0.725), and the 21-40% category remains significantly negative (-1.179). This indicates that lower proportions of Ukrainian refugees are associated with decreased voter turnout compared to the reference group. However, the fourth and fifth quintiles do not show significant differences from the reference group in this model. The controls are statistically significant, but economically insignificant, given their very small magnitude.

The interaction terms in Model 2 also remain statistically insignificant, indicating that the changes in voter turnout in 2023 are not significantly influenced by the proportion of Ukrainian refugees, even after controlling for median income and population size.

Thus, the DiD regression analysis indicates that there is no significant evidence to suggest that municipalities with a higher proportion of Ukrainian refugees show a significant increase in voter turnout in the 2023 elections compared to municipalities with an average proportion of Ukrainian refugees. The interaction terms between the year 2023 and the proportion categories are not statistically significant, suggesting that the presence of Ukrainian refugees does not significantly influence voter turnout. Additionally, controlling for socio-economic factors such as median income and population size reveals that these factors have their own significant effects on voter turnout. Therefore, these models do not provide sufficient evidence to support Hypothesis 3.

6. Robustness checks

6.1. Placebo test

6.1.1. Method

To ensure the validity of the findings and test the robustness of the observed effects, a placebo test is conducted. In the placebo test, the year 2021 is chosen as the placebo treatment year and data from 2023 is disregarded, while keeping all other aspects of the methodology unchanged. Thus, the PTA tests and DiD regressions are run in the same way as in the main analyses, except 2021 is seen as the treatment year. This choice allows me to analyze a period before the actual treatment, which began with the influx of Ukrainian refugees in February 2022. By doing so, I can test if any significant changes in support for anti-immigration parties and voter turnout occurred in 2021 that could be mistakenly attributed to the treatment effect. The pre-treatment periods for the placebo test will include the 2012 and 2017 elections.

To test for parallel trends, I, once again, visually inspect the trends in voter turnout and support for anti-immigration parties for the pre-treatment periods (2012 and 2017) and the placebo treatment period (2021). This involves plotting the trends for the treatment and control groups and checking for any significant divergences. Additionally, a regression-based test is conducted to formally verify the PTA by interacting the pre-treatment period indicators with the treatment variable and examining the significance of these interaction terms.

The same Difference-in-Differences (DiD) modela used in the regular analysis are applied for the placebo test. The dependent variables of interest are the share of votes for anti-immigration parties and voter turnout. The key independent variables include the placebo treatment year (2021), the proportion of Ukrainian refugees categorized into quintiles, and the interaction terms between the placebo treatment year and these quintiles. Additionally, control variables such as median income, population size, and historical support for anti-immigration parties are included to ensure consistency with the main analysis. See Section 4.2 for a more detailed description of the methodology.

The results of the placebo test provide crucial insights. Given that the actual treatment did not occur until 2022, I would not expect to see significant changes. However, If significant changes are observed in the placebo test, it would raise concerns about the original analysis, suggesting that potential confounding variables or pre-existing trends were not adequately controlled for. This would necessitate a re-evaluation of the original findings and potentially the use of additional robustness checks or alternative methodologies.

6.1.2.   Parallel Trends Assumption

Table C1 and C2 present the OLS regression results of the placebo PTA tests, where the effect of Ukrainian refugees on votes for anti-immigration parties is investigated. In both models of Table C1, the interaction terms are statistically insignificant at 10%, giving evidence to support the PTA. Figures C1.1 and C1.2 display the corresponding line graphs. These line graphs are both identical to each other and show the pre-trends of quintiles to be very similar, further supporting the PTA. The model with historical support is displayed in Table C2, from which it can be concluded that al interaction terms are statistically significant, and the line graph (Figure C2) also shows parallel trends similar to those depicted in Figures C1.1 and C1.2. Thus, there is enough evidence for me to believe that the PTA holds in this placebo test.

Table C3 presents the OLS regression results of the placebo PTA tests, where the effect of Ukrainian refugees on voter turnout is analyzed. Once again, the interaction terms in both models are statistically insignificant at 10%. The corresponding line graphs are presented in Figures C3.1 and C3.2. These two

graphs are also identical to each other and show the quintiles to follow similar paths. Therefore, there is enough evidence for me to believe that the PTA holds for this placebo test as well.

6.1.3. Results

The results of the DiD regression analyses of the effect of Ukrainian refugees on the share of votes for anti-immigration parties, with 2021 as the placebo treatment year, are presented in Table 5. When comparing the placebo results of the placebo base model (Table 5 Column 1) to that of the regular base model (Table 2 Column 1), a minor differences can be seen. However, in the placebo test, all interaction terms are insignificant, providing evidence that potential confounding variables or pre-existing trends are adequately controlled for. Column 2 of Table 5 includes median income, population and voter turnout as controls. Comparing these results to the main analysis (Table 2 Column 2), interaction terms are, once again, insignificant. The same can be said when comparing the results of the main analysis (Table 3) to the placebo (Table 6) when historical support is added as a moderator, using interaction terms. Thus, with this placebo test, I find insignificant interaction terms, which suggests that potential confounders are adequately controlled for.

Table 5   Placebo DiD regression results of the effect of Ukrainian refugees on votes for anti-immigration parties

Variables	(1) Share votes for anti-immigration parties	(2) Share votes for anti-immigration parties
2021	6.241***	1.628*
	(0.674)	(0.852)
Q1 (0-20%)	1.065*	0.505
	(0.609)	(0.550)
Q2 (21-40%)	1.143*	0.488
	(0.610)	(0.548)
Q4 (61-80%)	-0.456	-0.183
	(0.513)	(0.473)
Q5 (81-100%)	0.0921	0.340
	(0.559)	(0.524)
2021*0-20%	-0.494	-0.503
	(1.043)	(0.935)
2021*21-40%	-0.206	-0.0928
	(1.094)	(0.991)
2021*61-80%	0.372	0.111
	(0.874)	(0.811)
2021*81-100%	0.301	0.141
	(0.938)	(0.883)
Median income		0.000702***
		(9.10e-05)
Population		-1.04e-05***
		(1.84e-06)
Voter turnout		-0.512***
		(0.0464)
Constant	12.62***	33.02***
	(0.386)	(2.651)
Observations	1,002	1,002
R-squared	0.281	0.387

Note. Results of the placebo DiD regression. The dependent variable is the support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The placebo treatment period starts in January 2020. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6   Placebo DiD regression results of the effect of Ukrainian refugees on votes for anti-immigration parties, with historical support as a moderator

Variables	(1) Share votes for anti-immigration parties
2021	3.713***
	(0.725)
0-20%	0.216
	(0.410)
21-40%	0.264
	(0.454)
61-80%	0.127
	(0.381)
81-100%	-0.225
	(0.440)
2021*0-20%	-0.669
	(0.733)
2021*21-40%	-0.327
	(0.917)
2021*61-80%	0.310
	(0.712)
2021*81-100%	0.325
	(0.793)
Historical support	6.990***
	(0.748)
2021*Historical support	0.803
	(1.350)
0-20%*Historical support	1.526*
	(0.863)
21-40%*Historical support	0.677
	(1.112)
61-80%*Historical support	-1.416
	(1.020)
81-100%*Historical support	-0.280
	(1.004)
2021*0-20%*Historical support	0.443
	(2.096)
2021*21-40%*Historical support	0.234
	(2.078)
2021*61-80%*Historical support	0.420
	(1.708)
2021*81-100%*Historical support	-0.321
	(1.730)
Median income	0.000323***
	(7.28e-05)
Population	-1.54e-06
	(2.10e-06)
Voter turnout	-0.0180
	(0.0397)
Constant	2.940
	(2.189)
Observations	1,002
R-squared	0.621

Note. Results of the placebo DiD regression. The dependent variable is support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is the reference group. The placebo treatment starts in January 2020. Historical support is a dummy variable that equals 1 when the municipality belongs to the top 25% in terms of average share of votes for anti-immigration parties in 2012-2021. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7 presents the DiD regression results of the effect of Ukrainian refugees on voter turnout, with 2021 as the placebo treatment year. Once again, the interaction terms are insignificant at 10% for both models. Therefore, the results of this placebo test also suggest potential confounders or pre-trends have been controlled for.

Table 7   Placebo DiD regression results of the effect of Ukrainian refugees on voter turnout

Variables	(1) Voter turnout	(2) Voter turnout
2021	1.036	-4.385***
	(0.650)	(0.698)
Q1 (0-20%)	-0.351	-0.311
	(0.613)	(0.450)
Q2 (21-40%)	-1.171*	-0.860*
	(0.628)	(0.445)
Q4 (61-80%)	0.0782	0.637
	(0.587)	(0.416)
Q5 (81-100%)	1.173*	0.677
	(0.620)	(0.480)
2021*0-20%	0.108	-0.108
	(0.950)	(0.783)
2021*21-40%	0.141	0.150
	(0.968)	(0.737)
2021*61-80%	-0.546	-0.538
	(0.941)	(0.733)
2021*81-100%	-0.217	-0.441
	(0.961)	(0.820)
Median income		0.000690***
		(6.60e-05)
Population		-0.000942***
		(0.000113)
Constant	79.81***	58.19***
	(0.420)	(2.139)
Observations	1,002	1,002
R-squared	0.029	0.404

Note. Results of the placebo DiD regression. The dependent variable is voter turnout, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The placebo treatment period starts in January 2020. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6.2. One treatment group

As a secondary robustness check, I ran the same models as in my main analyses, using different treatment groups. Rather than using five treatment groups (quintiles), I used a 'low share' and 'high share' of Ukrainian refugees distinction. The low share group consists of municipalities with Ukrainian refugees per 1,000 inhabitants less than or equal to the average of the Netherlands (5.7). Conversely, the high share group consists of municipalities with Ukrainian refugees per 1,000 inhabitants higher than 5.7. The results are very similar to the main analyses; no statistically nor economically significant effects have been found, further supporting the robustness of my findings.

7. Conclusion and Discussion

Using data from 2012 to 2023 provided by the Dutch Electoral Council and Statistics Netherlands, I have explored the effect of Ukrainian refugees on voter sentiment. More specifically, this paper aims to answer the following research question:

What is the effect of contact with Ukrainian refugees on support for Dutch anti-immigration parties at the municipal level?

In order to study this relationship, three hypotheses have been formed and tested. The primary analyses, utilizing Difference-in-Differences (DiD) models, investigated the effect of Ukrainian refugee presence on the share of votes for anti-immigration parties and voter turnout during the 2023 Dutch General elections.

With regard to support for refugees, Allport (1954) states that contact with refugees increases tolerance for them, although empirical studies find conflicting results. Since unlike most other refugee crises in Europe, Ukrainian refugees are white and thus, look more like most Dutch people, my first hypothesis states that municipalities with a higher proportion of Ukrainian refugees will show a significant decrease in votes for anti-immigration parties. The results do not support this hypothesis, as the presence of Ukrainian refugees does not lead to a statistically or economically significant change in votes for anti-immigration parties.

Similarly, the second hypothesis states that the effect of the number of Ukrainian refugees on the vote share for anti-immigration parties is moderated by historical support for anti-immigration parties. My findings are not in line with this hypothesis, as no significant moderating effect has been found.

Moreover, the third hypothesis states that municipalities with a higher proportion of Ukrainian refugees will show a significant increase in voter turnout. The results do not support this hypothesis, as the presence of Ukrainian refugees does not lead to a significant change in voter turnout. These findings are not in line with those of Bratti et al. (2020), who find that voter turnout is higher in municipalities that are closer to refugee reception centers.

To answer my research question, the findings from the DiD regression analyses indicate that the that the presence of Ukrainian refugees do not have a significant impact on the share of votes for anti-immigration parties or voter turnout in Dutch municipalities during the 2023 elections. This suggests that the influx of Ukrainian refugees, who are predominantly white and European, did not provoke a

strong political reaction in terms of increased anti-immigration sentiment, unlike previous refugee crises involving non-European groups.

The findings of this study, although statistically insignificant, suggest that the influx of Ukrainian refugees did not lead to a significant political backlash in terms of increased anti-immigration votes. To an extent, this is consistent with the research by Pepinsky et al. (2022), which find increased tolerance for refugees in Hungary due to the predominantly white and European demographics of Ukrainian refugees. While my findings do not show a significant increase in tolerance, the lack of significant backlash aligns with the notion that racial and cultural similarities between the host population and refugees can mitigate negative political reactions. This contrasts with earlier studies (e.g., Jasny & Becker, 2020; Fremerey et al., 2024) that document an increase in far-right votes in response to refugee influxes from the Middle East, which suggests that racial and cultural perceptions may play a role in the shaping of public attitudes towards refugees.

The findings of this research have significant implications for both theoretical understanding and practical policymaking. Theoretically, the study contributes to the body of literature on intergroup contact and group threat theory by providing nuanced insights into how different demographic characteristics of refugee groups impact local attitudes and political behaviors. The absence of significant changes in anti-immigration sentiment in response to the influx of Ukrainian refugees, a predominantly white and culturally similar group, supports the idea that perceived cultural and racial similarities can mitigate threat perceptions and foster more neutral or positive local attitudes. This contrasts with reactions to previous refugee crises involving non-European groups, who, generally speaking, are culturally more distant from the Dutch public.

Practically, the research offers actionable insights for policymakers aiming to foster inclusive communities and mitigate anti-immigration sentiment. Namely, by understanding the factors that influence local attitudes towards refugees, such as cultural and demographic similarities, policymakers can design more effective integration and support programs that leverage these dynamics.

However, the results of this paper must be interpreted with caution. This is due to several limitations regarding the data. Firstly, the potential for self-selection bias exists, as Ukrainian refugees could choose their municipalities, possibly leading to non-random distribution. While efforts were made to control for this, the lack of comprehensive data on shelter availability and refugee settlement patterns limited the ability to fully account for self-selection. Secondly, the study relied on aggregate data at the municipal level, which may mask individual-level variations in voting behavior and attitudes towards refugees. Finally, the analysis was constrained by the availability of data. For example, there was no data available on unemployment per municipality, to control for the possible case that people in

municipalities with very low unemployment react more positively to Ukrainian refugees, as they can work there. Additionally, data on median income in 2023 was unavailable, which was proxied using 2022 data.

These limitations create suggestions for future research. Namely, future research should aim to collect more granular data on refugee settlement patterns and individual-level voting behavior to better understand the nuances of refugee impact on local politics. This should be done for Ukrainian and Middle Eastern refugees separately, such that the findings of such studies can be compared to each other more accurately. Additionally, exploring the role of media coverage and public discourse in shaping attitudes towards refugees could provide deeper insights. Furthermore, in case the war in Ukraine continues for a longer time, and Ukrainian refugees stay in the Netherlands, it would be very valuable to investigate the long-term effects of refugee presence on local communities and their political landscape.

Bibliography

Achard, P., Albrecht, S., Ghidoni, R., Cettolin, E., & Suetens, S. (2022). The effect of exposure to ethnic minorities on ethnic preferences (CEPR Discussion Paper No. DP17294).

Al Jazeera. (2023, November 22). Netherlands votes in tight election with far-right expected to make gains. *Al Jazeera*. https://www.aljazeera.com/news/2023/11/22/netherlands-votes-in-tight-election-with-far-right-expected-to-make-gains

Allport, G. W., Clark, K., & Pettigrew, T. (1954). *The nature of prejudice.* Reading, MA: Addison-Wesley.

Altındağ, O., & Kaushal, N. (2021). Do refugees impact voting behavior in the host country? Evidence from Syrian refugee inflows to Turkey. *Public Choice*, *186*, 149-178.

BBC. (2023, June 16). Europe's political earthquake: Dutch populist surge. *BBC News*. https://www.bbc.com/news/world-europe-67512204

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

Bratti, M., Deiana, C., Havari, E., Mazzarella, G., & Meroni, E. C. (2020). Geographical proximity to refugee reception centres and voting. *Journal of Urban Economics*, *120*, 103290.

Campo, F., Giunti, S., & Mendola, M. (2020). The political impact of refugee migration: evidence from the Italian dispersal policy. *University of Milan Bicocca Department of Economics, Management and Statistics Working Paper*, (456).

Card, D., Dustmann, C., & Preston, I. (2012). Immigration, wages, and compositional amenities. *Journal of the European Economic Association*, *10*(1), 78-119.

CBS. (2013, January 3). *408 Nederlandse gemeenten in 2013*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2013/01/408-nederlandse-gemeenten-in-2013#:~:text=De%20nieuw%20gevormde%20gemeenten%20Schagen,minder%20dan%2020%20duizend%20inwoners.

CBS. (2014, January 1). *Gemeentelijke indeling op 1 januari 2014*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2014#:~:text=Op%201%20januari%202014%20is,gemeenten%20in%20Nederland%20403%20bedraagt.&text=De%20gemeente%20Boarnsterhim%20is%20heringedeeld,Heerenveen%20en%20De%20Friese%20Meren.

CBS. (2015, January 1). *Per 1 januari 2015: 393 gemeenten*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2015/02/per-1-januari-2015-393-gemeenten

CBS. (2016, January 1). *Aantal gemeenten in 2016 daalt naar 390*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2016/01/aantal-gemeenten-in-2016-daalt-naar-390#:~:text=Op%201%20januari%202016%20vonden,het%20reeds%20bestaande%20Edam%2DVolendam.

CBS. (2017, January 1). *Gemeentelijke indeling op 1 januari 2017*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2017

CBS. (2018, January 1). *Gemeentelijke indeling op 1 januari 2018*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2018#:~:text=Op%201%20januari%202018%20is,gemeenten%20in%20Nederland%20380%20bedraagt.&text=1)%20De%20gemeente%20Littenseradiel%20wordt,en%20de%20nieuwe%20gemeente%20Waadhoeke.

CBS. (2019, January 1). *Gemeentelijke indeling op 1 januari 2019*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2019

CBS. (2020, January 1). *Gemeentelijke indeling op 1 januari 2020*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2020

CBS. (2021, January 1). *Gemeentelijke indeling op 1 januari 2021*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2021

CBS. (2022, December 29). *Aantal gemeenten daalt tot 342 op 1 januari 2023*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/nieuws/2022/52/aantal-gemeenten-daalt-tot-342-op-1-januari-2023

CBS. (2022, January 1). *Gemeentelijke indeling op 1 januari 2022*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2022

CBS. (2023, January 1). *Gemeentelijke indeling op 1 januari 2023*. Centraal Bureau voor de Statistiek. https://www.cbs.nl/nl-nl/onze-diensten/methoden/classificaties/overig/gemeentelijke-indelingen-per-jaar/indeling-per-jaar/gemeentelijke-indeling-op-1-januari-2023

CNN. (2023, November 22). Netherlands election: What you need to know. *CNN*. https://edition.cnn.com/2023/11/22/europe/netherlands-election-intl/index.html

Dustmann, C., & Preston, I. (2001). Attitudes to ethnic minorities, ethnic context and location decisions. *The Economic Journal*, *111*(470), 353-373.

EenVandaag. (2022, June 1). 1 op de 12 mensen wil nadenken over vluchteling uit Oekraïne in huis, Nederlanders bieden massaal hulp aan. *EenVandaag*. https://eenvandaag.avrotros.nl/panels/opiniepanel/alle-uitslagen/item/1-op-de-12-mensen-wil-nadenken-over-vluchteling-uit-oekraine-in-huis-nederlanders-bieden-massaal-hulp-aan/

Enos, J. (2023). Politicized ethno-racial shock as group threat: "Refugee crisis" immigration and anti-immigrant voting in Sweden. *Ethnic and Racial Studies*, *46*(5), 944-965.

Euro-Med Monitor. (2022, March 2). Europe's official, media handling of Ukrainian crisis exposes deep-rooted, racist policy against non-Europeans. *Euro-Med Monitor*. https://euromedmonitor.org/en/article/4934/Europe%27s-official,-media-handling-of-Ukrainian-crisis-exposes-deep-rooted,-racist-policy-against-non-Europeans

Fetzer, J. S. (2012). *Public opinion and populism*. In M. R. Rosenblum & D. J. Tichenor (Eds.), Oxford handbook of the politics of international migration (229–323). Oxford, UK: Oxford University Press.

Fisunoğlu, A., & Sert, D. Ş. (2019). Refugees and elections: the effects of Syrians on voting behavior in Turkey. *International Migration*, *57*(2), 298-312.

Fremerey, M., Hörnig, L., & Schaffner, S. (2024). Becoming neighbors with refugees and voting for the far-right? The impact of refugee inflows at the small-scale level. *Labour Economics*, *86*, 102467.

Gessler, T., Tóth, G., & Wachs, J. (2022). No country for asylum seekers? How short-term exposure to refugees influences attitudes and voting behavior in Hungary. *Political Behavior*, *44*(4), 1813-1841.

Government of the Netherlands. (2024, February 23). Two years of war in Ukraine: The Netherlands' aid efforts. *Government of the Netherlands*.

https://www.government.nl/latest/news/2024/02/23/two-years-of-war-in-ukraine-the-
netherlands-aid-
efforts#:~:text=The%20reception%20of%20Ukrainian%20refugees,in%20over%20100%2C0
00%20Ukrainian%20refugees

Ha, S. E. (2010). The consequences of multiracial contexts on public attitudes toward immigration. *Political Research Quarterly, 63*, 29–42.

Hainmueller, J., & Hiscox, M. J. (2007). Educated preferences: Explaining attitudes toward immigration in Europe. *International organization*, *61*(2), 399-442.

Hopkins, D. J., Sides, J., & Citrin, J. (2019). The muted consequences of correct information about immigration. *The Journal of Politics*, *81*(1), 315-320.

Jasny, J., & Becker, T. (2020). Refugees welcome, but not in my backyard? The impact of immigration on right-wing voting: evidence from Germany. *IZA Journal of Development and Migration*, *11*(1).

Jolly, S. K., & DiGiusto, G. M. (2014). Xenophobia and immigrant contact: French public attitudes toward immigration. *Social Science Journal, 51*, 464–473.

Karacuka, M. (2021). Refugees and votes: the impact of refugee influx and internet on voting decisions. *Journal of Refugee Studies*, *34*(3), 2933-2959.

Kiesraad. (2017, March 20). Officiële uitslag Tweede Kamerverkiezing 15 maart 2017. *Kiesraad.* https://www.kiesraad.nl/actueel/nieuws/2017/03/20/officiele-uitslag-tweede-
kamerverkiezing-15-maart-2017

Lancee, B., & Pardos-Prado, S. (2013). Group conflict theory in a longitudinal perspective: Analysing the dynamic side of ethnic competition. *International Migration Review, 47*, 106–131.

NH Nieuws. (2023, June 2). Omstreden opvang Oekraïners in Purmerend komt er maar mogelijk iets minder massaal. *NH Nieuws.* https://www.nhnieuws.nl/nieuws/327273/omstreden-opvang-
oekrainers-in-purmerend-komt-er-maar-mogelijk-iets-minder-massaal

Nieuwsuur. (2023, June 2). Opvang Oekraïners bij Nederlandse gastgezinnen komt op gang. *NOS.* https://nos.nl/nieuwsuur/artikel/2424825-opvang-oekrainers-bij-nederlandse-gastgezinnen-
komt-op-gang

NOS. (2016, February 16). Heftig protest tegen opvang asielzoekers: Heeft dat effect? *NOS.* https://nos.nl/artikel/2111331-heftig-protest-tegen-opvang-asielzoekers-heeft-dat-effect

NOS. (2022, September 1). Anti-AZC protest staat niet op zichzelf: Mensen denken en wij dan. *NOS*. https://nos.nl/collectie/13898/artikel/2441476-anti-azc-protest-staat-niet-op-zichzelf-mensen-denken-en-wij-dan

NOS. (2023, June 14). Politieke aardverschuiving: PVV veruit de grootste, coalitie afgestraft. *NOS*. https://nos.nl/collectie/13958/artikel/2498924-politieke-aardverschuiving-pvv-veruit-de-grootste-coalitie-afgestraft

NRC. (2016, February 16). Er zijn meer vrijwilligers dan vluchtelingen. *NRC*. https://www.nrc.nl/nieuws/2016/02/16/er-zijn-meer-vrijwilligers-dan-vluchtelingen-1590258-a772674

Pepinsky, T. B., Reiff, Á., & Szabo, K. (2022). The Ukrainian refugee crisis and the politics of public opinion: Evidence from Hungary. *Perspectives on Politics*, 1-26.

Pettigrew, T. F. (1998). Intergroup contact theory. *Annual Review of Psychology, 49*(1), 65-85.

PVV. (2023). Verkiezingsprogramma. *PVV*. https://www.pvv.nl/verkiezingsprogramma.html

Rickardsson, J. (2023). Opinion formation in a changing regional economy (PhD dissertation, Jönköping University, Jönköping International Business School).

RTV Drenthe. (2023, June 4). Onrust in Elp over opvang Oekraïners: Gemeente wil inwoners betrekken bij besluit. *RTV Drenthe*. https://www.rtvdrenthe.nl/nieuws/16430955/onrust-in-elp-over-opvang-oekrainers-gemeente-wil-inwoners-betrekken-bij-besluit

Schindler, D., & Westcott, M. (2018). Shocking racial attitudes: Black G.I.s in Europe. (CESifo Working Paper Series; No. 6723). CESifo Working Papers.

Schlueter, E., & Wagner, U. (2008). Regional differences matter: Examining the dual influence of the regional size of the immigrant population on derogation of immigrants in Europe. *International Journal of Comparative Sociology*, *49*(2-3), 153-173.

Semyonov, M., & Glikman, A. (2009). Ethnic residential segregation, social contacts, and anti-minority attitudes in European societies. *European Sociological Review, 25*, 693–708.

Sinclair, S., Granberg, M., & Nilsson, T. (2023). Love thy (Ukrainian) neighbour: Willingness to help refugees depends on their origin and is mediated by perceptions of similarity and threat. *British Journal of Social Psychology*.

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

Steinmayr, A. Exposure to refugees and voting for the far-right: (Unexpected) results from Austria. (IZA Discussion Paper No. 9790).

Stephan, W. G., Ybarra, O., & Morrison, K. R. (2009). *Intergroup threat theory.* In T. D. Nelson (Ed.), Handbook of prejudice, stereotyping, and discrimination (43–59). New York, NY: Psychology Press.

The Guardian. (2022, March 2). Civilised, European, look like us: Racist coverage of Ukraine. *The Guardian*. https://www.theguardian.com/commentisfree/2022/mar/02/civilised-european-look-like-us-racist-coverage-ukraine

Tilburg University. (2023). Update: Waardenonderzoek Nederland. *Tilburg University*. https://www.tilburguniversity.edu/nl/actueel/nieuws/update-waardenonderzoek-nederland

Usta, E. K. (2022). Effects of Refugee Inflow on the Voting Behavior of Natives: Application of Mobile Phone Data. *CESifo Economic Studies*, *68*(3), 219-252.

Von Hermanni, H., & Neumann, R. (2019). "Refugees welcome?" The interplay between perceived threats and general concerns on the acceptance of refugees – A factorial survey approach in Germany. *Journal of Ethnic and Migration Studies, 45*, 349–374.

Appendices

Appendix A: Data

Table A1   Overview of all municipal reorganizations and terminations from 2013-2023

Year	Reorganizations	Terminations
2013	Schagen (Schagen, Zijpe, Harenkarspel)	
	Goeree-Overflakkee (Goedereede, Dirksland, Middelharnis, Oostflakkee)	
	Molenwaard (Graafstroom, Liesveld, Nieuw-Lekkerland)	
2014	Alphen aan den Rijn (Alphen aan den Rijn, Boskoop, Rijnwoude)	Boarnsterhim
	De Friese Meren (Gaasterlân-Sleat, Lemsterland, Skasterlân)	
2015	Alkmaar (Alkmaar, Schermer, Graft – De Rijp)	Maasdonk
	Krimpenwaard (Bergambacht, Nederlek, Ouderkerk, Schoonhoven, Vlist)	
	Nissewaard (Bernisse, Spijkenisse)	
	Berg en Dal (Groesbeek, Millingen aan de Rijn, Ubbergen)	
2016	Gooise Meren (Bussum, Muiden, Naarden)	
	Edam-Volendam (Edam-Volendam, Zeevang)	
2017	Meierijstad (Schijndel, Sint-Oedenrode, Veghel)	
2018	Westerwolde (Bellingwedde, Vlagtwedde)	Littenseradiel
	Midden-Groningen (Hoogezand-Sappemeer, Slochteren, Menterwolde)	
	Waadhoeke (Het Bildt, Franekeradeel, Menameradiel)	
	Leeuwarden (Leeuwarden, Leeuwarderadeel)	
	Zevenaar (Rijnwaarden)	
2019	Het Hogeland (Bedum, Eemsmond, De Marne, Winsum)	
	Groningen (Groningen, Ten Boer, Haren)	
	Westerkwartier (Grootegast, Leek, Marum, Zuidhorn)	
	Noardeast-Fryslân (Dongeradeel, Kollumerland en Nieuwkruisland, Ferwerderadiel)	
	West Betuwe (Geldermalsen, Neerijnen, Lingewaal)	
	Haarlemmermeer (Haarlemmerliede en Spaarnwoude, Haarlemmermeer)	
	Vijfheerenlanden (Leerdam, Vianen, Zederik)	
	Noordwijk (Noordwijk, Noordwijkerhout)	
	Hoeksche Waard (Oud-Beijerland, Binnenmaas, Korendijk, Cromstrijen, Strijen)	
	Molenlanden (Giessenlanden, Molenwaard)	
	Altena (Aalburg, Werkendam, Woudrichem)	
	Beekdaelen (Onderbanken, Nuth, Schinnen)	
2021	Eemsdelta (Appingedam, Delfzijl, Loppersum)	Haaren
2022	Purmerend (Beemster, Purmerend)	
	Dijk en Waard (Heerhugowaard, Langedijk)	
	Maashorst (Landerd, Uden)	
	Land van Cuijk (Boxmeer, Cuijk, Grave, Mill en Sint Hubert, Sint Anthonis)	
2023	Voorne aan Zee (Hellevoetsluis, Brielle, Westvoorne)	
	Amsterdam (Amsterdam, Weesp)	

Note. Ameland, Baarle-Nassau, Renswoude, Rozendaal, Schiermonnikoog, Terschelling and Vlieland have been removed due to missing data.

Table A2   Categorization of political parties into *anti-immigration* and *other*

	2012	2017	2021	2023
Anti-immigration	Partij Voor de Vrijheid (PVV)	Partij Voor de Vrijheid (PVV)	Partij Voor de Vrijheid (PVV)	Partij Voor de Vrijheid (PVV)
	Democratisch Politiek Keerpunt (DPK)	Forum voor Democratie (FvD)	Forum voor Democratie (FvD)	Forum voor Democratie (FvD)
		Geen Peil	Jezus Leeft	JA21
		Jezus Leeft	JA21	Belang Voor Nederland/Groep Van Haga (BVNL)
		VoorNederland (VNL)	Wij Zijn Nederland	
Other	Volkspartij voor Vrijheid en Democratie (VVD)	Volkspartij voor Vrijheid en Democratie (VVD)	Volkspartij voor Vrijheid en Democratie (VVD)	Volkspartij voor Vrijheid en Democratie (VVD)
	Partij van de Arbeid (PvDA)	Partij van de Arbeid (PvDA)	Partij van de Arbeid (PvDA)	Democraten 66 (D66)
	Christen-Democratisch Appèl (CDA)	Christen-Democratisch Appèl (CDA)	Christen-Democratisch Appèl (CDA)	GroenLinks/Partij van de Arbeid (GL/PvdA)
	Socialistische Partij (SP)	Socialistische Partij (SP)	Socialistische Partij (SP)	Democratisch Appèl (CDA)
	Democraten 66 (D66)	Democraten 66 (D66)	Democraten 66 (D66)	Socialistische Partij (SP)
	GroenLinks (GL)	GroenLinks (GL)	GroenLinks (GL)	ChristenUnie (CU)
	ChristenUnie (CU)	ChristenUnie (CU)	ChristenUnie (CU)	Partij voor de Dieren (PvvD)
	Staatkundig Gereformeerde Partij (SGP)	Staatkundig Gereformeerde Partij (SGP)	Staatkundig Gereformeerde Partij (SGP)	Volt
	Partij voor de Dieren (PvvD)	Partij voor de Dieren (PvvD)	Partij voor de Dieren (PvvD)	Staatkundig Gereformeerde Partij (SGP)
	Piratenpartij	50+	50+	50+
	De Partij voor Mens en Spirit (MenS)	Ondernemerspartij	DENK	DENK
	Nederland Lokaal (NL)	VoorNederland (VNL)	BIJ1	BoerBurgerBeweging (BBB)
	Libertaire Partij (LP)	DENK	Code Oranje	BIJ1
	50+	Nieuwe Wegen	Volt	Piratenpartij/De Groenen
	Liberaal Democratische Partij (LibDem)	De Burger Beweging (DBB)	NIDA	Nieuw Sociaal Contract (NSC)
	Anti-Europa Partij Soeverein	Vrijzinnige Partij	Piratenpartij	Splinter
	Onafhankelijke Pioniers Nederland (SOPN)	GeenPeil	Libertaire Partij (LP)	Libertaire Partij (LP)
	Partij van de Toekomst (PvdT)	Piratenpartij	Jong	LEF - voor de nieuwe generatie
	Politieke Partij NXD	Artikel 1	Splinter	Samen voor Nederland
		Niet Stemmers	BoerBurgerBeweging (BBB)	Nederland met een Plan
		Libertaire Partij (LP)	NLBeter	PartijvdSport
		Lokaal in de Kamer	Lijst Henk Krol	Politieke partij voor Basisinkomen
		Stem Nederland	Oprecht	
		De Partij voor Mens en Spirit (MenS)	Jezus Leeft	
		Vrije Democratische Partij (VDP)	Trots op Nederland	
			Ubuntu Connected Front	
			Partij van de Eenheid	
			De Feestpartij	
			Vrij en Sociaal Nederland	
			Wij zijn Nederland	
			Modern Nederland	
			De Groenen	
			Partij voor de Republiek	

Note. This table contains the categorization of political parties into the anti-immigration group. This distinction was made based on the political parties' election manifestos. Whether a party falls into the anti-immigration category is based on whether its election manifesto includes statements in favor of a full asylum stop, comments about immigrants being a threat to Dutch culture and wanting to, for a large part, stop hosting international students.

Table A3   Overview of municipalities per quintile

Q1 (0-20%)	Q2 (21-40%)	Q3 (41-60%)	Q4 (61-80%)	Q5 (81-100%)
Aalten	Achtkarspelen	's-Hertogenbosch	's-Gravenhage	Aa en Hunze
Amersfoort	Albrandswaard	Alkmaar	Almelo	Aalsmeer
Baarn	Alphen-Chaam	Alphen aan den Rijn	Amstelveen	Alblasserdam
Barendrecht	Altena	Amsterdam	Apeldoorn	Almere
Beekdaelen	Beesel	Arnhem	Asten	Assen
Bladel	Bergen op Zoom	Berkelland	Barneveld	Beek
Brummen	Bernheze	Beverwijk	Bergeijk	Berg en Dal
Bunschoten	Best	Bronckhorst	Borger-Odoorn	Bergen
Castricum	Breda	Bunnik	Borsele	Beuningen
Cranendonck	Brunssum	Coevorden	Boxtel	Blaricum
Culemborg	Capelle aan den	De Fryske Marren	Dantumadiel	Bloemendaal
Delft	IJssel	De Wolden	Diemen	Bodegraven-
Den Helder	De Bilt	Deventer	Dinkelland	Reeuwijk
Deurne	De Ronde	Dijk en Waard	Doesburg	Boekel
Echt-Susteren	Venen	Doetinchem	Druten	Borne
Ede	Dongen	Drimmelen	Eersel	Buren
Gilze en Rijen	Duiven	Dronten	Emmen	Dalfsen
Goirle	Eijsden-	Edam-Volendam	Ermelo	Dordrecht
Hardenberg	Margraten	Eemsdelta	Haarlem	Drechterland
Harderwijk	Enschede	Eindhoven	Haarlemmermeer	Eemnes
Heerlen	Etten-Leur	Epe	Halderberge	Elburg
Heeze-Leende	Geldrop-Mierlo	Geertruidenberg	Hardinxveld-	Enkhuizen
Heiloo	Gemert-Bakel	Goeree-Overflakkee	Giessendam	Gennep
Hoorn	Gouda	Gorinchem	Hellendoorn	Goes
Houten	Groningen	Gulpen-Wittem	Heusden	Gooise Meren
IJsselstein	Heemskerk	Haaksbergen	Hillegom	Heerde
Katwijk	Heemstede	Harlingen	Hof van Twente	Hilversum
Krimpen aan den	Het Hogeland	Hattem	Hoogeveen	Hollands Kroon
IJssel	Hilvarenbeek	Heerenveen	Huizen	Horst aan de Maas
Lansingerland	Hoeksche	Helmond	Kaag en	Koggenland
Laren	Waard	Hendrik-Ido-	Braassem	Leusden
Losser	Hulst	Ambacht	Kampen	Lisse
Maassluis	Kerkrade	Hengelo	Kapelle	Maasdriel
Midden-Delfland	Laarbeek	Heumen	Land van Cuijk	Medemblik
Nieuwegein	Landgraaf	Krimpenerwaard	Maasgouw	Meppel
Nissewaard	Leiderdorp	Landsmeer	Meierijstad	Moerdijk
Oirschot	Leudal	Leeuwarden	Midden-Drenthe	Mook en
Oldenzaal	Loon op Zand	Leiden	Midden-	Middelaar
Oost Gelre	Maastricht	Leidschendam-	Groningen	Nederweert
Oss	Nijmegen	Voorburg	Montferland	Noord-Beveland
Oude IJsselstreek	Noardeast-	Lelystad	Montfoort	Noordoostpolder
Overbetuwe	Fryslân	Lingewaard	Neder-Betuwe	Noordwijk
Papendrecht	Oosterhout	Lochem	Noordenveld	Oisterwijk
Putten	Renkum	Lopik	Nunspeet	Oldebroek
Rhenen	Sittard-Geleen	Maashorst	Oegstgeest	Ommen
Ridderkerk	Steenbergen	Meerssen	Olst-Wijhe	Ouder-Amstel
Roerdalen	Stichtse Vecht	Middelburg	Ooststellingwerf	Peel en Maas
Roosendaal	Terneuzen	Molenlanden	Raalte	Pekela
Rotterdam	Teylingen	Nieuwkoop	Rheden	Reimerswaal
Rucphen	Tiel	Nijkerk	Rijswijk	Schouwen-
Scherpenzeel	Tilburg	Nuenen, Gerwen en	Roermond	Duiveland
Simpelveld	Twenterand	Nederwetten	Schagen	Sluis
Sint-Michielsgestel	Urk	Oldambt	Sliedrecht	Staphorst
Soest	Utrecht	Oostzaan	Smallingerland	Steenwijkerland
Stein	Velsen	Opmeer	Stadskanaal	Texel
Tubbergen	Voorne aan Zee	Opsterland	Stede Broec	Tholen
Uitgeest	Voorschoten	Oudewater	Súdwest-Fryslân	Vaals

Utrechtse Heuvelrug	Vught	Pijnacker-Nootdorp	Tytsjerksteradiel	Valkenburg aan de
Valkenswaard	Wageningen	Purmerend	Uithoorn	Geul
Veendam	Westerveld	Reusel-De Mierden	Venray	Veere
Veenendaal	Westervoort	Rijssen-Holten	Vlissingen	Vlaardingen
Veldhoven	Weststellingwerf	Schiedam	Waalwijk	Waterland
Vijfheerenlanden	Wijchen	Someren	Waddinxveen	Weert
Voorst	Wijdemeren	Son en Breugel	West Betuwe	West Maas en
Waalre	Woerden	Tynaarlo	Westerkwartier	Waal
Wijk bij Duurstede	Zaanstad	Venlo	Winterswijk	Westerwolde
Zeist	Zeewolde	Voerendaal	Wormerland	Westland
Zoetermeer	Zevenaar	Waadhoeke	Zaltbommel	Woudenberg
Zundert	Zwijndrecht	Wassenaar	Zoeterwoude	Zandvoort
Zutphen	Zwolle	Wierden	Zwartewaterland	
		Woensdrecht		
		Zuidplas		

Note. This table provides an overview of the municipalities in each quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. Ameland, Baarle-Nassau, Renswoude, Rozendaal, Schiermonnikoog, Terschelling and Vlieland have been removed due to missing data.

Table A4.1   Descriptive statistics all municipalities in the first quintile (0-20%)

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	69	2.98	3.3	0.88	0.8	3.9
Anti-immigration support (%)	69	18.99	17.6	8.66	5.13	56.83
Turnout (%)	69	79.96	80.45	4.92	62.63	93.22
Population	69	49680.43	31300	74836.34	9200	636600
Median income (€)	69	34668.48	35200	5090.91	24600	51300
Historical support	69	0.26	0	0.44	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the first quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Source: Dutch Electoral Council and Statistics Netherlands.

Table A4.2   Descriptive statistics all municipalities in the second quintile (21-40%)

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	65	4.42	4.4	0.29	4.0	4.9
Anti-immigration support (%)	65	19.30	17.83	8.89	4.53	48.58
Turnout (%)	65	79.09	79.69	4.92	64.19	91.323
Population	65	58183.46	38500	58331.21	9500	353600
Median income (€)	65	34244.62	34600	5137.99	24000	49700
Historical support	65	0.31	0	0.46	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the second quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Source: Dutch Electoral Council and Statistics Netherlands.

Table A4.3   Descriptive statistics all municipalities in the third quintile (41-60%)

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	69	5.48	5.5	0.31	5.0	6.1
Anti-immigration support (%)	69	18.17	16.50	8.19	4.68	47.94
Turnout (%)	69	80.29	80.92	4.73	67.02	89.38
Population	69	60790.22	37700	102842.90	9000	874100
Median income (€)	69	34232.61	34700	5024.37	24200	45600
Historical support	69	0.22	0	0.41	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the third quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Source: Dutch Electoral Council and Statistics Netherlands.

Table A4.4   Descriptive statistics all municipalities in the fourth quintile (61-80%)

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	67	6.92	6.9	0.48	6.2	7.8
Anti-immigration support (%)	67	17.87	16.47	7.82	4.88	40.18
Turnout (%)	67	80.24	80.86	4.60	63.45	89.21
Population	67	49210.82	31050	65522.14	7800	533000
Median income (€)	67	33704.85	33950	4922.24	24400	46900
Historical support	67	0.19	0	0.40	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the fourth quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Source: Dutch Electoral Council and Statistics Netherlands.

Table A4.5   Descriptive statistics all municipalities in the fifth quintile (81-100%)

Variables	Obs.	Mean	Median	St. Dev	Min	Max
Proportion Ukrainians (per 1,000 inhabitants)	64	11.15	10.1	4.05	7.9	28.7
Anti-immigration support (%)	64	18.36	17.45	8.16	4.02	45.40
Turnout (%)	64	81.42	81.75	4.83	67.45	98.26
Population	64	33128.52	23750	30265.53	7200	214300
Median income (€)	64	34356.84	34650	5188.55	24200	52700
Historical support	64	0.27	0	0.44	0	1

Note. This table contains the descriptive statistics per municipality, of all municipalities in the fifth quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The data used comes from 2012, 2017, 2021 and 2023. Median income in 2022 is used as a proxy for 2023. Source: Dutch Electoral Council and Statistics Netherlands.

Appendix B: Parallel Trends Assumption

Table B1   Formal PTA OLS regression results of the effect of Ukrainian refugees on votes for anti-immigration parties

Variables	(1) Share votes for anti-immigration parties	(2) Share votes for anti-immigration parties
2017	5.417***	10.32***
	(0.618)	(0.549)
2021	8.949***	12.02***
	(0.674)	(0.715)
2012*0-20%	1.103	0.518
	(0.683)	(0.467)
2012*21-40%	1.207	0.185
	(0.747)	(0.444)
2012*61-80%	-0.445	-0.416
	(0.496)	(0.410)
2012*81-100%	0.0372	0.706
	(0.558)	(0.442)
2017*0-20%	1.027	0.681
	(0.792)	(0.604)
2017*21-40%	1.079	0.249
	(0.780)	(0.565)
2017*61-80%	-0.467	-0.756
	(0.614)	(0.488)
2017*81-100%	0.147	0.276
	(0.698)	(0.539)
2021*0-20%	0.572	0.170
	(0.849)	(0.659)
2021*21-40%	0.937	0.111
	(0.911)	(0.701)
2021*61-80%	-0.0848	-0.635
	(0.709)	(0.593)
2021*81-100%	0.393	0.605
	(0.755)	(0.613)
Median income		2.69e-05
		(6.88e-05)
Population		-1.79e-05***
		(1.64e-06)
Voter turnout		-0.755***
		(0.0462)
Constant	9.915***	67.95***
	(0.384)	(2.820)
Observations	1,002	1,002
R-squared	0.434	0.695

Note. Results of the formal PTA test. The dependent variable is the average predicted support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B2   Formal PTA OLS regression results of the effect of Ukrainian refugees on votes for anti-immigration parties, with historical support as a moderator

Variables	(1) Share votes for anti-immigration parties
2017	-13.52***
	(0.825)
2021	-9.734***
	(0.714)
0-20%	0.227
	(0.939)
21-40%	0.121
	(0.800)
61-80%	0.187
	(0.780)
81-100%	0.195
	(0.857)
Historical support	8.758***
	(1.595)
2012*0-20%	-0.332
	(0.999)
2012*21-40%	-0.550
	(0.873)
2012*61-80%	-0.742
	(0.842)
2012*81-100%	-0.471
	(0.905)
0-20%*Historical support	-0.841
	(2.010)
21-40%*Historical support	-0.744
	(2.169)
61-80%*Historical support	-2.489
	(1.906)
81-100%*Historical support	-1.699
	(1.918)
2012*0-20%*Historical support	-0.0474
	(2.440)
2012*21-40%*Historical support	-0.339
	(2.524)
2012*61-80%*Historical support	-0.605
	(2.324)
2012*81-100%*Historical support	-0.0214
	(2.277)
2017*0-20%	-0.441
	(1.055)
2017*21-40%	-0.595
	(0.916)
2017*61-80%	-0.896
	(0.877)
2017*81-100%	-0.718
	(0.955)
2017*0-20%*Historical support	-0.223
	(2.478)
2017*21-40%*Historical support	0.0613
	(2.613)
2017*61-80%*Historical support	-0.369
	(2.328)
2017*81-100%*Historical support	0.312
	(2.324)
2021*0-20%	-0.102
	(1.118)

|	
2021*21-40%	-0.0457
	(0.935)
2021*61-80%	-0.114
	(0.898)
2021*81-100%	0.242
	(0.970)
2021*0-20%*Historical support	-0.314
	(2.513)
2021*21-40%*Historical support	-0.350
	(2.753)
2021*61-80%*Historical support	-0.612
	(2.286)
2021*81-100%*Historical support	-0.460
	(2.275)
Median income	-0.000270***
	(5.40e-05)
Population	-1.31e-05***
	(1.77e-06)
Voter turnout	-0.316***
	(0.0367)
Constant	63.67***
	(2.874)
Observations	1,336
R-squared	0.869

Note. Results of the formal PTA test. The dependent variable is the average predicted support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Historical support is a dummy variable that takes on the value of 1 when the municipality belongs to the top 25% in terms of average share of votes for anti-immigration parties in 2012-2021. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B3   Formal PTA OLS regression results of the effect of Ukrainian refugees on voter turnout

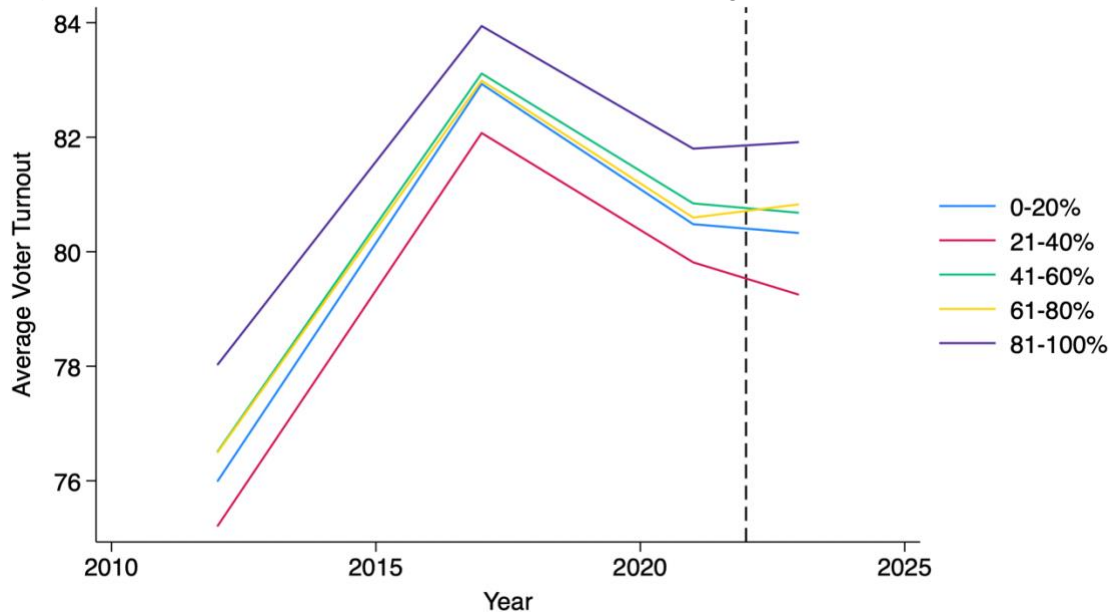| Variables	(1) Voter turnout	(2) Voter turnout
2017	6.609***	4.242***
	(0.623)	(0.561)
2021	4.341***	-0.814
	(0.696)	(0.781)
2012*0-20%	-0.518	-0.446
	(0.713)	(0.614)
2012*21-40%	-1.302	-1.045
	(0.641)	(0.655)
2012*61-80%	0.282	0.629
	(0.682)	(0.580)
2012*81-100%	1.518*	1.145
	(0.781)	(0.696)
2017*0-20%	-0.183	-0.0880
	(0.570)	(0.485)
2017*21-40%	-1.040*	-0.742
	(0.787)	(0.472)
2017*61-80%	-0.126	0.337
	(0.555)	(0.453)
2017*81-100%	0.829	0.352
	(0.579)	(0.511)
2021*0-20%	-0.243	-0.317
	(0.728)	(0.610)
2021*21-40%	-1.029	-0.746
	(0.739)	(0.589)
2021*61-80%	-0.468	-0.0573
	(0.738)	(0.608)
2021*81-100%	0.956	0.367
	(0.737)	(0.629)
Median income		0.000505***
		(5.53e-05)
Population		-0.000895***
		(0.000105)
Constant	76.50***	62.03***
	(0.487)	(1.710)
Observations	1,002	1,002
R-squared	0.326	0.501

Note. Results of the formal PTA test. The dependent variable is voter turnout, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The start of the Russia-Ukraine war and the consequent refugee influx in February 2022 marks the start of the treatment period. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure B1   Visual PTA test: the effect of Ukrainian refugees on votes, base model
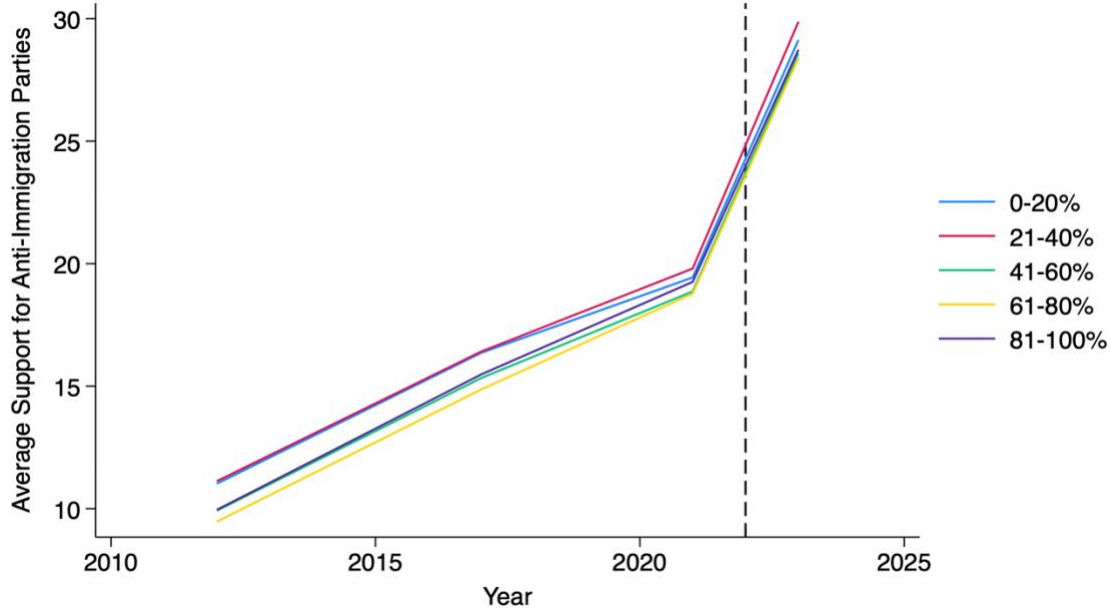
Note. Visual representation of the PTA test. The dependent variable is the average support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. No controls have been included. The vertical dashed line represents the start of the Russia-Ukraine war and the consequent refugee influx in February 2022.

Figure B2   Visual PTA test: the effect of Ukrainian refugees on voter turnout, base model

Note. Visual representation of the PTA test. The dependent variable is the average voter turnout, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. No controls have been included. The vertical dashed line represents the start of the Russia-Ukraine war and the consequent refugee influx in February 2022.

Appendix C: Robustness check

Table C1   Placebo formal PTA OLS regression results of the effect of Ukrainian refugees on votes for anti-immigration parties

Variables	(1) Share votes for anti-immigration parties	(2) Share votes for anti-immigration parties
2017	5.417***	9.852***
	(0.618)	(0.547)
2012*0-20%	1.103	0.449
	(0.706)	(0.452)
2012*21-40%	1.207	0.108
	(0.731)	(0.435)
2012*61-80%	-0.445	-0.285
	(0.496)	(0.394)
2012*81-100%	0.0372	0.839
	(0.558)	(0.536)
2017*0-20%	1.027	0.629
	(0.792)	(0.590)
2017*21-40%	1.079	0.199
	(0.780)	(0.557)
2017*61-80%	-0.467	-0.627
	(0.614)	(0.473)
2017*81-100%	0.147	0.379
	(0.698)	(0.537)
Median income		0.000215**
		(8.41e-05)
Population		-1.51e-05***
		(1.58e-06)
Voter turnout		-0.807***
		(0.0575)
Constant	9.915***	66.56***
	(0.384)	(3.476)
Observations	668	668
R-squared	0.327	0.661

Note. Results of the formal PTA test. The dependent variable is support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The placebo treatment period starts in January 2020. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table C2 Placebo formal PTA OLS regression results of the effect of Ukrainian refugees on votes for anti-immigration parties

Variables	(1) Share votes for anti-immigration parties
2012	-11.97***
	(0.920)
2017	-5.071***
	(0.789)
0-20%	-0.551
	(0.779)
21-40%	-0.169
	(0.845)
61-80%	0.223
	(0.749)
81-100%	0.258
	(0.805)
Historical support	6.384***
	(1.473)
2012*0-20%	0.632
	(0.834)
2012*21-40%	0.231
	(0.901)
2012*61-80%	-0.133
	(0.806)
2012*81-100%	0.0681
	(0.875)
0-20%*Historical support	1.374
	(1.961)
21-40%*Historical support	0.160
	(1.923)
61-80%*Historical support	-1.456
	(1.997)
81-100%*Historical support	-0.699
	(1.882)
2012*0-20%*Historical support	-0.0899
	(2.313)
2012*21-40%*Historical support	0.181
	(2.216)
2012*61-80%*Historical support	-0.174
	(2.189)
2012*81-100%*Historical support	0.315
	(2.080)
2017*0-20%	0.692
	(0.889)
2017*21-40%	0.214
	(0.966)
2017*61-80%	-0.257
	(0.840)
2017*81-100%	-0.287
	(0.917)
2017*0-20%*Historical support	-0.403
	(2.401)
2017*21-40%*Historical support	-0.379
	(2.239)
2017*61-80%*Historical support	-0.332
	(2.200)
2017*81-100%*Historical support	0.286
	(2.124)
Median income	0.000327***

	(7.56e-05)
Population	-1.42e-05***
	(1.97e-06)
Voter turnout	-0.509***
	(0.0526)
Constant	51.74***
	(4.111)
Observations	1,336
R-squared	0.702

Note. Results of the formal PTA test. The dependent variable is support for anti-immigration parties, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The placebo treatment period starts in January 2020. Historical support is a dummy variable that takes on the value of 1 when the municipality belongs to the top 25% in terms of average share of votes for anti-immigration parties in 2012-2021. Robust standard errors in parentheses.
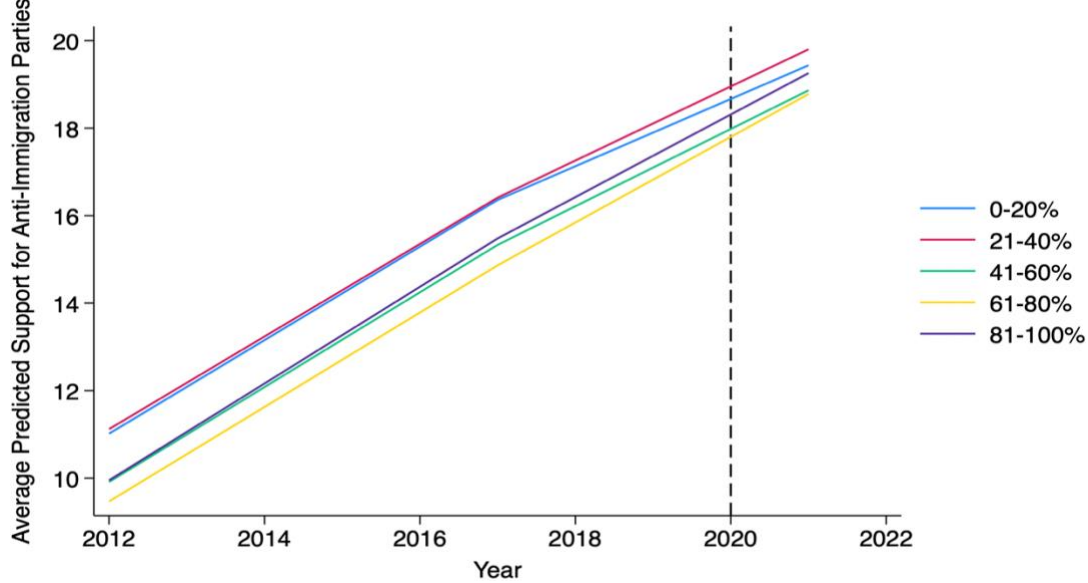*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

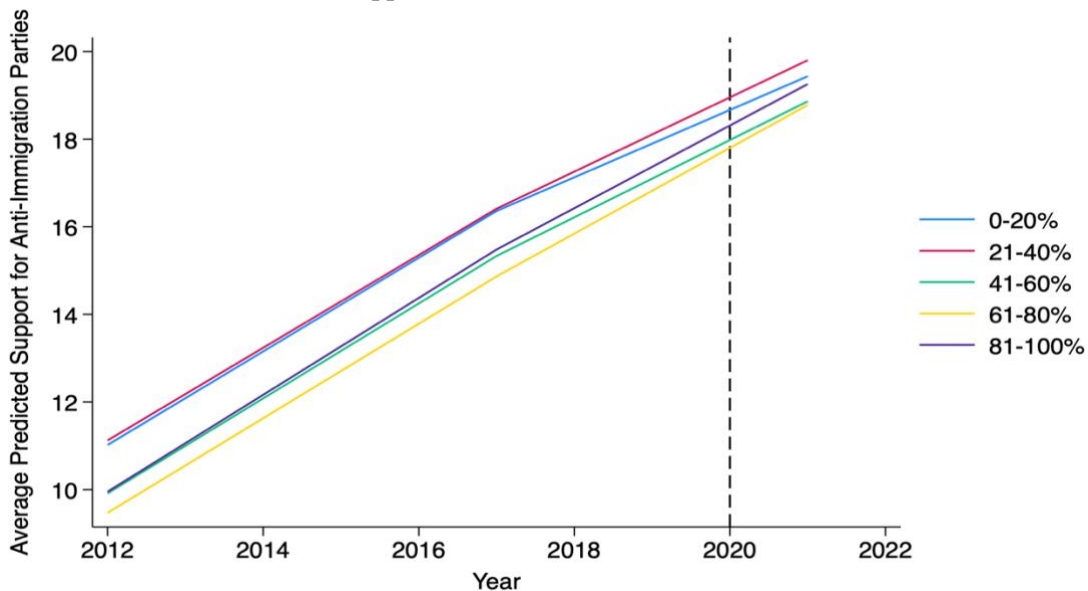**Figure C1.1**   Placebo visual PTA test: the effect of Ukrainian refugees on votes, base model
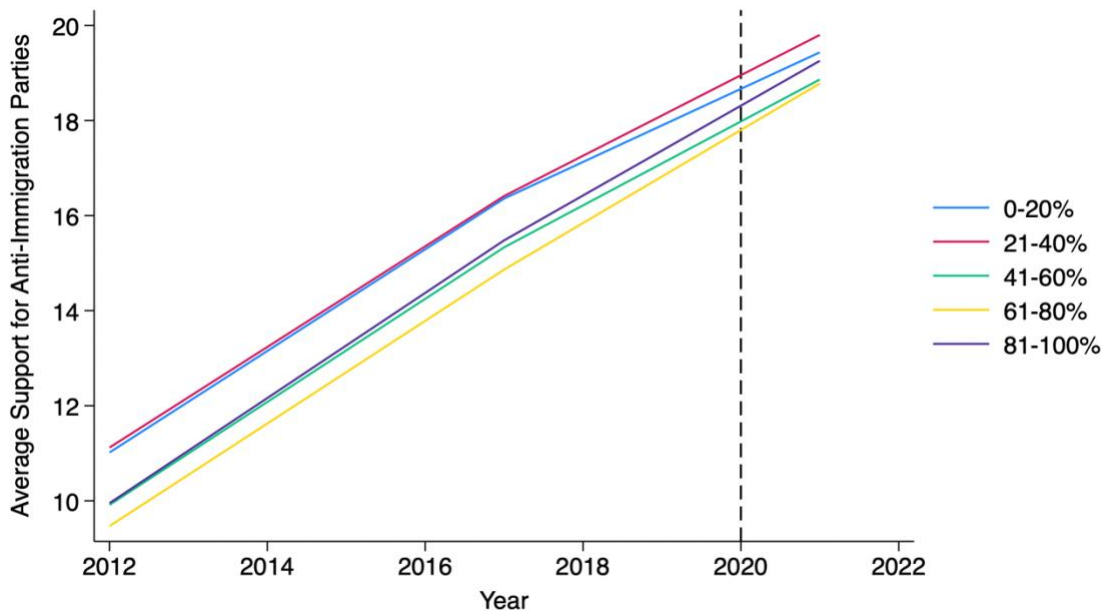
Note. Visual representation of the placebo PTA test. The dependent variable is the average support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. No controls have been included. The vertical dashed line represents the start of the placebo treatment period, in January 2020.

Figure C1.2   Placebo visual PTA test: the effect of Ukrainian refugees on votes, with controls

Note. Visual representation of the placebo PTA test. The dependent variable is the average predicted support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. Median income, population and voter turnout have been added as controls. The vertical dashed line represents the start of the placebo treatment period, in January 2020.

Figure C2   Placebo visual PTA test: the effect of Ukrainian refugees on votes, with controls and historical support as moderator

Note. Visual representation of the placebo PTA test. The dependent variable is the average predicted support for anti-immigration parties, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. Median income, population and voter turnout have been added as controls. Historical support is a dummy variable that takes on the value of 1 when the municipality belongs to the top 25% in terms of average share of votes for anti-immigration parties in 2012-2021. The vertical dashed line represents the start of the placebo treatment period, in January 2020.

Table C3   Placebo formal PTA OLS regression results of the effect of Ukrainian refugees on voter turnout

Variables	(1) Voter turnout	(2) Voter turnout
2017	6.609***	4.027***
	(0.623)	(0.561)
2012*0-20%	-0.518	-0.478
	(0.713)	(0.612)
2012*21-40%	-1.302	-1.057
	(0.981)	(0.822)
2012*61-80%	0.282	0.664
	(0.682)	(0.578)
2012*81-100%	1.518	1.154
	(1.285)	(1.582)
2017*0-20%	-0.183	-0.118
	(0.570)	(0.487)
2017*21-40%	-1.040	-0.749
	(0.887)	(0.470)
2017*61-80%	-0.126	0.382
	(0.555)	(0.450)
2017*81-100%	0.829	0.351
	(0.579)	(0.520)
Median income		0.000551***
		(6.16e-05)
Population		-0.000834***
		(0.000123)
Constant	76.50***	60.59***
	(0.487)	(1.894)
Observations	668	668
R-squared	0.429	0.574

Note. Results of the formal PTA test. The dependent variable is voter turnout, and the treatment groups are quintiles, based on the proportion of Ukrainian refugees per 1,000 inhabitants. The third quintile (41-60%) is used as the reference group. The placebo treatment period starts in January 2020. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
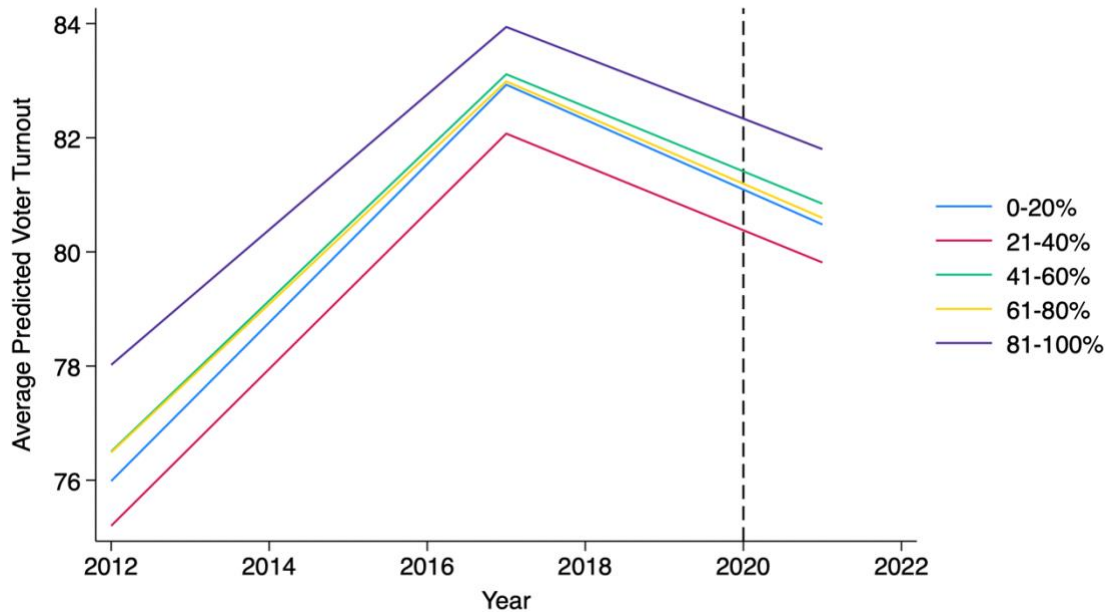
Figure C3.1   Placebo visual PTA test: the effect of Ukrainian refugees on voter turnout, base model
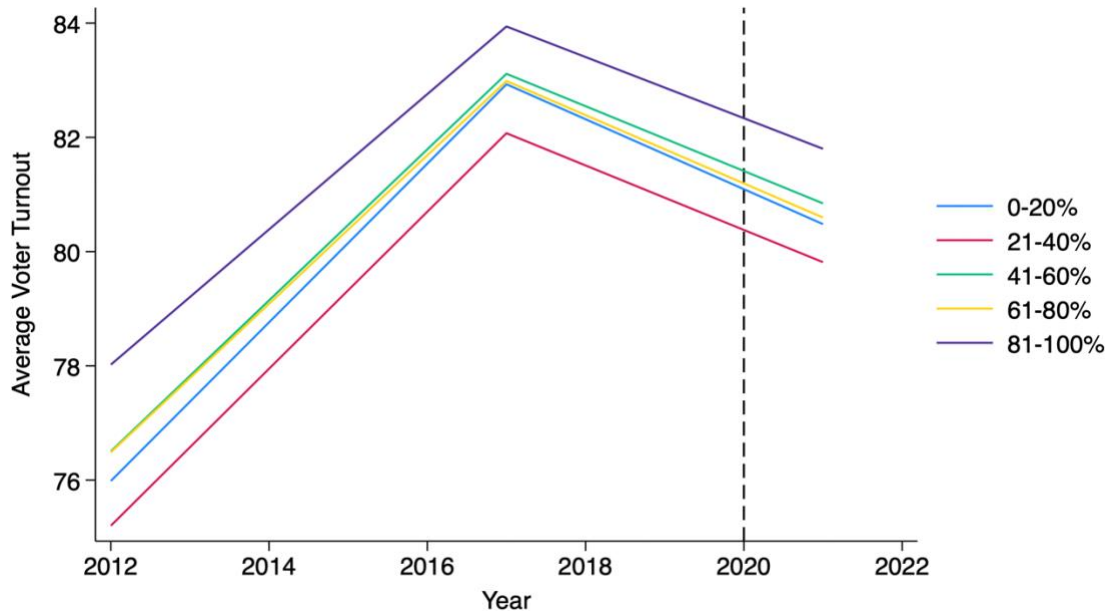
Note. Visual representation of the placebo PTA test. The dependent variable is the average voter turnout, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. No controls have been included. The vertical dashed line represents the start of the placebo treatment period, in January 2020.

Figure C3.2   Placebo visual PTA test: the effect of Ukrainian refugees on voter turnout, with controls

Note. Visual representation of the placebo PTA test. The dependent variable is the average predicted voter turnout, and each line represents a quintile, based on the proportion of Ukrainian refugees per 1,000 inhabitants. Median income and population have been added as controls. The vertical dashed line represents the start of the placebo treatment period, in January 2020.