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Refugee shelters, Neighbourhood Quality and Electoral Outcomes in Germany

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Abstract

Does refugee immigration affect the perceived quality of neighbourhood amenities, and is this an important factor for the opposition to immigration? In this paper, I use real estate listings and online reviews of businesses and public places to demonstrate neighbourhood change due to the establishment of a refugee shelter. The setting is Berlin during the European refugee crisis of 2015. Local authorities had to scramble to find suitable locations for refugee shelters; I show that these locations did not differ from control locations in terms of real estate prices, online reviews or political outcomes before immigration. When a shelter was established, rental prices and ratings for existing places declined in the immediate vicinity. Additionally, I show that the anti-immigrant German AfD party received a higher share of the vote near the refugee shelters. However, these effects are relatively small, and the measured decline in perceived neighbourhood quality is at most a partial mechanism through which shelters affect voting outcomes (an alternative mechanism could be the increased salience of the continent-wide crisis in the affected areas). The effect on rental prices and ratings is also very local, while the effect on voting outcomes is significant even at a greater distance.

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JEL Classification: D72, F22, J15, R23

1 Introduction

Immigration has been one of the central issues in recent European and US electoral campaigns. The European refugee crisis of 2015 in particular has received strong attention, and in Germany, it is widely understood to be the main driver behind the rise of the right-wing AfD party.[1] What explains this opposition to immigration?

One possibility is that voters oppose immigration out of economic self-interest, for example if their job security or wages are threatened. This view is supported by a literature showing negative effects of low-skilled immigration on wages and employment of low-skilled natives (e.g. Card (2001), Borjas (2003), Borjas and Monras (2017)); at the same time, it is especially low-skilled individuals who oppose immigration (Scheve and Slaughter (2001), Mayda (2006), Facchini and Mayda (2009)). On the other hand, Facchini et al. (2013) show that low-skilled natives are more hostile to immigration even in a context where immigrants are high-skilled, and Rozo and Vargas (2018) show that only culturally more distant international refugees provoke a backlash, whereas internally displaced persons help the left-wing, more pro-immigration party.

Therefore, anxiety over cultural change, weakened social norms and declining quality of local amenities may be the more important channels. Using survey data, Card et al. (2012) show that such concerns for local amenities are more predictive of opposition to immigration than labor market concerns (see also Dustmann and Preston (2007), Hainmueller and Hopkins (2014) and Hainmueller et al. (2015)). There are however few studies on how the quality of amenities changes due to immigration or ethnic heterogeneity, and even fewer which investigate whether this is an important mechanism driving voting outcomes.

In this paper, I investigate these questions in the context of the refugee crisis of 2014-2016 in Berlin. I use real estate data from the largest German listings website, immobilienscout24.de, to show how rental prices are affected by the presence of a refugee shelter. Additionally, I use place-ratings from the website Foursquare to show changes in how these neighbourhoods are perceived. The majority of Foursquare places are businesses such as restaurants and shops, but public places such as parks and metro stations are also included. Rental prices decline by 3%, and a rating given to an existing place becomes

[1] A post-election survey of AfD voters revealed that 92% of respondents thought that "the party (AfD) mainly exists to change the refugee policies with its initiatives", while 97% said that they feared a loss of German culture due to immigration (Infratest/dimap (2017))

20% less likely to be positive when a refugee shelter opens nearby. These phenomena point to a perceived decline in the quality of the neighbourhood. There is some evidence for increased creation of new businesses near refugee shelters, especially Turkish and Middle Eastern restaurants, which is consistent with neighbourhood changes which cater to the new inhabitants. Additionally, I show that in the electoral districts closest to refugee shelters, the percentage of voters voting for the AfD party increased by 10%. This is true both for the 2016 Berlin Senate Elections and the 2017 Federal Elections.

I also discuss the relevance of the decline in rental prices and ratings as a channel for the voting outcomes. Using these as intermediate outcomes changes the quantitative importance of proximity to a refugee shelter only moderately. I demonstrate that this method is likely biased in the direction of overestimating the importance of the rental price and ratings channel. Furthermore, areas with many public venues, such as parks and squares, experienced an especially strong decline in ratings when a shelter was opened nearby. However, these areas did not see a larger increase in right-wing voting. Similarly, the effect of shelters on rental prices and ratings is limited to very nearby places, while their effect on voting has a much wider radius.

These findings underline that the effect of shelters on right-wing voting mainly works through channels other than the decline in neighbourhood quality reflected in rental prices and ratings. One such alternative channel could be that the Europe-wide crisis is more visible in areas near a refugee shelter, increasing the salience of this issue in the minds of voters.

My main results come from difference-in-differences specifications. I use a complete panel of shelter locations, capacities and dates of operation to define treatment variables. To address concerns that the locations of refugee shelters are endogenously determined, I show that these locations did not differ from non-treated areas in a large variety of characteristics. This includes levels and trends of real estate prices, political outcomes, ratings and the types of local businesses. In addition, the results are robust to the use of an instrument, namely the availability of infrastructure to house refugees (in public schools).

The previous literature has shown that immigration and social heterogeneity can have a negative impact on the quality of local amenities, by lowering the willingness to engage in the community, contribute to public goods and sanction antisocial behaviour (see e.g. Alesina et al. (1999), Alesina and La Ferrara (2000), Miguel and Gugerty (2005), Dahlberg et al. (2012), and Algan et al. (2016)). I argue that the consequences of such changes would affect not only the quality of housing, but also the restaurants, shops and public places present in the Foursquare database.

Housing outcomes can be affected in various ways by immigration. The demand from immigrants can drive up prices in larger geographic areas (see e.g. Saiz (2007), Ottaviano et al. (2012)); but there is also some evidence that more locally, prices can decline due to natives valuing the area less (Accetturo et al. (2014) and Sá (2014)). This can lead to the out-migration of natives and residential segregation, such as in the case of 'white flight' from US urban centers (see Boustan (2010), Boustan et al. (2010)). The negative price effects I show are unlikely to be partially offset by an opposing demand effect, given that they are very locally constrained, and can therefore be interpreted more easily as a signal of a decrease in the subjective quality of local amenities.

With respect to political outcomes, the larger literature has often found that immigration, particularly of individuals with low skills or strong cultural differences, increases the electoral success of parties opposed to immigration (Barone et al. (2016), Halla et al. (2017), Harmon (2017)). This effect may be limited to low-skilled voters (Mayda et al. (2018)). Dustmann et al. (2016) and Gerdes and Wadensjö (2008) show an increase in right-wing votes in Denmark caused by refugee allocation, while Dinas et al. (2016) show the same for the Greek islands which house refugees. On the other hand, Steinmayr (2016) finds a negative impact of refugees on right-wing votes in Austria, noting that direct exposure can lead to decreased prejudice (the contact hypothesis).

Typically, the unit of observation in these papers are larger areas, e.g. counties or municipalities, rather than neighbourhoods around conspicuous immigrant housing, but Otto and Steinhardt (2014) find the same effect for neighbourhoods in Hamburg.

The wider economic consequences of refugee immigration have also received special attention in recent years. Akgündüz et al. (2015), Del Carpio and Wagner (2015), Borjas and Monras (2017), and Hennig (2018) focus on labour market changes, while Alix-Garcia et al. (2018) and Altindag et al. (2018) show positive effects on prices and production.

To this literature I add an investigation of a new and related outcome, namely how businesses and other amenities in the neighbourhood change due to the establishment of a refugee shelter. While the ratings are indeed negatively affected by the establishment of a shelter, I conclude that the contemporaneous increase in support for right-wing parties is not mainly a consequence of the neighbourhood decline, meaning that other mechanisms musr also be at work.

The paper is organized as follows: section 2 describes the data and the historical context. Section 3 provides estimation results both on electoral outcomes and on the establishment and perceived quality of venues. Section 4 explores whether the decline in real estate prices and ratings is a channel for the electoral impact. Section 5 discusses the robustness of different specifications, including the IV specification, while section 6 concludes.

2 Data and historical background

2.1 The refugee crisis in Berlin

During the 2014-2016 European Refugee crisis, more than 70 Thousand initial applications for asylum were made in Berlin. This represents roughly 2% of Berlin's population of 3.6 Million, the highest per-capita figure of any German Federal State except for the small city state of Bremen[2]. Because of its dense development and increasingly tight housing market, this meant that Berlin is the place where the refugee inflow was most acutely experienced by the local population.

The Berlin Office for Refugee Affairs (Landesamt für Flüchtlingsangelegenheiten, LAF) provides information on all shelters in operation, including their exact location, capacity and occupancy. I have obtained this list at two different points in time, once in September 2016 and once in January 2018. There is considerable overlap between the two lists, but some shelters have closed while others have opened between the dates.

Additionally, some shelters – especially among those located in gymnasiums of public schools – had already been closed in the summer of 2016. From these lists, I construct a panel of 177 shelters, which I believe to be mostly complete. 96 of those shelters where still in operation in January of 2018. I have also collected their opening and (where applicable) closing dates, to be able to pinpoint the exact month when a neighbourhood would be treated.

According to the LAF, resources where so strained during the refugee crisis that shelters were opened where it was possible, without consideration of political or social consequences. This was communicated to the media and also confirmed to me via email. I largely validate this claim in section 5 (Robustness and validity), showing that the eventual

[2] BAMF, Das Bundesamt in Zahlen 2014-2016, Asyl

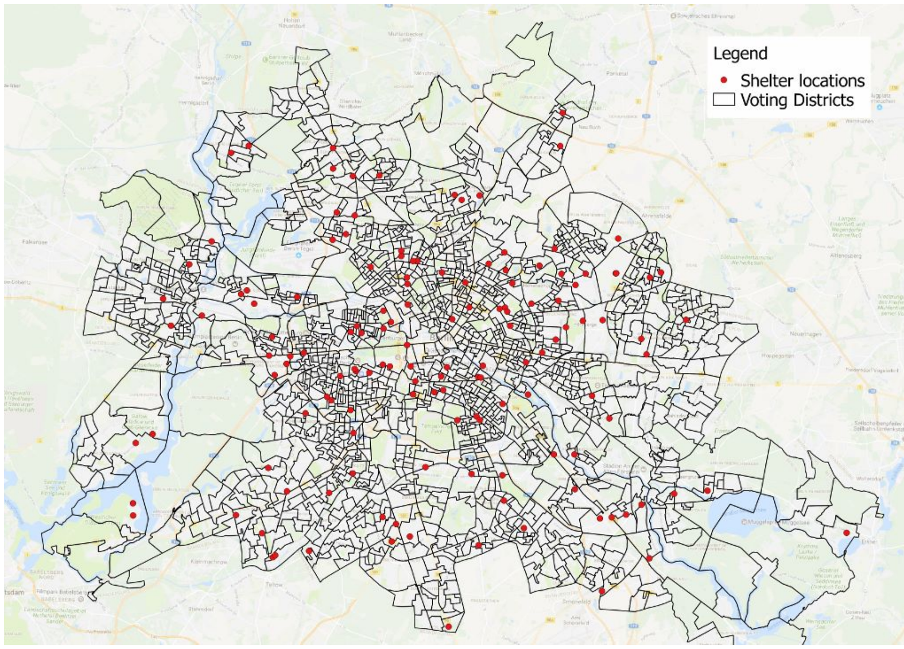

Fig. 1: Location of refuge shelters in Berlin

shelter locations do not differ from others either in terms of previous results for right-wing parties or in the composition, type and quality of local places.

The majority of shelters were established in pre-existing buildings. Frequently, these were gymnasiums of public schools (48 instances in my list), and I could confirm this for at least 89 other shelters, for example in unused administrative buildings. At least 19 shelters were temporary structures.

The fact that the premises of public schools where often used as locations for a shelter enables me to use the proximity of such a school as an instrument for the eventual proximity of a shelter (see section 4, robustness and validity). However, while the results are robust to the use of this instrument, the locations of schools actually show less balanced characteristics before the crisis than the true locations of shelters, which is why I prefer to simply use these true locations as treated areas in a differences-in-differences setting.

As can be seen in Figure 1, the shelters are distributed across Berlin; however, the more densely developed centre of the city has more shelters. The population living in the centre consequently is more likely to live close to a refugee shelter (Fig. 2).

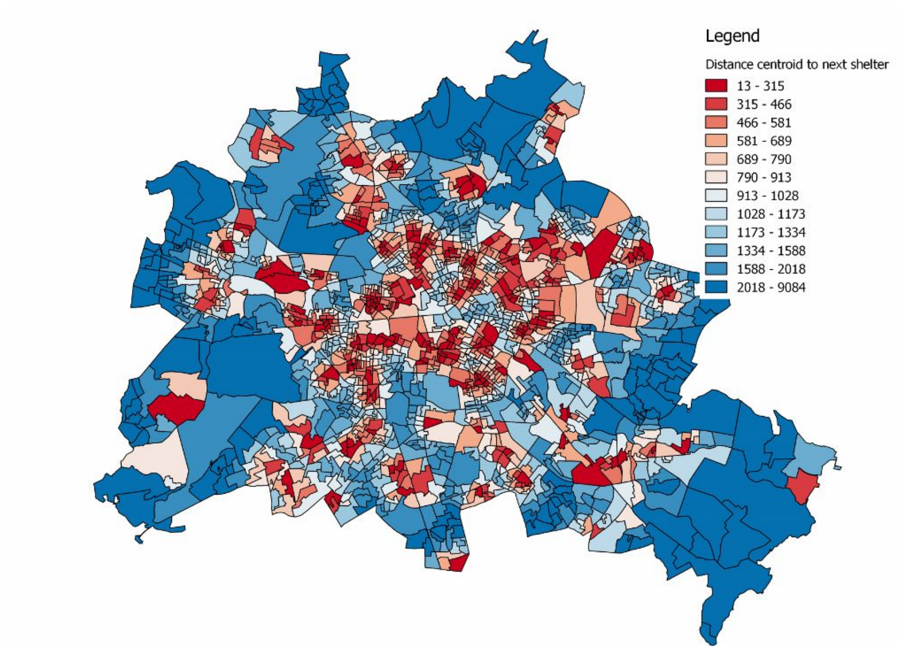

Fig. 2: Distance of voting tracts to nearest shelter

2.2 Independent variables

This distance to a shelter will be my main treatment, either as a continuous variable or as a dummy indicating that a shelter is close. In my preferred specifications, I simply create a treatment dummy T_{it}^{d}, indicating whether there is an open shelter within d meters of the observation. For real estate listings and place ratings, I use the exact address to calculate the distance; in the case of voting precincts, I use the centroid of their area.

During 2016, 1% (371 of 40,080 observations) of real estate listings are within 100m of a shelter. 4.5% (1,832) are within 200m, and 25% (9,942) within 500m. Of the voting precincts, 1% (18 of 1,470) are within 100m, 4% (61) are within 200m, and 23.5% (346) within 500m.

Shelters vary considerably in size. Their capacity ranges from 30 to 1200 places, with a mean of 300.[3] Additionally, some locations are close to several shelters, and distance is a continuous variable, with close proximity presumably having a higher impact.

I therefore create a treatment variable that takes both distance and capacity of all nearby shelters into account. It is defined as the sum of the capacities (in hundred beds) of the

[3] The largest shelter, at the former Tempelhof airport, temporarily had an even larger capacity of more than 4000 places.

three closest shelters, each divided by the square root of the shelter's distance to a place, or

$$T_{it} = \sum_{j=1}^{5} \frac{c_{jt}}{\sqrt{d_{ij}}}. \tag{1}$$

Shelters $j = 1, 2, 3$ have capacities of c_j, and are located at a distance of d_{ij} from place i (or the centroid of voting precinct i). [4]

The mean treatment value (when observations are the voting precincts) is .25 during the year of 2016, with a standard deviation of .14. 5% of voting districts have a treatment value of .55 or higher.

I discuss in section 5 how treated and untreated precincts did not differ from each other in trends or levels before the crisis (see e.g. the balance table 18).

2.3 Elections

My main unit of observation for election outcomes is the voting precinct, the districts served by one polling station. This is the basic unit at which votes are counted. There are 1779 such precincts in Berlin, serving on average 1343 eligible voters (see Table 1). The state election supervisor for Berlin publishes party vote totals and percentages at this level for every election held in Berlin, be they senatorial (state), federal or European elections.

The AfD party received 14.2% of the vote in the Berlin senatorial elections of 2016, and 12% of the Berlin vote in the 2017 federal elections. During previous elections, it received a much lower percentage of the vote - 4.9% in the Federal Elections of 2013 and 7.9% in the European elections of 2014 - and before 2013, it did not exist. It was also founded with a very different platform from the one it would adopt after the refugee crisis, namely one with a much larger focus on the European debt crisis and the Euro, rather than immigration.

This must be kept in mind when we use difference-in-difference specifications to estimate our effects of interest: earlier votes for the AfD do not necessarily capture the full potential of anti-immigrant votes before the refugee crisis.

[4] I only use the 3 closest shelters because the minimum distance of a place to the fourth-closest shelter is greater than 500m, a distance at which the impact of a shelter on a neighbourhood (beyond the impact of 3 closer shelters) is small.

Tab. 1: Voting tracts in Berlin, Federal Elections 2017

N: 1779 (in 2017)	Mean	Median	St.D.
Eligible voters	1,343	1285	386
Votes	698	681	195
Voting for AfD (%)	13.5	12.8	6.5
Area (km2)	.5	.2	1.2
Distance from centre (km)	8.7	8.1	4.5
Distance to nearest refugee shelter (km)	1.4	1.2	.98

As can be seen in the map Figure 3, the outer voting precincts, and particularly those in the east, voted more strongly for the AfD party than in the centre of the city. This is the reason I control for distance from the centre as well as district, interacted with the treatment dummy for the years 2016-2017, in my main specifications.

The median area of voting tracts is 190t m2, (mean: 500t m2), so that a representative district, if it were square, would have all points within roughly 250m of its centroid. Therefore, I define such precincts where the distance from the shelter to the centroid is 250m or less as treatment districts.

2.4 Real estate data

The real estate listings website immobilienscout24.de is the largest such service in Germany. Real estate agencies as well as private landlords use it to make their offers conveniently searchable for prospective buyers and tenants. Beyond currently available listings and accompanying detailed exposés, the website includes an "atlas" where clients can retrieve information about past listings in the vicinity of a given address, to form an impression of price developments in the area.

I have scraped this information from the atlas, since in contrast to the current listings, it includes listings going back to 2010. The available variables are the exact address, price, size, and number of rooms as well as the real estate agency handling the listing.

I was able to webscrape and geolocate roughly 250,000 individual ratings. The majority of these (about 200,000) are for apartment rentals, with the rest being house rentals or purchase listings. Berlin has experienced a real estate boom during the period under

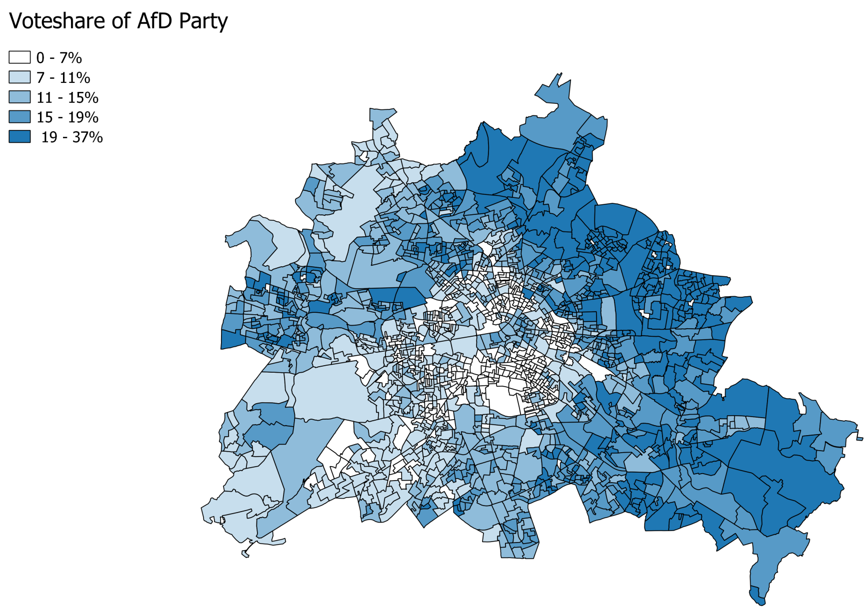

Fig. 3: Success of AfD party in Berlin, 2017 federal elections

study, which is reflected in my data by a 66% increase in the mean rental price from 6.76 Euro per square metre in 2010 to 11.23 Euro in 2018.

2.5 Ratings and Places data

I use data from the local search website Foursquare to construct additional variables. Foursquare makes its data available through an API, free of charge for non-commercial applications. It includes a large database of "venues" - geocoded places such as restaurants and other businesses, but also e.g. parks, streets and bus stops. Users can create these venues and give "tips" on them, which include a rating ("like", "dislike" and "meh") and a text review. For greater clarity, I refer to venues and tips as places and ratings.

The creation of places as well as the ratings come with a time stamp, making it possible to create a panel of many characteristics of areas over time - for example the number and type of businesses as well as average ratings of these businesses.

For Berlin, there are roughly 66 thousand unique places in the database, which have together received 81 thousand ratings (16.5 thousand places have received at least one rating). For each place, one or more categories are given - "Office" and "Café" are the

Number of Venues	68,902
- at least 1 rating	16,252
- at least 5 ratings	4,815
- Office	3200
- Café	1967
- Residential	1785
- Bakery	1743
- Bus Stop	1425
...	...
- Italian	1023
- Doner	380
- Turkish	264
- Middle Eastern	175

Tab. 2: Venues on Foursquare

Number of Tips	80,166
- 'liked'	.49
- 'disliked'	.04
- 'meh'	.06
- none	.4
- English	.56
- German	.36
- Russian	.03
- Turkish	.02

Tab. 3: Tips on Foursquare

most common, but there are also numerous places in categories related to immigration from the refugee origin countries - “Doner”, “Falafel” and “Middle Eastern”, for example.

The first set of variables I constructed from the Foursquare data are counts of newly created places by month and voting precint, as well their as counts in specific categories. I also construct the mean rating and mean price category of these places. In the absence of small-scale census data (the census is only broken down to the 12 districts of Berlin), these variables allow us to assess whether or not refugee shelter locations can truly be seen as similar to locations without shelters.

The aggregate variables on the level of the voting tract can also be used as outcome variables. They give us an indication of how the composition of neighbourhoods changes, e.g. if there is increased creation of new businesses of certain types, and if so if these differ in price and perceived quality from those created not in the proximity of a shelter.

It has to be kept in mind that this is not an official and complete business register. If business creation on Foursquare increases or declines in a certain area, this could be due to the fact that Foursquare users and developers give this area greater or lower attention.

Secondly, I consider if ratings given to places in a certain area are more or less likely to be positive or negative, what language is used in the text etc. This I can do for ratings of all places or only of places in specific categories. Note that there are almost as many places as there are ratings; the majority of places never receives any rating. My estimates on the probability of receiving a positive rating, which will include place fixed effects, are estimates off the minority of places which have received multiple ratings.

In addition to creating these outcome variables, I also use the Foursquare data to create covariates for the analysis of electoral outcomes. For example, the presence of a refugee shelter can have a different impact in areas where there is already a strong immigrant presence. Official population data for Berlin is only available at the coarse level of the district; using this finely grained data enables me to e.g. observe restaurants with immigrant cuisine and use it as an indicator for immigrant presence. I also use the average price ratings on foursquare as an indicator of the wealth of an area.

In Appendix C I show correlations of these Foursquare measures of wealth and foreign population with the official data available on the level of the 12 district.

3 Results

3.1 Real estate prices and listings

Prices: I first study the impact of refugee shelters on real estate prices. The observations are individual rental listings (apartments and houses)[5]. I regress the price per square metre on treatment and controls as follows:

$$y_{ijt} = \beta T_{it} + \gamma X_{it} + FE_t + FE_j + \epsilon_{ijt} \tag{2}$$

where i is the listing and j the voting tract. Since I have precise information on the operation dates of shelters, I can use a monthly panel where the treatment variable T_{tj} varies from month to month, when new shelters are opened. T_{ti} is defined first, for clarity of interpretation, as a dummy taking the value of 1 after a shelter opens within 100m of a place i.

The geographic fixed effects are on the level of the voting precinct, and time fixed effects are for individual months. I also include linear time trends for the voting precincts

[5] purchase listings are similarly impacted, but they are much fewer.

as a robustness check, but since they do not change the results but slow down calculations considerably, I omit them in my main specifications.

The controls included at basement are only size, a dummy for if the listing is for a house (rather than an apartment - the large majority), and the number of rooms (as a categorical variable).

The results show a decline by about 37 cents for those rentals very close (within 100m) of an operating refugee shelter (see table 4). That is about 3% of the average rent.

Tab. 4: Nearby refugee shelter and rental prices - treatment dummy

Outcome variable	Rental price (€ per m^2)		
Shelter within 100m	-0.360**	-0.372**	-0.375**
	(0.152)	(0.150)	(0.146)
FE voting precinct	✓	✓	✓
FE month × year (time)	✓	✓	✓
Distance from center × time		✓	✓
Linear trends by voting precinct			✓
R squared	0.201	0.829	0.833
N. of observations	208,390	208,390	208,390

Significant at: p < 0.1: *; p < 0.05: **; p < 0.01: ***. Standard errors clustered at place and time level.

Number of listings and repeated listings: If a refugee shelter increases the number of new listings in a neighborhood, it would be an indication that previous residents are moving away to avoid the immigrants. To study this, it is necessary to aggregate the number of listings by a geographical unit. I use the voting precincts for any such aggregation in this paper.

I regress the number of immoscout24.de listings on a treatment variable as follows:

$$N_{it} = \beta(close_i \times post_t) + \Gamma X_i \times post_t + FE_t + FE_i + \epsilon_{it} \tag{3}$$

N_{it} is the number of listings in voting precinct i in year t. The treatment variable is the interaction of a dummy $close_i$ (the closest shelter location is within 200m of the voting precinct centroid) with the post-crisis dummy $post_t$ (any year after 2015). Geographic controls X_i are interacted with the post-crisis dummy to avoid picking up any mechanical effect, by which denser precincts closer to the centre are more likely to be treated and also have different real estate dynamics beyond the impact of shelters.

The results can be seen in table 5. We note that the number of listings increases by roughly 2 per year after a shelter opened nearby (specification (1). The average number of listings per year is 16).

One limitation of my data is that I do not have the date at which a listings was withdrawn, so that I cannot observe how long an apartment stays on the market. However, some apartments are quickly re-listed on the platform - real estate agents could do this if they haven't found a new tenant and want to update the exposee e.g. with pictures to give it a more prominent position on the website. Apartments that remain unoccupied for a longer time are more likely to be re-listed in this way.

For the purposes of this study, I define listings for an apartment that has been listed less than 6 months before as re-listings. Since these are long-term rentals (rather than sublets or holiday rentals), I assume that these apartments have remained unoccupied in between the original listing and the re-listing.

When I subtract such re-listings from the number of listings per voting precincts, I obtain the number of new listings. If I regress these on our treatment variable, we see that it increased considerably less than the total number of listings (table 5, (2)). The difference is (mechanically) made up by re-listings (3). The effect on new listings is 1.1 relative to an average of 13, while the effect on re-listings is 1.1 relative to an average of 2.5 per year per voting precinct.

Taken together, this indicates that there are indeed slightly more new listings on the website after a shelter opened nearby. However, the effect on re-listings, and therefore on the likelyhood that an apartment remains vacant for a longer time, is more important in relative terms.

Tab. 5: Nearby refugee shelter and number of real estate listing

Outcome variable	Number of listings		
	(1) Total	(2) New listings	(3) Re-listings
Shelter within 100m	2.204***	1.088**	1.105***
	(0.444)	(0.322)	(0.271)
Distance from center × time	✓	✓	✓
FE voting precinct	✓	✓	✓
FE month × year (time)	✓	✓	✓
R squared	0.568	0.629	0.265
N. of observations	9,880	9,880	9,880

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at place and time level.

3.2 Public amenities and their Ratings

Next I investigate the impact of shelters on place ratings. Observations are individual 'tips' - ratings with a review/description text - of which there are 81,122 in Berlin during the years 2010 to 2017. I use a linear probability model taking the form

$$y_{ijt} = \beta T_{tj} + FE_t + FE_j + \epsilon_{ijt} \tag{4}$$

where j is an individual venue, e.g. a business. Using fixed effects on the level of the venue, the coefficient of interest β is only identified from those venues that exist before and after the establishment of refugee shelters. Since I have precise information on the operation dates of shelters, I can use a monthly panel where the treatment variable T_{tj} varies from month to month, when new shelters are opened. T_{tj} is defined first, for clarity of interpretation, as a dummy taking the value of 1 after a shelter opens within 200m of a place j. My preferred specification is however the one defined as above in (1), taking into account the distance and capacity of all nearby shelters.

I also use voting tract fixed effects rather than venue FE in some specifications, to allow for an effect on the establishment of new venues around refugee shelters, which could have systematically different ratings and reviews.

The outcome variables y_{ijt} are dummies, e.g. for whether or not a rating was positive or whether it was in German. For some regressions, I restrict the sample to certain places of special interest to us.

Tab. 6: Nearby refugee shelter and ratings of existing places, all places - treatment dummy

Outcome variable	(1) 'liked'	(2) 'disliked'	(3) 'meh'
Shelter within 200m	-0.12***	0.01	-0.02
	(0.044)	(0.018)	(0.028)
FE place	✓	✓	✓
FE month × year	✓	✓	✓
R squared	0.31	0.08	0.07
N. of observations	80,166	80,166	80,166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at place and time level.

The outcomes can be seen in tables 6 for the treatment dummy, and 7 for the continuous treatment variable. The results indicate roughly the same effects - as can be seen in table 7, ratings for a place are less likely to be positive after refugee shelters have opened in the vicinity of the venue. The likelihood of the rating being explicitly negative is unchanged, and an ambivalent rating ('meh') becomes more likely. The decline of positive ratings by 1.4 percentage points is not large when we consider that about 46% of tips on the platform are positive. The treatment variable is roughly 1 on average, and the 90th percentile is around 1.9. A 'highly treated' place would therefore be around 3 percentage points less likely to receive a high rating (we will see later that places very close to a shelter – within 100m – see a much larger impact). Use of the treatment dummy variable suggest somewhat smaller impacts (table 6).

I will use my continuous treatment variable in the remaining regressions in this subsection, since it gives a more complete picture of the intensity of refugee housing in an

Tab. 7: Nearby refugee shelter and ratings of existing places, all places - continuous treatment

Outcome variable	(1) 'liked'	(2) 'disliked'	(3) 'meh'
Shelters capacity/distance	-0.014**	0.001	0.008*
	(0.007)	(0.004)	(0.005)
FE place	✓	✓	✓
FE month × year	✓	✓	✓
R squared	0.31	0.08	0.07
N. of observations	80166	80166	80166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at place and time level.

area. When the results of regressions with the simpler treatment dummy differ from those presented here, I will note it in the discussion (those results are available on request).

The main coefficient does not change greatly when we restrict the sample to only those venues which have received 10 or more ratings or when we include the geographic controls introduced in the section on election outcomes (Table 8, specifications (1) and (2) respectively).

This decline on ratings could in principle only affect certain types of places. If we restrict our sample to public places such as parks and roads, or to Turkish and Middle Eastern restaurants, we see that the former are impacted at a similar magnitude as all places, while the latter are potentially less impacted (the coefficients are less precisely measured due to the smaller sample). If only German language ratings are considered, we again find no difference to the overall coefficient (these regressions on subsamples are reported in Table 9).

Newly established venues and their composition: We are also interested in the question of whether areas around refugee shelters experience changes in business activity. New businesses could open to cater to refugee demand, while at the same time, the area could become less attractive for other businesses. I study the establishment of new places on Foursquare in the vicinity of shelters, keeping in mind that this can only be an in-

Tab. 8: Nearby refugee shelter and ratings of existing places, all places

Model	(1) Restricted	(2) Geo. controls
	'liked'	
Shelters capacity/distance	-0.017**	-0.013*
	(0.008)	(0.007)
Distance to centre× (2016 or 2017)		0.00
		(0.00)
FE venue	✓	✓
FE Year	✓	✓
R squared adjusted	0.29	0.31
N	51,614	80,166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

Tab. 9: Nearby refugee shelter and ratings of existing places, subsamples

Subsample	(1) All places	(2) Public	(3) MEastern	(4) German review
Outcome variable		'liked'		
Shelters capacity/distance	-0.014**	-0.012	-0.002	-0.015
	(0.007)	(0.016)	(0.031)	(0.014)
FE voting tract	✓	✓	✓	✓
FE Year	✓	✓	✓	✓
R squared	0.31	0.35	0.27	0.35
N. of observations	80,166	13,113	3,169	26,585

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

dication of true business activity - not all businesses are recorded, and the activity of Foursquare users could itself be subject to changes in the neighbourhood.

It appears that there is a slight increase in the number of newly established venues driven by nearby shelters (table 10, (1)), as well as in the establishment of new Middle Eastern and Turkish restaurants (2). On average, 1.56 new places are created in a voting precinct each month, and .008 Middle Eastern and Turkish restaurants. So while the coefficient of .06 on the creation of all new places is not large relative to the base rate, the creation rate of the relevant ethnic restaurants of .002 is relatively high (and this is the value for the average treatment, not the areas at the 90th percentile of our treatment variables).

It should be noted however that these effects on the creation of new businesses are only weakly significant, and are insignificant when we use the 'dummy' treatment variable.

The average rating of newly established businesses is not affected (3), and neither is the average price level (4).

It would be interesting to investigate this further, since in the longer run we do expect a shelter to affect the categories of businesses created more than this limited evidence suggests.

Tab. 10: Nearby refugee shelter and newly established places

Outcome variable	(1) all venues	(2) Turkish & MEastern	(3) rating	(4) price
Shelters capacity/distance	0.063*	0.002*	-0.039	0.021
	(0.032)	(0.001)	(0.065)	(0.014)
FE voting tract	✓	✓	✓	✓
FE Year	✓	✓	✓	✓
R squared	0.814	0.077	0.195	0.124
N. of observations	11,161	11,161	3,067	5,867

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

3.3 Elections

For ease of interpretation, I will again first show the results using the simple treatment dummy, which is 1 the electoral precinct has any shelter within 200m from its centroid. In following The preferred model I use is a simple diff-in-diff model of the form

$$right\_voteshare_{it} = \beta(close_i \times post_t) + \Gamma X_i \times post_t + FE_t + FE_i + FE_d \times post_t + \epsilon_{it} \tag{5}$$

where i is the voting precinct and t denotes specific elections - -the Berlin senatorial elections of 2006, 2011 and 2016, as well as the federal elections of 2009, 2013 and 2017. $close_i$ is a dummy taking the value of 1 if the centre of the polling district is within 250 metres of a refugee shelter, and the dummy $post_t$ is one for the elections of 2016 and 2017. FE_i is the fixed effect on the polling station, while FE_t is the election fixed effect. I also use geographic variables X_i interacted with the post-dummy; these include the precinct's area and distance to the centre of Berlin. I prefer to include these due to the geographic concentration of treated areas near the centre of the city (which also have a smaller area).[6] As discussed before, each electoral district has around 1500 voters.

The results table are presented in Table 11). Specification (1) does not include any geographic controls other than the fixed effects. My preferred specifications (2) and (3) include distance to the centre of Berlin as the only such control. They differ in so far as (3) estimates only within-district effects by including an additional FE for each district after the refugee crisis; these additional controls would be important if e.g. there are differences in the impact between Western and Eastern districts. However, they do not change our main coefficient.

These specifications indicate that the voteshare of right-wing parties increased by 1.2 additional percentage points in those voting tracts where a refugee shelter is nearby. This is about 10% of the median AfD voteshare of 12.8%.

This magnitude is confirmed a model using the natural logarithm rather than the level of the outcome variable (model 4). The shelters increase the voteshare by about 10%.

[6] The previous level of right-wing support does not fully capture the potential for increase in radical votes in 2016 and 2017. The highest increase happened in the poorer and less densely populated outer areas of Berlin. Since many of the shelters are in the more densely populated inner residential areas, and since the outer polling tracts are larger in area, the outer polling stations also happen to be further away from shelters on average (see Figures 1 and 2 for visual evidence of this geographic correlation).

Tab. 11: Nearby refugee shelter and right-wing vote share, treatment dummy

Model	(1)	(2)	(3)	(4)
Outcome	right-wing voteshare			ln(rw voteshare)
Independent variables				
Shelter within 200m	0.006**	0.012***	0.012***	0.102***
	(0.002)	(0.001)	(0.001)	(0.019)
Distance to centre× (2016 or 2017)		0.006***	0.005***	0.016
		(0.001)	(0.001)	(0.009)
FE voting precinct	✓	✓	✓	✓
FE election	✓	✓	✓	✓
FE district × (2016 or 2017)			✓	
R squared (adjusted)	0.795	0.827	0.869	0.857
N. of observations	10,958	10,958	10,958	10,857

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district and year levels.

Interestingly, the geographic variables are less significant and have smaller importance relative to the treatment coefficient compared with specifications (2) and (3).[7]

The results when using the continuous variable indicate a stronger effect of the presence of shelters on voting outcomes (table 12), of 5 percentage points (model 1) or 3 points (model 2, where differences between districts are controlled for). We will see later that the effect of shelters on voters is present at a larger distance than 200m; it is possible that the continuous treatment variable captures e.g. the effect of some large shelters within a distance of 200-1000m of a voting precinct, something that the simple dummy does not capture.

We will see later (in section 4) that these result are in their sign robust to a number of different specifications, including the use of proximity of a public school as an instrument. I will however argue that this OLS specification is preferable; most importantly, the 'treated' areas do not have different political outcomes to untreated areas before the refugee crisis.

3.4 Heterogeneity of electoral impact

We expect the impact on electoral outcomes to be different from one voting tract to the other, depending on local characteristics. For example, we might think that having a shelter nearby has a stronger impact on right-wing voting in voting tracts of low density, simply because the shelter and refugees would be more visible in such an environment. I define density as eligible voters per $100m^2$, so that it has a mean of 0.79.

A voting tract where there is already a large foreign (and especially Middle Eastern) presence might also be differently impacted, although we can imagine arguments for an effect in either direction. Since census data on the level of voting tracts is not available, I use the Foursquare data to find a proxy for this variable, namely the number of Turkish and Middle Eastern restaurants. On average, there are .55 such establishments in a voting tract, but more than half of them do not have such a restaurant at all.

Lastly, voters in more wealthy areas could also react differently. As a (certainly imperfect) proxy for prosperity, I take the average price category of Foursquare places in the

[7] I will discuss this in more detail in section 4 (Robustness), but the distance from the centre likely picks up an effect that is not accounted for by the additive fixed effects model; the logarithmic specification, in contrast, possibly accounts for this effect by assuming that the location and time fixed effects interact in a multiplicative fashion on the voteshare.

Tab. 12: Nearby refugee shelter and right-wing vote share, continuous treatment variable

Model	(1)	(2)
Outcome	right-wing voteshare	
Independent variables		
Shelters capacity/distance	0.051***	0.030***
	(0.007)	(0.006)
Distance to centre× (2016 or 2017)	0.006***	0.005***
	(0.001)	(0.001)
FE voting precinct	✓	✓
FE election	✓	✓
FE district × (2016 or 2017)		✓
R squared (adjusted)	0.829	0.869
N. of observations	10,958	10,958

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district and year levels.

voting tract.

I interact these three variables - density, presence of Middle Eastern restaurants, and average price category of places - with our continuous treatment variable accounting for nearby shelters. The results from this regression can be seen in table 13. Density has indeed the expected effect (column 2) - where a new shelter would be more visible (lower density), it has a much stronger impact on right-wing voting. Voting tracts with higher presence of Middle Eastern or Turkish restaurants actually saw a lower impact, probably due to the fact that voters in these tracts are more used to, and more sympathetic towards, foreign immigration. Lastly, the price level as given by our proxy variable also has a negative interaction with the treatment variable in affecting rigt-wing voting (this last interaction is not significant when the treatment dummy is used).

These heterogeneous effects appear to be quite sizeable - recall that density as defined here is roughly .8 on average, and the number of ME restaurants .55. The coefficients on the interactions are therefore large relative to the direct effect. This has important implications for where to locate refugee shelters, if policy makers aim to mitigate the impact of shelters on an electoral backlash.

3.5 Type of shelter

The LAF distinguishes two main types of shelters, the Gemeinschaftsunterkunft (community shelter, GU) and the Notunterkunft (emergency shelter, NU). Presumably, refugees will be visible in the vicinity of both GU and NU, but the NU are more clearly a reminder of a crisis situation, and may be seen as a sign of its mismanagement. If these types of shelters have no different impact on our outcomes, it may be seen as a sign that voters simply object to the presence of refugees, while a stronger impact of NU would indicate that at least part of the political backlash is due to the perceived chaotic circumstances rather than simply immigration alone.

I investigate if the impact of a NU shelter is different from other shelters (mostly GU) by interacting the dummy for a nearby shelter with another dummy that indicates a NU. The negative impact on ratings is much higher for NU, which is what we would expect. However, the impact on electoral outcomes may even be smaller (the coefficient is not significant). This is unexpected, but perhaps voters in the vicinity of emergency shelters were reassured that they would only be temporary.

Tab. 13: Nearby refugee shelter and local characteristics, electoral outcomes

Outcome variable	right-wing voteshare			
	(1)	(2)	(3)	(4)
Shelters capacity/distance	0.051***	0.083***	0.064***	0.085***
	(0.007)	(0.012)	(0.009)	(0.010)
Shelters capacity/distance × Density		-0.039***		
		(0.007)		
Shelters capacity/distance × ME rest.			-0.030***	
			(0.004)	
Shelters capacity/distance × price level				-0.028***
				(0.006)
Distance to centre× (2016 or 2017)	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
FE voting tract	✓	✓	✓	✓
FE Year	✓	✓	✓	✓
R squared	0.829	0.832	0.834	0.830
N. of observations	10,958	10,958	10,958	10,151

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

Tab. 14: The impact of emergency shelters (NU) vs. community shelters

Outcome	(1) Right-wing voteshare	(2) Negative ratings
Independent variables		
Shelter within 200m	0.015***	-0.09**
	(0.005)	(0.04)
Shelter within 200m × shelter is NU	-0.019	-0.04**
	(0.012)	(0.02)
FE year	✓	✓
FE district	✓	
FE venue		✓
R squared	0.83	0.18
N. of observations	13,283	160097

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

4 Is the change in perceived neighbourhood quality a mechanism for voting outcomes?

The previous section established the impact of refugee shelters on real estate prices, the ratings and types of places in the neighbourhood and on contemporaneous electoral outcomes. However, this does not tell us how much the decline in perceived neighbourhood quality, as documented in the real estate and foursquare data, contributed to the electoral backlash against refugee immigration. In fact, I argue in this section that the changes documented in the ratings data are only a moderately important channel for the voting impact.

Mediation analysis: The first strategy is to use the intermediate outcome as a right-hand side variable in a regression of final outcomes on the treatment status and covariates. If this lessens the coefficient of treatment, the difference can, under strong assumptions, be interpreted as the part of the total effect explained by the changes in the intermediate outcome. Formally, the procedure is to estimate the system of equations

$$Y_{it} = \beta^t T_{it} + \Gamma X_{it} + \epsilon_{1_{it}} \tag{6}$$

$$M_{it} = \beta^m T_{it} + \Gamma X_{it} + \epsilon_{2_{it}} \tag{7}$$

$$Y_{it} = \beta_1^d T_{it} + \beta_1^{id} M_{it} + \Gamma_1 X_{it} + \epsilon_{3_{it}} \tag{8}$$

our outcome of interest Y_{it} is $right\_voteshare_{it}$, while the intermediate outcome (or mediator) M_{it} is either the average rental price $rprice_{it}$ in voting precinct i, or the proportion of ratings which are positive $liked_{it}$. The covariates X_{it} include fixed effects as in 5, as well as the appropriate geographic controls. β^t would then be interpreted as the total effect of shelters on voting, and β^d as the direct effect (that is, the effect not accounted for by our observed channel). The product $\beta^{id} \times \beta^m$ would be the indirect effect, mediated by the intermediate outcome $liked_{it}$.

This procedure, known as mediation analysis in statistics (see Heckman and Pinto (2015), Imai et al. (2010)), is prone to bias.[8] It requires that

[8] Despite these problems, mediation analysis has been applied in a number of papers recently, particularly in the economics of education (see e.g. Heckman et al. (2013), Oreopoulos et al. (2017)), but also in the more closely related literature on trade, labour markets and voting outcomes (Dippel et al. (2017))

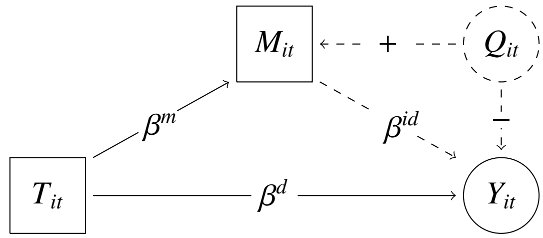

Fig. 4: Shelters treatment T_{it} affecting voting outcomes Y_{it} directly, and through ratings M_{it} as intermediate outcome; other, unobserved shocks to quality Q_{it}.

$$
\begin{aligned}
\{Y_{it}, M_{it}\} \perp\!\!\!\perp T_{it} | X_{it} = x \quad & \text{and} \\
Y_{it} \perp\!\!\!\perp M_{it} | T_{it} = t, X_{it} = x & \qquad (9)
\end{aligned}
$$

The first assumption simply states that there are no confounding unobserved variables affecting both treatment status and either the intermediate or final outcome variable. It is the same assumption needed for our estimation of total treatment effects above. The second assumption requires that there are no unobserved variables affecting both the outcome Y_{it} and the intermediate variable M_{it}, for the coefficients of 8 to be identified.

Despite my inclusion of fixed effects and other controls, this condition is unlikely to be met in our application. In particular, we can expect that there are unobserved shocks to the quality of a neighbourhood, affecting simultaneously real estate prices, the ratings of foursquare venues and the success of right-wing parties.

However, it may be possible to make additional assumptions on the direction of the influence of this unobserved shock on Y_{it} and M_{it}. If we assume that the unrelated and unobserved decline of neighbourhood quality would lower the ratings of businesses, and at the same time increase the electoral success of right-wing parties, we can show in which direction the coefficients β^d and β^{id} in 8 are likely biased. A regression of right-wing electoral success Y_{it} on real estate prices and foursquare ratings M_{it},

$$Y_{it} = \beta M_{it} + \Gamma X_{it} + FE_i + FE_t + \epsilon_{it}$$

finds a negative coefficient β, suggesting that this is indeed the direction of correlation (see table 15).

Tab. 15: Correlation of neighbourhood quality measures and voting outcomes

Outcome	right-wing voteshare	
Mean rental price	-0.046	
	(0.025)	
Average rating		-0.016
		.009
FE year	✓	✓
FE precinct	✓	✓
R squared	0.873	0.838
N	9,878	7,509

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at precinct and year level.

If we assume that equation 8 is primarily misspecified by the omission of the unobserved shock to neighbourhood quality Q_{it}, the true relationship between treatment, ratings and voting outcomes would be

$$Y_{it} = \beta_2^d T_{it} + \beta_2^{id} M_{it} + \beta^q Q_{it} + \Gamma_2 X_{it} + \epsilon_{3_{it}} \tag{10}$$

while the true specification for determining real estate prices and ratings is

$$M_{it} = \beta^m T_{it} + \beta^{qm} Q_{it} + \Gamma X_{it} + \epsilon_{2_{it}}. \tag{11}$$

The omitted variable bias resulting from the omission of Q_{it} in our specification 8 relates the estimated coefficients β_1^{id} and β_1^d to the true β_1^{id} and β_1^d; it is

$$\beta_1^{id} = \beta_2^{id} + \beta^q \frac{Cov(M,Q) \times Var(T)}{Var(M) \times Var(T) - Cov(M,T)^2} \tag{12}$$

and

$$\beta_1^d = \beta_2^d - \beta^q \frac{Cov(M,Q) \times Cov(T,M)}{Var(M) \times Var(T) - Cov(M,T)^2} \tag{13}$$

Derivations of these terms will be provided in the Appendix A. If we assume that $Cov(M,Q)$ is positive – a positive shock to unobserved neighbourhood quality increases real estate prices and ratings – and that β^q is negative – the same shock reduces right-wing voting – this tells us that β_1^{id} is biased downward (away from zero). So is β_1^d, since $Cov(T,M)$, the effect of shelters on average ratings, is also negative.

Estimating specifications 6 and 8, we find that the treatment effect β_1^d of a nearby shelter on voting outcomes is virtually unchanged when we include the average ratings in the voting precinct as a regressor. The effect of including real estate prices is more sizeable (see table 16). The effects of the both real estate prices and average ratings, β_1^{id}, have the expected negative sign, but it is small and insignificant.

The decrease of the treatment coefficient from 1.2 percentage points to .8 percentage points when the mean rental price is included suggests that potentially, a third of the effect of the establishment of the shelter on voting outcomes is due to the mechanism of neighbourhood decline. But as we have seen, β_1^d and β_1^{id} are likely to be biased downward in these regressions, so that this may overstate the importance of this channel. It provides an upper bound, meaning that most of the treatment effect is due to unmeasured mechanisms.

In the following, I present additional pieces of evidence, strengthening this conclusion.

Tab. 16: The impact of shelters on voting, RE prices and ratings as intermediate variable

Outcome	right-wing voteshare		
Shelters T_{it}	0.012***	0.008***	0.011***
	(0.001)	(0.001)	(0.001)
Mean rental price		-.0007	
		(0.0004)	
Average rating			-0.015
			(0.009)
FE year	✓	✓	✓
FE precinct	✓	✓	✓
R squared	0.836	0.872	0.838
N	7,509	7,509	7,509

Significant at: p < 0.1: *; p < 0.05: **; p < 0.01: ***. Standard errors clustered at precinct and year level.

Distance effect: Treatment effects diminish with distance. A shelter within 100m of the centre of a polling area, or within 100m of a venue, should have a larger impact than one within 500m. To investigate this, I use a different treatment definition, one that only takes the distance of the nearest shelter into account. I define four brackets, according to the proximity of the next shelter. In bracket 1, observations are within 100m of the next shelter, and in brackets 2, 3, and 4 the nearest shelter is within 100m-200m, 200m-500m and 500m-1000m respectively. This defines four different treatment groups. During 2016, 39% of voting precincts, 49% of listings, and 47% of ratings now fall into one of the treatment groups.

The results of a regression where these treatment dummies are interacted with post-crisis dummies (as before) are presented in table 17. We see the expected declining impact for voting outcomes, real estate prices, and negative tips. It is notable however, that the impact on the measures of neighbourhood quality falls much faster in distance than the impact on voting outcomes. The stark difference tells us that voters within 500m of the nearest shelter are still more likely to cast their vote for the right-wing party, while rental prices in their block do not decline and businesses in their own close vicinity do not experience a decline in ratings.

Tab. 17: The impact of shelters, decreasing with distance

Outcome	(1) RW voteshare	(2) rental price	(3) Positive rating
Independent variables			
Shelter within 100m	0.012***	-0.37**	- 0.12**
	(0.002)	(0.15)	(0.05)
Shelter within 100m-200m	0.013***	-0.05	-0.017
	(0.004)	(0.11)	(0.022)
Shelter within 200m-500m	0.009***	0.03	0.023
	(0.003)	(0.07)	(0.025)
Shelter within 500m-1000m	0.005**	0.01	-0.023
	(0.002)	(0.06)	(0.018)
FE year	✓	✓	✓
FE district	✓	✓	
FE venue			✓
R squared	0.83	0.83	0.18
N. of observations	13,283	208,390	80,166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

This set of results may not be conclusive, but it suggests that the impact of shelters on right-wing voting works through a channel other than the ratings decline discussed above. With the data at hand, we can not investigate all these possible channels, but one candidate is that a nearby shelter simply increases the visibility and salience of the refugee crisis to voters, leading them to vote for the anti-immigrant party even if there is no perceived decline in the quality of their neighbourhood.

5 Robustness and validity

5.1 Common trends and balance between treated and non-treated areas

An important concern is whether the placement of refugee shelters was influenced by political considerations - they could for example be located in areas where support for right-wing parties is weaker. Table 18 provides an overview of the differences between areas close to the eventual locations of refugee shelters (treated) and those further away. In terms of previous political outcomes, there was no difference between treatment and control groups. I test this not only for our outcome variable, the right-wing voteshare, but also for the share of the Green party (the most pro-immigration large party in Germany) and for the share of nonvoters (since many of the AfD voters came from this group).

Treated areas also did not have different average ratings before, and the share of Turkish or Middle Eastern restaurants relative to all places was also the same. On the other hand, there were more Foursquare places in the treated areas, probably because they tend to be closer to the centre of the city.[9]

This balance between treated and non-treated areas could however hide diverging trends. We could find that ratings in areas where shelters would eventually open were higher at the very beginning of our panel, and falling up to the time when shelters were opened. In that case, the treatment effect could simply be the continuation of that trend.

To address this concern, I will demonstrate that my cross-sectional treatment variables, capturing eventual proximity to refugee shelters, do not determine either ratings or voting outcomes at any time prior to the refugee crisis. The regression specification is

$$y_{i,t} = \alpha_t \left(treatment_i \times \mathbf{TD}_t \right) + \Gamma X_i + FE_i + FE_t + \epsilon_{i,t} \tag{14}$$

[9] Similar comparisons for other variables are available upon request.

Tab. 18: Balance table, treated and untreated voting precincts

	Non-treated		Treated		T-test
Variable	N	Mean/SE	N	Mean/SE	Difference
Rightwing vote share	7675	0.038	343	0.035	0.003
		(0.002)		(0.003)	
Greens vote share	7675	0.177	343	0.193	-0.016
		(0.001)		(0.007)	
Nonvoters	7675	0.414	343	0.407	0.006
		(0.001)		(0.006)	
Mean rental price (apartments)	6745	7.729	299	7.638	0.092
		(0.032)		(0.093)	
- price development (2011-14)	6496	1.574	294	1.603	-0.029
		(0.065)		(0.070)	
Average rating	7094	1.286	325	1.272	0.013
		(0.003)		(0.012)	
Ethnic restaurants	7675	0.014	343	0.017	-0.003
		(0.000)		(0.001)	

Notes: The covariates area and distance to center center are included in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

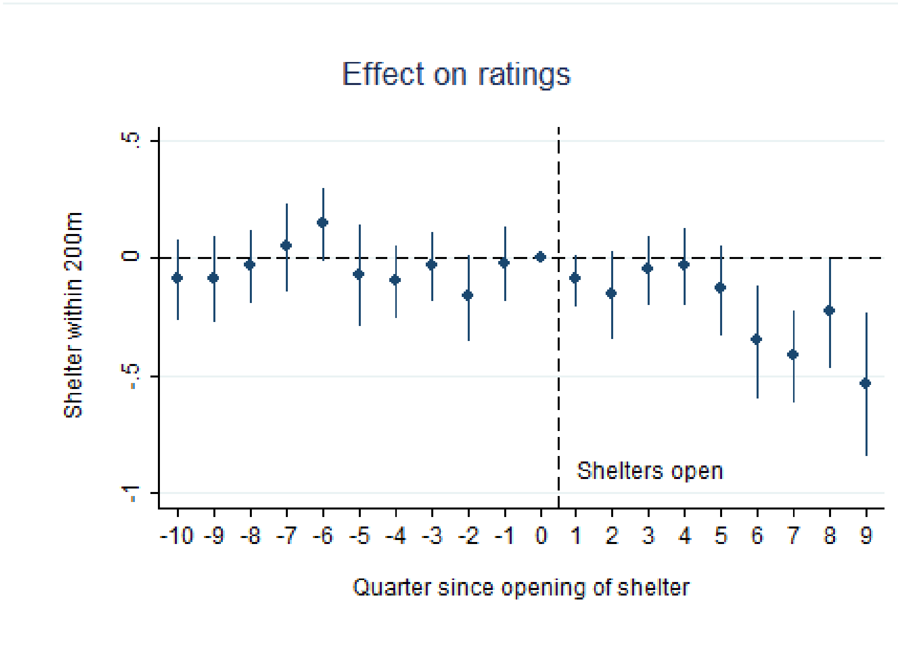

Fig. 5: Ratings and proximity to shelter location, before and after opening

where the outcome variable $y_{i,t}$ is either the probability of a positive rating or the right-wing voteshare. $\mathbf{TD}_t$is a period dummy (quarterly for ratings, yearly for election outcomes), and the treatment dummy is simply indicating the eventual opening of a shelter within 200m.

Figure 5 shows the coefficients from this regression (for positive ratings). As can be seen, the locations of shelters did not follow a different trend before the refugee crisis. It also becomes apparent that the effect of the shelter only appeared a year after opening.

Figure 6 shows the same coefficients for all federal and state elections since 2006. It becomes evident that there was no rising support for right-wing parties in these locations before the crisis (the regressions results and coefficient plots for other political outcomes, as well as for other ratings outcomes and treatment definitions, are available on request).

5.2 Places and ratings

Shelters were not opened in such voting tracts where tips where generally better or worse before the refugee crisis (table 19). I have also investigated the composition of venues in tracts which would eventually host a shelter along several dimensions; on most measures,

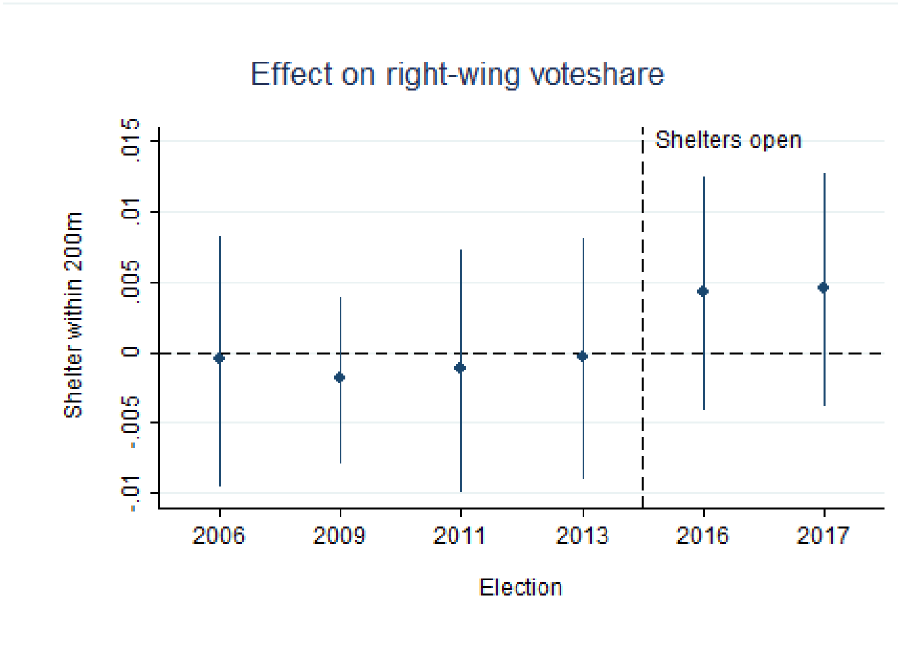

Fig. 6: Voting outcomes and proximity to shelter location, before and after opening

these are not different from others. This is notably true for the number of Turkish or Middle Eastern restaurants in the area relative to the total number of venues (reported in table 20). It appears therefore not true that the foreign population of a voting tract was a consideration when the locations of shelters were decided.

The average ratings of places, their average price and other characteristics are also not predictive of whether or not a shelter would be opened nearby (tables upon request). An exception is the number of total venues in a voting tract: this is significantly higher in such voting tracts which would be near a shelter, even when we control, as always, for the area and distance to the centre. This points to the fact that a general abundance of facilities meant a place for shelter could more likely be found. Conversely, it was not the case that shelters were established mostly 'out of view', in areas of low density (again, regression tables are available upon request). A look at the maps in section 2 also confirms this.

Instrumental variable estimation: Another strategy to address the potential endogeneity of shelter locations would be to instrument them with the infrastructure commonly used for them. Since school grounds, school sports facilities etc. were often used in Berlin, the distance to the next public school is one such candidate. I investigate this instrument in Appendix B.

Tab. 19: Nearby refugee shelter and tips in previous years

Outcome variable	negative rating						
Elections	(1) 2011	(2) 2012	(3) 2013	(4) 2014	(5) 2015	(6) 2016	(6) 2016
Nearby shelter	-0.057	-0.195	-0.054	0.955*	1.968	2.428**	2.849
	(0.062)	(0.589)	(0.116)	(0.526)	(1.528)	(0.951)	(1.885)
Distance to centre	-0.002	-0.060	-0.030***	-0.189***	-0.445***	-0.360***	-0.533***
	(0.005)	(0.046)	(0.009)	(0.040)	(0.122)	(0.073)	(0.144)
Area	0.002	0.050	0.035**	0.183***	0.518**	0.458***	0.576**
	(0.008)	(0.078)	(0.015)	(0.069)	(0.211)	(0.120)	(0.243)
FE district	✓	✓	✓	✓	✓	✓	✓
N. of observations 871	999	1206	1074	984	985	926	

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

Tab. 20: Nearby refugee shelter and Turkish and Middle Eastern restaurants in previous years

Outcome variable	negative rating						
Elections	(1) 2011	(2) 2012	(3) 2013	(4) 2014	(5) 2015	(6) 2016	(6) 2016
Nearby shelter	-0.005	-0.010	0.002	-0.008	0.004	-0.005	-0.015
	(0.009)	(0.010)	(0.008)	(0.010)	(0.015)	(0.013)	(0.017)
Distance to centre	-0.001*	-0.001**	-0.001**	-0.001	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Area	0.001	-0.002	-0.001	-0.001	-0.002	-0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
FE district	✓	✓	✓	✓	✓	✓	✓
N. of observations 1546	1623	1609	1420	1221	1301	1113	

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

My main results are quite robust to the use of this instrument, depending on treatment definitions. However, as I show, the instrumented treatment locations are actually less balanced with non-treatment locations then the true shelter locations. For this reason, I prefer to use the OLS estimations.

5.3 Identity of users

An objection to my use of Foursquare ratings as an outcome variable is that it could be that a refugee shelter simply attracts a different set of Foursquare users to an area. These users could be of a type that gives worse ratings, even though their experience is no less positive than that of users who frequented the area before.

Ideally, I would use user ID fixed effects interacted with place ID fixed effects, to only capture users giving repeated ratings to the same place. This is however impossible: there are 27 thousand different user IDs for 81 thousand ratings, in addition to the 16.3 place IDs in the ratings data. Including user fixed effects completely absorbs the remaining variation, making any treatment effect insignificant.

I can therefore only investigate if available user characteristics are impacted by the establishment of shelters. These characteristics are user gender and the language of the review text. The rationale for this is that if a different group of users were giving the reviews after the establishment of a shelter, they would likely differ in language and gender. The immigrants themselves for example would be more likely to be male and non-german.

Regressions of dummies for reviews in different languages - German, English, Turkish, and Arabic - on our treatment and control variables from the main specification show that this is not the case (table 21). As before, the 10% most treated areas have a value of 1.8 during 2017. Recall also that, in the whole dataset, the percentages of reviews in different languages are: 56% English, 36% German, 2% Turkish, and .1% Arabic.

There is also no effect on user gender (table 22). At baseline, 60% of reviews are by male users, and 30% by female users (the rest are by users who do not identify their gender). These percentages are not significantly affected by the treatment variable.

I conclude from this evidence that the users giving ratings are not discernibly different after the establishment of a shelter.

Tab. 21: Distance to refugee shelter and review language

Outcome variable	(1) German	(2) English	(3) Turkish	(4) Arabic
Independent variables				
Shelters capacity/distance	-0.001	-0.007	-0.002	0.001
	(0.009)	(0.008)	(0.002)	(0.001)
FE place	✓	✓	✓	✓
FE month	✓	✓	✓	✓
R squared	0.185	0.152	0.093	0.055
N. of observations	80,166	80,166	80,166	80,166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at place and month level.

Tab. 22: Distance to refugee shelter and review language

Outcome variable	(1) Male	(2) Female
Independent variables		
Shelters capacity/distance	-0.004	0.010
	(0.009)	(0.008)
FE place	✓	✓
FE month	✓	✓
R squared	0.077	0.066
N. of observations	80,166	80,166

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at place and month level.

6 Conclusions

This study suggests that a nearby refugee shelter decreases the perceived quality of local amenities such as restaurants. At the same time, the anti immigration AfD party has benefited from the presence of shelters in elections after the refugee crisis. It appears however that these are two independent outcomes, so that another mechanisms than the perceived decline of neighbourhood quality is responsible for the effect on votes.

There is limited evidence for increased creation of businesses in the vicinity of refugee shelters, and of Turkish and Middle Eastern restaurants in particular. This may go hand in hand with increased unobserved business closures; it would be interesting to return to this question in the future, and perhaps with different data.

It must be kept in mind that the Foursquare data represents subjective opinions about local venues, and that these opinions come from a selected group of individuals. However, taken together with e.g. the survey evidence from Greek islands in Hangartner et al. (2017), these results indicate that emergency housing of refugees is seen as a negative for the community.

The response to refugees may be different in less crisis-laden circumstances. The fact that some of the negative impacts found in this study are more severe for the more makeshift emergency shelters is an indication of this. This is of interest for the future management of refugee housing, as is the finding that more visible shelters, and shelters in areas without a previous presence of co-ethnic inhabitants, appear to provoke a stronger electoral backlash.

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Appendices

A Bias in indirect effect regression

Assume the true relationship between voting outcomes Y_{it}, proximity of shelters T_{it} and ratings M_{it} is

$$Y_{it} = \beta_2^d T_{it} + \beta_2^{id} M_{it} + \beta^q Q_{it} + \epsilon_{3_{it}}$$

Since we do not observe the shock to neighbourhood quality Q_{it}, we estimate

$$Y_{it} = \beta_1^d T_{it} + \beta_1^{id} M_{it} + \epsilon_{3_{it}}$$

Let **X** be the matrix of independent variables [T,M]. The estimated coefficients $\hat{\beta}$ are:

$$\hat{\beta} = \begin{bmatrix} \hat{\beta_1^d} \\ \hat{\beta_1^{id}} \end{bmatrix} = \frac{\mathbf{X'}Y}{\mathbf{X'X}}$$

which is

$$\hat{\beta_1^d} = \frac{Var(M) \times Cov(T,Y) - Cov(T,M) \times Cov(M,Y)}{Var(T) \times Var(M) - Cov(T,M)^2}$$

and

$$\hat{\beta_1^{id}} = \frac{Var(T) \times Cov(M,Y) - Cov(T,M) \times Cov(T,Y)}{Var(T) \times Var(M) - Cov(T,M)^2}$$

Developing these expressions by substituting the true specification for Y we have for $\hat{\beta_1^{id}}$:

$$\begin{aligned}
\hat{\beta_1^{id}} = & \frac{Var(T)\times Cov(M,\beta_2^d T+\beta_2^{id}M+\beta^q Q+\epsilon_3)-Cov(T,M)\times Cov(T,\beta_2^d T+\beta_2^{id}M+\beta^q Q+\epsilon_3)}{Var(T)\times Var(M)-Cov(T,M)^2} \\
= & \frac{\beta_2^{id}\Big(Var(T)\times Var(M)-Cov(T,M)^2\Big)+\beta_2^d\Big(Var(T)\times Cov(T,M)-Var(T)\times Cov(T,M)\Big)}{Var(T)\times Var(M)-Cov(T,M)^2} \\
& +\frac{\beta^q\Big(Var(T)\times Cov(M,Q)-Cov(T,M)\times Cov(T,Q)\Big)+V(T)\times C(M,\epsilon_3)-C(T,M)\times C(T,\epsilon_3)}{Var(T)\times Var(M)-Cov(T,M)^2} \\
= & \beta_2^{id}+\beta^q\frac{Var(T)\times Cov(M,Q)-Cov(T,M)\times Cov(T,Q)}{Var(T)\times Var(M)-Cov(T,M)^2}
\end{aligned}$$

Since $Cov(T,Q) = 0$ (the unobserved shocks are independent of treatment), this simplifies to

$$\hat{\beta_1^{id}} = \beta_2^{id} + \beta^q \frac{Var(T)\times Cov(M,Q)}{Var(T)\times Var(M)-Cov(T,M)^2}.$$

By the same logic,

$$\beta_1^d = \beta_2^d - \beta^q \frac{Cov(M,Q)\times Cov(T,M)}{Var(M)\times Var(T)-Cov(M,T)^2}.$$

B Instrumental variable estimation:

An appealing strategy to address the possible endogeneity of shelter location is to instrument the location of shelters with the infrastructure commonly used for them. Since school grounds, school sports facilities etc. were often used in Berlin, the distance to the next public school is highly predictive of the distance to the next shelter during the refugee crisis. Via this distance channel, it also predicts the treatment variable (shelters capacity/distance - see table 23). Equally, having a public school nearby increases the likelyhood of having a nearby shelter - this second specification is a much worse fit however, since there are many more public school locations in Berlin than shelter locations. For the IV regressions, I therefore prefer the continuous treatment variable, rather than the nearby shelter dummy.

Tab. 23: Public schools and refugee shelters, first stage

Outcome	(1) Shelter Capacity/Distance	(2) Nearby shelter dummy
Independent variables		
Distance to school	-.038***	
	(0.009)	
Nearby school dummy		0.014*
		(0.008)
Distance to centre	0.0	-0.003
	(0.006)	(0.002)
FE district	✓	✓
FE Year	✓	✓
R squared	0.79	0.015
N. of observations	18,947	18,947

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

When I instrument the shelter capacity/distance by the distance to the closest school in the panel model (equation 5), the coefficient is close to the one obtained in the OLS model (table 24). The IV performs much better when continuous distance to shelter is used than when we use a dummy, because the standard error is quite large. However, the direction of the coefficient is the same. This gives us additional confidence that shelter locations where not chosen according to the potential for political discontent.

The results on venue ratings are also robust to this instrumental variable strategy (tables upon request).

However, public school location turn out to be more predictive of political outcomes before the refugee crisis than the actual shelter location (table 25). The IV specification thus fails a placebo test which the OLS specification largely passes.

This circumstance and our knowledge of the historical and institutional situation – especially the information given by the responsible agency that shelters were opened wherever it was possible, without any political considerations – means that I prefer the OLS specification over the IV.

Tab. 24: Distance to refugee shelter and right-wing vote share, OLS and IV

Model	(1) OLS	(2) IV	(3) OLS	(4) IV
Independent variables				
Shelters capacity/distance	0.051***	0.035***		
	(0.001)	(0.004)		
Nearby shelter× (2016 or 2017)			0.012***	0.060
			(0.003)	(0.079)
Distance to centre× (2016 or 2017)	0.007***	0.007***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
FE polling station	✓	✓	✓	✓
FE election	✓	✓	✓	✓
N. of observations	13283	13283	13283	13283

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

Tab. 25: Nearby school in previous elections

Outcome variable	right-wing voteshare					
Elections	(1) 2006	(2) 2009	(3) 2011	(4) 2013	(5) 2016	(6) 2017
Distance to school	-0.015***	-0.002	-0.005	-0.009***	-0.025***	-0.014*
	(0.003)	(0.002)	(0.004)	(0.002)	(0.009)	(0.007)
Area	0.002**	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Distance to centre	0.002***	0.001***	0.002***	0.002***	0.010***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
FE district	✓	✓	✓	✓	✓	✓
N. of observations	1,591	1,652	1,596	1,617	1,779	1,779

Significant at: $p < 0.1$: *; $p < 0.05$: **; $p < 0.01$: ***. Standard errors clustered at district level in (3).

C Restaurant categories and prices on Foursquare

As discussed in section 2, I construct variables of foreign presence and of wealth in a voting precincts from the Foursquare data.

As an indication of the presence of foreigners in the area, I use the presence of Turkish and Middle Eastern restaurants. The scatterplot Figure 7 shows how this measure correlates, on the level of city districts where official data is avaiable, how the number of such restaurants is correlated with the percentage of inhabitants who are foreigners.

Figure 8 shows how on the same level, average real estate prices (per square meter) correlate with the average price ratings received by foursquare places. These correlations are positive as we would expect. It is strong (.82) in the case of the ethnic restaurants, but a bit weaker in the case of price ratings (.59).

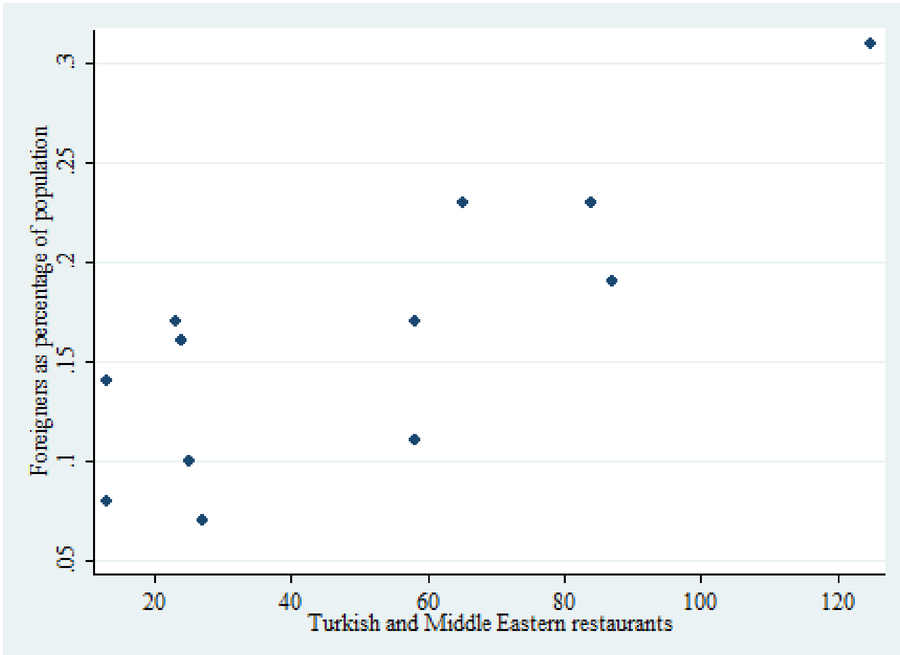

Fig. 7: Foreign population and foreign restaurants on Foursquare by district

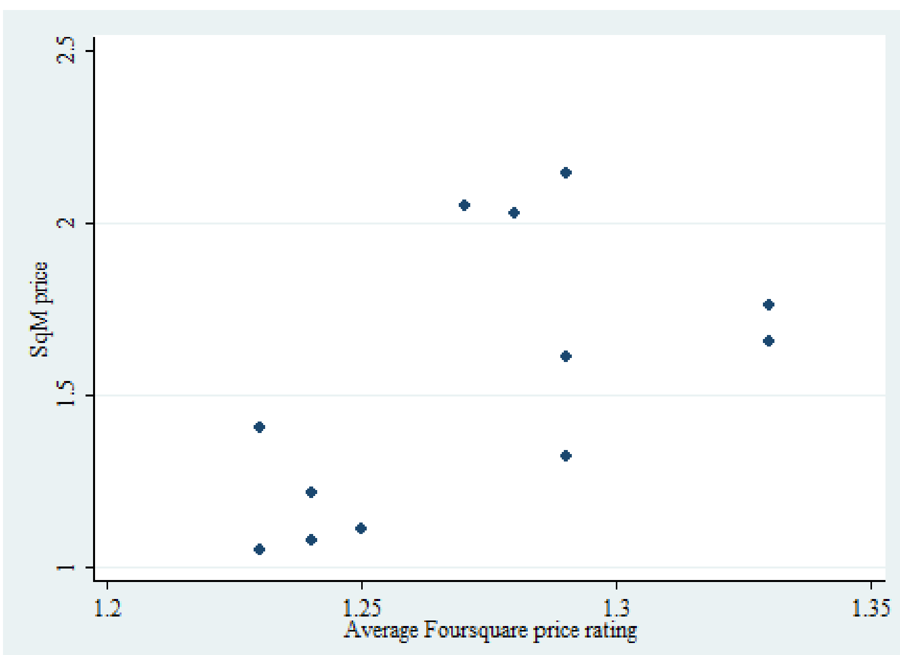

Fig. 8: Real estate prices and Foursquare price ratings by district