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The effect of asylum seeker reception centers on nearby house prices: Evidence from The Netherlands☆

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ABSTRACT

With 20,945 asylum applications in 2016, the Netherlands received the tenth highest number of asylum requests in Europe. From the time of their arrival, and until a decision on their asylum requests is made, asylum seekers are sheltered in asylum seeker reception centers (ASRCs) across the country. This paper tests whether the opening of reception centers affects the prices of nearby houses. In doing so, likely differential effects across urban and non-urban areas, as well as for ASRCs of distinct capacities to host asylum seekers, are considered. The analysis uses hedonic regressions that are based on a staggered difference-in-differences design. Estimation comes from 2009–2017 information on the transaction prices of houses (N = 347,479) and the locations and opening dates of nearby ASRCs (N = 75). The results indicate that the opening of ASRCs causes the prices of some houses to fall by approximately 9.3%. However, this estimated effect pertains solely to single-family houses in less densely populated areas and for ASRC of high hosting capacity, whereas in cities no economically or statistically significant effects are found. The findings of this study have implications for the design of public policies that regard the spatial dispersion of ASRCs.

1. Introduction

The inflow of asylum seekers[1] to European countries has increased rapidly in recent years. In 2011, the number of asylum applications was 309,040 and this number grew to 1.26 million in 2016. Countries are required to provide material reception[2] to asylum seekers, but countries can themselves decide on the location of shelter (European Migration Network, 2014; Proietti and Veneri, 2019). The inflow of asylum seekers in a specific place can potentially affect several aspects of that area, including the labor market and the provision of services or the housing market (Gheasi and Nijkamp, 2017). Housing market outcomes are the focus of this study, which investigates whether, for the case of the Netherlands, the opening of asylum seekers reception centers (ASRC) is a source of externalities that can be detected from local house prices. Our analysis is relevant for policy makers, as policies on the spatial allocation of asylum seeker reception tend to disperse ASRCs across space, in order to alleviate cities – but might this produce externalities where these are most pressing?

The empirical literature on how local communities regard the reception of asylum seekers is fragmented. Some studies have highlighted the existence of mixed attitudes, for example, humanitarianism and opposition (Fratesi et al., 2019; Hangartner et al., 2018; Zorlu, 2017). Others have investigated the effect of the inflow of asylum seekers and refugees on electoral outcomes (Bratti et al., 2017; Dennison et al., 2017; Dustmann et al., 2016; Otto and Steinhardt, 2014; Steinmayr, 2016; Witteveen, 2017). However, there is little evidence of how local inhabitants respond to ASRCs in terms of actual market behavior. Actual market behavior, instead of declared attitudes or voting patterns, offers a basis for more precise assessment of people's reactions towards ASRCs. Studies on attitudes in particular, tend to examine 'stated preferences', see for example Facchini et al. (2016), Grigorieff et al. (2017), or Hopkins et al. (2018), which may allow socially acceptable answers to impact findings. Unlike such studies, we consider preferences that are revealed in local housing markets. To our

☆ The views expressed herein are those of the authors and do not necessarily reflect the views of the OECD.

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[1] All individuals who have requested international protection and whose claim for protection status has not yet been determined.

[2] Material reception refers to a range of measures and provisions offered to asylum seekers during the procedure determining their international protection status, which can include housing, food, clothing, education and health care (AIDA, 2016).

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knowledge, the impact of ASRCs on house prices is only addressed in a working paper by Lastrapes and Lebesmuehlbacher (2017), which analyzes such impacts in England and Wales over 2004–2015, at the aggregate level of districts. Such aggregated analysis, however, may obscure the finer-scale patterns in how the prices of houses close to ASRCs, thus below the regional level, respond to ASRC openings. Our approach, instead, is to use micro-level data on house transactions; this approach considers that, as potential buyers for houses that are listed for sale compete with each other, the outcomes of this process may reflect an implicit valuation of perceived (dis)amenities of living *close* to an ASRC.

While a priori the sign and magnitude of the possible ASRC effect are ambiguous, we suspect that ASRCs might negatively impact the prices of nearby houses given several phenomena that are well-documented in the literature: the process of 'othering' from migrant residents (Brons, 2015); the perception of increased crime levels after the inflow of asylum seekers (Dempster and Hargrave, 2017); and the overcrowding of local public services and competition between incumbents and newcomers for access to services (OECD, 2018a).

However, the locations of ASRCs are heterogeneous as these include both cities and non-urban areas. This situation results from a system of reception that is decentralized under the rationale of de-concentrating the hosting locations while also attaining some cost-efficiency, as in areas of low-population density land prices are low. Hence, our analysis considers whether ASRCs have a differential impact across urban and non-urban areas. Our expectation is that the ASRCs effect, if any, is stronger in non-urban areas. While on the one hand the influx of asylum seekers might have positive externality-effects on local development by counteracting ageing and depopulation, see OECD (2018a), importantly, non-urban areas may have limited ability to absorb any negative externalities that ASRCs may bring about. For example, if compensatory amenities are not provided, non-urban residents might experience an overcrowding of public services. Moreover, non-urban residents have, in general, had less exposure to migrants as compared to the residents of cities, as in cities the composition of the population is, on average, more diverse; perhaps for this reason, in cities, sentiment towards migrants has been documented to be significantly more positive than in non-urban areas (Diaz-Ramirez et al., 2018). Even so, it is possible that the potential externalities from ASRCs are simply more visible in non-urban areas, particularly when relatively large ASRCs are involved.

This study of possible ASRC externality-effects uses a model that is well-established in the literature on revealed preferences, the hedonic price model. This type of model uses regression to disentangle house prices into implicit marginal prices for the individual attributes of houses. In our more specific case, we adopt a difference-in-differences approach that closely follows Pope and Pope (2015) and Slade (2018). The difference-in-differences approach allows us to compare housing prices in same-areas before and after the opening of ASRCs, and thereby difference away the possible influence of time-invariant omitted variables (Meyer, 1995). The identification relies on the assumption that price trends for houses nearby ASRCs and houses farther away, but within the same spatial submarket, would have remained similar if ASRCs had not been opened. In this quasi-experimental analysis, we pay specific attention to the definition of the so-called treatment and control groups as we isolate the price-effect of ASRCs.

Our estimation draws on a comprehensive dataset on house sales throughout the Netherlands from January 2009 to December 2017 as well as information on all existing and newly opened ASRCs.[3] This ensures high variation in the observed data, as we exploit the dispersed pattern of ASRC locations to investigate the potential ASRC-effect for houses across urban and non-urban areas. These areas are defined in a consistent way using the OECD-EC functional urban areas definition.

Our findings indicate that the opening of ASRCs may affect negatively the prices of nearby homes. However, the effect is of economic and statistical significance only in the particular case of single-family homes in non-urban areas, and solely associated with the largest of ASRCs, those that can host 500 or more asylum seekers. This result is robust with various changes in model specification and several falsification analyses. Our study's findings may inform policy makers who specify the allocation of ASRCs' in terms of their location and dimension.

The remainder of the paper is organized as follows. Section 2 provides a review of the literature and introduces the Dutch study area's institutional setting in relation to asylum seeker center dispersal policy. Section 3 introduces the empirical strategy, empirical model, and the data. Section 4 presents the results. Thereafter, Section 5 provides a discussion of our study and its findings, followed by conclusions in Section 6.

2. Literature review and institutional setting

2.1. Literature review

The literature on attitudes toward the hosting has generally focused on understanding how economic, humanitarian and religious concerns as well as education influence people's attitudes towards asylum seekers (Bansak et al., 2016; 2017; Crawley et al., 2013; Grillo, 2005). The literature specific to the Netherlands also investigates the relationship between proximity to ASRCs and attitudes toward asylum seekers, although results are non-conclusive. For instance, Lubbers et al. (2006) present a multi-level analysis based on a large-scale survey amongst a representative sample of the Dutch population that was conducted in 2000. Their study finds that local communities object more to large centers, as compared than to small centers, in neighborhoods with properties of higher value. Zorlu (2017) analyzes data from three representative surveys amongst residents of 10-kilometer zones that surround four ASRCs; the surveys were conducted in Ter Apel and Musselkanaal in 2012, in Burgum in 2013, and in Baexem in 2014. Their findings suggest that people who live closer to an ASRC do not have a negative attitude towards asylum seekers, nor is their attitude found to depend on the size of the center.

Previous studies have also investigated the effect of international migration on voting outcomes (Barone et al., 2016). Otto and Steinhardt (2014) find that an increase in the percentage of foreigners has a positive effect on the electoral success of extreme right-wing parties in Hamburg, Germany. Dustmann et al. (2016) find a similar effect in Denmark, except in the country's largest cities. However, the evidence points in a different direction when geographical proximity to ASRCs is considered. For instance, Steinmayr (2016) finds that in Austria local exposure to asylum seekers dampened natives' votes for anti-immigration parties during the 2015 state elections.

In the past, surveys on attitudes and voting behavior have been used to explore the perception of local communities regarding the provision of other types of public facilities (e.g., schools, hospitals, nursing homes, homeless shelters, or alcohol rehabilitation facilities), also based on geographic proximity (Bellettini and Kempf, 2013; Murray et al., 1998; Takahashi and Dear, 1997). Unlike information from opinions or votes, house prices capture how people respond to the creation of public facilities based on actual market behavior (Brookshire et al., 1982).

[3] According to Statistics Netherlands (CBS), the rate of home ownership at the time of our study is around 60%. Furthermore, it may be noted that the Dutch public housing sector is exceptionally large, from an international perspective, whereas the private rental sector is comparatively small. Hence, the most relevant price signals of possible ASRC externality-effects may be found in the market for owner-occupier housing.

(*footnote continued*)

Connections between house prices and migration are considered in an extensive body of literature. Some papers discuss how the rate of homeownership amongst foreigners, and thereby the impact of migration on house prices, varies across ethno-cultural groups or according with other factors such as socio-economic characteristics and length of stay (Nygaard, 2011). Other studies attempt to measure whether impacts of migration on house prices or rents are positive or negative (Gonzales and Ortega, 2013; Kalantaryan, 2013; Sà, 2015; Saiz, 2007). In this context, it should be noted that the net impact of immigration is determined by the results of the competition between former residents and newcomers both on the housing market and the labor market. The increase in housing demand that migration may bring about is suggested to be higher when housing supply is more elastic, migrants participate in the labor market complementarily to natives, migrants aim at homeownership, and when in the perception of former residents local amenities improve as a result of increased migration and cultural diversity (Accetturo et al., 2014; Card, 1990; Monnet and Wolf, 2017; Sanchis-Guarner, 2017).

Empirical studies of migration and city- or country-level house prices report effects of varying sizes and signs. For example, Saiz (2007), who studies the impact of immigration in American cities, finds that an immigration inflow equal to 1% of a city's population is associated with increases in house prices and rents of about 1%. Similarly, positive impacts of immigration on house prices are documented for the cases of Spain (see Gonzales and Ortega 2013), and Italy (see Kalantaryan 2013). In contrast, Sà (2015) reports a negative effect of immigration on house prices in the UK; an inflow of immigrants equal to 1% of the local population is found to reduce house prices by 1.6%. According to Sà (2015), the main reason for this fall in prices is the outflow of natives in response to immigration. Saiz (2003), however, documents a positive effect on rents and a negative effect on house prices in the case of Miami after the Mariel boatlift, which further underlines that the potential effects of immigration on aggregate outcomes in housing markets can be ambiguous.

2.2. Institutional setting

With 20,945 asylum applications in 2016, the Netherlands had the tenth highest number of asylum requests in Europe (Table 1). Migrants who request asylum in the Netherlands report to the Immigration and Naturalization Service office that is closest to their point of entry into the country. COA then receives them at its central reception facility in Ter Apel (Province of Groningen). After identification, the COA assigns asylum seekers to one of the various reception locations where they continue the process of requesting asylum.[4] Most asylum seekers then rely on the hosting service provided by COA at ASRCs, where they wait for a decision.

When reception capacity is needed, COA consults municipalities regarding their willingness to host asylum seekers. In the designation of ASRC locations, COA uses five criteria: first, unlike the Dutch provinces, not all municipalities are required to provide reception services, and locations near large municipalities are favored. Second, COA looks at the quality of locations in terms of infrastructure and real estate (e.g., whether the state of shelter units' maintenance is sufficient). Third, reception providers, which may be municipalities or private owners, are required to be flexible in order to cope with fluctuating flows of asylum seekers. Fourth, ASRCs have to be close to immigration agencies. Fifth, locations are ought to be not too expensive. In agreement with the selected municipalities, COA provides material reception by renting apartments from that municipality or from other public or private organizations; however, COA can also use its own buildings or initiate the development of new units. This limits the potential creation of added competition in local housing markets. Commonly, no public information is provided on the timing of new ASRC openings.

[4] Asylum seekers cannot decide themselves on the location of their hosting.

Table 1
Annual number of asylum applicants in several European countries.
Source: Eurostat data.

Country	2011	2012	2013	2014	2015	2016
Germany	53,235	77,485	126,705	202,645	476,510	745,155
Italy	40,315	17,335	26,620	64,625	83,540	122,960
France	57,330	61,440	66,265	64,310	76,165	84,270
Greece	9310	9575	8225	9430	13,205	51,110
Austria	14,420	17,415	17,500	28,035	88,160	42,255
United Kingdom	26,915	28,800	30,585	32,785	40,160	39,735
Hungary	1690	2155	18,895	42,775	177,135	29,430
Sweden	29,650	43,855	54,270	81,180	162,450	28,790
Switzerland	23,615	28,400	21,305	23,555	39,445	27,140
Netherlands	14,590	13,095	13,060	24,495	44,970	20,945
Bulgaria	890	1385	7145	11,080	20,365	19,420
Belgium	31,910	28,075	21,030	22,710	44,660	18,280
Spain	3420	2565	4485	5615	14,780	15,755
Poland	6885	10,750	15,240	8020	12,190	12,305
Denmark	3945	6045	7170	14,680	20,935	6180
Finland	2915	3095	3210	3620	32,345	5605
Norway	8990	9675	11,930	11,415	31,110	3485
Cyprus	1770	1635	1255	1745	2265	2940
Ireland	1290	955	945	1450	3275	2245
Croatia	–	–	1075	450	210	2225
Luxembourg	2150	2050	1070	1150	2505	2160
Malta	1890	2080	2245	1350	1845	1930
Romania	1720	2510	1495	1545	1260	1880
Czech Republic	750	740	695	1145	1515	1475
Portugal	275	295	500	440	895	1460
Slovenia	355	295	270	385	275	1310
Iceland	75	115	125	170	345	1125
Lithuania	525	645	400	440	315	430
Latvia	340	205	195	375	330	350
Estonia	65	75	95	155	230	175
Slovakia	490	730	440	330	330	145
Liechtenstein	75	70	55	65	150	80

Similar to the situation in several other European countries, in the Netherlands, asylum seekers are allowed to supply labor (OECD, 2016). However, in practice their potential labor market entry tends to be characterized by hurdles such as language barriers, administrative challenges, and uncertainties regarding their stay (European Commission, 2016; European Union, 2016; Fasani et al., 2018; Hainmueller et al., 2016; Harbo et al., 2017; Konle-Seidl and Bolits, 2016; Martín et al., 2016; Zimmermann, 2016).

In summary, the presence of asylum seekers is unlikely to create competition in the market for owner-occupied housing in the short term, as asylum seekers are hosted by ASRCs that are organized by renting apartments or using larger-scale specialized hosting locations, nor in the medium term, as entrance of asylum seekers and refugees into the labor market is characterized by challenges. This situation allows us to study ASRCs as a potential *external* source of (dis)amenities, in local communities, that internalize in the prices of nearby houses.

3. Methods and data

3.1. Methodological design

The primary goal of our analysis is to better understand how local communities perceive ASRCs from market behavior. The potential local externality-effect of ASRCs is estimated from variation in the selling prices of nearby houses, using hedonic models. Hedonic models may obtain a measure of capitalization that reflects people's preferences for living close to an ASRC, or farther away: does the opening of an ASRC impose a (dis)amenity?

The hedonic model, formalized in Rosen (1974), considers housing as a bundled good and allows us to disentangle house prices into implicit prices for structural and locational house characteristics, based on a multivariable regression model. Our regression model exploits variation in house prices across space and time, which helps to overcome

omitted variable bias which is common in hedonic analysis, by adopting a spatial difference–in–differences design. The basis of this quasi-experimental analysis is the comparison of selling prices that are observed in treatment groups and control groups, where treatment is the opening of an ASRC. In specific, we consider whether prices in the treatment group show significant change before and after the ASRC opening, as compared to the change, if any, in prices in the control group. The treatment group consists of houses in the near proximity of locations where, at any time during the study's temporal window, an ASRC opens. As the spatial extent of the potential treatment-effect is a priori unknown, we use a relatively sizeable outer treatment range of 2 kms while, similar to Schwartz et al. (2006) and Brooks and Lutz (2019), allowing effects within that range to vary across space. The control group consists of houses farther away from the locations where ASRCs are opened at any point in time prior to or during the window of study.[5] The fact that ASRCs have opened at different points in time benefits our analysis by allowing us to identify treatment effects even after adding time dummy variables.

To mitigate the influence of time-invariant omitted variables that could bias our estimation, we follow Pope and Pope (2015) and account for spatial fixed effects at the level of the (dis)amenity of interest, in our case the ASRC nearest to an observed house. The spatial fixed effects are allowed to vary on a quarterly basis. This then controls for the possible influence of time-varying spatial processes (see also Carpenter and Dobkin, 2011). Indeed, a fixed effect design that is purely spatial would allow for time-varying spatial processes to remain in the estimation. Our assessment, instead, purges the possible influence of such processes, which might reflect differential local economic development that correlates with ASRC openings, from the estimation. Indeed, price trends in treatment and control groups may due to the real-world setting not be perfectly parallel. Hence, as argued also by Angrist and Pischke (2008), our type of fixed effect approach helps to control for this.

In addition, in order to balance the data from which we identify the potential ASRC-effect, we initially consider only transactions in a symmetric window of two years before, and two years after, ASRC openings. It may be noted that the pace at which ASRCs open after a decision on this has been taken can vary widely. Indeed, this depends on whether an ASRC can be realized in an appropriate building that is readily available or whether refurbishment is necessary, as well as whether the ASRC materializes in temporary housing units or in buildings that are newly developed. Also, recall that commonly the opening of ASRCs is not announced publicly. Hence, in such cases, house prices possibly respond in an ad hoc fashion. As a result of the situation discussed above, the relevant temporal estimation window is a priori unknown. Hence, we optimize for the number of observed ASRCs, as we keep only ASRCs for which nearby housing transactions can be observed during the entire time-window. The two-year period may also allow for a sufficient baseline of prices, before the observed ASRC openings, as our study's window includes the peak-period of the asylum seekers inflow in the Netherlands, when shelter was provided with urgency.

The spatial extent of the local areas under study, and the associated spatial controls, is bounded by housing submarket areas. This prevents that the study area is defined too narrowly, which could otherwise cause ASRC effects to remain unobserved in case these are widely shared amongst the observed houses (Graves 1983). Vice versa, the size of spatial submarkets also implies a substantial 'weight' of transactions in the control group, which in turn helps to suppress the influence of any control observations that are contaminated with the treatment effect, as these observations might be relatively close to the treatment area, in the estimation. Moreover, submarkets boundaries are designated as to include highly substitutable property and so, at the submarket-level, prices can be expected to move similarly (Bourassa et al., 2007). Hence, defining the study area based on submarkets, in theory, supports our identifying assumption, which is that the prices of houses nearby ASRCs and houses farther away would have trended similarly had the ASRCs not been opened.

Our practical approach to the empirical analysis is as follows. First, we estimate a version of our main specification which considers all ASRCs, in any location and of any hosting capacity, and then confirm whether the resultant DID estimates are plausible, based on graphical evidence of price trends before and after ASRC openings. The analysis furthermore considers whether houses are located within or beyond the extensive margin of cities, and also provides estimates separately for single-family homes and apartments to further account for rural-urban differences in property (see Delfmann et al., 2014). Subsequently, we provide a heterogeneity analysis by ASRC hosting capacity and perform several robustness checks of our findings.

3.2. Empirical model

The potential externality effect of ASRCs on the prices of nearby houses is identified using a multivariable regression model. In specific, following Guo et al. (2014) and Daams et al. (2019), we work with a model that is similar to a standard hedonic spatial fixed effect model but which, instead of using dummy variables as spatial controls, implements spatial controls by first-differencing the observed data. In this case, first-differencing is applied to within-submarket pairs of housing transactions. This procedure cancels out all shared similarities between paired houses in terms of observed as well as unobserved characteristics (e.g. architectural style of the homes or the quality of nearby schools). This type of first-differencing helps to control for possibly endogenous omitted spatial processes, see the review of the spatial econometric literature by Gibbons and Overman (2012), and may as such serve as a simple but effective alternative to spatial instrumental variable models. Using first-differencing to implement spatial fixed effects is documented to perform well in the house price-based valuation of (dis)amenities (Kuminoff et al., 2010).

The specification of our main model is expressed as:

$$ln(P_{ar}) - ln(P_{bv}) = \sum_{k=1}^{K} \beta_k(\mathbf{X}_{ark} - \mathbf{X}_{bvk}) + \sum_{j=1}^{J} \beta_j(\mathbf{R}_{arj} - \mathbf{R}_{bvj}) + \varepsilon_{abvr} \quad (1)$$

where $ln(P_{ar}) - ln(P_{bv})$ is the first difference of the transaction price of house a sold at time r and house b sold at time v which are paired for having sold in the same ASRC-by-quarter unit; $(\mathbf{X}_{ark} - \mathbf{X}_{bvk})$ are the kth house characteristic ($k = 1, \ldots, K$), structural or locational attributes including a quarter-by-ASRC-zone fixed effect; $\mathbf{R}$ is a vector of seven indicator variables, including three variables that capture whether observed houses are located within the treatment area (as defined by three distance intervals of 0 to 500 m, 500 to 1000 m, and 1000 to 2000 m away from ASRCs), an indicator variable that indicates whether transactions took place post-treatment (i.e., after ASRC-opening), as well as the DID indicator variables of interest, which capture the interactions between the aforementioned three distance-interval variables and the post-treatment variable; and ε_{abvr} denotes standard errors that are spatially clustered at the ASRC-level in order to account for spatial autocorrelation in house prices.

3.3. Data

Information on all reception centers (ASRCs) in the Netherlands[6] is provided by Dutch Central Agency for the Reception of Asylum Seekers

[5] Indeed, home buyers might expect that a pre-existing ASRC, even if the center has closed before this study's temporal window, would open again in the future. Therefore, we cull houses in the associated locations from the control group to prevent possible 'contamination'.

[6] Emergency accommodation offered by municipalities during the high influx in 2015 and 2016 is not represented in this overview.

(COA).[7] These data have captured the address, capacity, and date of opening of 121 ASRCs.[8] These ASRCs are located across 53 out of all 76 housing submarkets in the Netherlands, which are defined by NVM agents based on market experience and to delineate areas where houses are considered to be highly substitutable. Fig. 1 shows the distribution of ASRCs and housing sales per square kilometer in the Netherlands. After restricting these data to our study's temporal window of analysis, the number of observed ASRCs locations is 75. As for the distribution of ASRCs across areas of high or low population density, it may be noted that 45% of ASRCs is outside high-density areas. High-density settlement is defined using the concept of city –or city core– developed by the European Commission and the OECD (OECD, 2012). According to this definition of 'functional urban areas', a city core is a cluster of contiguous cells of 1km^2 surface area with a total population of at least 50,000 inhabitants and a density of at least 1500 people per square kilometer.

The property observations in the NVM dataset cover 1,590,489 residential property sales throughout the Netherlands from January 2009 to December 2017. The database is a record of approximately 80% of all transactions on the Dutch market in the observed years and has been analyzed in several house price studies (Daams et al., 2016; 2017; 2019; Van Duijn et al. 2016; Van Ommeren et al. 2011). In addition to transaction price and date, the data include comprehensive information regarding the living area, parcel size, number of rooms, period of construction, type of heating, type of structure and the presence of insulation materials. This allows us to control for a broad range of variables that influence house prices as we aim to isolate the price-effect of ASRCs. From the original dataset, we keep all house transactions with complete information on the observed variables and which are located inside a treatment or control area. Descriptive statistics on the characteristics of the observed transacted houses are presented in Table 2. The descriptive statistics are presented for the pooled sample as well as for the treatment and control subsamples; comparison shows that the housing characteristics of observations across the two groups are similar.

Furthermore, the transaction data include address information, which allows us to geocode the dataset at the property level. Property-level coordinates are derived from the Registers for Addresses and Buildings maintained by the Netherlands Cadaster, Land Registry and Mapping Agency. Based on the obtained coordinates, we calculate the distance of each house to the nearest ASRC that has opened during the study's time-window. In the case of some houses, multiple ASRCs are located within the outer treatment radius. In such cases, in line with Schwartz et al. (2006), our analysis considers information on the nearby ASRC that opened first.

4. Results

4.1. Main results

4.1.1. Difference-in-differences

We begin by presenting the estimates of model (1) in which we study the effect of ASRC openings on the prices of nearby houses in the pooled sample (Table 3). Model (1) indicates joint significance for this main specification. The coefficients for the controls on property characteristics are as expected.[9]

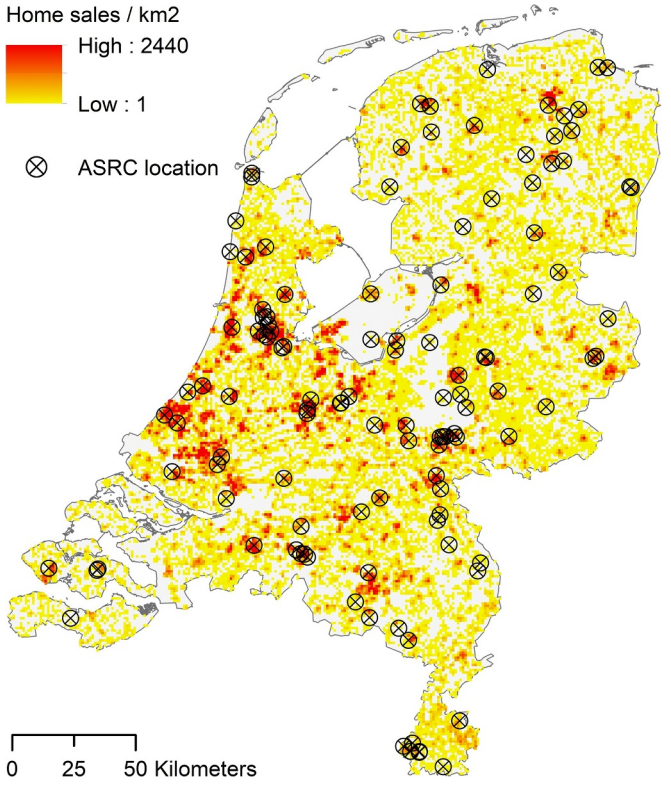


Fig. 1. Distribution of all observed ASRCs and housing sales per square kilometer.

We now turn to the estimates in model (1) for the variables that are explicitly involved in the difference-in-differences (DID) estimation. It may first be noted that the coefficients for the indicator variables that capture whether an observed property is located 0–500, 500–1000, or 1000–2000 m away from an ASRC are consistently positive and significant at the 5 percent or 1 percent level. This indicates that ASRCs are opened in locations where nearby houses sell, on average, at somewhat higher prices as compared to houses that are farther away but located within the same submarket. Houses that were sold post-treatment (that is, after opening of a nearby ASRC), regardless of their location within the observed submarket, are found to sell at prices that are not significantly different from sales prices prior to ASRC opening. Similarly, the coefficients for the distance-specific DID indicators are statistically insignificant in model (1), which uses housing transactions across the entire study area and all observed ASRC openings. However, heterogeneity in these data obscure price effects that are both economically and statistically significant.

We now crucially turn to models that use transaction subsamples that are partitioned on urban versus non-urban locations as well as by property type. The findings associated with these models, which are all except one reported in Table A in the Appendix, show insignificant ASRC effects in urban areas; also, in line with the absence of a significant ASRC effect in urban areas, no effect is found for apartments in non-urban areas. These findings are in line with the non-significant estimates in model (1), as the models discussed so far represent most of the observations in the unrestricted sample. In contrast, in the model that we discuss next, the coefficients associated with the DID indicators

[7] The COA is an independent administrative body that falls under the responsibility of the Dutch Ministry of Justice and Security. It is responsible for the reception, supervision and departure from the reception location of asylum seekers in the Netherlands.

[8] In case more than one center was located in the same building, we collapse the information as to enforce a single observation at the building-level.

[9] The estimates for individual housing characteristics are found in Table A in the Appendix. Premiums on house prices are found for properties with a larger parcel size. Central heating and insulation material are also valued by buyers. The type of structure adds value too, as detached properties have higher market values than other dwellings. Furthermore, houses built before 1945 or after 1980 sell at higher prices than houses that have been constructed between 1945 and 1980. For comparison of the estimates with other studies, see Daams et al. (2016) or Liu (2013).

Table 2
Descriptive statistics for the pooled sample of housing transactions (N = 347,479) as well as the treatment group (N = 69,221) and control group (N = 278,258).

Statistic	Pooled sample		Treatment group		Control group	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Price (euros)	254,402.9	144,550.7	253,218	157,629	254,697.6	141,107.9
Within 0 to 500 m from ASRC	0.01	0.11	0.06	0.24	0.00	0.00
Within 500 to 1000 m from ASRC	0.04	0.2	0.22	0.41	0.00	0.00
Within 1000 to 2000 m from ASRC	0.14	0.35	0.72	0.45	0.00	0.00
At least 2000 m away from ASRC	0.8	0.4	0.00	0.00	1.00	0.00
Post-treatment transaction	0.56	0.5	0.55	0.50	0.57	0.5
Within 0 to 500 m * Post	0.01	0.08	0.03	0.18	0.00	0.00
Within 500 to 1000 m * Post	0.02	0.15	0.12	0.32	0.00	0.00
Within 1000 to 2000 m * Post	0.08	0.27	0.39	0.49	0.00	0.00
Floor space (m2)	117.43	45.14	102.68	41.34	121.1	45.29
Number of rooms	4.5	1.52	4.01	1.47	4.63	1.51
No external space	0.33	0.47	0.54	0.5	0.28	0.45
Small-sized garden	0.17	0.38	0.06	0.25	0.20	0.40
Medium-sized garden	0.34	0.47	0.21	0.41	0.37	0.48
Large-sized garden	0.17	0.38	0.06	0.25	0.20	0.40
Constructed 1500–1905	0.06	0.23	0.10	0.31	0.05	0.21
Constructed 1906–1930	0.12	0.33	0.20	0.40	0.10	0.30
Constructed 1931–1944	0.07	0.26	0.12	0.32	0.06	0.24
Constructed 1945–1959	0.08	0.26	0.07	0.26	0.08	0.27
Constructed 1960–1970	0.14	0.35	0.14	0.35	0.15	0.35
Constructed 1971–1980	0.15	0.36	0.09	0.29	0.16	0.37
Constructed 1981–1990	0.12	0.33	0.09	0.29	0.13	0.34
Constructed 1991–2000	0.12	0.33	0.08	0.28	0.14	0.34
Constructed after 2000	0.13	0.34	0.10	0.30	0.14	0.34
Central heating	0.93	0.25	0.93	0.25	0.93	0.25
Insulation	0.83	0.37	0.82	0.38	0.83	0.37
Rowhouse	0.26	0.44	0.25	0.43	0.27	0.44
Duplex house	0.02	0.15	0.01	0.11	0.03	0.16
End-of-terrace house	0.11	0.31	0.09	0.28	0.11	0.32
Semi-detached house	0.15	0.35	0.07	0.26	0.16	0.37
Detached house	0.14	0.34	0.05	0.22	0.16	0.37
Downstairs apartment	0.04	0.21	0.08	0.26	0.04	0.19
Upstairs apartment	0.10	0.30	0.21	0.41	0.07	0.25
Maisonnette	0.02	0.14	0.03	0.16	0.02	0.14
Flat with central access	0.10	0.30	0.14	0.35	0.09	0.28
Flat with walkway access	0.06	0.23	0.07	0.26	0.05	0.22
Upstairs and downstairs apartment	0.00	0.06	0.00	0.07	0.00	0.05
Urban location (inside FUA core)	0.54	0.50	0.87	0.34	0.46	0.50
Non-urban location (outside FUA core)	0.46	0.50	0.13	0.34	0.54	0.50

Table 3
Estimation results, main specification.

	(1)Pooled model	(2)Non-urban single-family homes
Within 0–500 m * Post	0.007	0.003
	(0.017)	(0.031)
Within 500–1000 m * Post	0.004	−0.052***
	(0.014)	(0.020)
Within 1000–2000 m * Post	0.006	−0.001
	(0.013)	(0.013)
Post	−0.004	−0.011*
	(0.005)	(0.006)
Within 0–500m	0.045***	0.056**
	(0.014)	(0.023)
Within 500–1,000m	0.029**	0.029*
	(0.011)	(0.015)
Within 1000–2,000m	0.024***	0.051***
	(0.009)	(0.009)
Year-by-ASRC controls	Yes	Yes
Constant	−0.000	−0.000
	(0.000)	(0.000)
Observations	346,262	136,107
Adjusted R^2	0.723	0.713
F Statistic	28,177.240***	13,001.260***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Controls for housing characteristics are included, see Appendix Table A. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

reveal a negative price-effect that arises from ASRC openings.

Model (2) shows that single-family homes in non-urban areas that are 500–1000 m away from an ASRC sell at approximately 5.1% lower prices[10] after the ASRC's opening, as compared to the prices of houses in the control group.[11] This confirms our expectation that ASRCs may have a negative effect on the prices of nearby homes, conditional upon a relatively low residential density.

Furthermore, in model (2), the coefficients for the DID indicators associated with houses at 0–500 m and 1000–2000 m away from ASRCs are non-significant. In the case of the 0–500 m DID indicator, a possible explanation is that the associated houses, although relatively close to ASRCs and therefore likely exposed to any externalities, are too few in numbers for a reliable capitalization estimate to be obtained, as a relatively large standard error of the coefficient underscores. The insignificance of the DID indicator for houses at 1000–2000 m away from an ASRC, on the other hand, suggests that the ASRC-effect decays with distance as it becomes, on average, negligible after 1000 m. Besides this, one may note that the coefficient for the post-treatment variable, though weakly significant, suggests a slight fall in prices across the study area after ASRC opening.

[10] The percentage price effect can be obtained through $(e^{\beta}-1)$ transformation of the observed coefficient given the semilog functional form of the hedonic regression (Halvorsen and Palmquist, 1980).

[11] One may note that single-family homes represent a broad variety of structural types, from rowhouses to detached homes, rather than villas that might be associated with income or class effects (Daams et al., 2017).

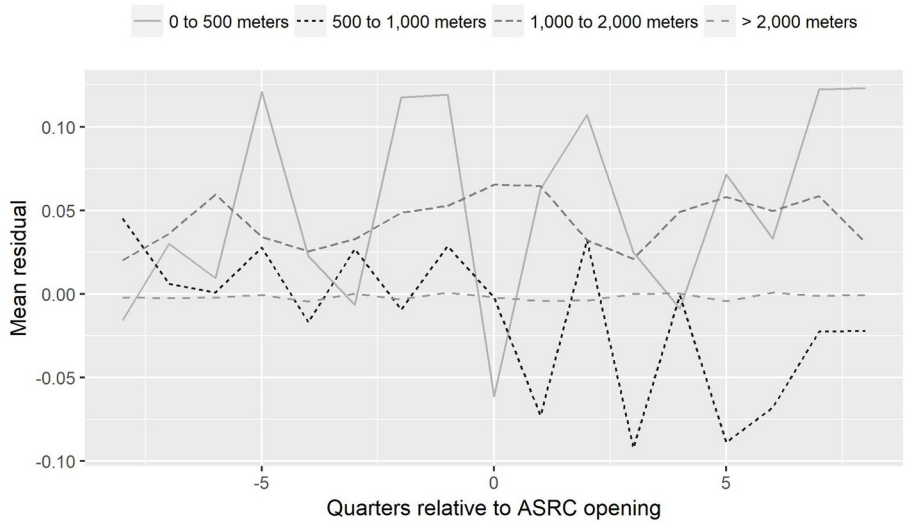


Fig. 2. Residual plot of log price regression.

To assess whether it is plausible that trends in the prices of houses nearby ASRCs would likely have remained parallel to the prices of houses farther away, had the ASRCs not been opened, we now assess price movements. If substantial pre-existing trends in prices can be discerned for houses in treated areas this might have confounded our estimations so far. In order to examine this, we conduct a graphical analysis of regression residuals. These residuals are obtained by re-estimating specification (2) in Table 3 while excluding the spatial indicators of treated areas, the post-treatment indicator, and their interactions. The residuals are then aggregated by quarter, across the 2-year periods before and after the ASRC opened, and discrete distance to the ASRC. The resultant average residuals are visualized in Fig. 2. The *x*-axis denotes the 8 quarters before and after ASRC opening. As the residuals are in log-form, multiplication of values along the *y*-axis by 100 gives approximate price levels in percentages.

The line for the category of houses that are located at least 2000 m away from the ASRCs (in the remainder area of their submarket) stays close to $y = 0$ across all observed quarters before and after ASRC opening. This is as expected, as this group contains the majority of transactions in our data and the regression residuals, overall, follow a normal distribution. Similarly, the line for houses at 1000 to 2000 m away from the ASRCs keeps a fairly constant level which is in line with the about 5.2% higher prices in model (2) for houses in this area.[12] In contrast, the line for houses closest to ASRCs, at 0 to 500 m away, is volatile. This is likely due to the market in this small area being thin, as noted above. The line of interest, however, is the line for houses at 500 to 1000 m away. This average-residuals line is relatively stable in the quarters before ASRC opening, but after the opening the line becomes more volatile and falls to levels around -0.05. This fall in price residuals in the post-opening period is in line with the magnitude of the -0.052 DID coefficient, for this particular treatment area, in model (2). This provides further assurance that our finding of a negative effect for ASRCs is not driven by a pre-existing price trend, or attenuated by an Ashenfelter dip, and underscores that the difference-in-differences estimates may effectively capture the outcomes of a causal process.

4.1.2. Heterogeneity in ASRC capacity-effects

As the results thus far indicate that, on average, the opening of ASRCs in non-urban areas has a negative impact on the prices of single-family homes, we now consider whether this effect is heterogenous with the capacity of ASRCs for hosting asylum seekers. To do so, we re-estimate specification (2) after re-partitioning the data based on ASRC-capacity. Models (3) to (5) in Table 4 show results for models ordered by an increasing hosting capacity. While each of these models indicates a negative and significant average price effect, the effect increases with capacity. For centers with a capacity to host 500 or more asylum seekers, the price effect is approximately -9.3%.[13] Importantly, moderately or strongly significant price effects are not found for ASRCs with capacities lower than 500 asylum seekers, which implies that the negative price-effect is driven by the largest category of ASRCs considered here (model 5). Furthermore, it may be noted that in model (5) price-levels nearby ASRCs, across the time-window of the analysis, tend to be higher than elsewhere in the observed submarkets, as well as that the coefficient on the post-treatment indicator is now solely significant in models (3) and (8) which, unlike model (5), do not concentrate on large ASRCs.[14] In order to further assess the DID-effect that is observed for the subsample of houses that are associated with an ASRC with a hosting capacity of 500 or more asylum seekers, we next consider several robustness checks of these results.

4.2. Robustness checks

To mitigate possible concerns about the empirical strategy we perform several robustness checks.[15] This investigation focuses on those main results that are statistically significant and appear to be of most economic and statistical relevance, that is, the results in model (5) for

[12] Price-effect after transformation of the 0.051 coefficient (c.f. Halvorsen and Palmquist 1980).

[13] It may be noted that, although the coefficient for the associated DID indicator is the largest and most significant (1% level) amongst the DID indicators in models (3) to (5), it also has a relatively large standard error. The relative lower precision at which the coefficient is measured is not surprising, as model (5) contains a limited number of observations ($N = 25{,}361$), amongst which only 91 are associated with the DID indicator for a 500 to 1,000 meter distance away from ASRCs; 37 and 629 observations take a positive value for DID indicators associated with distances of 0 to 500 meter and 2,000 meter or more, respectively.

[14] For completeness of our investigation, we also estimated possible capacity-effects in urban cores. This yielded no relevant findings across models by capacity level, also when we considered that the signal may be more fine-scale in cities and therefore also considered DID indicators for 250-meter distance intervals (see Appendix Tables C and D for estimation results).

[15] One otherwise relevant robustness check, based on the estimation of a repeat sales model, is not performed given that there are insufficient observations that both take a positive value on the DID indicators of interest and are associated with more than a single sale in the transaction data.

Table 4
Estimation results, specifications by ASRC quantitative capacity (C) to host asylum seekers.

	(3)$C > 50$	(4)$C > 250$	(5)$C > 500$	(6)$C < 50$	(7)$C < 250$	(8)$C < 500$
Within 0–500 m * Post	0.018 (0.033)	−0.001 (0.036)	−0.047 (0.055)	−0.032 (0.070)	0.005 (0.044)	0.013 (0.035)
Within 500–1000 m * Post	−0.047** (0.021)	−0.063** (0.029)	−0.098*** (0.032)	−0.072 (0.055)	−0.047* (0.026)	−0.041* (0.022)
Within 1000–2000 m * Post	0.003 (0.015)	−0.005 (0.016)	0.009 (0.021)	−0.022 (0.022)	0.011 (0.021)	−0.004 (0.015)
Post	−0.012* (0.007)	−0.004 (0.007)	0.005 (0.012)	−0.004 (0.028)	−0.015 (0.012)	−0.015** (0.007)
Within 0–500m	0.029 (0.025)	0.045* (0.023)	0.088*** (0.031)	0.163*** (0.039)	0.057* (0.033)	0.047* (0.027)
Within 500–1,000m	0.015 (0.015)	0.003 (0.021)	0.089*** (0.023)	0.120*** (0.043)	0.039* (0.020)	0.014 (0.016)
Within 1000–2,000m	0.049*** (0.010)	0.033*** (0.011)	0.039*** (0.014)	0.064*** (0.016)	0.048*** (0.014)	0.053*** (0.011)
Year-by-ASRC controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)
Observations	113,883	81,124	25,361	22,224	51,700	110,286
Adjusted R^2	0.712	0.713	0.717	0.721	0.711	0.713
F Statistic	10,840.750***	7760.661***	2469.043***	2211.758***	4887.639***	10,531.490***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

Table 5
Estimation results, robustness specifications by temporal window.

	(9) 1.5 years	(10)2.5 years	(11)No window
Within 0–500 m * Post	−0.034 (0.052)	−0.052 (0.050)	−0.022 (0.043)
Within 500–1000 m * Post	−0.121*** (0.033)	−0.085*** (0.028)	−0.068*** (0.023)
Within 1000–2000 m * Post	0.015 (0.023)	0.004 (0.019)	−0.005 (0.016)
Post	0.006 (0.012)	0.005 (0.012)	0.006 (0.012)
Within 0–500m	0.091*** (0.032)	0.095*** (0.030)	0.076*** (0.025)
Within 500–1,000m	0.092*** (0.025)	0.082*** (0.021)	0.069*** (0.017)
Within 1000–2,000m	0.038*** (0.014)	0.041*** (0.012)	0.046*** (0.008)
Constant	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Year-by-ASRC controls	Yes	Yes	Yes
Observations	19,090	30,315	47,854
Adjusted R^2	0.720	0.717	0.722
F Statistic	1891.438***	2955.513***	4789.268***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

single-family homes in non-urban areas where ASRCs with a hosting capacity of 500 or more asylum seekers have opened.

4.2.1. Adjusting the temporal window

The symmetric 2-year window used in the main analysis has practical advantages as it balances the sampling of transactions before and after ASRC openings as well as mitigate the possible influence of older price levels that would have relatively much weight in the estimation (Pope and Pope, 2015). In models (9) and (10), we respectively shorten or extend the temporal window by a half-year interval.

The findings for these models (see Table 5) indicate that the coefficient of interest, for the DID indicator for houses within 500 to 1000 m from ASRCs, is similar across the models in terms of its statistical significance, but its magnitude does respond to the choice of temporal window by several percentage-points. However, when in model (11) temporal restrictions on the sampling are dropped, the estimated ASRC effect's size attenuates but remains similar to the effect-size in the main results, and so maintains robustness with this change in specification.

4.2.2. Housing composition effects

In the main analysis, the prices of houses sold within treatment areas are found to be comparatively higher than the prices of houses sold elsewhere in the observed submarkets. A possible concern here is that there might be systematical differences in housing characteristics, between the houses that have sold before and after ASRC openings, which are correlated with the DID indicators. If so, this would imply that the findings could be driven by compositional differences of housing transactions rather than by the preferences that potential buyers have for living close to ASRCs or farther away. In order to evaluate this, following Pope and Pope (2015) and Slade (2018), we individually regress each of the 19 housing characteristics that are observed in the main specification on the indicator variables that relate to the timing and location of ASRC openings.[16] These specifications continue to control for ASRC-by-quarter fixed effects while clustering the standard errors at the ASRC-level. Like in our main specification, the DID indicators are the variables of interest. If these variables are substantially and significantly associated with the level of a housing characteristic, this is indicative of a housing composition effect. Regression results are presented in Table E in the Appendix.

The estimates show some baseline differences in the composition of houses across the distinct treatment areas. However, in the case of the DID indicators only three of the associated coefficients are significant. Post-ASRC opening, transactions of houses within 500 m from ASRCs do relative more frequently involve houses that have been built between the 1960s and 1980s, in a duplex style (significant at the 1% level), and transactions within 1000 to 2000 m away from ASRCs are comparatively more often associated with the presence of central heating (significant at the 1% level) and small-sized parcels (significant at the 10% level). These findings do not reveal strong housing composition effects, which in turn provides further assurance of the validity of our main results.

In an additional vein, it is possible that around the opening of ASRCs the overall competition for nearby houses has decreased. To investigate whether this is the case, we investigate the number of housing transactions before and after ASRC-opening on a quarterly basis. Transaction volumes are log transformed in order to ensure straightforward comparison across subsamples that vary in size as they group transactions at different distances from ASRCs. Across subsamples, as expected, transaction volumes become more stable with larger sample size. Relevant here is that the levels of transaction volumes are nevertheless internally stable across time as they move upward slightly. This suggests that the main DID results may reflect buyer preferences rather than unrelated changes in the interactions between buyers and sellers around the opening of ASRCs. (Fig. 3).

[16] This moves the variable that captures the observed housing characteristic to the left-hand side of the regression, whereas the DID indicators are on the right-hand side.

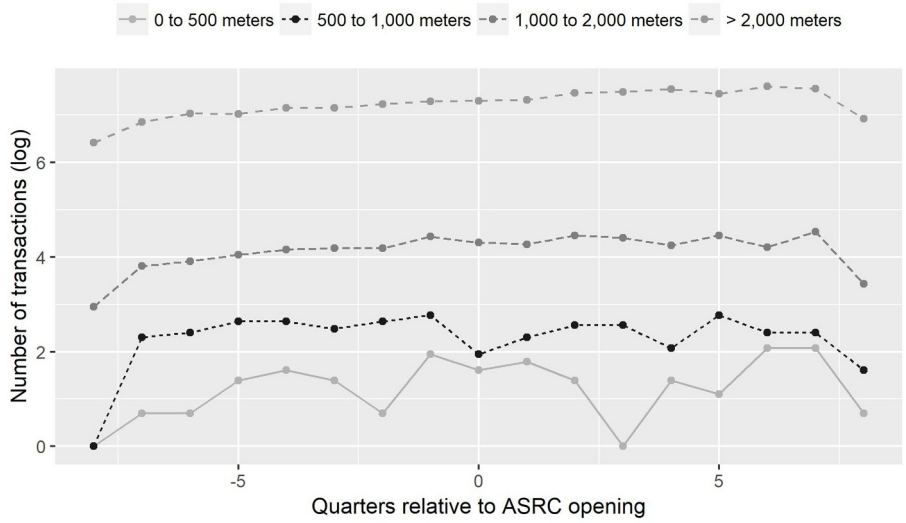


Fig. 3. Log counts of housing transactions by distance to ASRC.

4.2.3. Spatial contamination within the control group

The insignificance of the DID indicator for houses at 1000–2000 m away from an ASRC in the main results suggests that the ASRC-effect decays with distance. We now further examine this notion. Relevant here is the possibility that, amongst the observations that are 1000 to 2000 m away from ASRCs, some observations may be mechanically 'contaminated' as the distance interval across which treatment may occur is a priori unknown. If this is the case, then the ASRC effect may extend farther outward than the 1000-meter distance suggested by the main results. Hence, in specifications (12) and (13), we extend the range of the DID indicator for houses within 500 to 1000 m away from ASRCs with incremental 500-meter intervals.

The findings in models (12) and (13), in Table 6, show that the coefficient for the observed distance interval in each model, originally −0.098 in model (5) for a distance interval bounded at 1000 m, decreases in size to −0.053 for a 1500-meter upper interval bound (significant at the 5% level), and becomes negligible when the upper bound is extended to 2000 m; hence, both the DID effect-size as well as its significance average out with distance. This indicates that the main analysis appropriately notes that ASRC effects may most prominently capitalize in house prices over a distance of approximately 1000 m.

4.2.4. Falsification tests

Concerns may arise that the estimated negative ASRC-effect comes from possible endogeneity of ASRC site selection with house price levels, or, from spurious relationships in the estimation data. In order to assess whether this is plausible, we perform two falsification analyses, which are similar to tests in Badarinza and Ramadorai (2018) but tailored to the current study. The first of these considers the possibility that ASRCs have opened in types of locations where, regardless of the ASRC opening, house prices might have fallen in the post-treatment period, for example due to stagnations in residential quality.[17] If so, the estimated ASRC-effect should be persistent across placebo locations, where no ASRCs have opened, which are similar to the locations where true ASRCs are observed. This notion, indeed, considers that ASRCs may not open in any location within a given housing submarket. Joint assessment of ASRC data and 2007 land use data from Statistics Netherlands shows that the observed ASRCs[18] are consistently located in built areas where the use of land is predominantly non-residential (i.e., retail, catering, public and cultural amenities, and industrial land uses). Hence, for our falsification analysis, we simulate ASRC locations across these non-residential land use areas, outside of urban cores and in the relevant housing submarkets.[19] Under this precondition, we resample the locations of ASRCs in a spatially randomized way with replacement, reconstruct the DID indicators, and re-estimate specification (5) 1000 times. The resultant distribution of estimated coefficients for the DID variable of interest,

Within 500 to 1000 m * Post' is shown in Fig. 4 (panel A) which, for the same variable, also plots the original point-estimate of the coefficient (model 5) as a vertical dashed line. It can be observed that original DID estimate is located well outside the range of the coefficients that result from the simulation, which gives further assurance of the robustness of our main results.

In a similar second falsification test, we randomly draw artificial new opening dates for the observed ASRCs, within the range of true opening dates. Results for the associated 1000 model iterations are reported in Fig. 4 (panel B). If our main findings hold, the original DID point-estimate for the 'Within 500 to 1000 m * Post' indicator should once again not show substantial overlap with the effect-sizes obtained by simulation. The results show that 0.007% of the simulated DID coefficients suggest effect-sizes larger than the effect size in the main results. Once again, the

Table 6
Estimation results, robustness specifications by main DID distance interval.

	(12)i = 500–1,500m	(13)i = 500–2,000m
Within 0–500 m * Post	−0.048 (0.055)	−0.046 (0.055)
Within interval i * Post	−0.053** (0.024)	−0.006 (0.020)
Within 1000–2000 m * Post	0.032 (0.024)	–
Post	0.005 (0.011)	0.005 (0.011)
Within 0–500m	0.090*** (0.032)	0.088*** (0.031)
Within interval i	0.081*** (0.014)	0.047*** (0.013)
Within 1000–2,000m	0.020 (0.016)	–
Constant	−0.000 (0.000)	−0.000 (0.000)
Year-by-ASRC controls	Yes	Yes
Observations	25,361	25,361
Adjusted R^2	0.717	0.717
F Statistic	2469.499***	2673.344***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. For each model, the range of discrete distance interval i is defined by the associated column header. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

[17] While this hypothesized situation is unlikely given the staggered DID approach that considers ASRC openings across different points in time, we perform this test for extra security of our results.

[18] The reader may recall that here we consider ASRCs that have a hosting capacity of 500 or more asylum seekers and are *near* to single-family homes in non-urban areas.

[19] If a submarket includes two ASRCs, two placebo ASRCs will be resampled in that submarket. The original opening dates are kept.

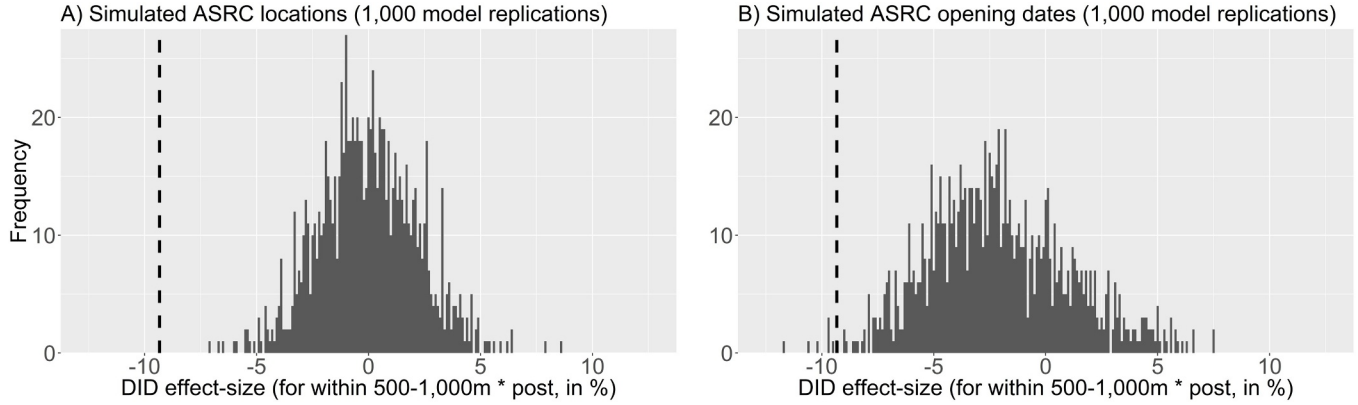


Fig. 4. Distributions of DID effect-sizes in models that use simulated information on ASRCs (1000 replications); the point-estimate of the effect size in model (5) is shown by the dashed lines.

point-estimate for the original DID variable is located well outside the mass of the estimates that come from artificially generated data. However, it should be noted that the distribution of simulated DID effect-sizes does not center on $x = 0$ (in Fig. 4, panel B) but approximately 2.1 percentage-points to the left, along the x-axis. This can be explained, as random opening dates can be drawn from the asymmetric 2-year period around the ASRC opening, which includes the post-opening period during which houses nearby ASRCs have received 'treatment'. Hence, although the opening dates are randomized, these may partly capture actual treatment effects. This may average out in the estimates from the simulation, thereby shifting the weight of the distribution of obtained effect-sizes slightly to the left. Taking this into account, the results for this second falsification test further confirm the robustness of our main results to random structure in the underlying data.

5. Discussion

While the study of how housing markets and patterns in migration relate is a dynamic and productive field of research, this study is amongst the first to present findings on how local residents regard the reception of asylum seekers, as evinced by actual market behavior. Our work here represents a novel empirical integration of the literature on migration of a particular kind, that of asylum seekers, and the literature that aims to better understand housing markets at the micro-level.

While a priori the effect of the opening of asylum seeker reception centers (ASRCs) on the prices of nearby houses is ambiguous, our expectation of a negative impact on prices is confirmed by the results. We find that the effect pertains solely to housing in less densely populated areas and for ASRC of high hosting capacity, while estimates for cities are economically or statistically insignificant. This suggests that in low-density areas ASRCs may exert stronger negative externalities than in cities, in the perception of local house buyers. Indeed, in areas of low population density, the reception of newcomers might overcrowd local public services and diversity or the presence of 'others' might be more noticeable than in cities (c.f. Brons, 2015 and Dempster and Hargrave, 2017). Indeed, besides a pre-existing higher presence of migrant inhabitants in cities, and an attitude of inhabitants there that tends to be more positive about migrants, recall Diaz-Ramirez et al. (2018) and Dustmann et al. (2016), in cities the agglomeration of human activity might obscure possible negative amenities. While in less densely populated areas in the medium to long term the inflow of asylum seekers may counteract ageing and depopulation similar to general migration flows, at the local level, within approximately 1 km away from ASRCs, negative effects may be present.[20] The reader may note here that our study is restricted to estimation of net-effects in the short period, and only captures effects that are not shared by all houses within local housing submarkets (c.f. Graves, 1983).

Our finding of effects for a subset of houses at 500 to 1000 m away, which decays in effect-size at distances beyond 1000 m, implies that the 1000-meter range approximately captures the treatment area surrounding ASRCs. However, no economically or statistically significant effects are obtained for houses in non-urban areas that are within 500 m from large ASRCs. This may on the one hand result from our transaction data in those areas being thin, but may also reflect that ASRCs are consistently located in zones that are characterized by non-residential land use where housing characteristics may deviate from those in the general sample, as our analysis of housing composition effects underlines. Our main estimates, however, are robust with several changes in specification.

Furthermore, the size of the estimated ASRC-effect, of approximately −9,3%, falls within the range of externality effects that existing house price studies have observed for other sources of (dis)amenity.[21] For instance, De Vor and De Groot (2011) find an average decrease of 12.2% in the prices of houses that have sold within 500 to 750 m from industrial sites in the Dutch Randstad region; Pope and Pope (2015) find house price increases between 1% to 3% in response to new Walmart stores; Daams et al. (2016) find 16% higher prices for houses nearby highly attractive nature; and, Schwartz et al. (2006) find that properties in New York sell at 3% lower prices when located within 2000 feet from a city-assisted housing site.

From a policy perspective, our paper may broaden the discussion about dispersal policies for asylum seekers which is increasingly relevant for policy makers in many countries and allows for several notions of practical relevance. Indeed, the findings suggest that, on average, the opening of ASRCs may not have a considerable effect on the prices of nearby houses. As house prices serve as a proxy for how residents respond to the designation of ASRCs, this then implies that ASRCs are not necessarily perceived as a source of disamenity. On the other hand, opening large ASRCs in sparsely populated areas may generate substantial negative externalities, although these estimated effects may apply to a limited number of properties. However, fewer or negligible externalities might be caused by smaller ASRCs in those areas or by ASRCs in cities.[22] In the context of spatial dispersion policy, future research could investigate whether such negative externalities can

[20] Only asylum seekers who are granted the refugee status are allowed to stay in the Netherlands in the medium to long term.

[21] See, for example, Farber's (1998) review of property value studies on undesirable facilities.

[22] According to recent news, see NL Times (2019), COA wants more ASRCs in the West of the Netherlands, which is the country's highly urbanized core, in order to spread out ASRCs more evenly. Our findings suggest this strategy might be efficient from a local-externalities perspective, although of course the public costs and benefits will also be determined by other factors, such as land prices at hosting locations or the possible longer-term effects of the spatial allocation of migration flows.

be effectively compensated through appropriate compensations or through other measures, including the design of more integrated policies of integration. The latter might include the creation of appropriate spaces for interaction between migrants and incumbent communities, which strengthen trust and linkages between people as well as facilitate access to services (OECD, 2018b).

6. Conclusions

This study has investigated the outcomes of public policy that allocates the hosting of asylum seekers across the Netherlands, by assessing how the opening of asylum seeker reception centers (ASRCs) impacts on the prices of nearby houses. The response of house prices to the opening of ASRCs is obtained by applying hedonic models in a staggered difference-in-differences context. Our findings indicate that the opening of ASRCs may cause the prices of houses within close range to fall by approximately 9.3%. Importantly, this estimated effect pertains to a limited subset of all observed houses, that is, single-family homes in non-urban locations that are close to ASRCs which can host 500 or more asylum seekers. In contrast, no evident ASRC-effects have been obtained for housing transactions in urban areas. The findings of this study may inform the design of public policies that optimize the spatial dispersion of ASRCs.

Declaration of Competing Interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jhe.2019.101658.

Appendix

Tables A–E

Table A
Estimation results in full, main specifications.

	(A1)	(A2)
Within 0–500 m * Post	0.007 (0.017)	0.003 (0.031)
Within 500–1000 m * Post	0.004 (0.014)	−0.052*** (0.020)
Within 1000–2000 m * Post	0.006 (0.013)	−0.001 (0.013)
Post	−0.004 (0.005)	−0.011* (0.006)
Within 0–500m	0.045*** (0.014)	0.056** (0.023)
Within 500–1,000m	0.029** (0.011)	0.029* (0.015)
Within 1000–2,000m	0.024*** (0.009)	0.051*** (0.009)
Floor space (log)	0.781*** (0.009)	0.644*** (0.006)
Number of rooms (log)	0.045*** (0.004)	0.057*** (0.004)
Garden small	−0.003 (0.011)	−0.048*** (0.016)
Garden medium	0.058*** (0.011)	0.018 (0.016)
Garden large	0.200*** (0.012)	0.180*** (0.016)
Constructed < 1906	−0.011 (0.011)	−0.182*** (0.007)
Constructed 1906–1930	−0.099*** (0.008)	−0.205*** (0.007)
Constructed 1931–1944	−0.112*** (0.008)	−0.158*** (0.007)
Constructed 1945–1959	−0.193*** (0.005)	−0.216*** (0.005)
Constructed 1960–1970	−0.268*** (0.003)	−0.228*** (0.004)
Constructed 1971–1980	−0.240*** (0.003)	−0.219*** (0.003)
Constructed 1981–1990	−0.169*** (0.003)	−0.151*** (0.003)
Constructed 1991–2000	−0.065*** (0.003)	−0.076*** (0.003)
Central heating	0.086*** (0.003)	0.077*** (0.004)
Insulation	0.010*** (0.002)	0.018*** (0.003)
Duplex house	0.107*** (0.005)	0.148*** (0.005)
End-of-terrace house	0.024*** (0.002)	0.042*** (0.002)
Semidetached house	0.106*** (0.003)	0.152*** (0.003)
Detached house	0.197*** (0.006)	0.275*** (0.005)
Downstairs apartment	0.074*** (0.012)	–
Upstairs apartment	0.054*** (0.012)	–
Maisonnette	−0.088*** (0.011)	–
Flat with central access	0.012 (0.012)	–
Flat with walkway	−0.053*** (0.012)	–
Up- and downstairs apartment	0.169*** (0.016)	–
Year-by-ASRC controls	Yes	Yes
Constant	−0.000 (0.000)	−0.000 (0.000)
Observations	346,262	136,107
Adjusted R^2	0.723	0.713
F Statistic	28,177.240***	13,001.260***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. The reference categories are end-of-terrace house; no garden; and construction after 2000. Models A1 and A2 represent models (1) and (2), in that order. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

Table B
Estimation results, models by degree of urbanization and house-type.

	(A3)Urban, all houses	(A4)Urban, single-family	(A5)Urban, apartments	(A6)Non-urban, all houses	(A7)Non-urban, apartments
Within 0–500 m * Post	0.001 (0.019)	0.021 (0.022)	−0.020 (0.025)	−0.026 (0.030)	−0.077 (0.056)
Within 500–1000 m * Post	0.004 (0.017)	0.014 (0.012)	−0.006 (0.022)	−0.043** (0.020)	−0.024 (0.030)
Within 1000–2000 m * Post	−0.003 (0.016)	0.015 (0.011)	−0.016 (0.023)	−0.007 (0.011)	−0.024 (0.018)
Post	0.003 (0.008)	0.008 (0.009)	0.009 (0.010)	−0.010* (0.006)	−0.000 (0.016)
Within 0–500m	0.048*** (0.015)	0.028* (0.016)	0.049** (0.019)	0.043* (0.022)	0.040 (0.043)
Within 500–1,000m	0.036*** (0.013)	0.013 (0.009)	0.052*** (0.016)	0.033** (0.015)	0.027 (0.025)
Within 1000–2,000m	0.026** (0.010)	0.019** (0.008)	0.030** (0.015)	0.051*** (0.008)	0.029** (0.014)
Year-by-ASRC controls	Yes	Yes	Yes	Yes	Yes
Constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Observations	188,507	98,092	89,790	157,094	19,970
Adjusted R^2	0.736	0.695	0.669	0.727	0.669
F Statistic	16,413.620***	8584.500***	7549.770***	13,076.610***	1679.479***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

Table C
Estimation results, models by ASRC capacity (C), FUA core sample.

	(A8)$C > 50$	(A9)$C > 250$	(A10)$C > 500$	(A11)$C < 50$	(A12)$C < 250$	(A13)$C < 500$
Within 0–500 m * Post	−0.025 (0.019)	−0.024 (0.021)	−0.020 (0.051)	0.043 (0.030)	0.019 (0.031)	−0.017 (0.026)
Within 500–1000 m * Post	−0.006 (0.017)	−0.002 (0.019)	−0.001 (0.037)	0.029 (0.025)	−0.012 (0.032)	−0.007 (0.023)
Within 1000–2000 m * Post	−0.007 (0.012)	−0.003 (0.013)	0.029 (0.041)	−0.000 (0.013)	−0.029 (0.029)	−0.017 (0.024)
Post	0.012 (0.008)	0.006 (0.009)	0.023 (0.016)	−0.009 (0.014)	0.008 (0.016)	0.007 (0.011)
Within 0–500m	−0.025 (0.019)	−0.024 (0.021)	−0.020 (0.051)	0.043 (0.030)	0.019 (0.031)	−0.017 (0.026)
Within 500–1,000m	−0.006 (0.017)	−0.002 (0.019)	−0.001 (0.037)	0.029 (0.025)	−0.012 (0.032)	−0.007 (0.023)
Within 1000–2,000m	−0.007 (0.012)	−0.003 (0.013)	0.029 (0.041)	−0.000 (0.013)	−0.029 (0.029)	−0.017 (0.024)
Constant	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observations	71,119	59,867	11,440	18,671	26,412	76,815
Adjusted R^2	0.708	0.697	0.658	0.666	0.664	0.677
F Statistic	7169.741***	5728.200***	916.547***	1555.337***	2175.650***	6716.099***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

Table D
Estimation results, models by ASRC capacity (C), FUA core sample and 250 m intervals.

	(A14) $C > 50$	(A15)$C > 250$	(A16)$C > 500$	(A17)$C < 50$	(A18)$C < 250$	(A19)$C < 500$
Within 0–250 m * Post	−0.030** (0.026)	−0.032 (0.027)	−0.007 (0.059)	0.051 (0.067)	0.040 (0.051)	−0.020 (0.035)
Within 250–500 m * Post	−0.023 (0.021)	−0.021 (0.023)	0.011 (0.064)	0.039 (0.031)	0.011 (0.034)	−0.017 (0.026)
Within 500–750 m * Post	−0.006 (0.020)	0.002 (0.022)	0.006 (0.046)	0.036 (0.031)	−0.009 (0.031)	−0.005 (0.026)
Within 750–1000 m * Post	−0.006 (0.017)	−0.006 (0.020)	−0.006 (0.039)	0.022 (0.028)	−0.014 (0.036)	−0.008 (0.024)
Within 1000–2000 m * Post	−0.007 (0.012)	−0.003 (0.013)	0.029 (0.041)	−0.000 (0.014)	−0.029 (0.029)	−0.017 (0.024)
Post	0.012 (0.008)	0.007 (0.009)	0.022 (0.016)	−0.009 (0.014)	0.008 (0.016)	0.007 (0.011)
Within 0–250m	−0.030** (0.026)	−0.032 (0.027)	−0.007 (0.059)	0.051 (0.067)	0.040 (0.051)	−0.020 (0.035)
Within 250–500m	−0.023 (0.021)	−0.021 (0.023)	0.011 (0.064)	0.039 (0.031)	0.011 (0.034)	−0.017 (0.026)
Within 500–750m	−0.006 (0.020)	0.002 (0.022)	0.006 (0.046)	0.036 (0.031)	−0.009 (0.031)	−0.005 (0.026)
Within 750–1,000m	−0.006 (0.017)	−0.006 (0.020)	−0.006 (0.039)	0.022 (0.028)	−0.014 (0.036)	−0.008 (0.024)
Within 1000–2,000m	−0.007 (0.012)	−0.003 (0.013)	0.029 (0.041)	−0.000 (0.014)	−0.029 (0.029)	−0.017 (0.024)
Constant	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Observations	71,119	59,867	11,440	18,671	26,412	76,815
Adjusted R2	0.708	0.697	0.658	0.667	0.664	0.677
F Statistic	6146.615***	4911.928***	785.940***	1333.738***	1865.087***	5756.434***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

Table E
Housing composition effects.

	(A20)Floor space (log)	(A21) Number of rooms (log)	(A22)Garden small	(A23)Garden medium	(A24)Garden large	(A25)Constructed < 1906	(A26)Constructed 1906–1930	(A27)Constructed 1931–1944	(A28)Constructed 1945–1959	(A29)Constructed 1960–1970
Within 0–500 m * Post	−0.078	0.071	0.038	−0.151	0.114	−0.012	−0.028	0.021	0.032	0.189***
	(0.081)	−0.063	(0.086)	(0.159)	(0.158)	(0.024)	(0.041)	(0.041)	(0.058)	(0.065)
Within 500–1000 m *	0.021	0.058	−0.026	0.115	−0.078	−0.019	0.008	0.065	−0.065	0.065
Post	(0.047)	−0.05	(0.062)	(0.112)	(0.082)	(0.021)	(0.031)	(0.060)	(0.043)	(0.065)
Within 1000–2000 m *	0.011	0.004	0.048*	−0.017	−0.034	−0.015	0.021	−0.019	−0.016	0.009
Post	(0.024)	−0.023	(0.028)	(0.040)	(0.042)	(0.012)	(0.015)	(0.016)	(0.033)	(0.032)
Post	−0.018	−0.014	0.012	0.006	−0.016	−0.013	0.002	0.008	0.011	−0.044*
	(0.016)	−0.014	(0.012)	(0.022)	(0.021)	(0.010)	(0.009)	(0.007)	(0.013)	(0.024)
Within 0–500m	0.128**	0.03	0.056	0.135	−0.192*	−0.021	−0.059**	−0.045*	−0.064**	−0.276***
	(0.063)	−0.049	(0.070)	(0.121)	(0.107)	(0.016)	(0.029)	(0.024)	(0.026)	(0.036)
Within 500–1,000m	−0.057	−0.05	0.092**	0.095	−0.200***	−0.009	−0.040*	0.030	−0.021	−0.141***
	(0.037)	−0.033	(0.037)	(0.062)	(0.048)	(0.017)	(0.023)	(0.033)	(0.028)	(0.023)
Within 1000–2,000m	−0.039**	−0.006	0.011	0.137***	−0.152***	−0.017*	−0.034***	0.018*	0.016	−0.019
	(0.018)	−0.017	(0.021)	(0.032)	(0.029)	(0.010)	(0.012)	(0.010)	(0.022)	(0.024)
Constant	0.000	−0.000	−0.000	−0.000	0.000	0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25,361	25,361	25,361	25,361	25,361	25,361	25,361	25,361	25,361	25,361
Adjusted R^2	0.001	0.000	0.001	0.003	0.006	0.001	0.001	0.001	0.000	0.001
F Statistic	3.724***	1.555	4.889***	11.425***	23.905***	3.973***	3.462***	4.798***	1.731*	4.938***

	(A30)Constructed 1971–1980	(A31)Constructed 1981–1990	(A32)Constructed 1991–2000	(A33)Central heating	(A34) Insulation	(A35)Duplex house	(A36)End-of-terrace house	(A37)Semidetached house	(A38)Detached house
Within 0–500 m * Post	−0.154	0.025	−0.039	−0.065	−0.060	−0.071	−0.083	−0.157	0.182
	(0.108)	(0.116)	(0.049)	(0.044)	(0.069)	(0.099)	(0.099)	(0.141)	(0.140)
Within 500–1000 m * Post	−0.065	−0.069	0.102	−0.009	−0.047	0.005	−0.016	0.016	−0.056
	(0.101)	(0.069)	(0.064)	(0.042)	(0.054)	(0.043)	(0.070)	(0.074)	(0.086)
Within 1000–2000 m * Post	−0.027	−0.012	0.010	0.057***	0.025	−0.003	0.004	0.019	−0.047
	(0.047)	(0.037)	(0.037)	(0.018)	(0.028)	(0.016)	(0.027)	(0.037)	(0.037)
Post	0.032	0.020	0.004	−0.012	−0.013	−0.012	−0.000	−0.042	−0.012
	(0.031)	(0.026)	(0.024)	(0.017)	(0.026)	(0.010)	(0.016)	(0.039)	(0.020)
Within 0–500m	0.571***	0.063	−0.068**	0.102***	0.121*	0.182**	0.152**	−0.117	−0.196**
	(0.068)	(0.058)	(0.029)	(0.039)	(0.064)	(0.091)	(0.071)	(0.088)	(0.086)
Within 500–1,000m	0.202**	0.103**	−0.013	0.041	0.053	0.023	0.135***	−0.178***	−0.125**
	(0.080)	(0.051)	(0.040)	(0.032)	(0.041)	(0.029)	(0.052)	(0.052)	(0.060)
Within 1000–2,000m	−0.012	0.041	−0.005	0.004	0.011	−0.007	0.063***	−0.049*	−0.108***
	(0.037)	(0.029)	(0.025)	(0.014)	(0.019)	(0.013)	(0.021)	(0.026)	(0.027)
Constant	−0.000	−0.000	0.000*	−0.000	−0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	25,361	25,361	25,361	25,361	25,361	25,361	25,361	25,361	25,361
Adjusted R^2	0.005	0.000	0.000	0.001	0.000	0.001	0.002	0.002	0.004
F Statistic	19.617***	2.597**	1.683	5.917***	1.784*	6.379***	9.205***	6.700***	15.685***

Notes: Dependent variable is the log difference of transaction price for spatially matched pairs of houses. Clustered standard errors (ASRC) are in parentheses. *, **, *** Significance at 10%, 5%, and 1%, respectively.

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