THE EFFECT OF ASYLUM SEEKER RECEPTION CENTERS ON NEARBY PROPERTY PRICES: EVIDENCE FROM FRANCE

A QUANTITATIVE APPROACH

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Abstract.

In 2020 alone France received 93.470 applications from asylum seekers. To put this into perspective with other European countries, it reached the number two spot of most applicants. Immediately after their arrival in France, the asylum seekers are typically sheltered in asylum seeker reception centers (ASRCs) across the country. The main goal of this research is to better understand how local communities perceive nearby ASRCs. It investigates to which magnitude the opening of a ASRC influences nearby property prices by using a well-establish hedonic price model. Estimation comes from 2014-2018 information on transacted house prices (N = 13,169,708) and the locations and opening dates of nearby ASRCs (*N* = 350). The results indicate that there is no effect on property prices in the 0 to 500 m distance interval after the opening of ASRCs. This means that ASRCs are not necessarily perceived as a source of disamenity for the local community. The empirical findings can be used by policy makers that are concerned with the allocation of ASRCs.

Keyword: Asylum seekers, Reception centers, House prices, Hedonic price model, Differen-in-Difference

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1. Introduction

The inflow of asylum seekers to European countries has increased rapidly in recent years. In 2010, the number of asylum applications was 235,300 and this number grew to a peak of almost 1.3 million in 2015 (Eurostat, 2020). The inflow of asylum seekers can have a socioeconomic impact in host societies. Research shows that migrants potentially affect the local labor markets, regional economic development, spatial distribution, and the housing market (Gheasi & Nijkamp, 2017). In this paper I focus on how local communities perceive nearby asylum seeker reception centers (ASRCs). Although previous studies have investigated how local communities perceive the ASRCs in their proximity, the empirical literature seems fragmented. Previous research mostly studied attitudes towards ASRCs with different methodologies, such as surveys (Lubbers, et al., 2006; Zorlu, 2017). One major downside of such an approach is that results may become biased because of respondents that give socially acceptable answers. This leaves the scientific gap for me to investigate the actual market behavior. Investing the actual market behavior solves the problem of receiving socially acceptable answers and therefore offers a more precise assessment of the local community's perception. The asylum seekers are often reported to be associated with nuisance such as higher noise and crime rates in neighborhoods (Dempster & Hargrave, 2017 ;The Newsmakers, 2017). These signs of socal impact on host soceities form the soceital relevance of this research.

Daams, et al., (2019), who studied the impact of ASRCs on nearby houses in The Netherlands, found that the opening of ASRCs causes the prices of some houses to fall by approximately 9,3% in less densely populated areas and for ASRC with high hosting capacity. Whereas in cities no economically or statistically significant effects are found. Similarly, Lastrapes (2020)**,** found a small but statistically significant negative effect on housing prices, especially for lower-priced and lower-quality housing units. Other studies executed on national and city level show varying signs and sizes. Sá (2015), finds that immigrants equal to 1% of the population have a negative effect of 1,6% on house prices in the UK and shows that there is a negative effect because of the mobility response of the native population. They often tend to respond to immigration by moving to another place. Saiz (2003), finds that an immigrant equal to 1% of the population have a positive effect of 1% on house prices in American cities. Unlike other studies Gonzales & Ortega (2013), and Kalantaryan (2013) found positive impacts on house prices respectively in Spain and Italy. The findings of previous studies can be explained by the underlying mechanism of the establishment of property values. Firstly, the physical characteristics are an important driver. These are the characteristics that relate to the actual structure of the building, such as size and age and. Secondly, the location characteristics are an important driver. These characteristics determine the property value on basis of location and their surrounding externalities such as the accessibility to a central location. Households are willing to pay a premium to be close to externalities that provide positive utility. Vice versa that negative externalities, will result in a lower property price (Tiwari & White, 2010).

Basing a hypothesis on the current body of literature and the underlying mechanism that determines the establishment of property values, I suspect that the opening of a ASRC might negatively impact the prices of nearby houses. Namely, besides anecdotal evidence that homeowners are opposed to the facilitation of these reception centers nearby their own houses (The Newsmakers, 2017), the literature also provides serval studies that, e.g., find that the local communities perceive crime levels to rise after the inflow of asylum seekers (Dempster & Hargrave, 2017). Also, the OECD (2018) indicated that there can be competition between local communities and asylum seekers for access to services. It should be noted, however, that ASRCs form a heterogeneous group since they differ in characteristics such as type of locations e.g., there are urban and non-urban areas, and the centers often vary in hosting capacity. To overcome this potential differential impact, this research considers how the signs and sizes of the estimations differ, if at all, between urban and non-urban areas. Previous literature found evidence that non-urban areas are affected more substantially by the inflow of refugees or asylum seekers, since non-urban areas have had less exposure to migrants before and the population is less diverse as opposed to residents in urban areas. (Diaz-Ramirez, et al., 2018; Dustmann, et al., 2019). I therefore suspect an opening of a ASRC in a non-urban area to negatively impact the prices of nearby houses even more.

In this paper, I will focus on the housing market to better understand how local communities perceive nearby ASRCs in France. I do this by analyzing local housing data. In 2020 alone France received 93.470 applications (Eurostat, 2021). To put this into perspective with other European countries, it reached the number two spot of most applicants (See Appendix). The applications are processed by the French Office for the Protection of Refugees and Stateless Persons (Office Français de Protection des Réfugiés et Apatrides, OFPRA) and the National Court of Asylum (Cour Nationale du Droit d'Asile, CNDA). Immediately after their arrival in France, the asylum seekers can choose to live within the community and make their own individual arrangements or accept housing in the reception center with welfare program run by the government while waiting for their dossiers to be dealt with. The welfare program is organized at national level by CADA (CADA, 2021). This party houses the asylum seekers in special therefore prepared accommodations (Lloyd, 2003).

This research brings new insights in the spatial distribution of asylum seekers and the empirical findings of this research can therefore be used by policy makers that are concerned with the allocation of ASRCs. I investigate to which magnitude the opening of a ASRC influences nearby property prices, by using a well-establish hedonic price model. The hedonic model considers housing as a bundled good and the model allows for an estimation of the relative contribution of the underlying characteristics of residential properties, such as a nearby ASRC, on a dependent variable, such as property value. I employ a difference-in-difference approach. With this model, it is possible to indicate whether prices in the predefined treatment group change before and after the ASRC opening, as compared to the change, if any, with prices in the control group. In this way the model reduces the change of omitted variables that are time-invariant (Kuminoff, et al., 2010). As valuation practices and policy analysis require a precise estimate of the distance over which the opening of ASRCs has an effect on house prices, I allow effects to vary with distance and, in addition, estimate the distance after which the effect, if any, becomes negligible. The spatial controls are evaluated at varying scales, as recommended in earlier hedonic studies. This is important, because the appropriate scale is not known in advance. (Abbott & Klaiber, 2011; Daams, et al., 2019; Graevenitz & Panduro, 2015).

The estimated model is based on a dataset on house sales throughout France from January 2014 to December 2018. The study's window of analysis for the opening of an ASRC is limited to all centers opened in 2016. Forming such a temporal window of analysis improves the distribution of the data and thereby helps to reduce bias. This is of importance, because using spatial controls that are defined too broadly can lead to omitted variable bias. The same is true for spatial control using a too-fine scale (Abbott & Klaiber, 2011). Depending on the scale at which omitted spatial processes are controlled for, this research shows significant as well as insignificant estimates for the variables of interest. When interpreting the most accurate models, with zip codes as spatial control, none of the 0 to 500 m distance intervals turned out to be significant. This implies that houses in this area that were sold post-treatment (that is, after opening of a nearby ASRC), are not found to sell at lower prices compared to sales prices prior to a ASRC opening.

The remainder of the paper is organized as follow. Section 2 introduces the empirical strategy, empirical model, and the data. Section 3 presents the results. Section 4 provides a discussion of this study and its findings, followed by the conclusion in Section 5.

2. Materials and Methods

2.1 Methodology

The main goal of this research is to better understand how local communities perceive nearby ASRCs. A way to determine this is by analyzing the market behavior, as the market reflects people's preferences. To investigate to which magnitude (external) variables contribute to the creation of value for heterogeneous goods, Rosen (1974) introduced the hedonic price model. The hedonic model considers housing as a bundled good and the model allows for an estimation of the relative contribution of the underlying characteristics of residential properties on a dependent variable. This means that the housing value can be disentangled into implicit prices that, when summed, equal the price of the residential property. For this research the hedonic price model has been used to investigate the potential externality effect of ASRCs on the prices of nearby property values.

More specifically, a difference-in-difference design is used. This model includes changing property values over space and time and therefore helps to reduce omitted variable bias, which is common in hedonic regression models. This quasi-experimental approach compares the difference in the outcome over time in a population enrolled in a program, namely the treatment group, against a population that is not (this forms the control group). Stated differently, the estimated model helps to establish whether prices in the predefined treatment group change after the opening of an ASRC, as compared to the change, if any, in prices in the control group. The treatment group consist of houses in the near proximity of ASRCs and are divided into three distance intervals, of 0 to 500 m, 500 to 1000 m, 1000 to 2000 m. The predefined treatment groups are the same as used in prior research, such as for example the paper of Daams, et al., (2019), because the spatial externality effect in the treatment group, if any, are not known in advance. The 0 to 500 m is used as the inner ring. The 500 to 1000 m radius as the middle ring and the 1000 to 2000 m as the outer ring. Setting up these difference radiuses helps to capture any diminishing external effects, if any, present in the data. The control group consist of all the transacted property data outside of the outer treatment range of 2 km. The difference-in-difference design requires a parallel trend assumption. This means that in the absence of the treatment effect, the difference between the treatment group and control group needs to be constant over time. A visual inspection shows that this assumption holds. The graph related to the visual inspection is included in the Appendix. Figure 1 shows the three distance intervals and the distribution of the residential property sales.

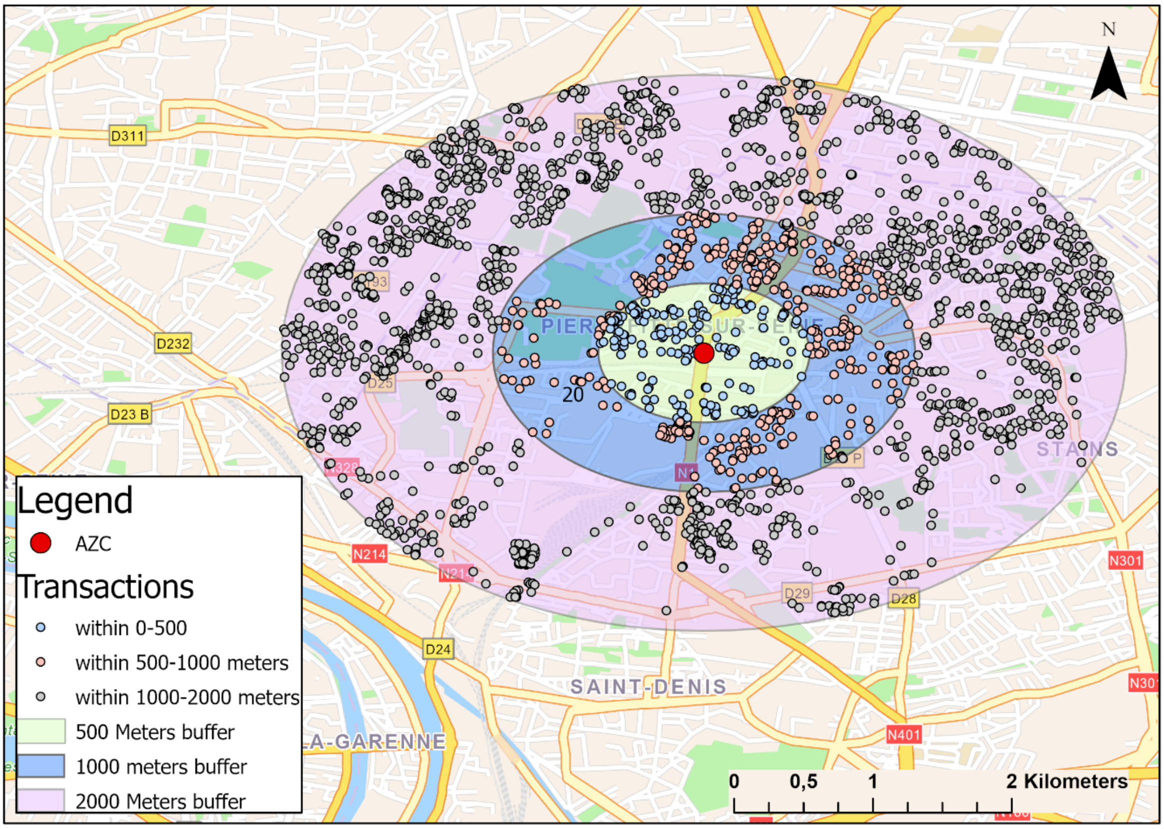

Figure 1. Visual display of the methodological design

To control for spatially fixed effects related to the location of the property, the department and zip code dummies are included. Following Bourassa, et al. (2007), I decided to include, in the final model as control variables, dummies related to zip codes rather than directly related to specific departments. This allows to have more populated categories, as, in case of usage of dummies based on zip code or department, a specific dummy can be equal to 1, only in a few cases. By doing so, I control for houses within the same department and zip code that might be correlated to each other (Mummolo & Peterson, 2018). The same applies for the fixed effects related to time, because price trends between the treatment and control groups could vary, as a result of real-world settings (Accetturo, et al., 2014). So, by adding time dummy variables on a quarterly basis, that are connected to observations collected at different moments in time (before or after the opening of multiple ASRCs), the specific time effect can be tested. Furthermore, the study's temporal window of analysis only includes transacted data two years before the opening of the ASRCs and two years after the opening of the ASRCs. Given the fact that the available sample is based on five years (from January 2014 up to and including December 2018) and to have a proper balance in terms of observations before and after the specific event (ASRCs opening), it has been decided to select only the areas in which the ASRCs have been opened in 2016. In this way in fact, it can be guaranteed a balance of two years before and two years after. The inclusion of areas, in which the ASRCs opening happened in a different year in respect to 2016, could affect this balance in terms of observations before and after the event.

What follows is an empirical approach that consist of different multivariable regression models. I started with an estimation of a standard hedonic spatially fixed effects model. Then I assessed whether these results were plausible and if alternative definition of the variables e.g. different scales of spatially fixed effects, like departments vs zip codes could enhance the goodness of fit of the model in terms of R Squared. This part of the research is an important evaluation because a hedonic study needs to control for many characteristics of houses and their locations that are correlated with the variable of interest. Because not all the variables can be observed, this may give rise to omitted variable bias. (Kuminoff, et al., 2010). Next, the likelihood of the differential effect between urban and non-urban areas are considered. Specifically, the following equation is estimated:

$$Ln\left(P_{ijt}\right) = \propto + \sum_{k=1}^{K} \beta_k \, X_{kit} + \beta_2 E_{it} + \ \beta_3 F_{it} + \beta_4 E * F_{it} + \beta_5 L_j + \ \beta_6 T_t + \varepsilon_{it}$$

Where Ln(P) is the log of the transaction price of property *i* that is located in department *j* at transaction year *t*. The $\propto$ represents the constant. X_{kit} is the kth relevant property characteristic (k = 1,…, K) for several property characteristics *k* of a property *i* sold in year *t*. Property characteristics that are included in the hedonic models are: living area (sq. ft.), no. of rooms, and plot area (sq. ft.), whether it is located in a urban or a non-urban area and the type of real estate. E_{it} are the indicator variables, which capture whether the observed houses are located within the treatment area's: 0 to 500 m, 500 to 1000 m, and 1000 to 2000 m. F_{it} is the indicator variable that indicates whether the transactions took place post-treatment (i.e., after ASRC-opening). $E * F_{it}$ are the variables of interest. These variables capture the treatment effect of the three-treatment areas and the post-treatment variable. These variables only indicate a value of 1 when the property is located within the treatment area and was transacted after the opening of an ASRC. L_j is a department dummy controlling for spatial fixed effects *j*. T_t indicates the different time periods in quarters *t* and is controlling for time fixed effect

(2014Q1 up to and including 2018Q4). ε_{it} is the error term in this equation. This denotes the standard errors, that are spatially clustered at the ASRC-level and timely clustered at quarterly-level, to account for spatial and time autocorrelation in house prices.

2.2 Data

Immediately after the arrival of the asylum seekers in France, they can choose to live within the community and make their own individual arrangements or accept housing in the reception center with welfare program run by the government while waiting for their dossiers to be dealt with. The welfare program is organized at national level by CADA (CADA, 2021). This institution keeps information about the addresses, capacity, and date of opening of 350 ASRCs (CADA, 2021). These ASRCs are geographically distributed over the 99 departments in France. Figure 2 shows the distribution of the ASRCs per square kilometer of France. In 2020, there were 46.632 places spread-out across France. After restricting the data to the study's temporal window of analysis, which only encompasses ASRCs opened in 2016 and that do not interfere with each other treatment radius, the remaining number of observed ASRCs locations for the analysis is 45. A full list of the observed ASRCs locations is included in the appendix. Regarding the data that is used to analyze if the ASRCs are in a high or low population density areas, the methodology to define functional urban areas (FUAs) is used, as developed by the OECD. This method uses population density and travel-to-work flows information to define the FUAs. In France, an urban center is defined as a cluster of contiguous grid cells. These cells are divided into one square kilometer and need to have a density of at least 1,500 citizens per square kilometer to be categorized as an urban center. Besides, the population within the urban centers must have a population of at least 50,000 citizens (OECD, 2020).

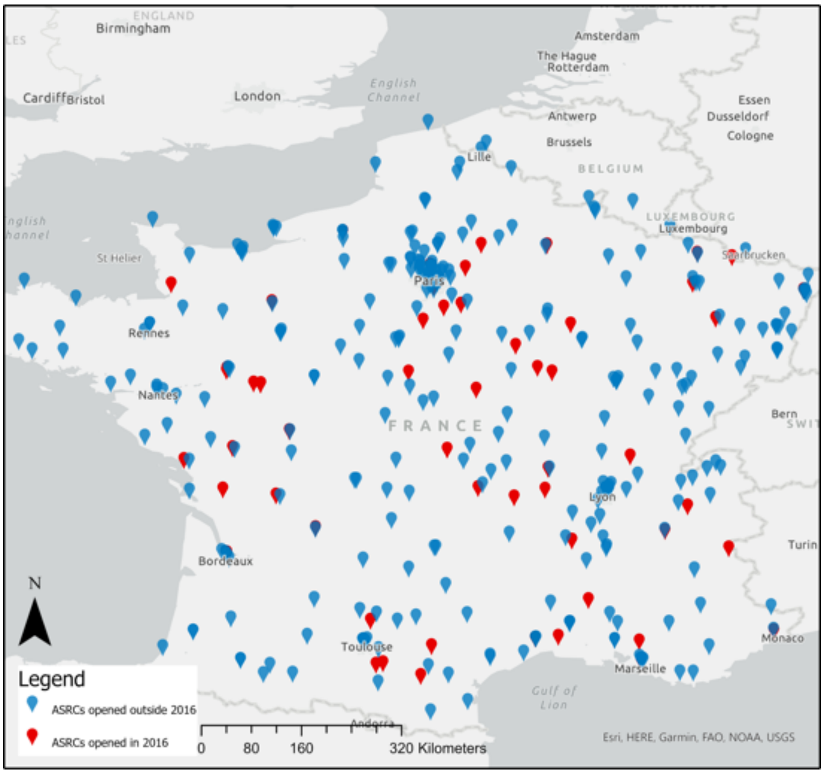

Figure 2. Distribution of all observed ASRCs

The dataset covers more than 13 million transacted residential properties throughout France in the period from January 2014 up to and including December 2018. This data is published and produced by the General Directorate of Public Finance (Direction générale des finances publiques, DGFiP). This data originates from notarial deeds and cadastral information (data.gouv.fr, 2021). The database provider does not mention how this number relates to the actual number of transacted residential properties that for this period. The dataset exists to meet the objective of transparency in the land and real estate market and contains full coverage (data.gouv.fr, 2021). Besides transaction price and date, the dataset includes information regarding living area, plot size, number of rooms and type of real estate. These variables are functioning as control variables in the model, and this allows for a better isolation of the price effect of ASRCs. From the original dataset, all house transactions with incomplete information regarding the observed variables were eliminated. I retained the complete observations which were located inside a treatment or control area. In addition, the dataset includes address information, among which home address, house number, zip code, city code, name of the city and the department code. Furthermore, the data includes geographical coordinates, which makes it possible to geocode the dataset at the property level.

On basis of the obtained coordinates, I calculated the distance of each transacted house to the nearest ASRC that opened within the timeframe of this study.

2.3 Data cleaning procedure

To improve the quality of the data I removed the inconsistencies in the dataset. To begin with I started with the translation of the variables from France to English with the help of the accompanying dataset documents. Then I removed the variables that were superfluous for this research. I erased duplicate or irrelevant observations. Furthermore, I erased the unwanted outliers. These outliers contained illogical values which affects the statistical analysis. Erasing these values helps to reduce the variability in the dataset. The approach that I used is to drop the 1% extreme values on both sides of the distribution. With regards to the handling of missing data, I used the listwise deletion approach. This approach removes the entire observation when it has one or more missing values.

2.4 Descriptive analysis

The descriptive statistics on all house transactions with complete information on the observed variables are presented in Table 1. It includes data of the pooled sample as well as the treatment- and control subsamples. The pooled sample contains 2,018,866 observations of which 10,805 observations are in the treatment group and 2,008,061 in the control group.

Pooled sample

The dependent variable of this research is a natural logarithm of the transaction variable. The mean transaction price in the window of the analysis is €275.751, -. The average transacted property has a 105 sqm surface and has 3,94 rooms. In addition, the mean of the plot size is 667 squared meters. Of all transacted houses, 0,54% are within the treatment area, the rest of the observations are used as control area. Furthermore, 20.5% of the transacted houses are in a FUAs, which means that they are characterized as urban. 79.5% of the transacted houses are geocoded outside of the FUAs and are therefore characterized as non-urban.

Table 1: Descriptive statistics

	Pooled sample		Control group		Treatment Group	
	mean	sd	mean	sd	mean	sd
Transaction price	275751,7	1230497	275764	1231965	273461,2	977050
Buffer 0 to 500 m	.002	.041	.001	.031	.142	.036
Buffer 500 to 1000 m	.003	.052	.001	.038	.242	.042

Buffer 1000 to 2000 m	.008	.084	.004	.062	.616	.057
Futher then 2000 m	.987	.106	.994	.0787	.000	.079
Post-treatment	.50	.499	.493	.499	.498	.499
*Buffer 0 to 500 m * post*	.001	.028	.000	.000	.142	.024
*Buffer 500 to 1000 m * post*	.001	.036	.000	.000	.242	.029
*Buffer 1000 to 2000 m * post*	.003	.057	.000	.000	.616	.039
Floor space m2	105,31	71,66	105,31	71,58	105,02	69,33
Number of rooms	3,94	1,57	3,94	1,57	3,84	1,56
Plot surface m2	667,35	871,60	668,62	872,86	431,88	921,91
Apartment	.043	.202	.043	.202	.100	.185
Industrial & commercial	.054	.003	.040	.003	.063	.190
House	.040	.196	.918	.195	.836	.261
Urban (whitin FUA)	.205	.404	.204	.403	.559	.496
Non-urban (Outside FUA)	.795	.404	.796	.403	.441	.496
Observations	2,018,866		2,008,061		10,805	

3. Results

3.1 Regression results

Table 2 represents the regression results of the externality effect of ASRCs on nearby property prices of the pooled sample, as well as the urban and non-urban subsamples. In model 1, the valid *n* after erasing outliers and list-wise deletion is 1,928,960. The result of the regression indicates a joint significance for the main specification. Most of the estimates are as expected. Premiums on house prices are found for larger houses in terms of living area, plot size and number of rooms. In addition, one may note that the coefficient for the post-treatment variable suggest a slight fall in prices across the study area after an ASRC opening. For the variables that are explicitly involved in the DID estimation, the model suggests that there is a negative correlation, which implies that the properties have been negativity effected by the opening of ASRCs in the proximity. These negative correlations turn out to be significant at a confidence level of 99%. However, the results show no diminishing external effect between the three distance intervals. The 0 to 500 m, 500 to 1000 m, 1000 to 2000 m, show price effects of respectively -7,7% (=(*exp* -0.08 - 1)*100), -10,9% and -7,4%. These figures are related to the coefficients of the interaction terms between the distance intervals from ASRCs and the pre/post opening effect. These coefficients explain the effect on property prices, in percentage terms, of the joint validity of distance from ASRCs and pre/post ASRCs opening dummies. From this model we can conclude that the results are in line with the hypothesis that ASRCs have a negative effect on property prices. Models 2 and 3 use the transaction subsamples that are partitioned on urban versus non-urban locations. The valid n after erasing outliers and list-wise deletion for the urban subsample is 392,715 and 1,536,145 for non-urban subsample. Most of the model's control variables are in line with model 1. Also, the DID variables reveal a negative price-effect and significant results. Except for the first distance interval 0 to 500 m and 500 to 1000 m, the non-urban subsample shows non-significant estimations. In all three models the departments of France were used as spatial controls.

Table 2: Estimation results, department fixed effects

	1 Pooled model	2 Urban area	3 Non-Urban area
*Buffer 0 to 500 m * post*	-.08***	-.125***	-.024
	.021	.031	.028

*Buffer 500 to 1000 m * post*	-.114***	-.125***	-.03
	.017	.022	.023
*Buffer 1000 to 2000 m * post*	-.077***	-.014***	-.086***
	.01	.012	.017
Post	-.01***	-.02***	-.01***
	.002	.004	.002
Buffer 0 to 500 m	.114***	.119***	.016***
	.014	.021	.018
Buffer 500 to 1000 m	.14***	.119***	.047***
	.011	.018	.016
Buffer 1000 to 2000 m	.191***	.124***	.112***
	.007	.016	.012
Floor space m2	.548***	.617***	.538***
	.002	.008	.002
Number of rooms	.135***	-.081***	.175***
	.002	.004	.002
Plot surface m2	.164***	.192***	.161***
	0.001	.004	.001
Year quarterly (N=20)	Yes	Yes	Yes
Departments (N=94)	Yes	Yes	Yes
Observations	1,928,960	392,715	1,536,145
Adjusted R-squared	0.445	0.495	0,398

Note: Dependent variable is log of transaction price. Controls for the housing characteristics are included. The model includes the constant term, quarterly fixed effects, and department fixed effects. Standard errors in parentheses with ***, **, * indicating significant at 1%, 5% and 10%, respectively.

However, the model's explanatory power is small. For instance, in model 1 only 44,5% of the variance of the dependent 'sales price' variable is explained by the independent variables, which entails that the error term is far from optimal. To solve this underlying issue and thus to improve the analysis, I evaluated the controls at multiple scales, as recommended in earlier hedonic studies. (Abbott & Klaiber, 2011; Daams, et al., 2019; Graevenitz & Panduro, 2015). Similar to these studies the zip code was used to control for the spatially fixed effect. It is an established possibility that spatial controls that are defined too broadly, may not mitigate omitted variable bias effectively (Daams, et al., 2019).

In Table 3 the spatial controls are tightened further to the spatial scales of the zip code, in order to verify if enhancements in terms of goodness of fit (e.g. Adjusted R-Squared) can be reached. Therefore, the only difference between Table 2 and Table 3 is the alternative inclusion of spatial fixed effects (department vs zip code). As the Adjusted R-Squared is higher in case of zip codes in comparison to the departments. For example, the pooled sample has an Adjusted R-Squared of 57,8% for zip codes vs 44,5% for departments. Therefore, the results of Table 3 can be considered as more appropriate if compared to the estimations of Table 2. The pooled samples in model 4 indeed show different estimates. For the variables that are explicitly involved in the DID estimation, the model suggests that there is a small negative price effect in the distance interval, of 500 to 1000 m of -1,8%. However, these negative correlations turn out to be nonsignificant. The distance interval of 0 to 500 m and 1000 to 2000 m show a small positive price effect of respectively 1,6% and 1,8%. Only the 1000 to 2000 m distance interval is still significant at a confidence level of 90%. This is contrary to the hypothesis. This small positive correlation can be explained by the design of this research. If houses in the control area are being sold at much higher prices compared to the transacted houses within the distance interval of 1000 to 2000 m, the isolation of the variables of interest could be affected. The control variables are still as expected and the coefficient for the post-treatment variable still suggests a slight fall in prices across the study area after ASRC opening. Furthermore, the model's explanatory power increased. In model 1, 57,8% of the variance of the dependent 'sales price' variable is explained by the independent variables. This indicates that the estimated parameters of this model are more reliable compared to the model with departments as spatial fixed effects. The latter is also true for the urban and non-urban estimated models[1] Model 5 suggests a small negative price effect in the distance intervals, of 0 to 500m and 500 to 1000 m, with respectively -2,8% and -4%. However, the 0 to 500 m distance interval turns out to be nonsignificant. The 500 to 1000 m distance interval is significant at a confidence level of 90%. The 1000 to 2000 m distance interval shows a similar small positive correlation like in model 4. A similar explanation applies for this subsample. Urban areas are more likely to have more amenities that are geographically spread, which may cause more property price fluctuations. The estimates of the non-urban subsample in model 6 show positive as well as negative signs. The distance interval of 0 to 500 m suggests a small positive correlation; however, this estimation is

[1] The regression was carried out with the implicit assumption that the parameters of the pooled sample (model 1 and 4) were constant over time. This assumption can be tested using a parameter stability test, a Chow test. The null-hypothesis of a Chow test is that there is no difference between the subsamples. In this test the data was split up into the predefined urban subsample and non-urban subsample and where then estimated. In addition, the estimations of the pooled sample were used as the restricted model. After regressing the restricted and subsamples, the resulting test statistic of the Chow test was 1,81 and the corresponding F-statistic was 0.96. Because the test statistic is greater than the F-statistic at a confidence level of 99% the null-hypothesis was rejected. Concluding that there is a difference between the parameters of the two subsamples. The poor significance level in the pooled sample as opposed to the subsamples were in fact already an indication for this. Besides, this result is in line with previously carried out research. Recall the paper of Daams, et al. (2019), where significant results were only found after dividing the subsamples into urban and non-urban subsamples. It can be concluded that the subsamples provide more accurate estimations, and it is therefore preferred to interpret these subsamples separately.

nonsignificant. The distance interval of 500 to 1000 m and 1000 to 2000 m reveal a small negative correlation. The there is no external effect within the 500 to 1000 m and -3,3% in the 1000 to 2000 m. Only the distance interval of 1000 to 2000 m shows a significant result at a confidence level of 95%.

So far, the previous models used quarterly year dummies to control for the time fixed effects. The findings associated with the yearly fixed effects are found in Table 5 in the Appendix. The variables of interest suggests no substantial difference in signs, sizes or significance in the estimations compared to the models in Table 3.

Table 3: Estimation results, zip code control

	4 Pooled model	5 Urban area	6 Non-Urban area
*Buffer 0 to 500 m * post*	.016	-.028	.038
	.019	.03	.025
*Buffer 500 to 1000 m * post*	-.018	-.041*	-.005
	.015	.021	.002
*Buffer 1000 to 2000 m * post*	.018*	0.24*	-.034**
	.009	.012	.015
Post	-.006***	-.018***	-.004**
	.002	.004	.002
Buffer 0 to 500 m	.022*	.05***	.009***
	.014	.022	.017
Buffer 500 to 1000 m	.055***	.063***	.046***
	.011	.016	.015
Buffer 1000 to 2000 m	.068***	.083***	.069***
	.007	.009	.011
Floor space m2	.547***	.545***	.551***
	.001	.003	.002
Number of rooms	.049***	-.056***	.071***
	.001	.004	.002
Plot surface m2	.189***	.225***	.182***
	0	.001	0
Year quaterly (N=20)	Yes	Yes	Yes
Zip code (N=5,810)	Yes	Yes	Yes
Observations	1,928,960	392,715	1,536,145
Adjusted R-squared	0.578	0.575	0.545

Note: Dependent variable is log of transaction price. Controls for the housing characteristics are included. The model includes the constant term, quarterly fixed effects, and zip code fixed effects. Standard errors in parentheses with ***, **, * indicating significant at 1%, 5% and 10%, respectively.

4. Discussion

The economic valuation of housing markets and patterns of migration is a dynamic and productive field of science. Were much research is concerned with attitudes towards migrants with qualitative approaches, this study explores the economic effect of ASRCs on housing markets by actual market behavior. By doing so this research aims to better understand how the inflow of asylum seekers effects the local housing markets. The methodologic integration of the monetary hedonic valuation method with varying spatial controls (also commonly referred to as ‘spatial fixed effects’) is powerful. Previous studies underline those spatial controls should be applied at varying scales as the appropriate scale is in advance unknown. Their hedonic modelling show that estimations for multiple spatially varying regressors tend to be sensitive to the scale of the fixed effects used to control for omitted variables. This research therefore used these varying scales to enhance outcomes of the estimates.

After narrowing down the spatial controls an overall improvement of models fit was noticeable. The zip-code turned out to be a better control compared to department control. It reduced omitted variable bias as we have seen a significant enhancement of the goodness of fit of the different models. This highlights the fact that these zip code variables have a significant discriminatory power over the house prices, and stronger effect in respect to departments. However, most of the variables of interest are nonsignificant (highlighting the lack of relationship between these variables and the house price), while two variables of interest, namely the pooled and urban distance intervals of 1000 to 2000 m, is statistically significant, but with an unexpected positive sign. In any case, as the significance is only at a 90% confidence level and as the value of the coefficients is close to zero, it can be assumed that also this effect is negligible and therefore confirm that no effect of ASRCs on property prices is present. Both in the pooled model as well as in the urban model the distance intervals of 1000 to 2000 m showed a small positive correlation, and significant at a 90% confidence level. This moderate significance level means that there is already a 10% chance of a type 1 error for these estimations. Besides, the use of distance intervals could have influenced the isolation of the variables of interest. If houses in the control area are being sold at much higher prices compared to the transacted houses within the last distance interval of 1000 to 2000 m, the estimations could be less accurate. In fact, this is more likely to happen in the urban subsample, since these areas are likely to have a more polycentric character, with all sorts of amenities geographically spread. It is also more likely to happen in the pooled sample since this data also contain the observations from the urban subsample.

Due to the large inflow of asylum seekers in recent years, policy about the distribution of these asylum seekers is getting more important. From a policy perspective, this research may broaden the discussion on how to distribute asylum seekers over space. This research finds that, on average, the opening of ASCRs does not have a considerable effect on the prices of properties within the 500 m range. For the distance intervals further away only, small effects were found. This means that ASRC are not necessarily perceived as a source of disamenity for the local community. Also, no substantial difference in the externalities between urban and non-urban were present. The small effects that were found in this research are in line with most of the previous carried out research. However, because the results of this research for the most part did not see any clear positive or negative significant results it does not support the provided results of a previous carried out research. Thereby this research contributes to the already fragmented scientific evidence. However, there is a way to improve the analysis. Narrowing down the analysis on the hosting capacity. This may help to provide a more accurate result since, prior research of Daams, et al. (2019), found that primarily negative external effects did exist for the ASRCs with high hosting capacities.

5. Conclusion

This paper has used a valuation method namely, a hedonic model in a staggered difference-in-difference context to investigate the outcomes of public policy that allocates the hosting of asylum seekers across France. Specifically, the study has assessed how the opening of asylum seeker reception centers (ASRCs) impacts the price of nearby properties. The study therefore connects to literature on spatially explicit analysis of house prices. The empirical findings can be used by policy makers that are concerned with the allocation of ASRCs. The findings of this research show signals that ASCRs negatively effect the prices of nearby houses. In particular, the models where the department dummy was used to control for spatial fixed effects, the results show a negative price-effect. However, these negative signals are not consistent over the analysis. When interpreting the most accurate models with zip codes as spatial control, none of the 0 to 500 m distance intervals turned out to be significant. This implies that houses in this area that were sold post-treatment (that is, after opening of a nearby ASRC), are not found to sell at lower prices compared to sales prices prior to a ASRC opening. This means that ASRCs are not necessarily perceived as a source of disamenity for the local community. For the 500 to 1000 m distance interval only houses in the urban areas are found to sell at price lower prices of approximately -4%. The empirical findings of this research may inform the design of public policies that optimize the spatial dispersion of ASRCs. However, there are some limitations to this research. The availability of data turned out to be a problem. The dataset which contained the transacted residential properties had only a few variables available that could be used as control variables. This may have possibly led to inflated parameters in the regression outputs. Furthermore, the CADA provided data about the location and openings date of the ASRCs, but lacked data e.g., about the capacity of these centers. As a result, it could not be determined whether the size of an ASRC influence the property prices. So, in the context of spatial dispersion policy, future research could investigate whether such negative externalities can be found for the opening of large ASRCs and compare these results with the opening of smaller ASRCs.

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APPENDIX A: List of observed ASRCs

Table 4: List of observed ASRCs
Source: Data.gouv.fr

No. of ASRCs	Building Name	Address	Sr No	Capacity	Opening Date
1	**CADA FOCH**	2 avenue du maréchal foch, 81200 mazamet, france	43	Unkown	01/01/2016
2	**CADA SOLSTÏS**	viltaïs8 rue ernest montuses03100 montlucon	59	Unkown	01/01/2016
3	**CADA COALLIA**	place du général de gaulle, 45300 pithiviers, france	263	Unkown	01/01/2016
4	**CADA ANGERS FRANCE HORIZON**	57 rue du maréchal juin, 49000 angers, france	281	Unkown	01/01/2016
5	**CADA ANGERS SHELTER OF PROVIDENCE**	48-76 rue lionnaise, 49100 angers, france	284	Unkown	01/01/2016
6	**CADA FTDA SAUMUR**	32 place saint pierre49400 saumur	285	Unkown	01/01/2016
7	**CADA SAUMUR FRANCE HORIZON**	342 rue marceau49400 saumur	286	Unkown	01/01/2016
8	**CADA SAUMUR ASEA-CAVA**	7-1 avenue balzac, 49400 saumur, france	287	Unkown	01/01/2016
9	**CADA CE CLER ROYAT**	4 avenue pasteur b63130 royat	70	Unkown	02/01/2016
10	**CADA SOS PARIS**	71 rue acheres75019 paris	187	Unkown	05/01/2016
11	**CADA DE L'APARE**	145 rue combe desdames 24000 perigueux	1	Unkown	06/01/2016
12	**CADA ARMY OF SALVATION FOUNDATION**	47 rue du dr albert schweitzer51100 reims	335	Unkown	06/01/2016
13	**CADA HERISSON BELLOR**	12 rue saint abdon09270 mazeres	25	Unkown	07/01/2016
14	**CADA DETOURS**	3 rue bellevue63590 cunlhat	67	Unkown	07/01/2016
15	**CADA MUTUAL HELP PIERRE VALDO**	30 avenue des cévennes, 07320 saint-agrève, france	119	Unkown	07/01/2016
16	**CADA TOWARDS THE FUTUR**	337 chem martin42153 riorges	129	Unkown	07/01/2016
17	**CADA 73**	avenue paul louis merlin73800 montmelian	142	Unkown	07/01/2016
18	**CADA FRANCE HORIZON**	5 rue de la moselotte54520 laxou	151	Unkown	07/01/2016
19	**CADA 77**	residence amandeallee des pommereaux77430 champagne sur seine	189	Unkown	07/01/2016
20	**CADA PIERREFITTE**	7 avenue lenine93380 pierrefitte sur seine	212	Unkown	07/01/2016
21	**CADA NORD 05**	118 route de grenoble05100 briancon	91	Unkown	08/01/2016
22	**CADA ADOMA THE CHESTNUT**	29 avenue de marboz01000 bourg en bresse	115	Unkown	09/01/2016
23	**CADA OF SAINT AVOLD**	14 rue de la forêt, 57730 folschviller, france	155	Unkown	09/01/2016
24	**CADA L'OASIS**	85 route de grigny91130 ris orangis	202	Unkown	09/01/2016
25	**CADA ORNE ALENCON ASS COALLIA**	orne territorial unit6 rue du college61000 alencon	232	Unkown	09/01/2016
26	**CADA DE L'ESCALE**	38-40 rue du coteau saint-hubert, 79000 niort, france	53	Unkown	06/02/2016
27	**CADA FTDA DE LA CHARENTE**	121 rue de saintes16000 angouleme	47	Unkown	06/03/2016
28	**CADA CRF CASTIGLIONE**	2090 route des milles13510 eguilles	96	Unkown	01/04/2016
29	**CADA RESIDENCE HENRI VINCENT**	16 avenue durossignol 02600 villers cotterets	172	Unkown	08/05/2016
30	**CADA TREMPLIN 17**	4 avenue aristide briand17100 saintes	50	Unkown	06/08/2016
31	**CADA ALTEA CABESTAN**	34 avenue de la resistance17000 la rochelle	51	Unkown	06/08/2016
32	**CADA LOIRE NORTH**	rue du 8 mai 194542130 boen sur lignon	127	Unkown	22/09/2016
33	**CADA PROTESTANT INSTITUTE**	rue de la croix blanche09700 saverdun	26	Unkown	01/10/2016
34	**CADA FTA LIMOUX**	rue dewoitine, 11300 limoux, france	73	Unkown	01/10/2016
35	**CADA BORD DU RHONE**	10 impasse du quartier30200 bagnols sur ceze	75	Unkown	01/11/2016
36	**CADA PETITE CAMARGUE**	356-422 boulevard gambetta, 30220 saint-laurent-d'aigouze, france	76	Unkown	01/11/2016
37	**FTDA AVRANCHES ASYLUM SEEKERS RECEPTION CENTER**	16-42 rue de lille, 50300 avranches, france	229	Unkown	01/11/2016
38	**CADA LESEMO FMS**	31 rue de cendrillon88000 epinal	162	Unkown	04/14/2016
39	**CADA MERMOZ AUXERRE**	6 avenue jean mermoz b89000 auxerre	324	Unkown	05/20/2016
40	**CADA AVALLON**	10 avenue victor hugo89200 avallon	325	Unkown	05/20/2016
41	**CADA DU CAIO**	6 rue du noviciat33000 bordeaux	5	Unkown	06/13/2016
42	**CADA SOS SOLIDARITES**	16 rue furtado33800 bordeaux	8	Unkown	06/13/2016
43	**CADA ROUVRAY**	4 espace marcel boillin21530 rouvray	311	Unkown	06/15/2016
44	**CADA MAD**	8 cour du chateau58400 la charite sur loire	320	Unkown	09/19/2016
45	**CADA THE ROSE OF THE WIND**	cada la rose des vents400 chemin de crecycs 50278 - mareuil les meaux77334 meaux cedex	190	Unkown	10/15/2016

APPENDIX B: Estimation results, zip code – yearly fixed effects

Table 5: Estimation results, yearly fixed effects

	4	5	6
	Pooled model	Urban area	Non-Urban area
*Buffer 0 to 500 m * post*	.016	-.028	.038
	.019	.03	.025
*Buffer 500 to 1000 m * post*	-.018	-.041*	-.005
	.015	.021	.002
*Buffer 1000 to 2000 m * post*	.018*	0.25*	-.034**
	.009	.012	.015
Post	.002	-.012***	.003**
	.002	.004	.002
Buffer 0 to 500 m	.023*	.05***	.009***
	.014	.022	.017
Buffer 500 to 1000 m	.055***	.062***	.047***
	.011	.016	.015
Buffer 1000 to 2000 m	.068***	.083***	.068***
	.007	.009	.011
Floor space m2	.547***	.545***	.551***
	.001	.003	.002
Number of rooms	.050***	-.056***	.072***
	.001	.004	.002
Plot surface m2	.189***	.225***	.182***
	0	.001	0
Yearly fixed effects (N=5)	Yes	Yes	Yes
Zip code (N=5,810)	Yes	Yes	Yes
Observations	1,930,936	392,862	1,538,074
R-squared	0.578	0.575	0.545

Note: Dependent variable is log of transaction price. Controls for the housing characteristics are included. The model includes the constant term, yearly fixed effects, and zip code fixed effects. Standard errors in parentheses with ***, **, * indicating significant at 1%, 5% and 10%, respectively.

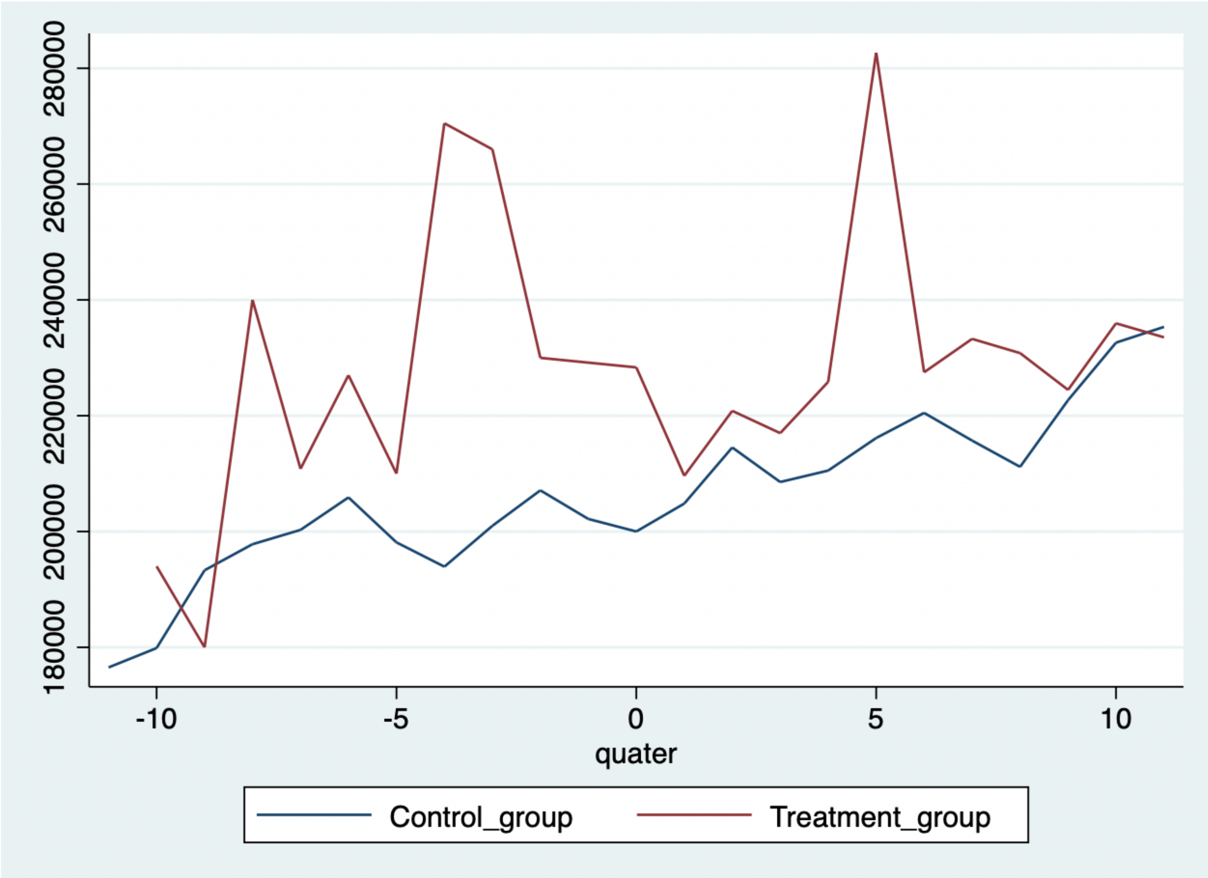
APPENDIX C: Institutional settings

Table 6: Number of applications in European Countries
Source: Eurostat data

	2015	2016	2017	2018	2019	2020
Belgium	44.665	18.280	18.340	22.530	27.460	16.710
Bulgaria	20.390	19.420	3.695	2.535	2.150	3.525
Czechia	1.515	1.475	1.445	1.690	1.915	1.160
Denmark	20.935	6.180	3.220	3.570	2.700	1.475
Germany	476.510	745.160	222.565	184.180	165.615	121.955
Estonia	230	175	190	95	105	50
Ireland	3.275	2.245	2.930	3.670	4.780	1.565
Greece	13.205	51.110	58.650	66.965	77.275	40.560
Spain	14.780	15.755	36.610	54.050	117.800	88.530
France	76.165	84.270	99.330	137.665	151.070	93.470
Croatia	210	2.225	975	800	1.400	1.605
Italy	83.540	122.960	128.850	59.950	43.770	26.535
Cyprus	2.265	2.940	4.600	7.765	13.650	7.440
Latvia	330	350	355	185	195	180
Lithuania	315	430	545	405	645	315
Luxembourg	2.505	2.160	2.430	2.335	2.270	1.345
Hungary	177.135	29.430	3.390	670	500	115
Malta	1.845	1.930	1.840	2.130	4.090	2.480
Netherlands	44.970	20.945	18.210	24.025	25.200	15.255
Austria	88.160	42.255	24.715	13.710	12.860	14.180
Poland	12.190	12.305	5.045	4.110	4.070	2.785
Portugal	895	1.460	1.750	1.285	1.820	1.000
Romania	1.260	1.880	4.815	2.135	2.590	6.155
Slovenia	275	1.310	1.475	2.875	3.820	3.550
Slovakia	330	145	160	175	230	280
Finland	32.345	5.605	4.995	4.500	4.520	3.190
Sweden	162.450	28.795	26.330	21.560	26.255	16.225
Iceland	370	1.125	1.085	775	845	640
Liechtenstein	150	80	150	165	50	35
Norway	31.115	3.490	3.520	2.660	2.265	1.375
Switzerland	39.445	27.140	18.015	15.160	14.195	10.990
United Kingdom	40.160	39.735	34.780	38.840	46.055	-
Total	1.393.930	1.292.760	735.015	683.170	762.170	484.675

APPENDIX D: Parallel trend assumption

Graph 1: **Parallel trend assumption**



APPENDIX E: Robustness check (Chow-test)

Pooled data
RSSp= 508875
Observations= 1930936
Number of variables= 5868

Subsample Urban
RSS= 97484
Observations= 392862
Number of variables= 885

Subsample Non-Urban
RSS= 408589
Observations= 1532759
Number of variables= 5314

Equation Chow Test

$$CHOW = \frac{(RSSp - (RSS1 + RSS2)/(k)}{(RSS1 + RSS2)/(N1 + N2 - 2k)}$$

$$1.82 = \frac{(508875 - (97484 + 408589)/(5868)}{(97484 + 408589)/(1930936 - (2 * 5868)}$$

F Statistic
F (k, T-2k)
F (5868, 1919200)
F = 0,96 (P 0,01)

Null-Hypothesis Chow Test
There is no difference between the subsamples.
1,82 > 0,96 REJECT THE NULL HYPOTHESIS