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Kindergarten Proximity and the Housing Market Price in Italy

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Abstract: This paper investigates the impact of kindergarten proximity on housing market prices in the eleven major Italian Municipalities over the period 2004–2017. For this purpose, we employ a hedonic property price model. We also differentiate the impact of kindergarten proximity on houses' market price between state and non-state premises. The findings highlight that (i) the level of housing price depends on kindergarten proximity; (ii) some quality school characteristics played a crucial role and (iii) the distinction between public and non-state kindergartens shows that the vicinity of the latter generates a more significant capitalization effect. Finally, the empirical evidence could be useful to several actors involved in urban planning when developing plans for the construction of new kindergartens in order to create a more homogeneous city.

Keywords: house value; kindergarten; neighborhood; capitalization

JEL Classification: I22; R3

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1. Introduction

Housing is a particular type of asset with a dual meaning as consumption and an investment good (Glindro et al. 2011). For this reason, the determinants of housing market price are a topic of great relevance. According to Gibbons and Machin (2003), the evaluation of housing prices by buyers are affected by several factors: (i) the real estate characteristics (e.g., the number of rooms and house condition); (ii) neighbourhood characteristics (e.g., low crime rates and neighbourhood peers); and finally (iii) other amenities (e.g., proximity to workplace, parks and shops) (Gibbons and Machin 2003). In addition, the quality (Brasington and Haurin 2006; Gibbons et al. 2013; Wen et al. 2017) and especially the proximity to school represents a concern to home buyers (Theisen and Emblem 2018). Regarding the proximity, the distance between the kindergartens and the houses is crucial, since it is supposed that their proximity to homes may affect housing market prices much more than the closeness of other school levels can do.

As it is mostly in early life that children need somebody (i.e., their parents) to take them to school daily, it is supposed that parents are inclined to live within walking distance of kindergarten. Therefore, it is expected that this preference influences the residential location and, in turn, property values. While the existing literature on schooling and house market prices has investigated the impact of school quality on housing price in numerous countries (Black 1999; Downes and Zabel 2002; Kane et al. 2003, 2006; Figlio and Lucas 2004; Brasington and Haurin 2006; Clapp et al. 2008; Gibbons and Machin 2008; Nguyen-Hoang and Yinger 2011; Machin 2011; Gibbons et al. 2013; Livy 2017; Yi et al. 2017; Towe and Tra 2019; Turnbull et al. 2017; Turnbull and Zheng 2019; Bonilla-Mejìa et al. 2019), there is no research focusing on the relationship between accessibility to kindergartens and housing price in Italy.

Therefore, this paper seeks to shed some light on the relationship between accessibility to kindergartens and housing price in Italy, estimating the impact of kindergarten proximity on houses' prices in the eleven major Italian Municipalities' neighbourhoods. A major factor in determining the price of a property is its location: the better the positioning of the property, the higher the asking price. To this end, we investigate the impact of kindergarten proximity on housing market prices employing the hedonic property price model. Then, we differentiate between state and non-state[1] premises the effect of the kindergartens' proximity on houses' market prices.

To estimate the impact of kindergarten proximity on housing market prices in the eleven major Italian Municipalities' neighborhoods, we exploit data from different sources. Data on housing market price, covering the period 2004–2017, are provided by the Osservatorio del Mercato Immobiliare (OMI) of the national Fiscal Agency (Agenzia delle Entrate). Data on the distance between kindergartens and the centre of neighbourhoods come from a personal dataset constructed combining addresses of childcare institutions provided by the Ministry of Education, Universities and Research (MIUR) with the geo-codes of the centre of the neighborhoods of interest. Neighborhoods are constructed employing the OMI internet map[2] that gives the boundaries of the neighborhoods for each Italian city. Finally, we also use the information on kindergarten (made available by the MIUR) and municipal characteristics (provided by the Ministry of Interior and the National Institute of Statistics).

The main results show that proximity to a kindergarten is capitalised into housing market price and confirm that close location to a kindergarten has a significant and positive effect on housing price, causing their capitalisation. In addition, the estimated coefficients are stable across all specifications with a weak increase in intensity over time. Finally, we find that the inclusion of variables detecting the quality of schools mitigates the proximity effect.

In addition, results are of particular interest when we divide our estimates between state and non-state kindergartens. We find that the degree of capitalisation depends mainly on the proximity to non-state kindergartens. This result is primarily due to the asymmetrical dislocation of private kindergarten/schools; on the contrary, public schools have a more uniform distribution. Although our study focuses on the Italian case, the extension of the analysis proposed here is relevant for the international reader, and the analysis of impact of kindergarten proximity on housing market prices is common to various countries and contexts.

The possibility that non-state kindergartens may prefer to offer their services in wealthier neighbourhoods increases the risk of endogeneity. We address this issue exploiting the long time series of housing market data in two ways: first, we depurate house prices per square meter from the neighborhoods fixed effect; second, kindergarten proximity measured in 2011 is regressed against depurated house prices registered after 2011 up to 2017.

The remainder of this paper is organised as follows. The next section provides an overview of the literature on the relationship between school proximity and housing market price. Section 3 describes the data and variables. Section 4 outlines the econometric strategy used to examine the questions of interest. Section 5 discusses the main results, and Section 6 presents some alternative estimations. The last section summarises and concludes the paper.

2. Related Literature Background

Up to now, only few studies have explored the relationship between housing market prices and school proximity despite this factor possibly affecting house values as the attractiveness of a house increases with the proximity to a school, especially with school-aged children due to commuting and safety worries in the district (Huang and Hess 2018).

In what follows, we expound on the existing literature on the linkage between school proximity and housing price classified as follows: (i) a substantial part of studies estimates the impact of school proximity on housing market prices through a pure hedonic model; (ii) other studies employ different techniques such as the spatial approach to improve the hedonic price model.

The first study investigating this topic employing the hedonic approach and measuring proximity to school with some specific ranges of distance was carried out by Des Rosiers et al. (2001). Their analysis focuses on the effect of distance of primary school on residential values in Quebec, Canada. Using data covering the period January 1990 and December 1991 on a sample of 4300 single-detached and 116 primary schools, the authors find that the proximity of primary schools strongly affects the market house price.

In line with the previous study, Chin and Foong (2006) exploit data on sales records of individual housing transactions (13,790) for 2000–2003. They observe the relationship between the housing prices and accessibility of both primary schools and junior high schools in Singapore and show that home buyers consider the proximity and school reputation in their home purchase decision. Findings suggest that accessibility to prestigious and primary schools is more important than access to junior high schools for households.

However, Owusu-Edusei et al. (2007) study the impact of school proximity and school quality on the house prices at the elementary, middle and high school level. They use data on 3732 house sales between 1994 and 2000 in the metropolitan area of Greenville, South Carolina, and measure the distance to schools following the criteria defined by Des Rosiers et al. (2001). Their empirical evidence confirms that proximity to schools at all levels and the quality of schools have a positive impact on housing prices.

Analysing the university's effect on house prices, Liu (2010) focuses on the houses near Zhejiang Campus in China and use the hedonic house price model. They show that the presence of the university impacts positively on the house price.

However, Metz (2015) considers a sample of 22,264 single-family home sales in the Denver Public School District during the period 2002–2004 to investigate the impact of school proximity and school quality on the house prices at three school levels (elementary, middle and high). The author concludes that the proximity to schools at all levels and the quality of schools have a positive impact on housing prices.

A study conducted by Sah et al. (2016) on a sample of 20,000 residential housing sales in San Diego County during 2010–2011 also deserves attention. This work investigates the public and private school proximity effects on housing prices. For the specific area analysed, where the public schools are open at the weekend and during the off-school hours, they find a proximity penalty effect on housing price when primary public schools are close to the house, and in particular, the results show that the prices decrease with distance from the coast.

Huang and Hess (2018) study the relationship between a residential property's price and the proximity to school using a continuous distance measure. They employ the quantile regression method of Koenker (2005)[3] on a sample of 1075 residential properties in Oshkosh, WI, USA, during the period January 2006 and July 2007 and find that the distance to all three school levels has a significant effect on housing prices.

As noted above, other studies use different approaches to investigate the relationship between housing market prices and school proximity.

Among these, the study carried out by Wen et al. (2014) explores the relationship between housing price and educational resources from kindergarten to the university level applying both the hedonic price approach and the spatial econometric model. Exploiting data on the Chinese house market during May 2012 for a sample of six cities and 660 communities in Hangzhou (China), they find that kindergartens, high schools, and college improve the nearby housing prices through accessibility. Moreover, elementary and junior high schools have a significant school district effect. Specifically, kindergarten's presence within one kilometre from residential communities leads to a substantial housing price increase.

More recently, Wen et al. (2017), in another work, consider the implication of educational policies to explore the relationship between educational facilities, quality and housing price and use data during the period 2011–2013 on a sample of 660 communities in six urban districts in Hangzhou (China). Results suggest that the presence of kindergartens, good schools and university impact positively on nearby housing price. They show that a *zero school choice* policy increases the school district effect.

According to Theisen and Emblem (2018), the proximity to kindergartens is more important than school accessibility for children aged 1–5 years. They employ data on property value that cover the period 2010–2017 for a sample of 15,307 house transactions in Kristiansand (Norway) and explore the relationship between house prices and the distance to kindergarten. To calculate distance, they use the methodology developed by Weber and Péclat (2017)[4] and show that house price decreases when the distance to the kindergarten increases.

In line with previous literature, our analysis is the first to investigate the impact of kindergarten proximity on Italy's housing prices. This paper starts filling this gap by estimating the degree of capitalisation of kindergarten proximity on housing prices in the eleven major Italian Municipalities (previous versions of this research appeared as working papers in Bergantino et al. 2014, 2021).

3. Data Collection and Variables

The data used for the empirical analysis refer to Italian Municipalities[5]. In particular, we focus on the eleven largest Italian cities with more than 250,000 inhabitants where location choices are more relevant for households with school-aged children. Moreover, we restricted the analysis only to the largest cities because they provide enough heterogeneity to identify the impact of kindergartens' location on the housing market for two main reasons: first the presence of many facilities distributed across the city; and second the possibility to measure housing prices at the level of the neighborhood. We consider the following municipalities: Turin, Milan, Verona, Genoa, Bologna, Florence, Rome, Naples, Bari, Catania and Palermo[6]. In this study, the housing market price is our dependent variable that equates to the average between the minimum and the maximum cost per square meter of residential real estate located in each micro-zone (neighborhood) of the target Municipalities. Data on housing market prices are taken from OMI[7] that provides several pieces of information at the level of municipal micro-zones (neighborhoods). Under the OMI definition, these micro-zones are sections of Municipality with uniform partitions of the real estate market since they present real estate with the same socio-economic and urban characteristics. To define micro-zones within a Municipality, the maximum deviation of the range of real estate market values in each micro-zone should be lower than 1.5. For each micro-zone, the dataset shows the minimum and maximum price per square meter. Moreover, prices are differentiated according to the following properties' characteristics: (i) the use (residential, commercial, offices, and productive activities); (ii) the condition (normal, historical, luxury, ruined, etc.) and finally (iii) the city area where it is located (city centre, mid-central zone, suburban zones, rural zones, etc.). All the data have been collected annually considering the quotations registered at the end of the year, starting from 2004 up to 2017. For the empirical analysis in this paper, we use the information on normal condition residential real estate for 2004–2017. To compute the straight-line distance between kindergartens and each micro-zone centre of the target cities, we use two different sources: first, using the kindergarten address provided by the open-data "*Scuola in Chiaro*" (unencrypted school) issued by the MIUR for the school year 2010–2011, we determine the kindergarten geo-codes; second, we constructed the micro-zone geo-codes starting from the OMI internet map that shows the boundaries of the micro-zones of Italian cities.

In Italy, kindergartens (scuole d'infanzia) are managed at the municipal level and provide a pre-school service for children between 3 and 5 years of age, although pre-school in Italy is not mandatory, according to the administrative data analyzed in a recent report of the Italian Government (Dipartimento per le politiche della Famiglia 2020), the national coverage rate in 2011 was about 95.3%, distributed quite uniformly across regions. On average, state kindergartens cover 65.7% of the facilities, and the rest is provided by private schools. We excluded from our analysis nurseries (asili nido) that provide services for children between 0 and 2 years old since we did not want to mix in the same analysis two preschool services that are completely different, for example in Italy although both services are provided at the municipal level, nurseries are considered among social services and kindergarten among education services. Therefore, we leave to future works the study of nursery locations.

Information on state and non–state kindergarten service structure is taken from data collected by the MIUR for the school year 2010–2011. For each kindergarten (scuole d'infazia), these data give information on (i) pupils; (ii) teaching staff, and (iii) structure. The data contain information on sex, year of birth, nationality, religious orientation, disability status, and type of disability regarding the pupils. The second group of data refers only to support teachers, discerning them according to the child's kind of disability. Finally, concerning the structure, the data provide details on the number of classrooms, schooling time, special facilities (antemeridian sections, Saturday sections, etc.) and size (square meters per pupils) of covered and uncovered playgrounds. Based on these data, we compute some key indices of kindergarten quality, such as the average class size, and the average size in square meters of playgrounds. Moreover, exploiting the data classification into state and non-state kindergartens makes it possible to assess the extent to which the competition between state and non-state childcare institutions could affect housing prices.

It is essential to analyze in more detail the time structure of our dataset. We focus on 2010/2011 school information to evaluate kindergarten proximity's impact on housing prices in the subsequent years up to 2017. In this way, we can measure the persistence of school localization on the house values and mitigate the endogeneity risk. Moreover, we also exploit information on housing market quotations before 2010 to depurate house prices from the influence of local amenities, the so-called neighborhood effect that we can identify as the main source of the potential risk of endogeneity.

Finally, as control variables, we also use municipal characteristics. This last piece of information is taken from two different sources: (i) the Ministry of Interior (Ministero dell'Interno) and (ii) the National Institute of Statistics (ISTAT). Table A1 in the Appendix A contains the description of variables included to account for factors that could affect the housing prices. Table 1 reports descriptive statistics[8].

Table 1. Descriptive statistics of variables.

Name of Variable	Obs.	Mean	Std. Dev	Min	Max
Price per m^2 (min)	668	2287.618	1150.026	769.167	8600
Price per m^2 (max)	668	3132.704	1521.486	1024.167	11,600
Kindergarten	668	446.555	276.879	87	762
Non-state kindergartens (dummy)	668	0.334	0.040	0.246	0.449
Public kindergarten distance (km)	668	1.706	35.382	5.120	889.318
Kindergarten distance (km)	668	2.622	63.532	7.252	1612.265
Non-state kindergarten distance (km)	668	5.290	84.419	11.842	1983.296
Quality of kindergarten					
Waiting list	668	0.034	0.025	0.002	0.150
Average class size	668	22.493	1.468	18.895	25.598
Schooling time 25	668	0.194	0.192	0.002	0.776
Schooling time 40	668	0.807	0.192	0.225	0.998
Foreign pupils	668	0.095	0.054	0.010	0.323
Foreign pupils born in Italy	668	0.074	0.044	0.006	0.264
Foreign pupils born in Italy 2	668	0.542	0.179	0.119	0.827
Pupils with disabilities	668	0.017	0.004	0.008	0.039
Disabled assistant	668	0.117	0.078	0.005	0.403

Table 1. *Cont.*

Name of Variable	Obs.	Mean	Std. Dev	Min	Max
Antemeridian sections	668	0.168	0.207	0	0.788
Antemeridian sections 2	668	0.292	0.255	0	0.892
Playgrounds per pupil	668	2.459	0.420	1.347	3.969
Playschool sections	668	0.083	0.045	0.006	0.352
Canteen service	668	0.932	0.128	0.433	1
Bus service	668	0.155	0.109	0.016	0.908
Preschool service	668	0.398	0.208	0.048	0.918
Postschool service	668	0.325	0.231	0.037	0.912
Saturday sections	668	0.088	0.096	0	0.492
Saturday	668	0.072	0.091	0	0.485
Local context variable at the municipal level					
Population	668	1,568,872	1,042,831	263,964	2,761,477
Population 0–14	668	13.423	1.449	10.830	15.956
Population $\geq$ 65	668	22.067	2.880	17.212	26.865
Foreign population	668	8.844	3.845	2.823	15.053
Household members	668	2.269	0.238	1.860	2.560
Households s	668	0.442	0.050	0.390	0.533
Cohabitations	668	0.711	0.206	0.416	1.550
Commuters	668	43.561	4.542	34.871	48.238
Municipality coastal	668	0.747	0.435	0	1
Altitude	668	4.419	1.015	2	5

Note: details about each variable are reported in Table A1.

4. Empirical Strategy

The main purpose of this paper is to assess the impact of the proximity of kindergartens on housing prices, minimizing the bias generated by the potential endogeneity of the kindergarten's location. To this end, the empirical framework is based on the basic hedonic housing price model developed by Rosen (1974). Thus, the price per square meter at year t of the average house in micro-zone (neighborhood) j of Municipality i is determined by our basic estimation model:

$$price_{ijt} = \alpha + H'_{ijt}\beta + M'_{it}\lambda + Q'_{ijkt}D_{ijk}\delta + D_{ijk}\mu + \eta_t + \theta_{ij} + \varepsilon_{ijt} \quad (1)$$

for $i = 1, 2, \ldots, N$, $j = 1, 2, \ldots, J$, $k = 1, 2, \ldots K$, $t = 1, 2, \ldots, T$.

Where H'_{ijt} is a matrix of house characteristics which account for the location and the quality; M'_{it} is the matrix of municipal characteristics, e.g., average income and structure of the population; Q'_{ijkt} is the quality, at year t, of all kindergartens k of all districts j of Municipality i; D_{ijk} is the straight-line distance of all kindergartens k of the city i to the center of micro-zone j, of Municipality i; η_t year effect; θ_{ij} is the neighborhood effect; finally, ε_{ijt} is the error term. The coefficients β, λ, δ and μ measure the marginal purchaser's willingness to pay for house, municipal, kindergarten quality and kindergarten proximity, respectively. Given that the main focus of the analysis is on μ[9], the regressor D_{ijk} must be isolated from the other vectors in the model (1). For this purpose, we perform a multi-step strategy. In the first step, by exploiting the classification of the Italian dataset on the real estate market, we consider the information on houses that have the same state of preservation (i.e., standard houses) and the same use (i.e., residential real estate and parking), so H'_{ijt} becomes a constant in our specification, we remove it from the model and Equation (1) becomes:

$$price_{ijt} = \alpha + M'_{it}\lambda + Q'_{ijkt}D_{ijk}\delta + D_{ijk}\mu + \eta_t + \theta_{ij} + \varepsilon_{ijt} \quad (2)$$

The product of variables Q'_{ijkt} and D_{ijk} yields the matrix Ω'_{ijt} that indicates, for each neighborhood, the sum of the quality, at time t, of all kindergartens of town i, weighted by the distances of all kindergartens to the center of the target micro-zone j, in town i. Therefore, Equation (2) becomes:

$$price_{ijt} = \alpha + M_{it}'\lambda + \Omega_{ijt}'\delta + D_{ijk}\mu + \eta_t + \theta_{ij} + \varepsilon_{ijt} \tag{3}$$

Since kindergartens and municipalities' structural characteristics can change only over a long-time span, we can remove the subscript t from the independent variables of the model. The time dimension remains valid only for the dependent variables since we will test the persistence of capitalization considering the housing prices at time $t + x$ where x goes from 2011 up to 2017. As a result, the model in Equation (3) becomes:

$$price_{ijt} = \alpha + M_i'\lambda + \Omega_{ij}'\delta + D_{ijk}\mu + \theta_{ij} + \varepsilon_{ijt} \tag{4}$$

However, we cannot identify θ_{ij} (neighborhood effect) separately from ε_{ij} (idiosyncratic error term) since we have no specific information on neighborhood characteristics. The problem is that since neighborhood characteristics are probably correlated with schools' feature, the OLS estimator will produce biased estimates of μ. To circumvent this lack of information, we exploit the long time series of housing prices and we perform a two-stage approach to compute correct estimates of μ. In the first stage, we estimate the following model:

$$price_{ijt} = \alpha + \ \eta_t \ + \theta_{ij} + \phi_{ijt} \tag{5}$$

where ϕ_{ijt} are the i.i.d error term and t goes from 2004 up to 2011, i.e., all the years before observing school characteristics. The model in (5) is estimated using the Within-the-Group estimator to obtain an estimate of $\hat{\theta}_{ij}$ that works as a proxy of the neighborhood effect on the housing price.

The final specification of the second stage model is reported in the following Equation (6):

$$\overline{price}_{ijt} = M_{it}'\lambda + \Omega_{ij}'\delta + D_{ijk}\mu + \varepsilon_{ij} \tag{6}$$

where the dependent variable $\overline{price}_{ijt}$ correspond to $(price_{ijt} - \hat{\theta}_{ij})$ equal to the housing price of each neighborhood j depurated from the neighborhood effect. In this way, we can estimate (through the OLS) the unbiased impact of kindergarten proximity on housing prices and its persistency up to the sixth year after the evaluation of a school's localization and quality and other municipal characteristics.

As a final step of our empirical strategy, since we are also interested in examining the impact of the presence of non-state kindergartens on the capitalization of kindergarten proximity, we add a dummy variable W_k in Equation (6) to differentiate between non-state and state kindergartens. Hence, Equation (6) takes the following form:

$$\overline{price}_{ijt} = M_{it}'\lambda + \Omega_{ij}'\delta + D_{ijk}\mu + W_k\ \Omega_{ij}'\delta\rho + W_k D_{ijk}\xi + \psi_{ij} \tag{7}$$

where W_k is the non-state kindergarten dummy variable[10]. We can further simplify Equation (7) by multiplying $W_k\ \Omega_{ij}'$, in order to express it with the matrix S_{ij} and, similarly, by multiplying $W_k D_{ijk}$ in order to express it with the vector P_{ij}. Equation (8) reports the final empirical model:

$$\overline{price}_{ijt} = M_{it}'\lambda + \Omega_{ij}'\delta + D_{ijk}\mu + {S_{ij}}'\rho + P_{ij}\xi + \psi_{ij} \tag{8}$$

where ξ captures the effect of non-state kindergarten proximity on housing price.

5. Empirical Results

In our basic specification, we estimate the model specified in equation (6) considering as dependent variables both the raw housing prices per sq. meter and the prices depurated from the neighborhood effect. Moreover, for each of them we consider the mean, maximum, and minimum housing value. In addition, since variables are expressed in different measurement units, we have standardized them imposing mean 0 and standard deviation equal to 1. In this way, we can compare the magnitude of the coefficient point estimates interpreting them in terms of standard deviation.

Table 2 reports only the proximity[11] findings. For the sake of readability, the coefficients of other variables employed are not displayed (these coefficients are reported separately in Table A3 of the Appendix A). Let us address in more details the structure of Table 2. Different blocks of the table consider different time spans of the housing prices, from 2011–2012 average up to 2016–2017 average, finally the last block refers to the average price over the entire period 2011–2017. Columns 1–4 present the empirical results not purified from the neighborhood fixed effect for all kindergarten proximity. Specifically, findings in column 1 refer to a simple model which regresses kindergarten proximity on housing market prices without considering any control variable. Column 2 shows the results of the model that includes quality characteristics of kindergartens as control variables. Column 3 exhibits the effects obtained taking into account the municipal features and, finally, column 4 refers to a model that considers both municipal and school characteristics. On the other hand, columns 5–8 contain results obtained running OLS on the same models employed in columns 1 to 4 considering as a dependent variable the price of hosing depurated from the neighborhood effect.

The main results confirm the impact of the kindergarten's proximity on the price of the house. In more detail, the school proximity coefficient estimates suggest that, overall, close location to a kindergarten has a significant and positive effect on housing price. As we expected, the capitalization effect becomes smaller after we depurate the housing price from the neighborhood effect but remains in most of the specification positive and statistically significant. In addition, comparing the results over time (2011–2017), we can observe a persistent capitalization effect. Specifically, the proximity of kindergarten to the house generates stronger capitalization considering the maximum housing value, a weaker impact is observed on minimum values; instead, the impact on the average value is in between.

Adding the variables that capture the quality of schools (see Table A3 in Appendix A)[12], we find that several quality variables such as the presence of foreign pupils, people who take care of the disabled, canteen service and number of schools opened on Saturdays can positively impact housing market prices. All the considered variables impact housing market prices even if they present a different magnitude. Foreign pupils' presence has the highest value and is equal to 1.225, while the lowest value, equivalent to 0.240, is for people who take care of the disabled. These results are signals that parents not only care about the location but also about the quality of kindergarten. This result is in line with the work of Turnbull et al. (2017), which shows how parents search and then choose schools that offer specific and additional services to solve organizational and working problems.

To sum up, in line with other empirical findings (i.e., Owusu-Edusei et al. 2007; Chin and Foong 2006; Wen et al. 2014, 2017; Huang and Hess 2018), our results confirm that home buyers consider the proximity to schools in their home purchase decision. Moreover, this analysis shows that the degree of capitalisation of kindergarten proximity in housing price depends mainly on proximity and some quality school characteristics.

Table 2. Estimation results. Proximity to kindergarten and house prices per square meter.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	$price_{ijt}$				$price_{ijt} - \hat{\theta}_{ij}$			
	Kindergarten Proximity vs. Housing Price 2011–2012							
Min	0.352	0.343	0.496	0.497	0.224	0.139	0.273	0.219
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.003] ***	[0.000] ***	[0.000] ***
Mean	0.357	0.341	0.501	0.501	0.305	0.173	0.317	0.254
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.359	0.338	0.502	0.503	0.329	0.181	0.323	0.258
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Observations	668	668	668	668	658	658	658	658
Adj. R-squared (Min)	0.122	0.461	0.425	0.602	0.042	0.418	0.484	0.537
Adj. R-squared (Mean)	0.123	0.452	0.411	0.501	0.089	0.562	0.631	0.691
Adj. R-squared (Max)	0.124	0.444	0.402	0.590	0.098	0.607	0.673	0.738
	Kindergarten Proximity vs. Housing Price (2012–2013)							
Min	0.358	0.341	0.493	0.488	0.245	0.134	0.257	0.183
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.007] ***	[0.000] ***	[0.000] ***
Mean	0.356	0.338	0.498	0.493	0.286	0.149	0.283	0.202
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.003] ***	[0.000] ***	[0.000] ***
Max	0.354	0.335	0.500	0.495	0.297	0.151	0.287	0.206
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Observations	668	668	668	668	658	658	658	658
Adj. R-squared (Min)	0.118	0.476	0.438	0.611	0.051	0.462	0.501	0.552
Adj. R-squared (Mean)	0.121	0.461	0.421	0.601	0.074	0.561	0.612	0.671
Adj. R-squared (Max)	0.119	0.447	0.405	0.591	0.083	0.597	0.651	0.709
	Kindergarten Proximity (2014–2015)							
Min	0.351	0.408	0.425	0.466	0.193	0.167	0.136	0.156
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.038] **	[0.032] **	[0.101]
Mean	0.340	0.405	0.421	0.464	0.359	0.240	0.210	0.213
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.001] ***	[0.000] ***	[0.016] **
Max	0.330	0.401	0.417	0.461	0.425	0.264	0.236	0.230
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Observations	408	408	408	408	398	398	398	398
Adj. R-squared (Min)	0.119	0.541	0.452	0.612	0.031	0.172	0.151	0.189
Adj. R-squared (Mean)	0.110	0.532	0.440	0.607	0.119	0.361	0.338	0.387
Adj. R-squared (Max)	0.097	0.522	0.428	0.598	0.169	0.482	0.462	0.519
	Kindergarten Proximity (2016–2017)							
Min	0.345	0.428	0.452	0.487	0.0511	0.0973	0.107	0.0909
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.366]	[0.196]	[0.101]	[0.348]
Mean	0.346	0.425	0.446	0.481	0.307	0.223	0.215	0.190
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.004] ***	[0.000] ***	[0.043] **
Max	0.346	0.421	0.441	0.475	0.433	0.278	0.259	0.230
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.003] ***
Observations	401	401	401	401	391	391	391	391
Adj. R-squared (Min)	0.112	0.518	0.429	0.593	0.001	0.180	0.171	0.191
Adj. R-squared (Mean)	0.113	0.512	0.420	0.590	0.081	0.271	0.252	0.289
Adj. R-squared (Max)	0.113	0.512	0.412	0.587	0.170	0.412	0.397	0.439
	Kindergarten Proximity (2011–2017)							
Min	0.351	0.345	0.486	0.486	0.204	0.141	0.209	0.151
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.010] ***	[0.000] ***	[0.015] **
Mean	0.355	0.345	0.491	0.492	0.295	0.178	0.269	0.200
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.357	0.343	0.493	0.495	0.325	0.187	0.285	0.215
	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***	[0.000] ***
Observations	668	668	668	668	658	658	658	658
Adj. R-squared (Min)	0.119	0.451	0.411	0.591	0.035	0.285	0.300	0.352
Adj. R-squared (Mean)	0.114	0.443	0.401	0.584	0.080	0.476	0.489	0.549
Adj. R-squared (Max)	0.112	0.439	0.390	0.580	0.098	0.541	0.578	0.640
No control variables	Yes	No	No	No	Yes	No	No	No
Kindergarten quality	No	Yes	No	No	No	Yes	No	No
Local context variables	No	No	Yes	No	No	No	Yes	No
All control variables	No	No	No	Yes	No	No	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$. Bootstrap standard error, p value in brackets regarding the null hypothesis that the estimated coefficients are equal to zero. All variables are standardised with mean 0 and standard deviation 1. Each line of the table refers to three different levels of housing prices per sq. meter: minimum, average and maximum. Each column refers to a different specification of the model in terms of control variables included among the regressors. Columns from 1 to 4 consider as dependent variables the raw price of housing, instead, columns from 5 to 8 consider as dependent variables the price of housing depurated from the neighbourhood effect. Different blocks of the table consider different time spans of the housing prices, from 2011–2012 average up to 2016–2017 average, finally the last block refers to the average price over the entire period 2011–2017.

6. Alternative Estimations and Robustness Check

In what follows, we describe the results of the alternative estimations (Table 3). We now report the results regarding the model specified in equation (8), where we divide public from non-state kindergartens to investigate in more detail the proximity impact on the housing price. In addition, in this case, for readability reasons, the coefficients of other variables are not exhibited. The structure of Table 3 follows the structure of Table 2, in particular, columns 1–4 present the empirical results not purified from the neighborhood characteristics for all kindergarten proximity. Specifically, findings in column 1 refer to a simple model which regresses kindergarten proximity on housing market prices without considering any control variable. Column 2 shows the results of the model that includes quality characteristics of kindergartens as control variables. Column 3 exhibits the results obtained, taking into account the municipal characteristics, and finally, column 4 refers to a model that considers both municipal and school aspects. On the other hand, columns 5–8 contain results obtained running OLS on the same models employed in columns 1 to 4 considering as a dependent variable the price of housing depurated from the neighborhood effect.

Table 3. Alternative estimation results dividing between public and non-state kindergarten.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$price_{ijt}$				$price_{ijt} - \hat{\theta}_{ij}$			
Public Kindergarten Proximity (2011–2012)								
Min	0.161	−0.026	−0.021	−0.069	0.229	−0.154	−0.089	−0.072
	[0.031] **	[0.760]	[0.685]	[0.353]	[0.000] ***	[0.001] ***	[0.075] *	[0.177]
Mean	0.289	−0.047	−0.036	−0.100	0.220	−0.165	−0.099	−0.085
	[0.000] ***	[0.519]	[0.466]	[0.087] *	[0.000] ***	[0.007] ***	[0.041] **	[0.116]
Max	0.336	−0.055	−0.041	−0.109	0.212	−0.172	−0.105	−0.094
	[0.000] ***	[0.414]	[0.427]	[0.035] **	[0.001] ***	[0.004] ***	[0.029] **	[0.085] *
Non State Kindergarten Proximity (2011–2012)								
Min	0.071	0.119	0.309	0.209	0.137	0.464	0.623	0.532
	[0.370]	[0.122]	[0.000] ***	[0.001] ***	[0.030] **	[0.000] ***	[0.000] ***	[0.000] ***
Mean	0.025	0.161	0.371	0.283	0.151	0.475	0.637	0.547
	[0.754]	[0.008] ***	[0.000] ***	[0.000] ***	[0.026] **	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.003	0.172	0.382	0.305	0.161	0.480	0.646	0.555
	[0.967]	[0.006] ***	[0.000] ***	[0.000] ***	[0.019] **	[0.000] ***	[0.000] ***	[0.000] ***
Observations	658	658	658	658	668	668	668	668
Adj. R-squared (Min)	0.042	0.518	0.491	0.571	0.122	0.567	0.467	0.660
Adj. R-squared (Mean)	0.091	0.665	0.642	0.731	0.122	0.560	0.456	0.658
Adj. R-squared (Max)	0.110	0.711	0.686	0.770	0.124	0.555	0.450	0.653
Public Kindergarten Proximity 2012–2013								
Min	0.231	−0.031	−0.001	−0.081	0.245	−0.155	−0.085	−0.076
	[0.000] ***	[0.670]	[0.991]	[0.254]	[0.000] ***	[0.005] ***	[0.088] *	[0.146]
Mean	0.301	−0.046	−0.022	−0.110	0.227	−0.167	−0.097	−0.089
	[0.000] ***	[0.478]	[0.660]	[0.065] *	[0.000] ***	[0.005] ***	[0.056] *	[0.095] *
Max	0.328	−0.052	−0.032	−0.122	0.212	−0.175	−0.105	−0.099
	[0.000] ***	[0.365]	[0.501]	[0.026] **	[0.002] ***	[0.005] ***	[0.031] **	[0.068] *
Non State Kindergarten Proximity 2012–2013								
Min	0.022	0.088	0.271	0.178	0.126	0.456	0.615	0.525
	[0.745]	[0.168]	[0.000] ***	[0.003] ***	[0.063] *	[0.000] ***	[0.000] ***	[0.000] ***
Mean	−0.008	0.117	0.321	0.234	0.143	0.468	0.632	0.540
	[0.913]	[0.053] *	[0.000] ***	[0.000] ***	[0.041] **	[0.000] ***	[0.000] ***	[0.000] ***
Max	−0.024	0.129	0.336	0.256	0.156	0.476	0.642	0.549
	[0.748]	[0.022] **	[0.000] ***	[0.000] ***	[0.027] **	[0.000] ***	[0.000] ***	[0.000] ***
Observations	658	658	658	658	668	668	668	668
Adj. R-squared (Min)	0.054	0.544	0.510	0.587	0.122	0.581	0.478	0.672
Adj. R-squared (Mean)	0.081	0.657	0.625	0.709	0.121	0.571	0.464	0.665
Adj. R-squared (Max)	0.088	0.694	0.663	0.745	0.120	0.562	0.450	0.658

Table 3. *Cont.*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$price_{ijt}$				$price_{ijt} - \hat{\theta}_{ij}$			
Public Kindergarten Proximity 2014–2015								
Min	−0.017	−0.167	−0.167	−0.245	0.212	−0.180	−0.191	−0.166
	[0.827]	[0.184]	[0.048] **	[0.040] **	[0.018] **	[0.010] **	[0.000] ***	[0.009] ***
Mean	0.155	−0.159	−0.192	−0.274	0.196	−0.184	−0.198	−0.171
	[0.051] *	[0.110]	[0.033] **	[0.011] **	[0.024] **	[0.009] ***	[0.000] ***	[0.008] ***
Max	0.241	−0.143	−0.192	−0.270	0.184	−0.185	−0.204	−0.175
	[0.003] ***	[0.180]	[0.009] ***	[0.005] ***	[0.021] **	[0.013] **	[0.002] ***	[0.008] ***
Non State Kindergarten Proximity 2014–2015								
Min	0.238	0.316	0.343	0.358	0.154	0.562	0.709	0.592
	[0.006] ***	[0.017] **	[0.001] ***	[0.003] ***	[0.143]	[0.000] ***	[0.000] ***	[0.000] ***
Mean	0.227	0.353	0.455	0.433	0.159	0.561	0.714	0.592
	[0.020] **	[0.005] ***	[0.000] ***	[0.000] ***	[0.140]	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.204	0.348	0.484	0.443	0.162	0.559	0.716	0.590
	[0.038] **	[0.008] ***	[0.000] ***	[0.000] ***	[0.092] *	[0.000] ***	[0.000] ***	[0.000] ***
Observations	398	398	398	398	408	408	408	408
Adj. R-squared (Min)	0.037	0.209	0.167	0.222	0.121	0.618	0.512	0.672
Adj. R-squared (Mean)	0.121	0.406	0.362	0.427	0.111	0.610	0.501	0.668
Adj. R-squared (Max)	0.167	0.534	0.498	0.561	0.102	0.602	0.490	0.661
Public Kindergarten Proximity 2016–2017								
Min	−0.202	−0.189	−0.145	−0.235	0.180	−0.179	−0.189	−0.161
	[0.004] ***	[0.096] *	[0.095] *	[0.042] **	[0.043] **	[0.012] **	[0.001] ***	[0.014] **
Mean	0.040	−0.177	−0.173	−0.268	0.177	−0.183	−0.196	−0.168
	[0.622]	[0.082] *	[0.047] **	[0.015] **	[0.027] **	[0.016] **	[0.001] ***	[0.011] **
Max	0.187	−0.150	−0.171	−0.259	0.174	−0.184	−0.201	−0.173
	[0.015] **	[0.127]	[0.022] **	[0.009] ***	[0.038] **	[0.016] **	[0.002] ***	[0.010] **
Non state Kindergarten Proximity (2016–2017)								
Min	0.287	0.277	0.281	0.273	0.183	0.583	0.728	0.600
	[0.001] ***	[0.043] **	[0.010] ***	[0.025] **	[0.091] *	[0.000] ***	[0.000] ***	[0.000] ***
Mean	0.300	0.340	0.432	0.386	0.189	0.576	0.730	0.597
	[0.002] ***	[0.009] ***	[0.000] ***	[0.001] ***	[0.058] *	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.275	0.342	0.478	0.413	0.192	0.569	0.730	0.592
	[0.003] ***	[0.005] ***	[0.000] ***	[0.000] ***	[0.067] *	[0.000] ***	[0.000] ***	[0.000] ***
Observations (Min Med Max)	391	391	391	391	401	401	401	401
Adj. R-squared (Min)	0.018	0.222	0.181	0.228	0.111	0.598	0.491	0.661
Adj. R-squared (Mean)	0.092	0.322	0.274	0.332	0.115	0.594	0.482	0.661
Adj. R-squared (Max)	0.178	0.471	0.422	0.487	0.116	0.591	0.478	0.656
Public Kindergarten Proximity (2011–2017)								
Min	0.114	−0.143	−0.084	−0.190	0.222	−0.181	−0.105	−0.098
	[0.071] *	[0.122]	[0.246]	[0.025] **	[0.001] ***	[0.002] ***	[0.039] **	[0.068] *
Mean	0.266	−0.127	−0.075	−0.184	0.214	−0.189	−0.112	−0.106
	[0.000] ***	[0.089] *	[0.183]	[0.009] ***	[0.002] ***	[0.001] ***	[0.018] **	[0.051] *
Max	0.329	−0.112	−0.067	−0.172	0.207	−0.194	−0.117	−0.112
	[0.000] ***	[0.093] *	[0.180]	[0.006] ***	[0.001] ***	[0.001] ***	[0.016] **	[0.042] **
Non State Kindergarten Proximity 2011–2017								
Min	0.098	0.184	0.306	0.262	0.143	0.483	0.628	0.548
	[0.159]	[0.037] **	[0.000] ***	[0.000] ***	[0.040] **	[0.000] ***	[0.000] ***	[0.000] ***
Mean	0.038	0.200	0.361	0.309	0.156	0.491	0.640	0.558
	[0.590]	[0.004] ***	[0.000] ***	[0.000] ***	[0.027] **	[0.000] ***	[0.000] ***	[0.000] ***
Max	0.006	0.198	0.370	0.317	0.165	0.496	0.648	0.564
	[0.938]	[0.003] ***	[0.000] ***	[0.000] ***	[0.017] **	[0.000] ***	[0.000] ***	[0.000] ***
Observations	658	658	658	658	668	668	668	668
Adj. R-squared (Min)	0.036	0.356	0.31	0.390	0.115	0.558	0.451	0.651
Adj. R-squared (Med)	0.081	0.542	0.499	0.590	0.114	0.551	0.441	0.645
Adj. R-squared (Max)	0.098	0.631	0.591	0.677	0.121	0.549	0.438	0.640
No control variables	Yes	No	No	No	Yes	No	No	No
Kindergarten quality	No	Yes	No	No	No	Yes	No	No
Local context variables	No	No	Yes	No	No	No	Yes	No
All control variables	No	No	No	Yes	No	No	No	Yes

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Bootstrap standard error, p value in brackets regarding the null hypothesis that the estimated coefficients are equal to zero. All variables are standardized with mean 0 and standard deviation 1. Each line of the table refers to three different levels of housing prices per sq. meter: minimum, average and maximum. Each column refers to a different specification of the model in terms of control variables included among the regressors. Columns from 1 to 4 consider as dependent variables the raw price of housing, instead, columns from 5 to 8 consider as dependent variables the price of housing depurated from the neighborhood effect. Different blocks of the table consider different time spans of the housing prices, from 2011–2012 average up to 2016–2017 average, finally the last block refers to the average price over the entire period 2011–2017.

The segmentation between public and non-state kindergartens shows that only the latter generate a positive impact on house prices. In particular, the school proximity coefficient for the private kindergartens shows a significant and positive effect on housing price; instead, the same coefficient for public facilities is statistically equal to zero or even negative in some specifications. For example, if we consider as a dependent variable the mean value of housing prices registered in 2012–2013, we find that the private kindergartens' proximity effect goes from 0.143, when we exclude all control variables, to 0.540 when we add all controls. In the same specification, the public kindergartens' proximity effect goes from 0.227, when we exclude all control variables, to minus 0.089 when we add all controls. Our results show similar patterns in the case of other specifications.

The plausible interpretation is that public schools have a more homogeneous distribution on the territory; on the contrary, private schools can have an asymmetrical dislocation. Therefore, private schools/kindergartens generate a greater capitalization of real estate to the public schools/kindergartens that present a more uniform distribution.

In other words, if the kindergartens were all equidistant from the centroid of the micro-zone, the capitalisation effect could disappear. On the contrary, there is a capitalisation effect when the kindergartens are more concentrated in some areas with respect to other ones. The capitalisation effect seems to depend on private kindergartens that do not act like public institutions. The latter are located mainly in the same place as other types of educational institutes.

Based on the discussion above, the introduction in our analysis of the distinction between public and private kindergarten allows us to observe how the degree of capitalisation of kindergarten proximity in housing price depends mainly on non-state kindergartens' distance. In other words, house prices decrease as the distance to private kindergarten increases.

7. Conclusions

The paper aimed to investigate the impact of kindergarten proximity on housing market prices in Italy. In more detail, we focused on the eleven major cities in the country. Although several empirical studies investigate the capitalization of the quality and proximity of schools in the housing market, no research has, so far, focused on the Italian context.

Therefore, this paper has started filling this gap by estimating the impact of kindergarten proximity on housing prices. To this end, we employed a hedonic property price model, exploiting the panel dimension of the Italian dataset to control for endogeneity. It has then been investigated whether non-state kindergartens' presence generates a different impact than state kindergarten proximity on the market price of houses. Empirical results have shown that homebuyers do consider the proximity to kindergartens in their home purchase decision. The main results confirm the capitalization of the house to the kindergarten proximity. In other words, the school proximity coefficient estimates suggest that, overall, close location to kindergarten has a significant and positive effect on housing price.

Moreover, findings have shown that non-state kindergarten is the main determinant of the capitalization of kindergarten proximity in housing price. These original results can be interpreted as evidence of the higher utility that non-state kindergartens provide to households with respect to state institutions. Our results, in fact, show that public schools have a more homogeneous distribution on the territory; on the contrary, private schools can have an asymmetrical dislocation, and they are present in any location where it is deemed necessary to provide this facility. Therefore, the unequal presence on the territory of private kindergartens leads to greater capitalization of real estate with respect to the public kindergartens that present a more uniform distribution.

To conclude, given this positive relationship between private kindergarten proximity and housing market price, our findings could be useful in letting real estate developers and urban planners decide where to locate kindergartens to develop a city more homogeneously. Our results could also support investors in valuing the education facilities in the investment return and families in the buying of property.

Finally, the crucial caveat to be highlighted descends from: (i) the limited number of Italian Municipalities even if they present homogeneous characteristics and (ii) the nature of data employed that do not allow us to understand the different effects of kindergarten proximity between households with children and those without children. Thus, further research on this topic could be based on larger and more detailed datasets to go beyond the limitations of this current work.

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Appendix A

Table A1. Description of variables.

Variable	Description
Price per m^2 (min)	Min house value simple avg 2011–2014
Price per m^2 (max)	Max house value simple avg 2011–2014
Kindergartens	Total number of kindergartens at micro-zone level
Non-state kindergartens	% non-state kindergartens at micro-zone level
Kindergarten Distance	Average distance from the center of the micro-zone to the kindergartens (km)
Public kindergarten Distance	Average distance from the center of the micro-zone to the public kindergartens (km)
Non-state Kindergarten Distance	Average distance from the center of the micro-zone to the non-state kindergartens (km)
Quality of kindergarten	
Waiting list	Pupils on waiting list (Pupils on waiting list/Pupils)
Average class size	Average number of pupils per classroom (Pupils/Classrooms)
Schooling time 25	Ratio of pupils attending kindergarten 25 h per week with respect to the pupils
Schooling time 40	Ratio of pupils attending kindergarten 40 h per week with respect to the pupils
Foreign pupils	% of Foreign Pupils (Foreign Pupils /Pupils)
Foreign pupils born in Italy	% of Foreign Pupils born in Italy (Foreign Pupils born in Italy/Pupils)
Foreign pupils born in Italy 2	% of Foreign Pupils born in Italy (Foreign Pupils born in Italy/Foreign Pupils)
Pupils with disabilities	% of Pupils with Disabilities (Pupils with Disabilities/Pupils)
Disabled assistant	Ratio of Disabled Assistant (Disabled Assistant/Pupils with Disabilities)
Antemeridian sections	% of Antemeridian Sections (Antemeridian Sections/Sections)
Antemeridian sections 2	Kindergartens that have only antemeridian sections
Playgrounds per pupil	Square meters per pupil of covered and uncovered playgrounds
Playschool sections	Kindergartens with playschool sections
Canteen service	Kindergartens with canteen service
Bus service	Kindergartens with bus service
Preschool service	Ratio of pupils using preschool service with respect to the pupils
Postschool service	Ratio of pupils using postschool service with respect to the pupils
Saturday sections	% of sections operating on Saturday (sections operating on Saturday /sections)
Saturday	Kindergartens with sections operating on Saturday
Local context variable at municipal level	
Population	Population at 31 December 2010
Population 0–14	% of population 0–14-year-old with respect to the population-year 2010
Population $\geq$ 65	% of $\geq$ population 65-year-old with respect to the population-year 2010
Foreign population	% of foreign population-year 2010
Household members	Number of household members-year 2010
Households	Ratio of households with respect to the population-year 2010
Cohabitations	ratio of cohabitations with respect to the population-year 2010
Commuters	Numbers of Commuters-year 2009
Municipality coastal	1 for Municipality coastal, 0 otherwise
Altitude	Level: 1 (low)—5 (high)

Table A2. Descriptive statistics of variables.

Name of Variable	Public Kindergartens					Non-State Kindergartens				
	Obs.	**Mean**	**Std. Dev**	**Min**	**Max**	**Obs.**	**Mean**	**Std. Dev**	**Min**	**Max**
Quality of kindergarten										
Waiting list	668	0.045	0.036	0.002	0.198	668	0.015	0.015	0	0.0314
Average class size	668	22.809	1.282	19.941	25.31	668	21.891	1.947	17.135	26.245
Schooling time 25	668	0.186	0.213	0.001	0.845	668	0.213	0.162	0.004	0.734
Schooling time 40	668	0.815	0.213	0.155	1	668	0.788	0.162	0.268	0.996
Foreign pupils	668	0.12	0.075	0.009	0.426	668	0.046	0.021	0.007	0.137
Foreign pupils born in Italy	668	0.095	0.063	0.005	0.35	668	0.031	0.016	0.005	0.117
Foreign pupils born in Italy 2	668	0.063	0.2	0.126	0.803	668	0.369	0.145	0.049	0.78
Pupils with disabilities	668	0.023	0.006	0.007	0.047	668	0.005	0.003	0.001	0.031
Disabled assistant	668	0.116	0.113	0.004	0.464	668	0.032	0.044	0	0.493
Antemeridian sections	668	0.175	0.214	0	0.832	668	0.154	0.203	0	0.948
Antemeridian Sections 2	668	0.344	0.289	0	0.938	668	0.193	0.22	0	0.861
Playgrounds per pupil	668	2.253	0.618	715	4.218	668	2.841	0.216	0	0,782
Playschool sections	668	0.033	0.043	0	0.244	668	0.18	0.091	0.019	0.657
Canteen service	668	0.91	0.183	0.229	1	668	0.966	0.076	0.515	1
Bus service	668	0.178	0.146	0	0.95	668	0.103	0.074	0	0.574
Preschool service	668	0.276	0.269	0.004	0.944	668	0.641	0.179	0.145	0.912
Postschool service	668	0.216	0.291	0	0.976	668	0.546	0.162	0.124	0.94
Saturday sections	668	0.001	0.004	0	0.062	668	0.199	0.241	0	0.948
Saturday	668	0.003	0.007	0	0.938	668	0.242	0.253	0	0.96

Table A3. Control variables' estimate results for 2012–2013.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$price_{ijt}$				$price_{ijt} - \hat{\theta}_{ij}$			
Public Kindergarten Proximity	0.301	−0.046	−0.022	−0.110	0.227	−0.167	−0.097	−0.089
	[0.000] ***	[0.478]	[0.660]	[0.065] *	[0.000] ***	[0.005] ***	[0.056] *	[0.095] *
Non-State Kindergarten	−0.008	0.117	0.321	0.234	0.143	0.468	0.632	0.540
	[0.913]	[0.053] *	[0.000] ***	[0.000] ***	[0.041] **	[0.000] ***	[0.000] ***	[0.000] ***
Quality of kindergarten								
Average class size		−0.218		−0.560		−0.0661		−0.0821
		[0.019] **		[0.000] ***		[0.433]		[0.401]
Schooling time 25		18.85		22.68		16.19		11.77
		[0.148]		[0.084] *		[0.127]		[0.149]
Schooling time 40		16.78		21.08		14.27		10.99
		[0.198]		[0.107]		[0.181]		[0.178]
Foreign pupils		1.049		0.402		1.225		0.193
		[0.064] *		[0.383]		[0.010] ***		[0.558]
Foreign Pupils born in Italy		−1.488		−0.799		−1.328		−0.300
		[0.007] ***		[0.069] *		[0.004] ***		[0.356]
Foreign Pupils born in Italy 2		0.735		−0.458		0.731		−0.122
		[0.000] ***		[0.001] ***		[0.000] ***		[0.378]
Pupils with disabilities		−0.179		−0.201		−0.187		−0.141
		[0.003] ***		[0.002] ***		[0.000] ***		[0.013] **
Waiting List		−0.0709		0.0675		0.193		−0.0279
		[0.111]		[0.269]		[0.000] ***		[0.643]
Disabled assistant		0.217		0.0538		0.240		0.0155
		[0.004] ***		[0.532]		[0.000] ***		[0.843]
Playgrounds per pupil		0.142		−0.150		0.0501		−0.165
		[0.061] *		[0.068] *		[0.535]		[0.019] **
Antemeridian sections		−0.109		0.00833		−0.645		0.705
		[0.827]		[0.987]		[0.106]		[0.145]
Saturday		−1.829		−1.062		−0.941		−0.452
		[0.002] ***		[0.044] **		[0.003] ***		[0.128]
Sections Saturday		1.302		1.014		0.754		0.517
		[0.015] **		[0.050] **		[0.003] ***		[0.060] *
Playschool sections		−0.0328		−0.0729		−0.100		−0.0766
		[0.421]		[0.232]		[0.005] ***		[0.040] **
Antemeridian sections		−0.908		−1.615		0.0641		−1.383
		[0.000] ***		[0.000] ***		[0.764]		[0.000] ***
Canteen service		0.689		0.444		0.797		0.720
		[0.000] ***		[0.043] **		[0.000] ***		[0.000] ***
Bus service		0.0191		−0.0820		−0.00506		−0.210
		[0.774]		[0.213]		[0.937]		[0.001] ***
Preschool service		−0.121		−0.247		−0.165		−0.252
		[0.290]		[0.175]		[0.095] *		[0.036] **
Postschool service		0.195		−0.226		0.0480		−0.128
		[0.094] *		[0.271]		[0.643]		[0.442]

Table A3. *Cont.*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$price_{ijt}$				$price_{ijt} - \hat{\theta}_{ij}$			
Local context variables								
Population			1.940	0.713			3.616	4.644
			[0.000] ***	[0.703]			[0.000] ***	[0.010] ***
Population 0–14			7.388	4.806			0.939	0.570
			[0.000] ***	[0.269]			[0.409]	[0.891]
Population≥ 65			14.61	10.74			1.769	0.594
			[0.000] ***	[0.168]			[0.406]	[0.936]
Foreign population			−7.300	−4.179			−5.188	−6.288
			[0.000] ***	[0.402]			[0.000] ***	[0.186]
Cohabitations			−0.242	0.0156			−0.454	−0.594
			[0.015] **	[0.967]			[0.000] ***	[0.094] *
Households			5.587	5.040			−10.58	−15.78
			[0.000] ***	[0.254]			[0.000] ***	[0.001] ***
Household members			8.402	6.869			−11.59	−18.21
			[0.000] ***	[0.246]			[0.000] ***	[0.006] ***
Commuters			0.771	1.295			0.574	1.210
			[0.000] ***	[0.084] *			[0.000] ***	[0.128]
Altitude			3.410	3.132			0.0634	0.0914
			[0.000] ***	[0.089] *			[0.906]	[0.958]
Municipality coastal			−5.321	−3.548			−4.321	−5.290
			[0.000] ***	[0.318]			[0.000] ***	[0.122]
Number of observations	658	658	658	658	668	668	668	668
Adj. R-squared	0.081	0.657	0.625	0.709	0.121	0.571	0.464	0.665

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ Bootstrap standard error, p value in brackets regarding the null hypothesis that the estimated coefficients are equal to zero. All variables are standardised with mean 0 and standard deviation 1. Each column refers to a different specification of the model in terms of control variables included among the regressors. Columns from 1 to 4 consider as dependent variables the raw price of housing, instead, columns from 5 to 8 consider as dependent variables the price of housing depurated from the neighborhood effect.

Notes

1. In the Italian education system, state schools are administered by the State, while non-state schools can be run by either private entity or local governments (Law 62/2000).
2. https://www1.agenziaentrate.gov.it/servizi/geopoi_omi/index.php The method of Koenker is based on the conditional median.
3. They use the geo-route command in Stata.
4. Municipalities are the lowest level of government in Italy.
5. Among the Municipalities with more than 250,000 inhabitants only Venice has been excluded from the analysis because of its lagoonal structure.
6. Osservatorio del Mercato Immobiliare (OMI), the official data repository on housing market prices managed by the National Fiscal Agency (Agenzia delle Entrate).
7. Table A2 in Appendix A reports the descriptive statistics distinguishing between public and non-state kindergartens variables.
8. All variables include in our analysis are standardized with mean zero and unitary standard deviation.
9. μ captures the degree of capitalization of kindergarten proximity on housing price.
10. Note: among the regressors in Equation (7), there is also a variable that defines the percentage of non-state kindergartens in a Municipality. For a sake of simplicity, it is not displayed explicitly in the model.
11. Proximity is measured as the inverse of distance. We use the inverse to interpret the coefficients' point estimates as the direct effect of proximity of kindergartens on housing prices.
12. Table A3 in the Appendix A contains the complete empirical results obtained when we consider as dependent variable the mean value of housing price during the period 2012–2013. We have chosen to focus on this period since it better explains the degree of capitalisation of kindergartens on housing prices with respect to other years.

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