

# KINDERGARTEN PROXIMITY AND THE HOUSING MARKET PRICE IN ITALY

Angela Bergantino, Antonella Biscione, Annunziata de Felice, Francesco Porcelli, Riccardo Zagaria

# **CESPIC WORKING PAPER** 2021/03

# Kindergarten Proximity and the Housing Market Price in Italy

Angela Stefania Bergantino Department of Economics, Management and Business Law, University of Bari Aldo Moro, Bari, Italy

Antonella Biscione Department of Bioeconomic Strategies in the European Union and in the Balkans CESPIC, Catholic University "Our Lady of Good Counsel", Tirana, Albania

> Annunziata de Felice Department of Law University of Bari Aldo Moro, Bari, Italy

> Francesco Porcelli Department of Law University of Bari Aldo Moro, Bari, Italy

#### Riccardo Zagaria Italian National Institute of Social Security

**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.

Keywords: house value, kindergarten, neighborhood, capitalization.

Jel Classification: I22, R3

#### **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). Also, 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. There is no research focusing on the relationship between accessibility to kindergartens and housing price in Italy to the best of our knowledge.

Therefore, this paper sheds some light on this debate, estimating the impact of kindergarten proximity on houses' price in the eleven major Italian Municipalities. 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<sup>1</sup> premises the effect of the kindergartens' proximity on houses' market price.

To estimate the impact of kindergarten proximity on housing market prices in the eleven major Italian Municipalities, we use various sources. Data on housing market price, covering the period 2004-2017, is 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 in the following way. Using data on the addresses of childcare

 $<sup>^{1}</sup>$  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).

institutions provided by the Ministry of Education, Universities and Research (MIUR), the geo-codes of the centre of the districts of interest are collected exploiting the OMI internet map<sup>2</sup> that shows the boundaries of the neighbourhoods (as identified by OMI) of Italian cities. Besides, 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).

This analysis's main findings show that proximity to kindergarten is capitalised into housing market price and confirm that close location to kindergarten has a significant and positive effect on housing price, causing their capitalisation. Also, the estimated coefficients are stable across all specifications with a weak increase in intensity over time. Finally, we find that adding the variables that capture the quality of schools mitigates the proximity effect.

Besides, 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.

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

For several years, the literature on schooling and house market prices has investigated the impact of school quality on housing price (Black, 1999; Downes and Zabel, 2002; Kane et al., 2003, 2006; Figlio and Lucas, 2004; Brasington and Donald, 2006; Clapp et al., 2008; Gibbons and Machin, 2008; Nguyen-Hoang and Yinger, 2011;

<sup>&</sup>lt;sup>2</sup> http://wwwt.agenziaentrate.gov.it/geopoi\_omi/index.php

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).

Conversely, few studies have explored the relationship between housing market prices and school proximity despite this factor may affect house values since the attractiveness of a house increases with the proximity to a school, in particular with school-aged children due to commuting and safety worries in the district (Huang and Hess, 2018).

In what follows, we expound 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. They are using data covering the period January 1990 and December 1991 on a sample of 4,300 single-detached and 116 primary schools. They 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.

Yet, 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 3,732 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, Chen (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.

Yet, 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 near to the house, and in particular, the results show that the prices decrease with distance from the coast.

Haung 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<sup>3</sup> (2005) on a sample of 1,075 residential property in Oshkosh, US, 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) apply both the hedonic price approach and the spatial econometric model to explore the relationship between

<sup>&</sup>lt;sup>3</sup> The method of Koenker is based on the conditional median.

housing price and educational resources from kindergarten to university level. Exploiting data on the Chinese house market during May 2012 for a sample of 6 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. In particular, 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 of on properties 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.

#### **3 Data collection and variables**

<sup>&</sup>lt;sup>4</sup> They use the geo-route command in Stata.

The data used for the empirical analysis refers to Italian Municipalities<sup>5</sup>. We focus our research on the eleven largest cities with more than 250,000 inhabitants where location choices and more relevant for households with school-aged children. We consider the following municipalities: Turin, Milan, Verona, Genoa, Bologna, Florence, Rome, Naples, Bari, Catania and Palermo<sup>6</sup>. Our dependent variable is the housing market price that equates to the average between the minimum and the maximum cost per square meter of residential real estate located in each micro-zone of the target Municipalities. Data on housing market prices are taken from OMI that provides several pieces of information on micro-zones. Under the OMI definition, these microzones 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 microzone, 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. 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. The source of the micro-zone geo-codes is the OMI internet map that shows the boundaries of the micro-zones of Italian cities.

Information on state and non-state kindergarten quality is taken from data collected by the MIUR for the school year 2010-2011. For each kindergarten, this data gives information on (i) pupils; (ii) teaching staff, and (iii) structure. The data contains

<sup>&</sup>lt;sup>5</sup> Municipalities are the lowest level of government in Italy

<sup>&</sup>lt;sup>6</sup> Among the Municipalities with more than 250,000 inhabitants only Venice has been excluded from the analysis because of its lagoonal structure.

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 provides information 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 this data, it is possible to 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 details 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. 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.

Finally, as control variables, we use municipal characteristics. This information is taken from two different datasets carried out by: (i) the Ministry of Interior (Ministero dell'Interno) and (ii) the National Institute of Statistics (ISTAT). Table A.1 in the Appendix contains the description of variables included to account for factors that could affect the housing prices. Table 1 reports descriptive statistics<sup>7</sup>.

Name of Variable	Obs.	Mean	Std. Dev	Min	Max
Price per m <sup>2</sup> (min)	668	2287.618	1150.026	769.167	8600
Price per m <sup>2</sup> (max)	668	3132.704	1521.486	1024.167	11600
Kindergarten	668	446.555	276.879	87	762
Non-state kindergartens	668	0.334	0.040	0.246	0.449
Kindergarten distance	668	17.066	35.382	5.120	889.318
Public kindergarten distance	668	26.221	63.532	7.252	1612.265
Non-state kindergarten distance	668	52.909	84.419	11.842	1983.296
Quality of kindergarten					
Waiting list	668	0.034	0.025	0.002	0.150
Average class size	668	22493	1468	18895	25598

Table 1. Descriptive statistics of variables

<sup>7</sup> Table A2. in Appendix reports the descriptive statistics distinguishing between public and non-state kindergartens variables.

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
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					
Population	668	1568872	1042831	263964	2761477
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

#### 4 Empirical strategy

The main purpose of this paper is to assess the impact of the proximity of kindergartens on housing prices. To this end, the empirical framework is based on the basic hedonic housing price model developed by Rosen (1974). Thus, the price at year t of the house in micro-zone (neighborhood) j of Municipality i is determined by our basic estimation model:

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

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

where  $H'_{ijt}$  is a matrix of house characteristics;  $M'_{it}$  is the matrix of municipal characteristics;  $Q'_{ijkt}$  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;  $\eta_t$  year effect;  $\theta_{ij}$  is the neighborhood effect; finally,  $\varepsilon_{ijt}$  is the error term. The coefficients  $\beta$ ,  $\lambda$ ,  $\delta$  and  $\mu$  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  $\mu$ <sup>8</sup>, 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 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:

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

The product of variables  $Q'_{ijkt}$  and  $D_{ijk}$  yields the matrix  $\Omega'_{ijt}$  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:

 $<sup>^{8}\,\</sup>mu$  captures the degree of capitalization of kindergarten proximity on housing price

$$price_{ijt} = \alpha + M'_{it}\lambda + \Omega'_{ijt}\delta + D_{ijk}\mu + \eta_t + \theta_{ij} + \varepsilon_{ijt}$$
(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 xgoes from 2011 up to 2017. As a result, the model in equation (3) becomes:

$$price_{ijt} = \alpha + M'_i \lambda + \Omega'_{ij} \delta + D_{ijk} \mu + \theta_{ij} + \varepsilon_{ij}$$
(4)

However, we cannot identify  $\theta_{ij}$  (neighborhood effect) separately from  $\varepsilon_{ij}$  (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  $\mu$ . To circumvent this lack of information we exploit the long time series of housing prices and we perform a twostage approach to compute correct estimates of  $\mu$ . In the first stage, we estimate the following model:

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

where  $\phi_{ijt}$  are the i.i.d error term and t go 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):

$$\overline{price}_{ijt} = M'_{it}\lambda + \Omega'_{ij}\delta + D_{ijk}\mu + \varepsilon_{ij}$$
(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 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<sup>9</sup>. Multiplying  $W_k \Omega'_{ij}$  with  $W_k D_{ijk}$  the equation (7) is expressed as:

$$\overline{price}_{ijt} = M'_{it}\lambda + \Omega'_{ij}\delta + D_{ijk}\mu + S_{ij}'\rho + P_{ij}\xi + \psi_{ij}$$
(8)

where  $\xi$  captures the effect of non-state kindergarten proximity on housing price.

#### **5** Empirical results

In our basic specification, we estimate each regression equation considering three dependent variables: the mean, maximum, and minimum housing price value. Moreover, the housing price is taken either in its original or depurated neighborhood effect estimated in the first stage regression. Besides, 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.

<sup>&</sup>lt;sup>9</sup> 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.

Table 2 reports only the proximity<sup>10</sup> findings. For the sake of readability, the coefficients of other variables employed are not displayed.

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 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.

<sup>&</sup>lt;sup>10</sup> Proximity is measured as the inverse of distance. We use the inverse in order to interpret the coefficients' point estimates as the direct effect of proximity of kindergartens on housing prices.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			× /			$t - \hat{\theta}_{ii}$	x=/
Kind			Housing P	rico 9011_9		l lj	
						0.273	0.219
							[0.000]***
							0.254
							[0.000]***
							0.258
							[0.000]***
							658
							0.542
							0.699
							0.742
	-	-				0.257	0.183
							[0.000]**
							0.202
							[0.000]***
							0.206
							[0.000]**
							658
							0.558
							0.677
							0.715
0.120					0.000	0.000	0.110
0.351					0 167	0 1 3 6	0.156
							[0.101]
							0.213
							[0.016]**
L ]							0.230
							[0.000]**
							398
							0.193
							0.391
							0.531 0.522
0.100					0.101	0.110	0.011
0.345					0.0973	0.107	0.0909
							[0.348]
							0.190
							[0.043]**
							0.230
							[0.003]**
							[0.003]*** 391
							0.196
							$0.196 \\ 0.290$
							0.290 0.443
0.113					0.415	0.400	0.440
0.351	0		• •		0.141	0.209	0.151
							[0.015]**
							0.200
							[0.000]**
							0.215
							[0.000]**
							658
							0.358
							0.553
0.128	0.443	0.396	0.583	0.104	0.547	0.581	0.643
\$7	N	NT.	NT.	37	۸T	NT.	<b>Ъ</b> Т
Yes	No	No	No	Yes	No	No	No
No	Yes	No	No	No	Yes	No	No
	$(1)$ $Kinde$ $0.352$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.359$ $[0.000]^{***}$ $668$ $0.124$ $0.127$ $0.129$ $Kinde$ $0.358$ $[0.000]^{***}$ $0.356$ $[0.000]^{***}$ $0.356$ $[0.000]^{***}$ $0.354$ $[0.000]^{***}$ $0.354$ $[0.000]^{***}$ $0.351$ $[0.000]^{***}$ $0.340$ $[0.000]^{***}$ $0.340$ $[0.000]^{***}$ $0.340$ $[0.000]^{***}$ $0.340$ $[0.000]^{***}$ $0.340$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.345$ $[0.000]^{***}$ $0.345$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.345$ $[0.000]^{***}$ $0.345$ $[0.000]^{***}$ $0.345$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.346$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$ $0.357$ $[0.000]^{***}$	(1) (2) prives in the second system of the second	$\begin{tabular}{ c c c c } (3) \\ \hline $price_{ijt}$ \\ \hline $Kindergarten Proximity vs$ $0.352 & 0.343 & 0.496$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.357 & 0.341 & 0.501$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.359 & 0.338 & 0.502$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 668 & 668 & 668$ \\ 0.124 & 0.467 & 0.429$ \\ 0.127 & 0.457 & 0.417 & 0.417$ \\ 0.129 & 0.448 & 0.408$ \\ \hline $Kindergarten Proximity vs$ $1$ \\ 0.356 & 0.338 & 0.493$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.356 & 0.338 & 0.498$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.354 & 0.335 & 0.500$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 668 & 668 & 668$ \\ 0.128 & 0.480 & 0.443 & 0.127 & 0.464 & 0.424$ \\ 0.125 & 0.451 & 0.410$ \\ \hline $Kindergarten Prox$ & 0.351 & 0.408 & 0.425$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.340 & 0.405 & 0.421$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.330 & 0.401 & 0.417$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.330 & 0.401 & 0.417$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.346 & 0.425 & 0.446$ \\ 0.123 & 0.544 & 0.459$ \\ 0.115 & 0.536 & 0.444$ \\ 0.109 & 0.529 & 0.432$ \\ \hline $Kindergarten Prox$ & 0.345 & 0.428 & 0.452$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.346 & 0.421 & 0.401$ \\ 10.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.346 & 0.425 & 0.446$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.335 & 0.345 & 0.433$ \\ 0.119 & 0.517 & 0.417$ \\ \hline $Kindergarten Prox$ & 0.351 & 0.345 & 0.486$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.365 & 0.345 & 0.493$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.357 & 0.343 & 0.493$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.367 & 0.345 & 0.493$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.357 & 0.345 & 0.491$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.357 & 0.345 & 0.493$ \\ [0.000]^{***} & [0.000]^{***} & [0.000]^{***} & 0.357 & 0.$	(1)         (2)         (3)         (4)           price <sub>ijt</sub> Kindergarten Proximity vs Housing P           0.352         0.343         0.496         0.497           [0.000]***         [0.000]***         [0.000]***         [0.000]***           0.357         0.341         0.501         0.501           [0.000]***         [0.000]***         [0.000]***         [0.000]***           0.359         0.338         0.502         0.503           [0.000]***         [0.000]***         [0.000]***         [0.000]***           668         668         668         668           0.124         0.467         0.417         0.602           0.127         0.457         0.417         0.602           0.129         0.448         0.403         0.493           [0.000]***         [0.000]***         [0.000]***         [0.000]***           0.356         0.338         0.493         0.493           [0.000]***         [0.000]***         [0.000]***         [0.000]***           0.354         0.335         0.500         0.495           [0.000]***         [0.000]***         [0.000]***         [0.000]*** <td< td=""><td><math display="block"> \begin{array}{ c c c c c } (3) (4) (5) \\ \hline price_{ijt} \\ \hline \\ </math></td><td><math display="block">\begin{array}{ c c c c c c c c c c c c c c c c c c c</math></td><td><math display="block"> \begin{array}{ c c c c c c c c c c c c c c c c c c c</math></td></td<>	$ \begin{array}{ c c c c c } (3) (4) (5) \\ \hline price_{ijt} \\ \hline \\ $	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$

Table 2. Estimation results. Proximity to kindergarten and house prices per square meter
Tuble 1. Estimation results, richning, to minuergarten and nouse prices per square meter

\*\*\*p<0.01, \*\*p<0.05, p< \*0.10.

Bootstrap standard error, p value in brackets. All variables are standardised.

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. 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.

Yet, we focus on each dependent variable. When we consider the mean value of housing price as the dependent variable, the estimated coefficients are stable across all specifications with a weak increase in intensity over time. When taking the minimum value of housing price as reference, the proximity effect is lower concerning the medium and maximum value. It decreases more and more over time, especially in the years 2016-2017. Therefore, we can observe a persistency effect, although it decreases over time.

On the contrary, the maximum value of housing price appears to be stronger than the other two values even if the magnitude of proximity kindergarten decreases during the years considered.

Adding the variables that capture the quality of schools, we find that these mitigate the proximity effect. It follows that although proximity plays a key role, other variables affect the housing market price. Tables A.3 in the Appendix 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. Several quality variables such as the presence of foreign pupils, people who take care of the disabled, canteen service, number of schools opened on Saturdays can positively impact housing market prices. All the considered variables impact on 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.

They are signals of quality to parents (Turnbull et al., 2017) that 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.

#### 6 Alternative estimations and robustness check

In what follows, we describe the results of the alternative estimations (Table 3). We have re-run the baseline specification dividing public and non-state kindergartens to investigate in more details the proximity impact on the housing price. Also, in this case, for readability reasons, the coefficients of other variables are not exhibited. The column sequence follows Table 2, 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 re	esults dividing between	Public and	l non-state kindergarten
------------------------------------	-------------------------	------------	--------------------------

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
VARIABLES		pri	ce <sub>ijt</sub>			$price_{ijt} - \hat{\theta}_{ij}$			
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	[0.000] 658	[0.000] 658	[0.000] 658	668	668	668	668	
R-squared (Min)	0.049	0.520	0.495	0.575	0.124	0.570	0.470	0.666	
R-squared (Mean)	0.045	0.520 0.672	0.435 0.647	0.734	0.124 0.127	0.570 0.566	0.470	0.663	
R-squared (Max)	0.095 0.112	0.072	0.690	$0.734 \\ 0.777$	0.127	0.560 0.562	0.461 0.454	0.659	
Public Kindergarten Proximity 2012-2013	0.114	0.715	0.030	0.111	0.143	0.002	0.404	0.009	
Min	0.231	-0.031	-0.001	-0.081	0.245	-0.155	-0.085	-0.076	
141111	0.231 [0.000]***				0.245	-0.155 [0.005]***			
M		[0.670]	[0.991]	[0.254]			[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	
R-squared (Min)	0.061	0.549	0.514	0.593	0.128	0.584	0.483	0.677	
R-squared (Mean)	0.085	0.663	0.629	0.712	0.127	0.574	0.467	0.669	
R-squared (Max)	0.093	0.699	0.667	0.751	0.125	0.565	0.455	0.661	
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	
Weah	[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	
max	[0.003]***		-0.192 [0.009]***	-0.270 [0.005]***			-0.204 [0.002]***	-0.175	
Non state Kindergarten Proximity 2014-2015	[0.003]***	[0.180]	[0.009]****	[0.005]****	[0.021]**	[0.013]**	[0.002]****	[0.008]	
	0.000	0.910	0.949	0.950	0.154	0 500	0.500	0 500	
Min	0.238	0.316	0.343	0.358	0.154	0.562	0.709	0.592	
Maaa	[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	
N.	[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	
R-squared (Min)	0.042	0.212	0.171	0.225	0.123	0.621	0.519	0.679	
R-squared (Mean)	0.125	0.413	0.368	0.432	0.115	0.614	0.505	0.672	
R-squared (Max)	0.173	0.542	0.500	0.565	0.109	0.608	0.495	0.666	

continue to the next page ...

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		pri	ce <sub>ijt</sub>			price <sub>i i</sub>	$\theta_t - \hat{\theta}_{ij}$	
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
R-squared (Min)	0.022	0.226	0.185	0.234	0.118	0.603	0.496	0.665
R-squared (Mean)	0.098	0.328	0.278	0.338	0.120	0.601	0.488	0.664
R-squared (Max)	0.182	0.476	0.428	0.491	0.120	0.599	0.482	0.662
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
R-squared (Min)	0.041	0.360	0.315	0.400	0.123	0.562	0.458	0.655
R-squared (Med)	0.087	0.547	0.505	0.595	0.126	0.558	0.449	0.652
R-squared (Max)	0.109	0.633	0.595	0.683	0.128	0.554	0.443	0.648
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

\*\*\*p<0.01, \*\*p<0.05, p< \*0.10.

Bootstrap standard error, P-Value in brackets. All variables are standardised.

This segmentation shows a crucial role of private kindergarten proximity. The findings highlight that non-state institutions' presence greatly impacts the capitalisation of kindergarten proximity in housing price concerning Public kindergartens. The school proximity coefficient for the private kindergartens shows a significant and positive effect on housing price. If we consider the mean value of housing price as the dependent variable, we find that private kindergartens' standard deviation shows a significant increase. In particular, during the two-year 2012-2013, the standard deviation pass from 0.143 when we introduce the proximity effect to 0.468 when we add the variables that capture schools' quality impact. Finally, introducing factors that account for the local kindergarten context, the standard deviation achieves a value equal to 0.632. Using the other two alternative dependent variables, the standard deviation of private kindergarten records the same trend. 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 Final remarks

The paper aimed to investigate the impact of kindergarten proximity on housing market prices in Italy. In particular, 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 results can be interpreted as evidence of the higher quality of non-state kindergartens with respect to state institutions. In particular, it seems that households perceive a higher quality of non-state kindergartens run by local governments.

Broadly speaking, 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 the limited number of Italian Municipalities even if they present homogeneous characteristics. Further research on this topic could be based on larger datasets to go beyond the limitations of this current work.

#### References

- Black, S. (1999). Do better schools matter? Parental valuation of elementary education. *Quarterly* Journal of Economics, 114(2):578–599.
- Bonilla-Mejìa, Lopez, E. and McMillen, D. (2019). House Prices and School Choice: Evidence from Chicago's Magnet Schools Proximity Lottery. *Journal of Regional Science*, 60(5): 33-56.
- Brasington, D. and Donald, R.H. (2006). Educational outcomes and house values: a test of the value added approach. *Journal of Regional Science*, 46(2): 245-268.
- Chen, Y. (2010). The influence of university on house pricing: a theoretical analysis of Zhejiang University. *Journal of Zhejiang Ocean University*, 27(3): 148–151.
- Chin, H. C. and Foong, K. W. (2006). Influence of School Accessibility on Housing Values. *Journal of Urban Planning and Development*, 132 (3): 120-129.
- Clapp, J. M., Nanda, A. and Ross, S. L. (2008). Which school attributes Matter? The influence of School District Performance and Demographic Composition on Property Values. *Journal of Urban Economics*, 63(2): 451-466.
- Cushing, B. J. (1984). capitalisation of interjurisdictional fiscal differentials: an alternative approach. Journal of Urban Economics , 15 (3): 317–326.
- Des Rosiers, F., Lagana, A. and Theriault, M. (2001). Size and Proximity Effects of Primary Schools on Surrounding House Values. *Journal of Property Research*, 18(2): 149-168.
- **Downes, T. A. and Zabel, J. E. (2002).** The impact of school characteristics on house prices: Chicago 1987–1991. *Journal of Urban Economics*, 52(1): 1–25.
- Fack, G. and Grenet, J. (2010). When do better schools raise housing Prices? Evidence form Paris pubic and private schools. *Journal of Public Economics*, 94(1): 59-77.
- Figlio, D. N. and Lucas, M. E. (2004). What's in a Grade? School Report Cards and the Housing Market. American Economic Review, 94(3): 591-604.
- Gibbons, S. and Machin, S. (2003). Valuing English primary schools. *Journal of Urban Economics*, 53(2): 197-219.
- Gibbons, S. and Machin, S. (2008). Valuing school quality, better transport, and lower crime: evidence from house prices. *Oxford Review of Economic Policy*, 24(1): 99-119.
- Gibbons, S., Silva, O. and Weinhardt, F. (2013). Everybody Needs Good Neighbours? Evidence from students' outcomes in England, *The Economic Journal*, 123 (571): 831-874.
- Glindro, E. T., Subhanij, T., Zhu, H. and Szeto, J. (2011). Determinants of House Prices in Nine Asia Pacific Economies. *International Journal of Central Banking*, 7(3): 163-204.
- Huang, P. and Hess, T. (2018). Impact of distance to school on housing price: Evidence from a quantile regression. *The Empirical Economics Letters*, 17(2):149–156.
- Kane, T. J., Staiger, D. O. and Samms, G. (2003). School Accountability Ratings and Housing values.
   In W. Gale and J.Pack (Eds.), Brookings-Wharton papers on urban affairs (pp.83-137).
   Washington, DC: Brookings Institution.

- Kane, T. J., Riegg, S. K. and Staiger, D.O. (2006). School Quality, Neighborhoods, and Housing Prices. American Law and Economics Review, 8: 183–212.
- Koenker, R. (2005). Quantile Regression, Cambridge University Press, New York, NY.
- Livy, M. R. (2017). The effect of local amenities on house price appreciation amid market shocks: The case of school quality. *Journal of Housing Price*, 36: 62-72.
- Machin, S. (2011). Houses and Schools: Valuation of School Quality through the Housing Market. Labour Economics, 18(6): 723-729.
- Metz, N. I.(2015). Effect of Distance to Schooling on Home Prices. *The Review of Regional Studies*, 45(2): 151-171.
- Nguyen-Hoang, P. and Yinger, J. (2011). The Capitalisation of School quality into House Values: A Review. *Journal of Housing Economics*, 20(1): 30-48.
- **Owusu-Edusei, K., Espey, M. and Lin, H. (2007).** Does close count? School proximity, school quality, and residential property values. *Journal of Agricultural and Applied Economics*, 39 (1): 211–221.
- Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. Journal of Political Economy, 82 (1): 34–55.
- Sah, V., Conroy, S.J. and Narwold, A. (2016). Estimating School Proximity Effects on Housing Prices: The Importance of Robust Spatial Controls in Hedonic Estimations. *The Journal of Real Estate Finance and Economics*, 53: 50-76.
- Theisen, T. and Emblem, AW (2018). House prices and proximity to kindergarten costs of distance and external effects?. *Journal of Property Research*, 35(4): 321-343.
- Towe, C. and Tra, CI (2019). Hedonic Analysis and Time-Varying Capitalization: An Application Using School Quality. *Journal of Regional Science*, 59(2): 250-280.
- Turnbull, G.K. Zahirovoch-Herbert, V. and Zheng, M.(2017). Uncertain School Quality and House Prices: Theory and Empirical Evidence. *Journal of Real Esatate Finance and Economics*, 57(2): 167-191.
- Turnbull, G.K. and Zheng, M.(2019). A meta-Analysis of School Quality Capitalization in US House Prices. *Real Estate Economics*,
- Weber, S. and Péclat, M. (2017). A simple command to calculate travel distance and travel time. *Stata Journal*, 17(4): 962-971.
- Wen, H., Zhang, Y. and Zhang, L. (2014). Do educational facilities affect housing price? An empirical study in Hangzhou, China. *Habitat International*, 42: 155-163.
- Wen, H., Xiao, Y. and Zhang, L. (2017). School district, education quality, and housing price: Evidence from a natural experiment in Hangzhou, China. *Cities*, 66: 72-80.

Yi, I., Kim, E. and Choi, E. (2017). Linkage among School Performance Housing Prices, and Residential Mobility, *Sustainability*, 9, 1075: 1-18.

# APPENDIX

## Table A.1. Description of Variables

Variable	Description
Price per m <sup>2</sup> (min)	Min house value simple avg 2011-2014
Price per m <sup>2</sup> (max)	Max house value simple avg 2011-2014
Kindergartens	Total number of kindergartens at municipal level
Non-state kindergartens	% non-state kindergartens at municipal level
Kindergarten Distance	Average distance from the center of the micro-zone to the kindergartens
Public kindergarten Distance	Average distance from the center of the micro-zone to the public kindergartens
Non-state Kindergarten Distance	Average distance from the center of the micro-zone to the non-state kindergartens
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	
Population	Population at 31st December 2010
Population0-14	% of population 0-14-year-old with respect to the population -year 2010
Population≥ 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 A.2. Descriptive statistics of variables

		Publ	ic Kinderga	rtens		Non-state Kindergartens						
Name of Variable	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		

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables		pri	ce <sub>ijt</sub>	$price_{ijt} - \hat{\theta}_{ij}$				
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 A.3. Control variables estimate results for 2012-2013

continue to the next page ...

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Variables		price <sub>ijt</sub>					$_{ijt} - \hat{\theta}_{ij}$	$\hat{ heta}_{ij}$	
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]	
$Population \ge 65$			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	
R-squared	0.085	0.663	0.629	0.712	0.127	0.574	0.467	0.669	

\*\*\*p<0.01, \*\*p<0.05, p< \*0.10.

Bootstrap standard error, P-Value in brackets. All variables are standardised.