Research Proposal

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TITLE:

Growing demand for childcare; the effect of childcare centres on housing prices in England.

ABSTRACT

In English society, an increase in women's labour participation has created a growing demand for childcare, besides school. The heated up real estate market, with a rapid rise in housing prices over the decade, makes it harder and especially more expensive to buy the right house. This research analyses if childcare also affects housing prices in Brighton and Sunderland. With the use of hedonic price modelling, this research finds that the spatial distance between childcare centres and houses does influence the price of a sold house. The direction of the effect of distance to childcare depends on city context, housing type and price segments. The research found a positive effect of distance to childcare in the Sunderland, whilst the distance effect was negative in Brighton. Furthermore, the middle price segments and terraced housing in both cities also examined a positive effect of a nearer distance to childcare. Therefore, the results support the idea that distance to childcare is more important for home buyers with children.

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INTRODUCTION

MOTIVATION

The importance of public and non-public facilities as characteristics for house prices is commonly accepted. These amenities affect how homebuyers perceive a house's worth. However, the importance and the effects of certain specific characteristics are not always clear. Besides the increase in housing prices in the UK, another societal development is peaking, namely the increase of dual working parents. In a continuously growing number of households, it now is normal for both parents to work; this is mainly due to an increase in women's participation in the labour force and a shift in acceptance of mothers' participation in the labour market. However, this shift does not account for all countries (Cipollone, Patacchini and Vallanti, 2014). According to the Office of National Statistics (2019), 75% of the mothers of dependent children are working in the UK. In comparison to 2000, when just 66% of the mothers of dependent children were working, this proves a significant growth of women participating in the labour market. Consequently, this puts greater pressure on families with children to seek sufficient childcare, as the report by Working Families (2019) stated, almost 80 per cent of the families with children, consider childcare arrangements as key before applying for a new job or accepting a promotion.

The competition between family households for sufficient facilities for their kids potentially affects the house prices of family types of housing, in more childcare-dense regions or children's friendly areas. Furthermore, OECD (2019) showed that for both lone mothers and couples the gross childcare fees in England are the highest in Europe. Nevertheless, the English government does support families with subsidies, in the form of either free childcare or help with childcare costs for children below the age of 16. Therefore, only for couples do the net costs, after government support, remain the highest in Europe. Yet, English lone mother's childcare costs, after subsidies, still are the third most expensive in the European countries. In that sense, every reduction of costs to be made, for instance with lower transaction costs, will likely be considered more by parents. This suggests that parents might want to live as close to a childcare provider as possible. To reduce the expensive costs of childcare in the UK. Consequently, with the growing importance of childcare for parents, it becomes more relevant to look at the effect of these childcare facilities on house prices.

ACADEMIC RELEVANCE

There is general acceptance within the literature that amenities, either public or private and at a small or large distance from a house, affect the price paid for a house (Rosen, 1974). The effect of schools as amenities is a highly popular relationship researched in academic literature (Black, 1999; Gibbons & Machin, 2003; Cheshire & Sheppard, 2006). Yet, considering the spatial pattern of amenities has received less attention in the literature, although the location-specific characteristics of an amenity determine its effect (Nilsson, 2014). Furthermore, research on the effect of childcare on housing prices is also not abundant. To date, only the papers by Theisen and Emblem (2018) and Bregantino et al (2021) found that childcare does indeed affect housing prices. However, both research focussed on the housing markets in Norway and Italy respectively, thus leaving the English context unobserved. Most importantly, Theisen and Emblem found that the effect of childcare on housing prices was stronger than the effect of schools on housing prices. However, where the effect of school quality on housing prices in the English context is researched (Gibbons and Machin, 2003; Gibson (2008), it remains remarkable that the effect of childcare remains under-researched in an English context, and therefore focussing on this amenity, provides an opportunity to contribute to the literature debate.

RESEARCH PROBLEM STATEMENT

The focus of academic literature on the effect of childcare on housing prices is limited. Moreover, the changing population demographics and the increase of female participation in the workforce have put greater emphasis on childcare. In the English context, the effect of childcare on housing prices misses any prior research. Although, literature suspects an effect of these facilities on surrounding prices (Theisen and Emblem, 2018; Bergantino et al, 2021). In addition, the design of the English childcare system makes it one of the most expensive in Europe. Putting greater emphasis on the importance of the case study focus on the UK. Following OECD (2019) reports on childcare in Europe, the UK and Netherlands are the most expensive, because private childcare providers dominate the market for childcare and there are no fee regulations. In the context of growing housing prices, it is therefore important to focus on a possible relationship between them. Furthermore, housing prices consider the transaction price of a sold house, thus excluding the rental sector. Consequently, leading to the following main and sub-questions.

The main research question is:

- What is the effect of childcare centres on surrounding house prices in England?

The main research question is divided into three sub-questions:

- Based on existing literature, what is the expected effect of childcare centres on nearby house prices?

- In addition, what is the effect of distance on the spatial interaction between childcare and owner-occupied house prices?

- Is there a difference in effect observable between different towns, housing types and price segments?

THEORETICAL FRAMEWORK

THE ROLE OF CHILDCARE

Research into the importance of childcare is mainly done from the perspective of labour mobility of working mothers. In general, academic literature suggests that childcare enables the participation of parents, especially mothers, in the labour market (Morrissey, 2017). It is accepted that increasing childcare costs provide evidence of a lower probability of participation by women, the cost of childcare is a parameter for the likelihood of a mother's employment, both single and married (Connely, 1992; Connely & Kimmel, 2003). However, the effect of childcare varies between countries and societies. A key deterministic of childcare are the costs and the local fee regulations. It should therefore be considered, to what extent do parents and single mothers receive subsidies from governments? Besides the affordability of childcare, conveniently located childcare is also an important form of support for working mothers of young children (Kawabata, 2014). The accessibility is an incentive to work especially for mothers in low-income households (Del Boca, 2015). Sandstrom & Chaundry (2012) address that low-income working family, especially immigrants' parents, select childcare, when there are no relatives to take care of their kids, according to cost, location and availability of the provider. According to Vincent, Braun & Ball (2008), the costs determine which types of childcare providers are open and used by different social classes.

Literature suggests a positive effect of the proximity of childcare facilities on the mother's labour participation. However, a clear consensus on the best location for childcare facilities in respect of parents and the mother is missing. Most research emphasises proving the positive externalities of childcare close to home. Mulder and van Ham (2006) outlined three best-case scenarios for the location of childcare, respectively, very close to home, very close to work, and on the way from home to work. Yet, the focus on childcare near dwelling, as a measure of geographical access, outweighs the others, according to Mulder and van Ham for three reasons. First, the location very close to home is more stable than the work location. Second, including unemployed mothers in their analysis, made the workplace undefinable. Third, for couples with a less gendered division of childcare responsibilities, childcare near residence is most suitable, as it is within reach for both partners. Adding to the discussion on best location is the positive correlation found by Contreras, Puentes & David Bravo (2012) between having a day-care centre close to either their home or place of work when the centre's hours of operation match labour hours. While opening times depend on the pure focus on a childcare provider. Childcare providers can specialise in particular age, after- and preschool or a combination of them. Therefore, the location and availability are closely related but do indeed affect the choices of parents.

In addition, the research by Dussaillant (2016) puts the distance aspect in perspective of usage by mothers. Investigating the effect of the proximity of a childcare centre on the usage by mothers in Chili. Dussaillant constructed this research by looking into the relationship between the mother's employment and the attendance at childcare of the child. Whereas the distance to the nearest childcare facility relates to the mother's decision to send their children to that facility. Evidence was found in a variation in attendance rate of about 3 percentage points. Furthermore, Attanasio and Vera-Hernandez (2009) & Urzua and Veramendi (2011), find that enrolment and attendance to the nearest childcare centre are highly predictive. To conclude, the distance toward a childcare provider seems to have a positive effect on usage and attendance.

AMENITIES

General acceptance within literature addresses the importance of amenities for households' choices to move towards a certain area (Ding et al, 2010). International literature underlines different amenities affecting housing prices, such as the presence of parks and 'consumer city' amenities, such as restaurants, cinemas and theatres. From research, it has become clear that many housing characteristics and neighbourhood amenities have a measurable and statistically significant impact on house prices. To outline the entire field of research here will not serve the purpose of this paper. Therefore, the focus will be on how specifically educational facilities and the density of facilities add to housing prices as amenities.

SCHOOL AMAMENITIES AFFECT ON HOUSING PRICES

Research into the effects of amenities, like schools, receives sufficient attention. As addressed by Gibbons & Machin (2004) this has possibly to do with the journalistic value of the topic and the idea that schools are one of the main characteristics in determining where to live. Concerning the near similarity between schools and childcare centres, the focus of this part will shine on the effects of schools on housing prices. While the gap in research into childcare facilities in relation to housing prices, therefore, seems rather odd. It remains unclear why literature does not see childcare as a main characteristic for determining where to live. The concept of school is broad and academic literature on the relationship between schools and housing prices varies in what attributes of school are included (Black, 1999; Gibbons & Machin, 2003; Cheshire & Sheppard, 2006). Furthermore, measuring school attributes to housing price acquired in combination with other variables, such as crime (Dubin & Goodman, 1982) or demographics (Clapp, Nanda & Ross, 2008). Outlining the possibilities of researching the relationship between educational facilities and housing prices.

In literature, there is general acceptance of the impact of schools on housing prices ((Black, 1999; Gibbons & Machin, 2003; Cheshire & Sheppard, 2006). Yet, the right way of measuring the effects of schools varies. Dubin and Goodman (1982) estimated the impact of school characteristics and crime measures on housing prices in Baltimore. Including them as variables for neighbourhood characteristics in a bundle with structural housing characteristics, such as dwelling type. They showed how a unit increase in school quality affects the increase in house price by $2,253. While, Black (1999), examined the general relation between schools' quality and housing prices, from a parental perspective. Showing that parents are willing to pay 2.5 per cent, more for a 5 per cent increase in test scores. Both measures prove a positive effect on schools. For Britain, Gibbons and Machin (2003) were the first to fill the gap in valuing primary schools in England. The findings of that research showed that on average, a 10% improvement of the proportion of the target level age of 11, increases postcode sector house prices by 6.9%. Consequently, finding significant effects of schools on housing prices in the English context. Where Cheshire and Sheppard (2006) explored the variation between schools, either primary or secondary level, attributed to the quality of the schools, into the price of houses. According to Cheshire and Sheppard (2006, p. F401); 'This distance-related premium might be expected to be higher for primary schools since children younger than 10 or 11 are more likely to be taken to school by a parent, increasing the cost of distance'. The British education system assigns a primary and secondary school to each house, nonetheless, parents can freely request another school. Although, the mean average shows that between 1998 and 2000 less than 2.5% of the parents successfully appealed. The research summarised the quality of secondary schools and the stronger effect on the hedonic price of a home than primary school quality. While the popularity of the topic led to specifying the concept of school's quality or demographics. For instance, Clapp, Nanda & Ross (2008) examined, with the use of panel data, student test scores and the racial and ethnic composition of the student body in Connecticut, and found that demographic attributes weigh more than the changes in test scores for the price to pay for homes. Their analysis concluded that people base their judgements on easily available signals, instead of test scores, which are not transparent or simple. Nevertheless, what and how to determine the quality of schools is open for interpretation. Wen et al (2018) outline two methods found in literature, either focussing on input or output measures of quality like test scores or teacher salaries or using school ranking and other subjective measures.

Unlike other studies, Brasington & Haurin (2006) also implied spatial statistics as an identification strategy. Instead of the school's quality alone as a value-adding effect, they found that households consistently value a district's average proficiency test scores and expenditures. This brings an extra dimension to the view on the value of schools. By measuring spatial accessibility in means of transport, which focuses on distance, or proximity of education within a certain distance, including the ratio of schools within a district (Wen et al, 2018). Sah, Conroy and Narwold (2016), concentrated on different scenarios of the effect of school proximities, both negative and positive. Using spatial dummies concerning the distance in feet to schools, they created different scenarios. Noticing that the positive externalities outweigh the negative externalities in the first 500 feet and peak at a distance of 1500 feet. Ending the observation of the negative externalities after that distance. Negative externalities in the sense that schools are associated with the nuisance of more traffic, noise and light pollution. In addition, the elementary schools were split into private and public schools to see different effects. Concluding, there is a school proximity penalty for houses closer to school. The reason for this contradiction to other literature originates from the model or the context of San Diego where more parents use cars to bring kids to school. However, possible negative externalities require sufficient attention to give a clear overview of the situation.

CHILDCARE AMENITIES

Furthermore, looking explicitly into the location-specific aspect, empirical studies have shown that there is a positive relationship between the location of schools and housing prices (Metz; 2013; Sah, Conroy, and Narwold, 2016; Huang, 2018). Agarwal et al (2016) even noticed a decline in housing prices in Singapore when schools announced to relocate. However, research on children's day-care or even after-school care happens less often. To date, three empirical studies examined the effects of other childcare facilities than schools, specifically kindergarten. The most relevant, for this research, into the effect of childcare on housing prices, are Theisen and Emblem (2018) and Bergantino et al (2021). First, Theisen and Emblem examined the distance toward kindergarten as a local attribute for housing prices. Focusing specifically on one Norwegian town, Kristiansand. For the research, they reformed the bid-rent curve, instead of using the distance towards the central business district they used the distance to kindergarten. The results of this research suggest a stronger effect of kindergarten than schools. Namely, houses in a further distance to kindergarten had a lower price than housing closer to kindergarten. Second, even more relevant, is the research by Bergantino et al (2021) into the importance of the proximity of kindergartens on housing prices. They focussed on possible effects in eleven major Italian municipalities with the use of the hedonic property price model. However, for this research, the kindergartens were divided into two different types, public and private. This conceptualisation is an example of the nation-specific characteristic of children's care facilities. Considerable focus on a national design of childcare needs attention in the relationship between housing prices and childcare. Subsequently, they concluded that house buyers do indeed consider the proximity to kindergartens in their home purchase decision. Thus, the close location has a significant and positive effect on housing prices. Like the amenities a school brings to housing prices, it seems that these effects remain apparent in childcare centres. Although, proof from the English context is missing.

In addition, as discussed above, literature acknowledges that spatiality affects housing prices, whether in distance or density of amenities in the surrounding areas of housing. However, the access to basic 'public' facilities misses an equal distribution over space. To reflect the difference between areas and the effect of amenities is to consider spatial equity. Spatial equity addresses either the equal access to public facilities, measured in distance or cost or the equal distribution of facilities, concerning the needs and preferences of residents (Truelove, 1993). Because the spatial distribution of public and private facilities varies between regions, the effects of these facilities, as amenities on housing prices, will vary between regions. The effect of a childcare centre on housing prices, therefore, relates to the distribution of childcare facilities in the area. For instance, Truelove researched the spatial equity of day-care centres in the metropolitan area of Toronto. Measuring the spatial distribution of day-care centres and examining the different types of day-care to see whether equal distribution varies in type of carer. To see whether day-care experiences equal spatial access he examined the number of children with no day-care centres within specified distances. At first, observing good access as being within walking distance of about 1000 to 2000metres. This distance suggested that many families do not experience equal access to childcare centres. However, increasing the accessibility levels increased the number of children within a distance of childcare. Showing that the level of spatial equity is dependent on the method of measurement and the number of facilities in the area. Spatial equity is measured, most often, from an environmental perspective, Landry and Chakraborty (2009) noted in their research into the spatial distribution of tree coverages, that a significantly lower proportion of tree coverages is observed in neighbourhoods with low-income residents and renters. Thus, relating to the housing market, affecting the areas with a higher share of renters harder. Furthermore, urban planners see the spatial distribution of amenities as an important determinant of urban development and shaping spatial structure. For instance, Brueckner, Thisse and Zenou (1999) addressed that the spatial pattern of exogenous amenities within cities influences the relative location of different income groups. Nilsson (2014) who found that the open landscape, as an amenity, is valued higher in areas where density is high and undeveloped land is scarce provides an example of the effects of spatial distribution on housing prices. Thus, highlighting the location-specific effects due to the spatial distribution of amenities. To conclude, the level of effects by amenities is dependent on the accessibility of facilities in regions, which, in turn, is dependent on the distribution of these facilities in regions. Therefore, to reflect the effect of childcare on housing prices requires a focus on its distribution of it within different areas.

MEASURING HOUSE PRICE EFFECTS

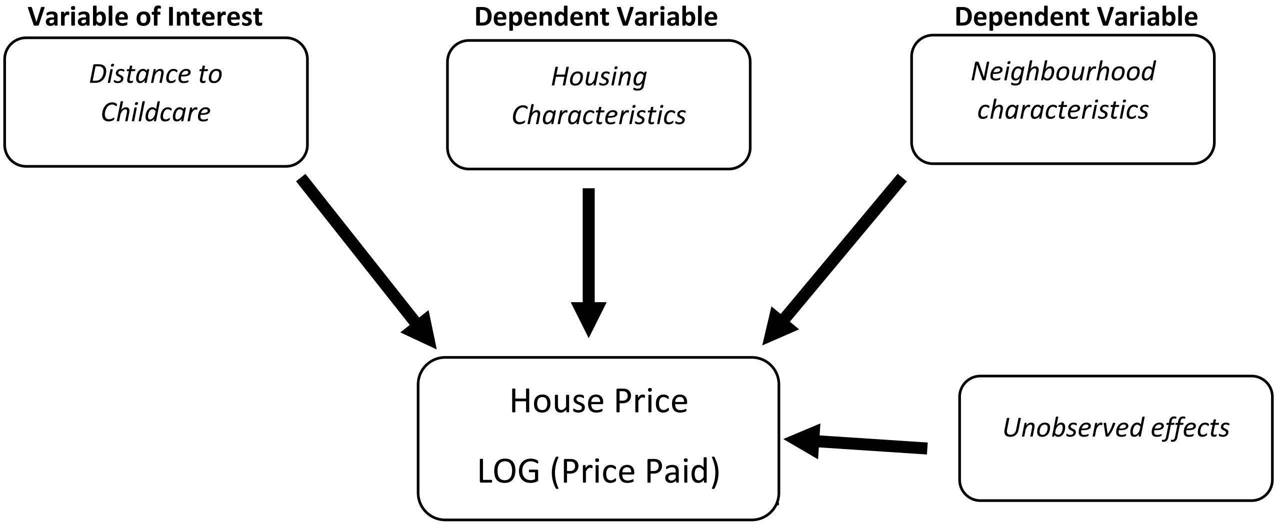
In research on housing prices, a widely used method is the hedonic price model by Rosen (1974). The model by Rosen takes housing as combined goods and creates an opportunity to disentangle house prices into implicit prices for different characteristics, either structural or locational. However, research on housing prices remains challenging. There is no clear base for selecting attributes for housing and local characteristics. Thus, how to specify the hedonic model and which variables to include will be critical in determining price estimates for individual characteristics. The focus is to outline some key characteristics to build a sufficient model.

At first, according to Nelson (1985), a key point of consideration is that the effect of adjacent land uses on house values varies by location. Therefore, location-specific characteristics can have different effects. Furthermore, academic literature has a general acceptance of the effect of demographics on housing prices (Case, Mayer, 1995). Demographics play a vital role in determining the start or end of a housing market cycle. As certain age groups, seek different types of housing, due to their income and lifestyle. Therefore, a large share in certain age groups pushes the demand for the type of housing related to these groups. For instance, families seek family housing. Furthermore, Case & Mayer (1995) mention the effect of manufacturing employment rates, distance to downtown, new construction and aggregate school enrolments on housing prices. This set of amenities affecting housing prices is calculated from an equilibrium equation, which instead of having house prices as a key determinant focuses on the price of housing in a jurisdiction. While, Agnew & Lyons (2018), do use the hedonic price modelling for both month rent and sale price, to see whether the effects are different between the two sectors in the housing market. They mention that employment access is outstandingly one of the most valuable amenities for cities. In their research on the effect of employment on housing prices, they focussed on the effect of employers from the Foreign Direct Investment in Ireland. Concluding that 1000 extra jobs after 1-2 years lead to a price effect of at least 2%. Although, there is some spatial variation. Additionally, a positive relationship was observed between the effect of green spaces and parks on housing prices (Daams, Sijtsma, Van der Vlist., 2016; Park et al, 2017). In the Dutch context, Daams, Sijtsma and van der Vlist showed, through the combination of spatiality and the hedonic price method, that the perceived attractiveness of natural spaces has a 16% price effect within 0.5 kilometres and decreases to 1.6% for properties 7 kilometres away from the park. Park et al showed how the neighbourhood environment, conceptualised as the accessibility of parks, decreases the housing prices when the distance toward the park increases. With the hedonic price method, they also noticed that the greater walking accessibility to the park increases the value of the park in housing prices.

Furthermore, important to reflect on in analysing house prices is the possibility of negative externalities. As Pope & Pope (2015) addressed, to what extent do local benefits of accessibility outweigh the costs of negative externalities. In the case of childcare centres, academic literature is yet to address the negative externalities of childcare locations. A certain provider or amenity in proximity will be beneficial when the dominance of positive externalities relatively outweighs the negative ones, created by the amenity itself. However, as, Sah, Conroy and Narwold (2016) mentioned, the negative externalities of schools are found in additional peak traffic or nuisance. Overall, research on the relationship between childcare facilities and housing prices in the English context is missing. The literature expects a positive effect of childcare on housing prices in the proximity of childcare centres. The distance toward a childcare provider is the determinant in measuring the effect. However, each country organises its childcare differently, which can change the level of effect between countries. Some national governments, like the English parliament, provide subsidies to parents for the cost of childcare and partly provide free childcare, possibly affecting the relation between housing prices and the location of childcare, as the subsidies lower the initial cost of childcare for parents. Nevertheless, the distance aspect creates the cost of transportation to a childcare centre. While the spatial distribution of childcare providers can also affect the strength of the effect childcare has on housing prices.

Conceptual Model

Figure 1: conceptual model



HYPOTHESES

Based on established findings, amenities affect the housing prices and the level of effect is context- and amenity specific. The effect of distance to childcare centres has been proven in Norway and Italy (Theisen and Emblem, 2018; Bergantino et al, 2021). Reflecting to our first research question on the expected effect, literature suggests that this also accounts for England. Hence, a positive relationship between distance to childcare and prices of owner-occupied house prices. However, as the research question specifies on the English context, it should be noted that the English childcare system is heavenly privatised, and therefore differs to prior research. This could potentially affect the relationship between housing types and distance to childcare centres, because of the high prices for childcare. While, literature also expects a negative effect on living very close, due to noise pollution or traffic. Besides, the effect of childcare is most likely to only be relevant for families, and thus we expected that the relation predominantly accounts for family-type of accommodation. Therefore, the expectations, in consideration of the literature and the context, lead to the following hypotheses that are examined in the quantitative part of the research;

Hypothesis 1: an increase in distance to a childcare centre has a negative effect on the price of a sold house

Hypothesis 2: houses in the nearest proximity to childcare centres experience a negative externality

Hypothesis 3: the effect of the distance to childcare providers differs among housing types and prices, more specifically, the distance aspect will have a positive effect for family type of housings, such as semi-detached and terraced, and negative effect for flats or detached houses. While the distance effect of childcare is positive for the middle price segment in both cities., and thus negative for lower and higher price segments.

METHODOLOGY & DATA

DATASET

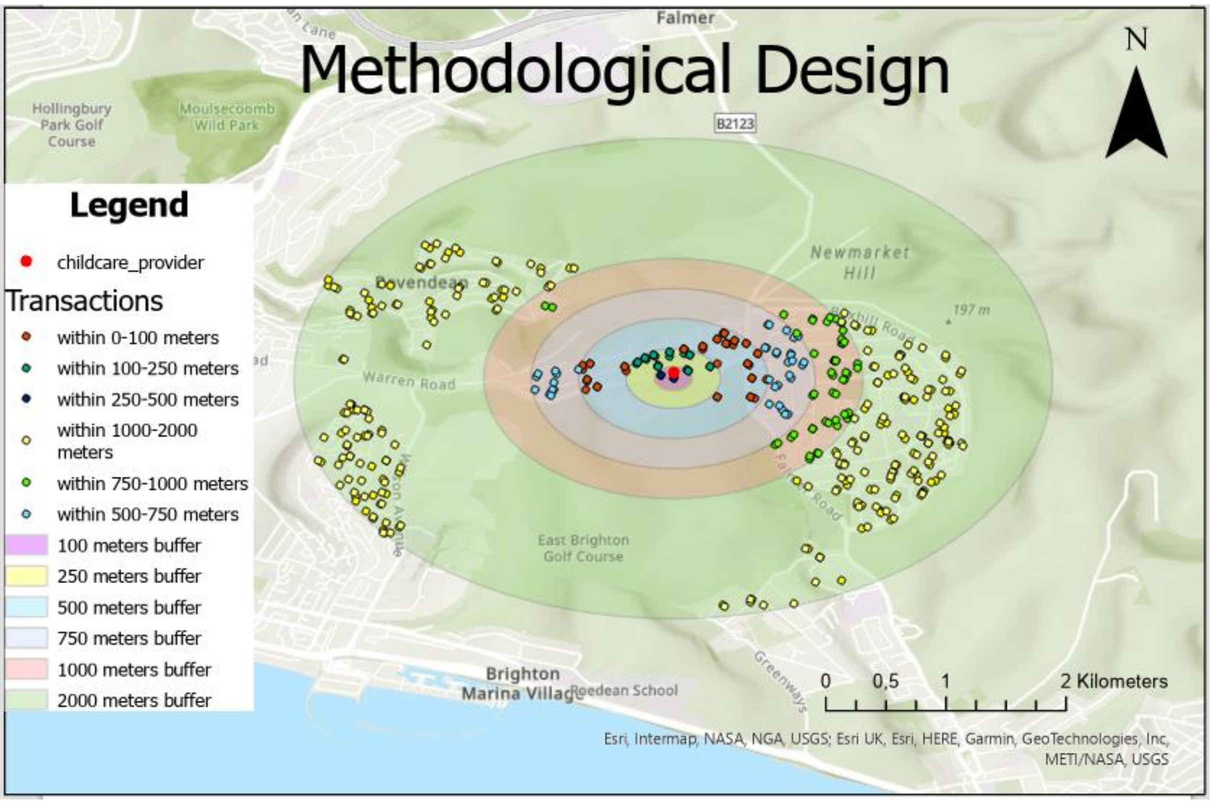
To analyse housing prices in the English context, required the extraction of data from the HM Land Registry. HM Land Registry includes property sales for England and Wales since 1995. However, the data is relatively limited, as the property characteristics include the address, paid price, date of transaction, building type, whether the property is free- or leasehold, and whether the house is newly built or not. Some key features are missing in this dataset, like the number of floors, bedrooms and the square metres of the house. Furthermore, the data of childcare providers are also publicly available from Ofsted (Government UK, 2021). The childcare providers included in the research come from the recent inspection reports of August 2020 on childcares done by Ofsted. This dataset contains the setting name, address, registration date and the number of registered places. The UK classifies childcare as domestic and non-domestic. Overall, it derives roughly three types of childcare, group-based, school-based and childminders (Department for Education, 2021). Where group- and school-based providers are classified as non-domestic, which entails they take care of children in premises that are not someone's home, and childminders as domestic. This research includes non-domestic childcare providers, which is in line with the research by Theisen and Emblem (2018) and Bergantino et al (2021). Firstly, because childcare on non-domestic premises offered 82% of all childcare places, whilst childminders and domestic childcare consider 18% of all places (Ofsted, 2021). Secondly, childminders work from home, these locations could be highly correlated with housing price.

This paper aims on the towns of Brighton and Hove, and Sunderland. These cities were selected because they are quite similar in population size and physical location, besides, these cities were chosen to illustrate any broad regional differences in property markets (Gabbins, Machin; 2003). In size, Brighton and Hove have approximately 292.000 inhabitants and Sunderland accounts for about 275.000 (ONS, 2021). Therefore, these towns are roughly about the same size, making them suitable for comparison. Furthermore, these towns are both located at the sea, however, in an economic sense, they are also each other's opposite. Brighton is located in the richer Southeast of England and is known for its tourism. While Sunderland is in one of the most deprived areas in the North. In addition, Sunderland is a dockyard town and used to be one of the largest port and trading towns in the UK. The difference between both cities enlightens, the so-called, North-South divide existing within England (Green, 1987). Where in modern times, the South has become richer and the North remains less affluent. The selection can also illustrate how certain city characteristics might affect the relationship with housing prices. For instance, tourism could also have a disturbing effect on the relationship with childcare, when a share of housing is bought as a second home or to let, it might become less relevant to control for childcare's location.

In addition, focussing on the key determinant of interest of this study, estimates suggest there are about 67.900 childcare and early years providers in England, while there are 88 non-domestic childcare providers in Brighton and Hove. This is more than twice the number of Sunderland that counts 33 non-domestic childcare providers. Although the cities are about the same size, they do not have the same level of childcare availability. The difference in spatial pattern between them ensures that the research controls for the effect of accessibility to childcare. If an amenity is accessible for most buyers, it might have less impact on house prices, because the benefit of being close diminishes. Thus, the cities selected in this paper capture a wealthy and a deprived city, with different levels of childcare accessibility, which provides a better overview for generalisation in England and data of comparison for analysing the effect of childcare on housing prices.

The research focuses on the spatial distance between houses and childcare providers. Therefore, the location and the distance between the childcare centres and housing were mapped with ArcGis. This program makes it possible to create maps and measure the distance between houses and childcare centres. The geocoding tool converts the address of an individual housing and childcare centre into geographic coordinates. Each house transaction contains information about its location by its street name, house number, postcode and town. The geocoding tool connects this information with its geographical code that identifies a point or area on the surface of the earth. This is also done for each childcare centre. However, not all childcare locations could be successfully receive a geocode references. Therefore, Brighton only has 87 childcare providers and Sunderland 31 providers in this research. These geocodes are then put into a map like, figure 2. Figure 2 reflects the methodological build-up of the distance buffers for an individual childcare provider in Brighton. However, this method is repeated for each childcare provider in both towns. Besides, the figure does not show buffers interfering with each other, which does happen when childcare providers are more densely located. The red dot in the middle reflects a childcare provider's location, in this case in Brighton. Next, the buffer tool creates spatial distance rings to find which houses are within a specific distance. ArcGis Pro provides two method parameters for the creation of buffers, Planar or Geodesic. This research conducts a geodesic method, because it suits with specifying a Buffer Distance value in linear units, such as meters. All other smaller dots reflect the location of individual house transactions within a specific distance buffer. This process is in line with Sah, Conroy and Narwold (2016) who addressed the limitations of most research into schools' proximity by not using the street address. The benefits of a street address are that the main entrance is usually located on the street address and therefore housing distance to the street address represents the true distance toward a childcare centre. By addressing a zero or one to house in a specific distance towards childcare providers, in combination with Stata, this spatial data was converted to dummies to be analysed with OLS.

Figure 2: Display of distance buffers in Brighton



DATASET CLEANING

The focus of the research will be on two different English cities, namely Brighton (including Hove) and Sunderland. The research period of interest starts after the financial housing crisis in 2010 up until the end of 2020, the total extracted dataset consists of 76.560. Nonetheless, the dataset subtracted from the HM land registry consists of errors; some duplicates existed within the dataset. To improve the quality of the data, confiscating these 229 duplicate observations, consisted of the same address, date and price paid. Second, the dependent variable, the transaction price is transformed into a logarithmic function of the price paid. To control for the OLS assumptions, I dropped outliers at a 1% level, to create a more normally distributed dependent variable. Lastly, removing observations with missing values for control variables. Consequently, the dataset used consists of 74.710 observations of which 23.164 are located in Sunderland and 51.546 in Brighton. Due to mismatch of address and geocoding referencing only 87 childcare providers for Brighton and 31 providers for Sunderland are included.

CONCEPTUALISATION

The key variable of interest in this research is the distance from a childcare provider. As discussed above buffers were created to capture the distance intervals for individual housing transactions with the childcare provider. The distance toward the childcare providers relates to Sah, Conroy and

Narwold (2016), who focussed on school proximity effects on feet level of 500, 1500 & 3000ft. Instead of focussing on the ratio of childcare facilities in the neighbourhood areas. Transforming the distance used by Sah, Conroy and Narwold to metres, these buffers are set at about 150, 500 and 900 metres. To give a better overview of the positive or negative externalities of childcare, more buffers were created. This is also similar to Theisen and Emblem (2018), who focussed on kindergarten in Norway; however, they included more categories and further distance. The spatial distance buffers in this research are grouped in <100, 100-250, 250-500, 500-750, 750-1000 & 1000-2000m and beyond 2000 - 5000, + 5000 metre. To account for, a childcare provider which is as close as possible to an individual's house (Mulder and van Ham, 2006). In the likelihood, that these homeowners have kids and consider childcare, in practice they still have the freedom of using other childcare facilities. Nevertheless, this research considers parents choosing childcare closest to their houses, as is addressed in the literature. Consequently, the spatial distance buffers show which part of the housing sold is within a walking distance of childcare providers (Truelove, 1993).

Due to the relatively high number of childcare providers, especially in Brighton, buffers overlap each other, and a transaction could be located in multiple buffers. To note, this is also the reason a map is not included for all buffers within a city. To prevent using transactions in multiple buffers, a transaction is selected only once, in the first buffer it falls in. Although some literature on the effect of schools, looked at the quality of schools (Black; 1999), the quality of a childcare provider is not included in this research. Since Ofsted regulates and controls childcare regularly by inspection, the difference between childcare providers is limited. Moreover, the quality of an individual childcare provider is in general hard to measure, in comparison to schools, as kids do not take exams at a childcare provider. Furthermore, the inspection rapports by Ofsted only control all types of childcare on their overall effectiveness, with either outstanding or good, which address the minimal differences between childcare providers. Nonetheless, the size of a childcare location is a good alternative for quality (Theisen and Emblem; 2018). There is more variety between childcares regarding the total number of places available. Besides, the registration date is included as characteristics for a childcare provider, to control for the fact a provider was already in business or not. While, a certain reputation of a childcare provider might also play a role.

In consideration of Truelove (1993), table one was established to examine the distribution of the housing transactions among the distance buffers, for each city. Table one, shows clearly that houses in Brighton are relatively close to a childcare provider. More than half of the transactions are within 500 meters of childcare. Considering that nearly all homeowners can access a childcare provider within walking distance, the spatial effect of distance might become irrelevant for house-buyers in Brighton. Especially, when we look at the distribution of childcare in Sunderland, here the largest part of the transactions is beyond 1000 meters. Further acknowledging the difference between both towns. Regarding both cities combined, the sprawl of houses concerning the childcare providers seems more evenly distributed. This possibly shows that the spatial distribution does indeed influence the childcare effect.

Table 1: Distribution Observations over Cities

	Distance to childcare								
	0-100m	100-250m	250-500m	500-750m	750-1000m	1000-2000m	2000-5000m	>5000m	Total
BRIGHTON	2,725	11,388	15,063	6,197	13,598	2,453	122	0	51,546
	5.3%	22.1%	29.2%	12.0%	26.4%	4.8%	0.2%	0.0%	
SUNDERLAND	177	631	2,228	3,458	3,216	11,396	2,051	7	23,164
	0.3%	1.2%	4.3%	6.7%	6.2%	22.1%	4.0%	0.0%	
Total	2,902	12,019	17,291	9,655	16,814	13,849	2,173	7	74,710
	5.6%	23.3%	33.5%	18.7%	32.6%	26.9%	4.2%	0.0%	

Furthermore, the control variables contain housing- and neighbourhood characteristics, and year effects. Housing characteristics include the categorical variable and property type. Which initially consists of five types, detached, semi-detached, terraced, others, flat and maisonette. However, due to the low number of observations in the category “other”, this group joined with detached. Leaving a categorical variable with four options. Similar to the categorization of housing types by Gibbons and Machin (2003). In addition, the expectation is that family type of housing might be more sensitive to the distance aspect in relation to the childcare provider. In general, the paper assumes that only people with children consider childcare providers.

For the neighbourhood effects, individual housing transactions required spatial aggregation towards the different geographical levels in the UK. The office for national statistics (2020) provides datasets to aggregate each postcode of housing characteristics to all other output areas within the UK. In this research, the lower super output area (LSOA) and middle super output area (MSOA) were included. Within the UK, different levels of geography hierarchy were designed to report on small area statistics. The geographical level closest to neighbourhood level data is the LSOA. However, the lowest level of income statistics for small areas is on the middle super output layer (MSOA). This is a level above LSOA in the geography hierarchy and generally includes areas with at least 5000 inhabitants. For income levels, housing prices will be aspect to be higher in areas with higher income levels. The neighbourhood control variables that were included on the LSOA level are population demographics, education, employment and living environment. Population demographics consist of percentages of the age group; <15, 16-29, 30-44, 45-64, >65. Academic literature has a general acceptance of the effect of demographics on housing prices (Case, Mayer, 1995). Where, the age group below 15 is separated into low, average and high shares of kids. This variable will reflect the population demographics in the models. To control for the possible extra effects of the number of kids in relation to childcare providers' accessibility. The number of kids in a neighbourhood might have a negative relation with housing prices, in combination with distance to childcare, because the number of kids affect the overall availability of childcare providers.

The Office for National Statistics (2019) publishes data on English indices of deprivation. This is an official measure of the relative deprivation of neighbourhoods on the LSOA level in England. The latest releases date from 2019 and contain findings on employment, living environment and education. The concept of deprivation entails people in a specific neighbourhood lacking any kind of resource, not just income. The neighbourhoods' scores are based, on a relative scale, according to their level of deprivation. Therefore, these variables are only suitable to compare neighbourhood effects, instead of determining the individual effect of these variables on the determinant. Nevertheless, the general direction of these variables should have a negative signal, because an increase in score entails a more deprived neighbourhood. As house buyers, prefer less deprived neighbourhoods. Firstly, employment is measured as the proportion of the working-age population excluded involuntarily from the labour market. Agnew & Lyons (2018) noticed that an increase or decrease in financial employment rates does affect local housing prices. Case & Mayer mentioned the effect of manufacturing employment rates on housing prices. In that, the relative ranking of employment rates is interesting to include, controlling whether these have an additional effect. Secondly, education measures the lack of skills and attainment of the local population. As Gibson (2003) showed that homeowners are willing to pay more for higher educated neighbourhoods. Therefore, it is important to include a sense of educational levels, to compare neighbourhoods. Thirdly, the living environment score measures the quality of both in- and outdoor local environments. To account for the effects of green spaces and the amount of natural space (Daams, Sijtsma, van der Vlist, 2016; Park et al, 2017). Though this variable is not measured in the amount of green space or distance toward the park, it shows the quality of an LSOA in comparison to other areas, which can be analysed as the effect of having more or less green space. At last, the variable transaction year will control for year fixed effects.

The descriptive statistics of the variables are included in table 2. The table includes the descriptive for both cities, this to further illustrate the difference between them, for all relevant variables. First, for natural log of price, for comparison also addressed with mean price paid, addresses the price differences between the two cities, Brighton’s mean price paid for a house is more than twice as high then Sunderland. Second, the mean distance towards a childcare provider for Sunderland is about twice the distance as for Brighton. Subsequently, the difference in mean distance is expected to impact the relative importance of distance for house buyers between the two. Third, the mean of available places is higher in Sunderland than Brighton. Although Brighton has more childcare providers in absolute numbers, the relative size, regarding spaces is large in Sunderland. This is as expected because the cities are about the same size, population wise.

Furthermore, the property type structure of the cities layout is quite different. The share of flats is large for Brighton, almost 50% of a sold housing falls into this category, while Sunderland has a high proportion of sold terraced and semi-detached housing, 40% and 37% respectively. The difference in accommodation distribution might play a significant role in the relation between childcare and housing prices, for different types. As discussed, family type of housing is expected to have a stronger effect. Likewise, Sunderland has a slightly higher number of newly build than to Brighton. This possibly explains why more housing in Sunderland is further from childcare, as newly built housing the England is usually at the border of cities. The allocation of income class over the cities demonstrates another big difference. Although this reflects their relative location, the table further explains how Brighton and Sunderland are different to each other, with the highest income being the largest group in Brighton, while the lowest income is the largest share in Sunderland. Moreover, the scores on neighbourhood characteristics reflect that Sunderland is more deprived in each feature, as the higher the score the more deprived an area is.

Table 2: Descriptive Statistics

	BRIGHTON				SUNDERLAND			
Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Natural log of price paid	12.609	0.497	10.31	13.996	11.633	0.563	10.309	13.955
Mean price paid €	338250				133400			
Distance to Childcare	397.2	304.55	0	2352.54	792.385	392.55	4.325	5805.628
0-100m	0.053				0.008			
100-250m	0.221				0.027			
250-500m	0.292				0.096			
500-750m	0.120				0.149			
750-1000m	0.264				0.139			
1000-2000m	0.048				0.492			
2000-5000	0.002				0.089			
>5000m					0.0003			
Size Childcare Provider	44	22.922	10	128	60	30.768	6	136
Openings year Childcare	2005.8	9.08	1991	2019	2009.4	8.17	1990	2019
Property Type								
Detached	0.110				0.135			
Flat/Maisonettes	0.491				0.093			
Terraced	0.155				0.402			
Semi-Detached	0.244				0.370			
New Build								
NO	0.975				0.928			
YES	0.025				0.072			

Income Class								
lower	0.117				0.737			
middle	0.373				0.231			
higher	0.510				0.032			
Share of Kids								
low	0.389				0.183			
average	0.280				0.451			
high	0.331				0.367			
Employment Score	0.084	0.050	0.019	0.352	0.148	0.074	0.032	0.366
Living Environment Score	-0.086	0.620	-1.131	2.111	6.460	6.012	0.438	23.949
Education Score	13.725	13.850	0.297	87.733	25.500	18.406	1.324	87.024
Transaction Year								
2010	0.083				0.064			
2011	0.083				0.066			
2012	0.081				0.065			
2013	0.093				0.076			
2014	0.111				0.096			
2015	0.109				0.098			
2016	0.106				0.104			
2017	0.094				0.107			
2018	0.086				0.108			
2019	0.083				0.116			
2020	0.071				0.099			
Observations (N)	51.546				23.164			

METHODOLOGY

The main purpose of this paper is to examine the effect of the proximity of childcare centres on housing prices. The mathematical function for this research aligns with that of the hedonic price model of Rosen (1974) & Bergantino et al (2021), taking housing price as the independent variable. Therefore, constructing a multilinear model to evaluate the relationship between the dependent variable (price paid) and the independent variables, with distance to childcare providers as the key variable of interest. This is to test the null hypothesis (H0). Which considers that the distance to a childcare centre has no additional significant effect on the price paid for a house. The independent variables are separated into three categories; housing attributes (H) and neighbourhood characteristics (I), time-fixed effects (T). Consequently, the function of the dependent variable in relation to the categories can be defined as;

$$\text{Price Paid} = f\,(H, I, T)$$

At first, the baseline model will consist of just the natural log price paid and distance to childcare, both in continuous distance and distance dummies. Then, I will estimate and compare the model for two cities separately and then again for the total dataset. To see whether location affects these results, as Sah, Conroy and Narwold (2016) suggested. Some cities might have more or fewer amenities or different wealth levels. In England, the wealthiest areas are in the Southeast and the least wealthy are in the North. This, so-called north south divide (Green, 1987), is represented on different levels, such as social and economic. Furthermore, childcare centres' distribution can spatially differ over the cities more spread either out or denser. Therewith, possibly influencing its effects on the surrounding housing prices. Consequently, it examines the effect of distance to childcare provider in Brighton in model 1 and Sunderland in model 2, through coefficient β_1. To control for OLS assumptions, the natural logarithm of price paid is conducted.

$$log\ (Price\ Paid_{itb})\ = a + \beta_1 D_{itb} + \beta_2 P_{its} + X_{itb} + \gamma_{ib} + \delta t\ +\ \varepsilon_{itb} \tag{3}$$

$$log\ (Price\ Paid_{its})\ = a + \beta_1 D_{its} + \beta_2 P_{its} + X_{its} + \gamma_{is} + \delta t\ +\ \varepsilon_{its} \tag{4}$$

With $log\ log\ (PricePaid_{itb})$ as the natural logarithm of the price paid for property type i, at year of sale *t*, in English city *b* for Brighton, s for Sunderland, and a is the constant. The distance toward a childcare provider are *D* dummy variables for distance buffers. While P_{its} is variable reflecting the size of childcare providers regarding total available places. The different buffer distances included are within 100 metres, 100-250 m, 250-500m, 500-750m, 750-1000 m, 1000-2000m & 2000-5000m and >5000m. This dummy indicates whether a house is within a specific distance of a childcare centre. X is a set of property characteristics about the property type and whether the house is new build or not. γi represents exogenous property characteristics including quality of neighbourhood indicators, like population dynamics, and the deprivation scores on education, living environment and employment at the LSOA level, and neighbourhood income levels at MSOA level. While, δt are the year fixed effects for house prices, and ε is the random error term that accounts for the unobservable effects. Ordinary Least Squares (OLS) is used to estimate the relationship, which is in line with previous research into the distance towards childcare (Bergantino et al, 2021).

After analysing the cities individually, the third model examines the relationship between childcare centres and housing prices further in a combined context. Thus, representing the total effect in the English context. Combining both cities to remove the north-south divide and analyse the total effect of childcare, irrespective of an individual city's distribution of facilities and housing transitions. Besides, a city dummy is included in the model as dummy *C*, to capture the difference between the cities.

$$log\ (Price\ Paid_{itbs})\ = a + \beta_1 D_{itbs} + \beta_2 P_{its} + \beta_3 C_{bs} +\ X_{itbs} + \gamma_{ibs} + \delta t\ +\ \varepsilon_{itbs} \tag{5}$$

RESULTS

This section will reveal the main results of this research. The results were analysed to follow the multiple regression models outlined in the methodology section. First, I discuss the results of the baseline models. Second, presenting a discussion on the results of each city to illustrate the effect of spatial distribution of childcare providers in both cities. This is to consider the possible effects of the distribution of childcare on the effects on housing prices. Finally, looking into the combined model, and controlling the model, with robustness checks for price segments and housing types.

Table 3: Baseline Models

VARIABLES	(1) BASELINE DISTANCE Log (Price Paid)	(2) BASELINE BUFFER Log (Price Paid)
Distance Childcare	-0.000461***	
	0.00001	
Distance Childcare 0-100m		-0.0287**
		-0.0131
Distance Childcare 100-250m		
Distance Childcare 250-500m		-0.0498***
		-0.00754
Distance Childcare 500-750m		-0.261***
		-0.00868
Distance Childcare 750-1000m		0.0510***
		-0.00758
Distance Childcare 1000-2000m		-0.652***
		-0.00792
Distance Childcare 2000-5000m		-0.600***
		-0.0148
Distance Childcare >5000m		-0.535**
		-0.24
Constant	12.55***	12.48***
	-0.00411	-0.00579
Observations	74,710	74,710
R-squared	0.065	0.147
Adjusted R-squared	0.065	0.147

***p<0.01, **p<0.05, *p<0.1

Table 3 shows the estimation results for the baseline models where distance to a childcare provider is related to house prices, with and without distance intervals. The relationship between continuous distance variable and housing prices, without any additional variables, displays a negative signal parameter, meaning that when distance increases, relative to a childcare provider, the price of a house decreases. This negative sign is statistically significant at the 1% level of significance. Therefore, in this simplest form, the result is in agreement with the prediction from theory and in line with H1. In addition, the model with distance to childcare separated in dummies, which is set up to see whether there is a negative externality in direct vicinity of childcare provider, does indeed show a negative signal, compared to 100-250 meter. Therefore, prices are lower at the direct vicinity of childcare providers, at a significance level of 5%. Which is in line with the theoretical expectation. Yet, the distance of 750-1000m has a positive signal, meaning that compared to the distance buffer of 100-250 meter, the price of a house is 5.1% higher, at 1% level of significance. This not in line with theory and the expectations, because it was expected that all buffers would be negative in relation to the 100-250 meter distance buffer. Notably, all other distance dummies are negative at a least 5% level significance. Thus, childcare providers do indeed create a negative impact on house prices in the very near vicinity of kindergartens, when no other variables are included in the model. Yet, it remains unclear where the positive externality ends, and thus interesting to see whether the distance dummies are effected by cities individual distribution or other variables not included in the baseline model.

table 4: Estimated Results

VARIABLES	(4) Brighton Log (Price Paid)	(5) Sunderland Log (Price Paid)	(6) Total Log (Price Paid)
Distance Childcare 0-100m	0.0106	-0.105**	-0.00186
	-0.00786	-0.0443	-0.0081
Distance Childcare 100-250m			
Distance Childcare 250-500m	0.0140***	-0.0112	0.0148***
	-0.00463	-0.021	-0.00465
Distance Childcare 500-750m	0.00678	-0.0822***	0.0141**
	-0.0061	-0.0197	-0.00568
Distance Childcare 750-1000m	0.0627***	-0.0998***	0.0780***
	-0.00964	-0.0197	-0.00606
Distance Childcare 1000-2000m	0.157***	-0.110***	0.0293***
	-0.0103	-0.0188	-0.00645
Distance Childcare 2000-5000m	0.175***	-0.0166	0.101***
	-0.0355	-0.0207	-0.0109
Distance Childcare >5000m	~	0.169	0.333
		-0.231	-0.254
Size Childcare	0.00101***	0.000107	0.00144***

	-8.86E-05	-0.000103	-6.67E-05
Year opened Childcare	-0.000940***	0.000343	-0.000544***
	-0.000193	-0.000386	-0.000173
Property Type			
Detached	0.613***	0.935***	0.743***
	-0.0099	-0.015	-0.00803
Flat/Maissonettes			
Terraced	0.573***	0.483***	0.559***
	-0.00557	-0.011	-0.00472
Semi-Detached	0.520***	0.268***	0.445***
	-0.00402	-0.0109	-0.00398
new_build, YES	0.264***	0.306***	0.344***
	-0.0111	-0.0101	-0.00744
INCOME	0.0129*	-0.0946***	-0.0190***
lower			
	-0.00694	-0.00792	-0.00502
middle			
higher	0.0746***	0.280***	0.0268***
	-0.00425	-0.0166	-0.00398
Share of Kids,			
low			
average	-0.0307***	-0.0858***	-0.0883***
	-0.00495	-0.00806	-0.0042
high	-0.0728***	-0.0929***	-0.127***
	-0.00521	-0.0101	-0.00445
Employment Score	-0.310***	-0.510***	-0.375***
	-0.0532	-0.0852	-0.0445
Living Environment Score	0.0689***	-0.00794***	-0.0125***
	-0.00414	-0.000559	-0.00052
Education, Skills and Training Score	-0.00898***	-0.0107***	-0.00968***

	-0.000192	-0.000364	-0.000174
CITY; Brighton			0.989***
			-0.00642
Years 2010	-0.0685***	0.0640***	-0.0344***
	-0.0075	-0.0123	-0.00676
2011	-0.0748***	0.00938	-0.0537***
	-0.00767	-0.0122	-0.00678
2012	-0.0449***	-0.0220*	-0.0392***
	-0.00748	-0.0123	-0.00665
2013			
2014	0.101***	0.0181	0.0789***
	-0.00708	-0.0112	-0.0062
2015	0.192***	0.0306***	0.147***
	-0.00709	-0.0113	-0.00624
2016	0.252***	0.0301***	0.191***
	-0.00753	-0.0115	-0.00658
2017	0.294***	0.0335***	0.215***
	-0.00791	-0.0117	-0.00686
2018	0.256***	0.0450***	0.187***
	-0.0116	-0.0116	-0.00759
2019	0.241***	0.0623***	0.178***
	-0.0118	-0.0116	-0.00768
2020	0.279***	0.0616***	0.201***
	-0.0121	-0.0119	-0.00785
Constant	14.15***	11.08***	12.45***
	-0.388	-0.775	-0.349
Observations	51,546	23,164	74,710
R-Squared	0.402	0.538	0.658
Adjusted R-Squared	0.401	0.5375	0.658

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

The estimated results for the Brighton, Sunderland and the combined total model are presented in Table 4. Looking at the Brighton model, it indicates that house prices are higher when distance to childcare increases in Brighton. The adjusted R^2 of this model is 0.402, which means that 40% of the variance of the natural logarithm of the price paid is explained by the independent variable included. Furthermore, compared to the 100-250 meter dummy, the Brighton model found no statistically significant negative effect of lower house prices in the direct vicinity. In addition, the highest price paid for houses are found in the 2000-5000 meter distance, compared to 100-250 meter dummy. Consequently, prices in a 2000-5000 meter interval are 18% higher than housing prices in 100-250 meter distance of a childcare provider in Brighton, ceteris paribus. Which is not in line with the literature of Theisen and Emblem (2018) and Bergantino et al (2021). Except for the distance dummies 0-100 and 500-750 meter, all other dummies are significant at a 1% level of significance. The positive coefficient for the spatial distance dummies 250-500m, 750-1000m, 1000-2000m and 2000-5000m suggests that house prices increase when a house is in further proximity to a childcare centre, compared to houses in a distance of 100-250metres, corrected for all other variables. Considering the mismatch between the theoretical expectation and the outcomes of the estimated model, a possible explanation could be the high share of flats/maisonettes in Brighton. Table 3, in former chapter, showed that almost half of the accommodation types in Brighton are flat/maisonettes. Likewise, this are not the type of housing to have strong relation with distance to childcare, as households living in flats, are usually not families.

Moreover, the size of a nearest childcare has a slightly positive effect on house prices at a 1% level of significance. Therefore, an increase in size of childcare has a positive effect on price paid for a house, corrected for all other variables. While, openings year has a negative signal parameter. Consequently, for an additional increase in openings year the price of house decreases, ceteris paribus, at a 1% level of significance. Which is in line with expectations, because a greater number of places, increases the availability a child will be accepted, the heterogeneity of age might be larger and therefore accommodate parents preferences For property type, a detached house has the strongest effect, followed by semi-detached and terraced, compared to flats, at a significant level of 1%. The signs are in line with expectations, because flats are in general cheaper than the other accommodation types. Yet, that terraced type of accommodation is more expensive than semi-detached, 57.3% and 51.9%, compared to flats, is not in line with expectations. An explanation could be the presence of terraced house with architectural value, dating back to either the Regency or Georgian era, such as Brunswick terrace. This model does not control for this sense of architectural value of each house.

In addition, a MSOA neighbourhood which has a relative higher income level has a positive effect on housing price, in comparison to average income levels in Brighton MSOA's, at a 1% level of significance. Although lower income levels suggest a positive effect as well, this is not significant. Therefore, the outcomes of this variable are in line with theory. Furthermore, an increase in the share of children in the LSOA seems the have a negative effect on housing prices, ceteris paribus. In light of the pressure on childcare providers, the relation can be explained by the idea that people either prefer to buy house in less child dense areas, because of the difficulty to organise childcare and education or neighbourhoods with a higher share of kids are not the areas with higher share of owner-occupied housing, but areas with a large share of rental / social housing in Brighton. Both employment and education scores show the expected negative sign, as an increase of this score means a more deprived neighbourhood. While, living environment suggest a negative effect, and therefore suggest that the living environment is less relevant for home buyers in Brighton. Yet, the descriptive statistics table showed that the mean score for living environment in Brighton is already very low. Consequently, the living environment of neighbourhoods can still be relatively less deprived, compared to other areas. All LSOA neighbourhood scores are significant at a 1% level. To end, the year effects variable indicates that housing prices are lower before 2013 and have increased afterwards. Peaking in 2017, followed by 2020, compared to 2013. Thus, a house bought in Brighton in 2017 is 29.4% higher, compared to buying in 2013, ceteris paribus. Which is relatively in line with expectation, as house prices have indeed increased over the years since 2013. All transaction years have a significant level of 1% in Brighton.

Column 2 shows the estimated results of the multiple regression model for Sunderland. As discussed in the methodology, this city is rather the opposite of Brighton, both in terms of location and prosperity. The Sunderland model shows a different pattern of impact parameters for the distance dummies, in respect of Brighton, which was expected by theory. Moreover, the adjusted R^2 of this model is 0.538, therefore, 54% of the variance of the natural logarithm of the price paid is explained by the independent variables included. Which is higher than Brighton. Looking at the distance intervals, all but >5000m meter are negative, compared to the left-out category 100-250m. Yet, the distances 250-500m, 2000-5000m & >5000m are insignificant, while 0-100m is significant at 5% and all others are significant and 1%. Furthermore, housing in the nearest distance of a childcare provider in Sunderland examines a negative effect of -10.5%, compared to 100-250m, corrected for all other variables. This is in line with expectation of a negative externality when living in the nearest proximity of childcare provider,. Thus, looking only at distance dummies the Sunderland model seems more in line with literature, compared to the Brighton model. This could be explained by the lower number of childcare providers in Sunderland or the difference in distribution of housing types.

Nevertheless, both size of childcare as year opened have a positive parameter in Sunderland but both are insignificant. Here, the difference between property types is greater. Still, all accommodation types are more expensive than flat, yet the difference between the detached and flats are more in line with expectations, namely, a 90% higher price for a detached house, compared to flat. Reflecting to Brighton and the difference in share of flats in Sunderland, it becomes clear that the relative share of a certain type of accommodation, does indeed matter for price differences between them. Besides, terraced is still higher than semi-detached houses. Especially, the relative size of the difference is rather contrary to expectation. New build still has a positive impact parameter in Sunderland, so, a new built house in Sunderland has 30% additional price increase, ceteris paribus. While, both income levels are significant at 1% level of significance in Sunderland. Consequently, the price of a house sold is higher in a higher income level area, and lower in a lower income level area, compared to the average income levels. Additionally, all neighbourhood scores have a negative signal, and thus are in line with expectations, as people prefer to live in less deprived areas, in respect of Employment, Living Environment and Education. Lastly, not all transaction years are significant, but in comparison to 2013, the strongest signal is experienced in 2010 and 2019, 6.4% and 6.2% respectively. This suggest that prices in Sunderland have only just arrived at the same levels, as in 2010. This not really in line with expectations, although the North-East of England did not experience a similar increase in housing prices, as the south, it still experienced an increase in house prices. Overall, the Sunderland model seems more in line with theory than Brighton. Still, the difference between the results in the English cities requires further explanation, therefore after analysing a combined model, a robustness check of the model will control for price segments and property types. To see whether the model reacts different for family-type of housing.

Model three shows the effect of childcare providers on housing prices in both cities combined, controlled with city dummy to control for the difference between the two. The adjusted r-square for this model is 0.658, therefore explaining about 66% of the variation. Table 3, showed that housing transactions see different distribution over the distance buffers when conducting the combined city model. Hence, a different effect was expected than for individual city models. Still, the result suggest that prices increases over distance instead of decrease, compared to the 100-250 meter distance. Thus, not being in line with theoretical expectations. Although, the nearest dummy of 100-250 meter suggests a negative externality, this is not significant. Besides, the furthest dummy >5000 meters that shows a positive signal, is also not significant. The other distance dummies are all significant at 1% level, except for 500-750 meters which is significant at 5% level. The outcomes might be disturbed by the fact that the total model does not represent families or family type of accommodation well enough, therefore the effect of childcare remains unclear, and requires further dissolving the models.

The control variables in the total model more less have the expected signal parameters, and are all significant at 1% level. The size of childcare has positive effect on housing prices, because it increase the availability to place kids, corrected for other variables. Openings year has a minor negative signal, so home buyers have a preference for longer opened childcare providers, possibly to do with the reputation of providers that are opened longer. Yet, property type still suggests that semi-detached is below terraced, compared to flats. Even so, new build house are more expensive than existing buildings, about 34% price increase, corrected for all other variables. The share of childcare, both average and large, have a negative effect. As discussed, the share of kids in an area might represent a less wealthy areas, or areas with a higher share of social housing. These areas might be less attractive for house buyers and thus negative effect price paid. Likewise, lower income class entails a negative parameter, compared to average income, and high income shows a positive parameter. Hence, the income levels of a MSOA influence housing prices. All neighbourhood score have the expected negative direction, because the lower the score the less deprived the LSOA. The difference between Brighton and Sunderland is sufficient with a positive parameter of 98% and further illustrates the huge gap in housing prices between English cities and regions. Overall, the direction of the year effects show a price increase since 2013, and a price decrease before 2013. Still, the distance dummies need some clarity, as there mismatch with expectation. The following chapter continues our analysation of the possible relationship.

ROBUSTNESS CHECKS

PRICE SEGMENTS

Table 5 considers three price segments, low, middle and high, for housing prices in Brighton. Column one shows the effect of the lower segment. Splitting up the sample equal or lower to £245.000 reduces the adjusted R2 to 0.1366. The parameters suggest a price increase up to 1000-2000 meter, after which it decrease. Yet, compared to the nearest dummy, the distance intervals 100-250 meter, 250-500 m, 500-750 meter, and 2000 – 5000 meter are insignificant. The increase in insignificance is explained by the fact that the dummies are created on distance towards a childcare, irrespective of the price sold of a house. Therefore some categories will have relatively low observations after dividing the sample. Although the 1000-2000m distance interval remains the most expensive, the furthers distance category 2000-5000 meter has the strongest negative effect. This could reflect the idea that home-buyers in the cheaper segment do prefer to be in walking distance of childcare providers, as Truelove (1997) described for 1000-2000 meter, but that do not have to be in the closest proximity, which might affect the size of the houses relatively to the price in m², which is not considered here. For the other variables, a signal parameters also changed worthwhile for interpretation (Appendix B). For property type, the negative parameter of detached jumps out. This could be explained by detached housing not being common in this price range, and when it appears, the houses are in such a state that they have to be cheap, relatively to flats. Overall, the results suggest the household composition of this category could be starters and young professionals, whom do not care that much on distance to childcare and do not prefer detached housing, but still do not want to be too far away from the city.

Table 5: Price pattern Brighton

	(6)	(7)	(8)
VARIABLES	LOW	MIDDLE	HIGH

	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)
Distance Childcare 0-100m			
Distance Childcare 100-250m	0,00509	-0.00998**	-0,0113
	-0,00926	-0,00402	-0,0101
Distance Childcare 250-500m	0,00537	-0.00826**	0,0028
	-0,00911	-0,00397	-0,00986
Distance Childcare 500-750m	0,0101	-0.00826*	-0.0350***
	-0,0105	-0,00441	-0,0106
Distance Childcare 750-1000m	0.0463***	-0.00961*	0.0308**
	-0,0133	-0,00536	-0,0139
Distance Childcare 1000-2000m	0.0647***	-0,00109	0.0697***
	-0,0153	-0,00559	-0,0139
Distance Childcare 2000-5000m	-0,0289	-0.0638***	0.0726**
	-0,0555	-0,0229	-0,0325
Property Characteristics	YES	YES	YES
Area Fixed Effects	YES	YES	YES
Year Effects	YES	YES	YES
Constant	12.45***	11.67***	12.25***
	-0.0101	-0.0167	-0.00913
Observations	51.546	23.164	74.710
R-squared	0.404	0.538	0.532
Adjusted R-squared	0.404	0.537	0.531

Robust standard errors in paratheses.

***p<0.01, **p<0.05, *p<0.1

Moreover, in the middle price segment in Brighton ranging from £245.000 to £362.500 all distance intervals are at least significant at a 5% level of significance, when 2000-5000 meter is the left-out category. While the adjusted R2 declined to 0.09. The signal parameter are all positive, with the nearest dummy having the strongest effect of 6.4%, and entail that it is preferable for home-buyers in the middle price segment to live closer to a childcare provider, compared to furthest distance, but there is no negative externality for the nearest proximity. This could be explained by the option that this category represents couples with kids in Brighton. Whom prefer to live close to facilities needed in their daily life.

Additionally, column 3 controls the high price segment in Brighton, which is on and above £362.500. For this highest price category the adjusted R2 is 0.22. With the nearest dummy 0-100 meter is the reference category, all distances, but 100-250 and 250-500 meter, are significant at a 1% or 5% level. The furthest distance dummies has strongest positive impact, with 7.3% price increase compared to housing in the nearest proximity. Thus, the distance aspect in this category seems less relevant, because in this category costs of travelling might be less of an issue, or more wealthier people can afford their own nanny, or even send their kids to boarding schools, of which a couple are located in the Brighton area. Therefore, the price segments suggest that distance to childcare is most relevant for middle price segment, compared to high and low, therefore is in line with H3.

Table 6 reflects the different price segments in Sunderland. Column 1 reflect the lower price segment which ranges to £85.000. This segment has an adjustment R^2 of 0.187. The left out category is the nearest distance, 100-250 meter. For this category, the distance intervals 500-750 meter, 750-1000 meter and >5000 meter are insignificant. Both 250-500 meter and 1000-2000 meter are significant at 10% level, which is acceptable in relation to the number of observation 7.728. And the 0-100 meter and 2000-5000 meter are both significant at 1% and 5%, respectively. The parameters suggest a negative externality for living in the nearest vicinity, compared to 100-250 meter. Besides, the effect of other variables are relatively in line with the lowest category in Brighton (Appendix C) .

Table 6: Price pattern Sunderland

VARIABLES	(6) LOW Log (Price Paid)	(7) MIDDLE Log (Price Paid)	(8) HIGH Log (Price Paid)
Distance Childcare 0-100m			
Distance Childcare 100-250m	0,00509	-0.00998**	-0,0113
	-0,00926	-0,00402	-0,0101
Distance Childcare 250-500m	0,00537	-0.00826**	0,0028
	-0,00911	-0,00397	-0,00986
Distance Childcare 500-750m	0,0101	-0.00826*	-0.0350***
	-0,0105	-0,00441	-0,0106

Distance Childcare 750-1000m	0.0463***	-0.00961*	0.0308**
	-0,0133	-0,00536	-0,0139
Distance Childcare 1000-2000m	0.0647***	-0,00109	0.0697***
	-0,0153	-0,00559	-0,0139
Distance Childcare 2000-5000m	-0,0289	-0.0638***	0.0726**
	-0,0555	-0,0229	-0,0325
Property Characteristics	YES	YES	YES
Area Fixed Effects	YES	YES	YES
Year Effects	YES	YES	YES
Constant	12.45***	11.67***	12.25***
	(0.0101)	(0.0167)	(0.00913)
Observations	51.546	23.164	74.710
R-squared	0.404	0.538	0.532
Adjusted R-squared	0.404	0.537	0.531

Robust standard errors in paratheses.

***p<0.01, **p<0.05, *p<0.1

Column 2 explains the middle price segment for Sunderland, which is between £85.000 and £142.000. the middle prices segment accounts for adjustment R2 of 0.149 The reference category this time is 250-500 meter, leaving only 0-100 and 100-250 meter insignificant. Yet, the model indicates that living closer than 250 meter creates a negative externality and whilst increasing the distance also has a negative impact, especially when a bought house is located beyond >5000 meter. So again, this category prefers to live relatively close, likewise to Brighton's middle price segment.

The last column explains the pattern for the highest price class in Sunderland. This range starts from £142.000 onwards. This category has a relatively large adjusted R2 of 0.35 compared to the previous price segments. The model indicates that price decreases when distance to childcare increase up till beyond 5000 meter. Possibly after that distance there are some large estates with large housing and gardens. Therefore, influencing the pattern for this segment. Nonetheless, only the 0-100 meter distance dummy is insignificant and the positive impact is thus not statistically relevant. Overall the robustness check on price segments for housing prices derived some interesting results. For both Brighton and Sunderland, the effect of living close to a childcare provider, was strongest for the middle price segment, especially for Brighton, the middle class segment was in line with theory, whilst the city model itself was not. And therefore price segments do have different effect on the relation with the distance to childcare, which is most likely explained by the type of households situated in certain home-buyers price segments.

PROPERTY TYPES

Beyond the price differences between cities, price varies among accommodation type as well. Therefore, an additional robustness check for the different accommodation type is applied, to see whether the effects vary per accommodation type per city. To control whether family type of housing does indeed see a stronger effect in respect of distance to childcare. Table 7 analyses the property effect for Brighton. Starting with detached houses, as expected from previous models, the strongest effect for this category is found in the furthest distances, compared to 100-250 meter. Yet, second highest positive impact parameter is found in the nearest proximity of childcare providers in Brighton. Except for 750-1000 meter, all distance variables are significant at either 5% or 1% level. With the adjusted R^2 estimated at 0.171. Thus, detached home buyers either prefer to be very close or very far in Brighton. Possibly, home-buyers prefer either to be close to amenities, but otherwise do not care for cost of travelling or having own private nannies. Looking at the other included variables, when significant, the parameters are in line with theoretical expectations (Appendix D) .

Table 7: Robust Property Type Brighton

	(12)	(13)	(14)	(15)
	Detached	Flat	Terraced	Semi-detached
VARIABLES	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)
Distance Childcare 0-100m	0.135**	-0.318***	0.373***	0,0139
	-0,054	-0,016	-0,0328	-0,0117
Distance Childcare 100-250m		-0.321***	0.297***	
		-0,0143	-0,0202	
Distance Childcare 250-500m	0.0880***	-0.332***	0.238***	0.0329***
	-0,0251	-0,0143	-0,0189	-0,00729
Distance Childcare 500-750m	0.0650**	-0.312***	0.171***	0.0209**
	-0,026	-0,0151	-0,0189	-0,0102
Distance Childcare 750-1000m	0,0637	-0.173***	0.134***	0.122***
	-0,0422	-0,0167	-0,0179	-0,0168
Distance Childcare 1000-2000m	0.133***			0.0563**
	-0,0367			-0,0231

Distance Childcare 2000-5000m	0.445***	-0.252***	0.212***	0.120*
	-0,0629	-0,0573	-0,0618	-0,0723
Property Characteristics	YES	YES	YES	YES
Area Fixed Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Constant	5.076**	19.40***	14.59***	11.72***
	-2,189	-0,536	-0,716	-0,556
Observations	5.661	25.307	8.002	12.576
R-squared	0,175	0,23	0,521	0,436
Adjusted R-squared	0,171	0,229	0,52	0,435

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

The second column for flat/maisonettes further builds on the idea that, for this type of housing, the distance to childcare is irrelevant. Compared to 1000-2000 meter, all other distance buffers have a negative impact parameter and are significant at a 1% level, showing the highest price for housing is found in the 1000-2000 meter distance. All other variables are significant at a 1% level, while the adjusted R^2 variables is 0.229. Except for living environment all parameters are in line with expectations. Moreover, the third column, indicates the effect for terraced housing in Brighton. The adjusted R^2 is relatively large at 0.52. The parameter for the distance intervals are all significant at a 1% level, and all have a positive impact parameter, related to the 1000-2000 meter. It shows how the nearest distances regarding a childcare provider entail the strongest impact. Thus, firstly for terraced housing distance to childcare does have a positive effect and with a 37.3% the effect is sufficiently, compared to the 1000-2000 meter buffer, but also compared to other categories and the price segments in Brighton. In addition, the strong positive signal parameter for employment score is remarkable (Appendix D). So, except for some contraries, it seems that terraced housing in Brighton is indeed more captivated by distance to childcare.

Additionally, column 4 examines the price effects for semi-detached housing in Brighton. In relation to the left-out category, 100-250 meter, the distance between 750-1000 meter, has the strongest positive parameter of 12.2% .While, the 0-100 meter and 2000-5000 meter are both insignificant, the other distance dummies all have a positive parameter, comparing to 100-250 meter. Although it was expected that semi-detached would have a stronger relationship with distance to childcare, it seems that the nearest distance is not that important, yet to be within walking distance remains important. The adjusted R^2 of 0.435 is explaining a sufficient part of the variance of the independent variable. Again, the employment score has a very high positive parameter (Appendix D). Thus, seems less relevant what employment levels are in neighbourhood for semi-detached home buyers. Other variables are all significant and the signals are similar to the previous models.

Table 8: Robust Property Type Sunderland

VARIABLES	(16) Detached Log (Price Paid)	(17) Flat Log (Price Paid)	(18) Terraced Log (Price Paid)	(19) Semi-detached Log (Price Paid)
Distance Childcare 0-100m	-0.906***	0.537***	-0.194***	-0.337***
	-0,203	-0,0969	-0,0656	-0,045
Distance Childcare 100-250m	-0.940***	0.208***		
	-0,0849	-0,0388		
Distance Childcare 250-500m	-0.938***	0.184***	-0.0982***	-0.107***
	-0,059	-0,0322	-0,0277	-0,0316
Distance Childcare 500-750m	-1.048***	0.0871***	-0.193***	-0.211***
	-0,0555	-0,0285	-0,0265	-0,0296
Distance Childcare 750-1000m	-1.043***	0.0869***	-0.130***	-0.281***
	-0,056	-0,0287	-0,0266	-0,0296
Distance Childcare 1000-2000m	-1.065***		-0.174***	-0.291***
	-0,0489		-0,0255	-0,028
Distance Childcare 2000-5000m	-0.958***	0.277***	-0.124***	-0.193***
	-0,0512	-0,0383	-0,0271	-0,0341
Distance Childcare >5000m			-0,0418	-0.304***
			-0,283	-0,0315
Property Characteristics	YES	YES	YES	YES
Area Fixed Effects	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
Constant	17.98***	6.145***	16.36***	11.51***
	-3,984	-2,176	-1,214	-0,997
Observations	3.128	2.148	9.315	8.573
R-squared	0,255	0,381	0,507	0,414
Adjusted R-squared	0,248	0,374	0,506	0,412

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

The last table 8 considers the robustness check of accommodation types for Sunderland. In the same order as for Brighton, the first column indicates the effect for detached houses. Detached houses show a strong incentive to be further away from a childcare provider. With the furthest distance dummy as left out category, all dummies are significant, but show a strong negative parameter. Thus, the prices of the few detached houses in that distance are very expensive. The other variables still show similar parameter directions. Additionally, flats show an unexpected relationship, the nearer distance dummies have a strong positive parameter, compared to 100-250 meter dummy. All distance intervals are significant at 1% level. An explanation could be that are only a few flats are very close to childcare providers, and therefore expensive or effecting the regression. Another potential reason is that the size of flats might be larger near childcare centres.

Moreover, terraced housing is line with expectations, the nearest dummy has a negative externality, and an increase in distance creates a negative price effect. Thus, for this type of 'family' housing there is positive effect of living nearby childcare providers. Only the >5000 meter dummy is insignificant, while the adjusted R^2 entails 0.506. A note on the other variables is that new build shows a strong effect of 43.6%, compared to not new buildings. So, terraced housing in Sunderland aligns with expectations from literature. To end, semi-detached housing in Sunderland examines the same pattern as terraced housing, acknowledging the negative externalities of living close by and a decrease in price when distance increase. Although, the negative externality is relatively large. Nonetheless, all interval dummies are negative compared to, 100-250 meter dummies, and therefore, the pattern is in line with literature. Likewise, the additional variables also seem to have the same effect as for terraced housing. Except for the high parameter of living closely for flats, for Sunderland, both terraced and semi-detached type of housing, show a positive relation between distance to childcare and housing prices. Similarly, terraced housing in Brighton showed the same importance of distance for housing prices in that category.

DISCUSSION

The past decade has seen an increase in housing prices, but also an increase in the participation of women in the labour market. Childcare is looked at as an incentive to participate in the labour market (Del Bosco). Yet, the cost of childcare in England is expensive. Therefore, this research examined whether the accessibility of childcare could be an incentive for house buyers to pay more for houses. Although literature addresses this in a non-English context (Theisen and Emblem, 2018; Bergantino et al, 2021), this research adds to the current debate that this relationship also accounts for the housing market within England.

In contrast to Theisen and Emblem (2018), this research found that the relationship between distances to childcare does not account for all English cities. In contradiction to the Norwegian town Kristiansand, the English city of Brighton, showed that an increase in distance to childcare had an increasing positive price effect, while Theisen and Emblem predicted that prices decline with increasing distance. A possible explanation for this is that there are location-specific factors at play in Brighton. Brighton is a city with a lot of tourism, therefore, a share of housing could be bought as a second-home for private holidays or as an investment to let out. For these types of investment, the distance aspect to childcare providers is less relevant, an extra variable with distance to the beach might provide an explanation for this effect, or if the data entailed whether home-buyers where first-time or second-time buyers, I could have controlled for this effect. Nonetheless, as a city not aligning with general literature is also a possibility. For instance, Sah, Conroy and Narwold (2016) found that San Diego had conflicting results with literature, or as noted by Nillson (2014) that location-specific factors affect the value of amenities.

While, the Sunderland model showed similar results to Theisen and Emblem (2018), where the distance to childcare does have a positive price effect. It also enlightened the negative externality of living in the direct proximity of childcare providers. Therefore, it shows that deciding on which city to focus on is a determinant of the results of the research done, and therefore is in line with Nilsson's (2014) findings. Furthermore, this addresses the likes of spatial equity and the spatial distribution of amenities, if childcare providers are so common to every area or neighbourhood, the sense of paying additionally for the accessibility of childcare diminishes. The high number of childcare providers in Brighton might remove the spatial aspect of paying more for housing near childcare. Where Nilsson concluded that the density in population and housing affected the valuation of green spaces, this paper suggests that the accessibility, in respect of the distance to childcare, affects the relationship of childcare distance to housing prices. Thus, the lower number of childcare availability within the town of Sunderland most likely affected the level of importance given to the distance towards childcare. In addition, the larger part of the houses sold in Sunderland were in a larger distance from childcare providers, compared to Brighton. Acknowledging the spatial distribution effect on the value of an amenity. Nonetheless, in further research, the number of childcare within a city, relative to its population size, is an important consideration for selecting a case study, to better predict and evaluate the effect.

To note, quality of childcare is hard to measure and very subjective to parents opinion and therefore not included, while for Brighton the quality of childcare could be more important, relating to the paper by Cheshire and Sheppard (2006) and Gibbons and Marcin (2003) who used the quality of schooling as a measurement besides the distance. Excluding quality therefore is viewed as a limitation of this research. Instead, this research did included size of childcare and, which had a positive signal, thus the available places and therefore the accessibility in that sense indeed has an influence on housing prices. Further research, could decide to further focus on the quality of childcare.

Nonetheless, including both cities in a combined model, as Bergantino et al (2021) did for eleven Italian cities, still showed a negative price effect. Where Theisen and Emblem's (2018) hypotheses expected a peak in price effect in the proximity of childcare and a decline after that. The baseline model showed this positive relationship between housing prices and distance to childcare. Yet including other variables and classifying distance dummies disturbed this relationship. Future research could consider different distance intervals or other variables to see whether a measurement error was at place. Nonetheless, negative externalities at a short distance, which was suggested by Sah, Conroy and Narwold (2016), did occur in some models, especially in the Sunderland context. Whilst effects varied by different price segments and accommodation type, suggesting that family type of housing and price segments have a stronger relation with distance to childcare. Yet, flat and maisonettes in Sunderland examined a very strong effect near childcare's in Sunderland. Different to Theisen and Emblem, this research included more accommodation types, compared Theisen and Emblem (2018). Nevertheless, to have a clearer overview of the effect for families, further research should try to include household composition, to make sure a house buyers represents a certain household group. Besides, some variables had opposing effects, in the robustness checks, thus limiting the trustworthiness of the data. Although, the data was subtracted from public data bases, there remains the notion of data limitations, or mistakes during the research, hence explaining some variables not being in line with expectations.

CONCLUSION

Amenities influence housing prices and the spatial distribution and availability of amenities determines their value. Whilst the availability of childcare influences the participation of women in the labour market, this study found that childcare centres also affect surrounding housing prices. While the selection of Brighton, proved a limitation to finding a significant effect of proximity of childcare for the entire city, focussing on the middle price class of sold houses did indeed proof a positive effect of living close. Hence, this added to the literature debate to reflect on location-specific factors and consider the spatial distribution of childcare in a city, but also acknowledge the differences in effect between price segments. Yet, the research conducted also found sufficient results to contribute to the literature that distance to childcare is an amenity for housing prices in England. Namely, for the city of Sunderland, the middle price segments, and in general, the family type of accommodations a positive effect of distance to childcare on housing price was found. The strongest effect was found in areas not in the nearest proximity to a childcare centre, especially within 100 to 250 metre distance to a childcare centre. Therefore, childcare also has a negative externality on housing in the nearest proximity, estimated within 100 metres. Subsequently, this study found differences between cities and further research could focus on other countries or more English cities, as well as looking at the effects of quality of childcare and household composition. Nonetheless, as a policy implication, it shows that urban planners can affect the housing market by stimulating or limiting the equal spatial distribution of amenities, in relation to childcare providers.

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OLS ASSUMPTIONS

Assumption 1: $E(\varepsilon t) = 0$

The first assumption considers the linearity of residuals, which will not be violated by including a constant term (B0) in the regression model. Since every model in the analysis entails ?

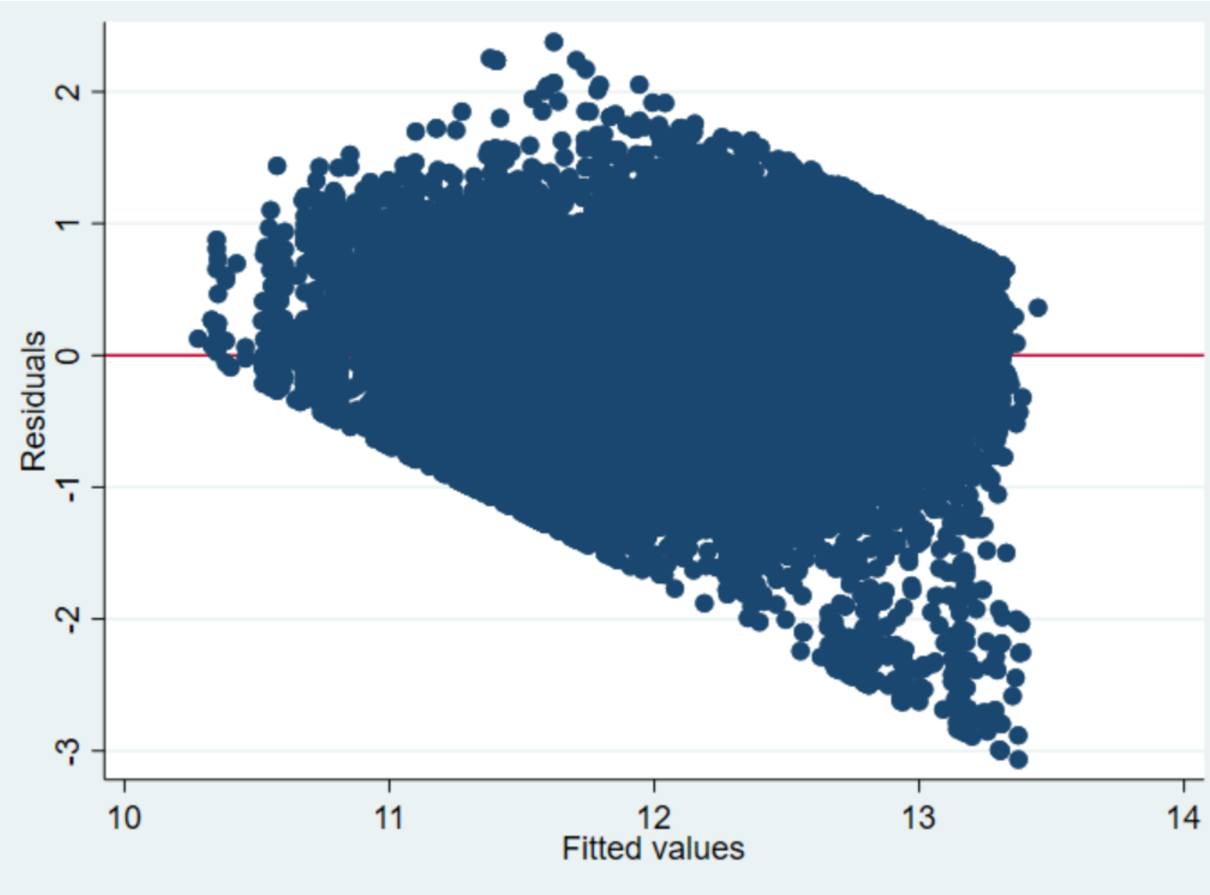
Assumption 2: $Var(\varepsilon t) = \sigma < \infty$

To check whether the error terms show heteroskedascity, the Breusch-Pagan/Cook-Weisberg test is consulted. The H0 hypothesis entails that the residuals' variance is constant. Furthermore, the null hypothesis is rejected at a 5% significance level.

Ho: constant variance

Chi2 = 216.45

Prob > chi2 = 0.000

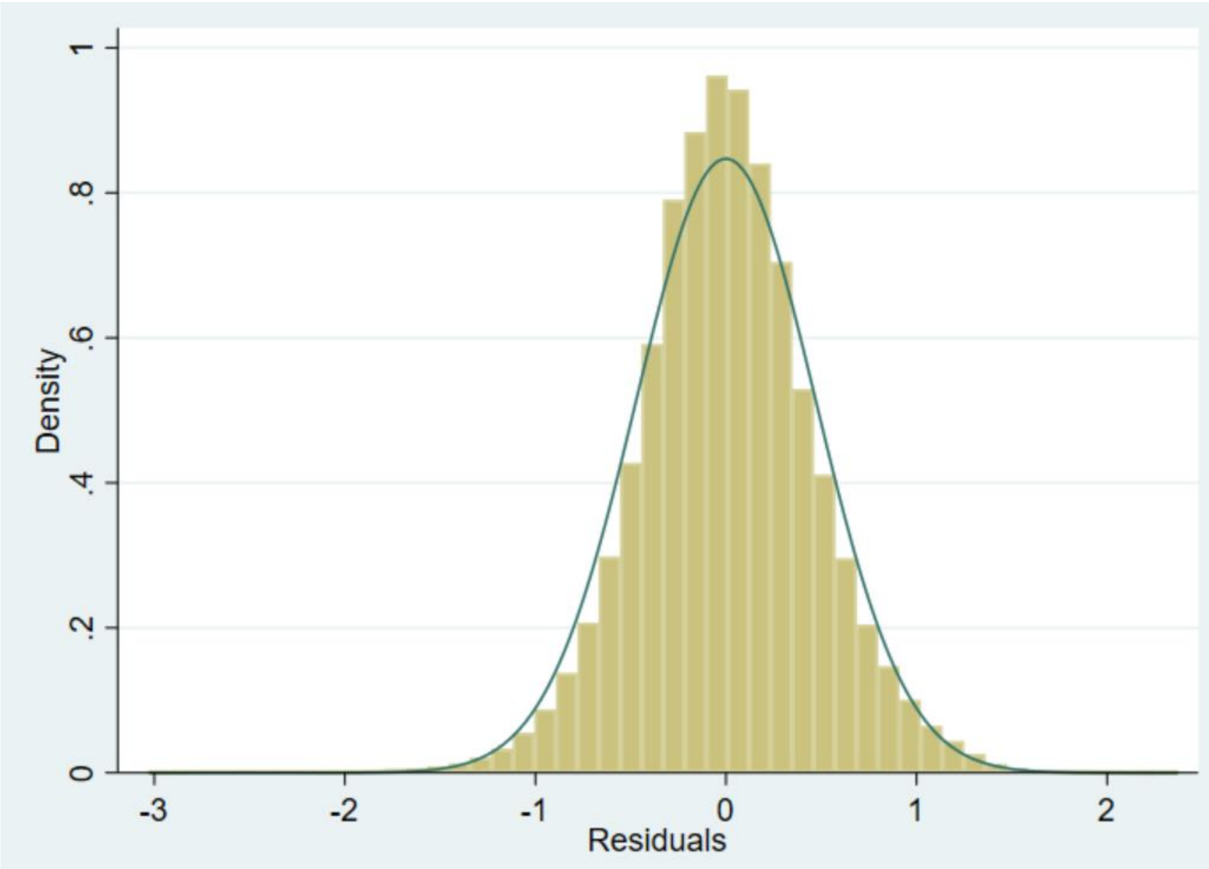


Assumption 3; $cov(\varepsilon i, ej) = 0 \ for \ i = j$

The residuals should be uncorrelated with each other. The dataset applied in this research consists of cross-sectional observations. Therefore the covariance between the residuals is zero, so no issue of autocorrelation in our sample.

Assumption 4; Normally distributed error terms

As demonstrated by the figure below, the distribution of the residuals in our model can be assumed as normal.



Multicollinearity

Multicollinearity is an inherent assumption and implies to the case where the dependent variables must not be correlated with each other (Brooks & Tsolakos, 2010). Multicollinearity issues can occur if the VIF of a variable is higher than 10. However, values greater than 5 indicate possible multicollinearity. As shown by the table below, all VIF values of the three models used in our analysis are significantly lower than 5, and thus it can be assumed that there are no multicollinearity issues.

Variable	**MODEL 1**	**MODEL 2**	**MODEL 3**
Distance to Childcare			
0-100m	1.27	1.05	1.22
100-250m	1.64	1.17	1.56
250-500m	1.78	1.5	1.78
750-1000m	1.4	1.69	1.46
1000-2000m	1.31	2.29	1.84
>2000m	1.01	1.63	1.21
Property Type			
Detached	1.26	2.38	1.34
Terraced	1.48	3.8	1.7
Semi-Detached	1.32	3.53	1.6
New Build	1.04	1.16	1.06
Income Class			
lower	1.54	1.9	2.36
higher	1.54	1.18	1.64
Share of Kids			
average	1.57	2.11	1.54
high	1.78	3.05	1.8
Employment Score	2.28	4.5	3.19
Living Environment Score	1.6	1.38	1.66
Education Score	2.45	5.56	3.35
Transaction Year			
2010	1.74	1.72	1.73
2011	1.73	1.75	1.74
2012	1.72	1.73	1.73
2014	1.95	2.04	1.98
2015	1.94	2.07	1.97
2016	1.92	2.12	1.97
2017	1.82	2.15	1.91
2018	1.76	2.16	1.87
2019	1.74	2.24	1.88
2020	1.64	2.08	1.76
Mean VIF	1.64	2.22	1.81

APPENDIX A: Operationalisation

Concept	Dimensions	Measurements / values	Variable	Aggregate level
House price	Price	Transaction prices	Hedonic price model LN(TransactionPrice)	Street address
	Types	Detached; Semi-detached; Terraced; Flat/Maisonette; Other	Categorical variable Property type; Detached - D Property type; Semi-detached - S Property type; Terraced - T Property type; Flat/Maisonette - F	
	Construction	New/Old	Dummy variable. Construction (1=new)	
	Year of transaction	Years 2010 till 2021	Year fixed effect	
Childcare	Distance	<100 meter 100- 250meter 250- 500meter 500 - 750meter 750 - 1000meter 1000 - 2000 meter	Whether a house is within a certain distance buffer relative to the closest childcare location	Individual level
	Size	Available places in numbers	Continuous	
	Openings Year	Year opened	categorical	
Neighbourhood characteristics**	Population dynamics	Share of kids in percentage	Low (<13% Average (13% - 17.5). High (>17.5%)	LSOA
	Income	Income levels	Lower (<= 40000) Middle (>=40000 & <=50000) Higher(>=50000)	MSOA level
		Score	ratio	LSOA
	Education deprivation	Score	ratio	LSOA
	Education deprivation	Score	ratio	LSOA

	Living Environment Other*			LSOA

Appendix B: Robustness Check Price Brighton

Table 5: Price pattern Brighton

VARIABLES	(6) Low Brighton Log (Price Paid)	(7) Middle Brighton Log (Price Paid)	(8) High Brighton Log (Price Paid)
Distance Childcare 0-100m			
Distance Childcare 100-250m	0.00509	-0.00998**	-0.0113
	-0.00926	-0.00402	-0.0101
Distance Childcare 250-500m	0.00537	-0.00826**	0.0028
	-0.00911	-0.00397	-0.00986
Distance Childcare 500-750m	0.0101	-0.00826*	-0.0350***
	-0.0105	-0.00441	-0.0106
Distance Childcare 750-1000m	0.0463***	-0.00961*	0.0308**
	-0.0133	-0.00536	-0.0139
Distance Childcare 1000-2000m	0.0647***	-0.00109	0.0697***
	-0.0153	-0.00559	-0.0139
Distance Childcare 2000-5000m	-0.0289	-0.0638***	0.0726**
	-0.0555	-0.0229	-0.0325
Size Childcare	-0.000414***	0.000160***	0.00109***

	-0.000105	-4.41E-05	-9.35E-05
Year opened Childcare	-3.28E-05	-8.37E-05	0.000251
	-0.000245	-9.44E-05	-0.000211
	-0.423***	0.0865***	0.335***
Detached			
	-0.0114	-0.00369	-0.00714
	0.182***	0.0855***	0.202***
Flat/Maissonettes			
Terraced			
	-0.00952	-0.00299	-0.00701
	0.148***	0.0778***	0.110***
Semi-Detached			
	-0.00784	-0.00241	-0.00555
	-0.0102	-0.00663	-0.0151
new_build, YES			
	-0.00393	0.0503***	0.0494***
	-0.0164	-0.00556	-0.00983
INCOME, lower			
	0.00977	-0.000323	
	-0.00791	-0.00323	
middle			
			-0.0322***
			-0.00886
higher			
	-0.00598	0.00483**	0.0415***
	-0.00542	-0.00214	-0.00975
Share of Kids, low			
average	0.0207***	-0.0169***	-0.0787***
	-0.00586	-0.00242	-0.00593
high	0.0325***	-0.0232***	-0.118***
	-0.00612	-0.00249	-0.00601
Employment Score	-0.436***	-0.0251	0.838***
	-0.0553	-0.0257	-0.0784
Living Environment Score	-0.0227***	0.0128***	0.0613***
	-0.00428	-0.00183	-0.00404

Education, Skills and Training Score	-0.000474**	-0.00141***	-0.0100***
	-0.000235	-9.20E-05	-0.000324
CITY, BRIGHTON AND HOVE			
year = 2010	-0.0220***	-0.0199***	-0.0319***
	-0.00835	-0.00433	-0.0113
year = 2011	-0.0347***	-0.0236***	-0.0236**
	-0.00831	-0.00438	-0.0112
year = 2012	-0.00321	-0.0125***	-0.0296***
	-0.0084	-0.00432	-0.0111
year = 2013			
year = 2014	0.0448***	0.0137***	0.0365***
	-0.00835	-0.00391	-0.00972
year = 2015	0.0836***	0.0319***	0.0552***
	-0.00889	-0.00378	-0.00931
year = 2016	0.0721***	0.0444***	0.0807***
	-0.0096	-0.00386	-0.00913
year = 2017	0.0767***	0.0548***	0.0924***
	-0.0109	-0.00394	-0.00919
year = 2018	0.0347**	0.0564***	0.0583***
	-0.0152	-0.00543	-0.0135
year = 2019	0.0391***	0.0602***	0.0654***
	-0.015	-0.00548	-0.0136
year = 2020	0.0421***	0.0632***	0.0771***
	-0.016	-0.00569	-0.0136
Constant	12.16***	12.73***	12.48***
	-0.491	-0.189	-0.421
Observations	17,480	16,862	17,204
R-Squared	0.138	0.101	0.221
Adjusted R-Squared	0.136	0.099	0.22

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

Appendix C: Robustnesss Check Prices Sunderland

Table 6: Price pattern Sunderland

	(10)	(11)	(12)
VARIABLES	Low Sunderland	Middle Sunderland	High Sunderland

	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)
Distance Childcare 0-100m	-0.0622**	-0.0361	0.0918
	-0.0286	-0.0237	-0.0885
Distance Childcare 100-250m		-0.00684	
		-0.0129	
Distance Childcare 250-500m	-0.0334*		-0.0767***
	-0.0172		-0.0281
Distance Childcare 500-750m	-0.0071	-0.0296***	-0.0998***
	-0.0168	-0.00724	-0.0263
Distance Childcare 750-1000m	-0.0132	-0.0356***	-0.0919***
	-0.0171	-0.00727	-0.0262
Distance Childcare 1000-2000m	-0.0313*	-0.0206***	-0.158***
	-0.0163	-0.00604	-0.025
Distance Childcare 2000-5000m	-0.0550***	-0.0151*	-0.0806***
	-0.0199	-0.00804	-0.0264
Distance Childcare >5000m	0.0878	-0.233***	0.413**
	-0.166	-0.00909	-0.185
Size Childcare	0.000695***	0.000199***	-0.00161***
	-0.000112	-6.05E-05	-0.000153
Year opened Childcare	0.000803**	0.000169	-0.00155***
	-0.000318	-0.000221	-0.000539
Detached	-0.0446**	0.157***	0.453***
	-0.0178	-0.0104	-0.0167
Flat/Maissonettes			
Terraced	0.174***	0.0799***	0.111***
	-0.0102	-0.00663	-0.0151
Semi-Detached	0.0743***	0.0311***	0.116***
	-0.00905	-0.00641	-0.016
new_build, YES	-0.0440**	0.137***	0.0144
	-0.0179	-0.00621	-0.0125
INCOME, lower	-0.00645	-0.0143***	0.0195**

middle	-0.0136	-0.00492	-0.00982
higher	-0.226***	0.00474	0.406***
	-0.0422	-0.0238	-0.0161
Share of Kids, low			
average	-0.0543***	-0.0143***	-0.0271***
	-0.0108	-0.00433	-0.00865
high	-0.0507***	-0.00792	-0.0509***
	-0.0116	-0.00567	-0.0127
Employment Score	-1.219***	-0.121**	1.437***
	-0.0668	-0.0511	-0.119
Living Environment Score	-0.00767***	4.17E-05	0.00248***
	-0.000539	-0.00033	-0.00071
Education, Skills and Training Score	0.000945***	-0.00245***	-0.0108***
	-0.000316	-0.000218	-0.000588
CITY, BRIGHTON AND HOVE			
year = 2010	0.0577***	-0.0161**	0.0349**
	-0.0146	-0.0073	-0.0168
year = 2011	0.00692	-0.0130*	0.00394
	-0.0138	-0.00746	-0.0163
year = 2012	-0.0236*	-0.0155**	0.00153
	-0.0138	-0.00755	-0.0159
year = 2013		-0.00446	
		-0.00713	
year = 2014	0.0148	-0.0141**	0.0386***
	-0.0125	-0.00677	-0.0148
year = 2015	0.0148		0.0469***
	-0.0128		-0.0145
year = 2016	-0.0142	-0.00572	0.0502***

	-0.0126	-0.00671	-0.0151
year = 2017	-0.00433	0.0114*	0.0701***
	-0.0125	-0.00679	-0.0148
year = 2018	-0.0184	0.00175	0.0741***
	-0.0125	-0.00681	-0.015
year = 2019	-0.00999	0.00791	0.0925***
	-0.0123	-0.00684	-0.0148
year = 2020	-0.0148	0.00928	0.116***
	-0.0126	-0.00737	-0.0146
Constant	9.632***	11.33***	15.28***
	-0.639	-0.443	-1.088
Observations	7,728	7,733	7,703
R-Squared	0.191	0.153	0.353
Adjusted R-Squared	0.1874	0.1493	0.35

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

Appendix D: Robustness Property type Brighton

Table 7: Robust Property Type Brighton

	(12)	(13)	(14)	-15
	Detached	Flat	Terraced	Semi-detached
VARIABLES	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)	Log (Price Paid)
Distance Childcare 0-100m	0.135**	-0.318***	0.373***	0,0139
	-0,054	-0,016	-0,0328	-0,0117
Distance Childcare 100-250m		-0.321***	0.297***	
		-0,0143	-0,0202	
Distance Childcare 250-500m	0.0880***	-0.332***	0.238***	0.0329***
	-0,0251	-0,0143	-0,0189	-0,00729
Distance Childcare 500-750m	0.0650**	-0.312***	0.171***	0.0209**
	-0,026	-0,0151	-0,0189	-0,0102
Distance Childcare 750-1000m	0,0637	-0.173***	0.134***	0.122***
	-0,0422	-0,0167	-0,0179	-0,0168

Distance Childcare 1000-2000m	0.133***			0.0563**
	-0,0367			-0,0231
Distance Childcare 2000-5000m	0.445***	-0.252***	0.212***	0.120*
	-0,0629	-0,0573	-0,0618	-0,0723
Size Childcare	0.00311***	-0.000601***	0.00202***	0.00174***
	-0,000443	-0,000115	-0,000195	-0,000153
Year opened Childcare	0.00376***	-0.00336***	-0.000950***	0.000502*
	-0,00109	-0,000268	-0,000356	-0,000277
new_build, YES	0.220***	0.245***	0,0405	0.142***
	-0,071	-0,0126	-0,0301	-0,0193
INCOME, lower	0.114*	-0.0608***	0.180***	0.0856***
	-0,0677	-0,00983	-0,0199	-0,00968
middle				
higher	0.0557**	0.0358***	0.0670***	0.115***
	-0,0258	-0,00584	-0,00971	-0,00689
Share of Kids, low				
average	0.294***	-0.0566***	-0.161***	-0.0923***
	-0,0362	-0,00587	-0,0176	-0,00826
high	0.376***	-0.106***	-0.262***	-0.142***
	-0,0369	-0,00633	-0,0168	-0,0089
Employment Score	-1.282***	-0.625***	1.255***	0.443***
	-0,431	-0,0643	-0,136	-0,0944
Living Environment Score	0,0254	0.0366***	0.0597***	0.0802***
	-0,0255	-0,00492	-0,00961	-0,00699
Education, Skills and Training Score	-0.0129***	-0.00435***	-0.0152***	-0.0116***
	-0,00167	-0,000316	-0,000529	-0,00028
year = 2010	-0.0650**	-0.0549***	-0.0853***	-0.108***
	-0,0254	-0,0109	-0,0159	-0,0132
year = 2011	-0.0526**	-0.0766***	-0.0877***	-0.0909***
	-0,0254	-0,0114	-0,0156	-0,0131
year = 2012	-0.0893***	-0.0381***	-0.0263*	-0.0721***

	-0,0248	-0,0109	-0,0155	-0,0131
year = 2013				
year = 2014	0.0686***	0.100***	0.137***	0.0987***
	-0,0253	-0,01	-0,0149	-0,0121
year = 2015	0.125***	0.201***	0.197***	0.193***
	-0,0268	-0,00989	-0,0146	-0,0123
year = 2016	0.0669**	0.261***	0.289***	0.292***
	-0,0332	-0,0101	-0,0153	-0,012
year = 2017	0.0697**	0.339***	0.318***	0.330***
	-0,0329	-0,0105	-0,0145	-0,0121
year = 2018	0.132***	0.195***	0.445***	0.234***
	-0,0482	-0,0169	-0,0178	-0,0195
year = 2019	0,0778	0.175***	0.440***	0.243***
	-0,0488	-0,0172	-0,0178	-0,0195
year = 2020	0.145***	0.206***	0.465***	0.269***
	-0,0503	-0,018	-0,0178	-0,0198
Constant	5.076**	19.40***	14.59***	11.72***
	-2,189	-0,536	-0,716	-0,556
Observations	5.661	25.307	8.002	12.576
R-Squared	0,175	0,23	0,521	0,436
Adjusted R-Squared	0,171	0,229	0,52	0,435

Robust standard errors in paratheses.
***p<0.01, **p<0.05, *p<0.1

Appendix E: Robustness Property type Sunderland

Table 8: Robust Property Type Sunderland

VARIABLES	(16) Detached Log (Price Paid)	(17) Flat Log (Price Paid)	(18) Terraced Log (Price Paid)	(19) Semi-detached Log (Price Paid)
Distance Childcare 0-100m	-0.906***	0.537***	-0.194***	-0.337***

	-0,203	-0,0969	-0,0656	-0,045
Distance Childcare 100-250m	-0.940***	0.208***		
	-0,0849	-0,0388		
Distance Childcare 250-500m	-0.938***	0.184***	-0.0982***	-0.107***
	-0,059	-0,0322	-0,0277	-0,0316
Distance Childcare 500-750m	-1.048***	0.0871***	-0.193***	-0.211***
	-0,0555	-0,0285	-0,0265	-0,0296
Distance Childcare 750-1000m	-1.043***	0.0869***	-0.130***	-0.281***
	-0,056	-0,0287	-0,0266	-0,0296
Distance Childcare 1000-2000m	-1.065***		-0.174***	-0.291***
	-0,0489		-0,0255	-0,028
Distance Childcare 2000-5000m	-0.958***	0.277***	-0.124***	-0.193***
	-0,0512	-0,0383	-0,0271	-0,0341
Distance Childcare >5000m			-0,0418	-0.304***
			-0,283	-0,0315
Size Childcare	-0.000764*	- 0.00378***	-0,000183	0.00266**
	-0,000403	-0,000392	-0,00013	-0,000157
Year opened Childcare	-0,00218	0.00281***	-0.00205***	0,000372
	-0,00198	-0,00108	-0,000604	-0,000497
new_build, YES	-			
	-0,0215	-0,0286	-0,0109	-0,0237
INCOME, lower	-0,00249	0.0992***	-0.113***	-0.149***
	-0,0278	-0,034	-0,0106	-0,0137
middle				
higher	0.396***	0.191***	0.370***	0.112***
	-0,0418	-0,0655	-0,0179	-0,0354
Share of Kids, low				
average	0,0312	-0.0772***	-0.0822***	-0.174***
	-0,0336	-0,0246	-0,00968	-0,0135
high	0,0206	-0.153***	-0.118***	-0.163***
	-0,04	-0,0356	-0,013	-0,0154
Employment Score	-0,67	1.276***	-0,0751	-1.129***
	-0,412	-0,271	-0,121	-0,116
Living Environment Score	-0.0167***	-0.0149***	-0,000782	-0.00856**

	-0,00226	-0,00235	-0,000901	-0,000713
Education, Skills and Training Score	-0.00942***	-0.0196***	-0.0107***	-0.00957**
	-0,0015	-0,00134	-0,000481	-0,000582
year = 2010	0,0123	0.140***	0.0432***	0.0758***
	-0,0453	-0,0434	-0,0162	-0,02
year = 2011	-0,015	0,0314	-0,017	0,0302
	-0,0467	-0,0436	-0,0159	-0,0197
year = 2012	-0,0604	-0,0246	0,0101	-0.0454**
	-0,0403	-0,0469	-0,0162	-0,0202
year = 2013				
year = 2014	0,0106	-0.0648*	0.0439***	0,0159
	-0,0376	-0,0386	-0,0144	-0,0187
year = 2015	0,0489	-0,0338	0.0558***	0,0173
	-0,0408	-0,0399	-0,0137	-0,019
year = 2016	-0,0148	-0.0692*	0.0691***	0.0359*
	-0,041	-0,0384	-0,0139	-0,0191
year = 2017	-0,00893	-0,0197	0.0902***	0,0253
	-0,0422	-0,0405	-0,0138	-0,019
year = 2018	0,0284	-0,014	0.0825***	0,0305
	-0,0412	-0,041	-0,0143	-0,0188
year = 2019	0.0757*	0,00522	0.113***	0,0145
	-0,0404	-0,0415	-0,0143	-0,0187
year = 2020	0.107***	-0.0999**	0.125***	0.0415**
	-0,0409	-0,0418	-0,015	-0,0195
Constant	17.98***	6.145***	16.36***	11.51***
	-3,984	-2,176	-1,214	-0,997
Observations	3.128	2.148	9.315	8.573
R-Squared	0,255	0,381	0,507	0,414
Adjusted R-Squared	0,248	0,374	0,506	0,412

Robust standard errors in paratheses.

***p<0.01, **p<0.05, *p<0.1

Appendix F: Correlation Matrix

	Natural log of	Property Type	New Build	Distance to	Income Class	Transactio n Year	Education Score	Living Environme	Employme nt Score	Share of Kids
Natural log of price paid	1									
Property Type	-0.1453	1								
New Build	-0.0229	-0.0941	1							
Distance to Childcare	-0.3151	0.083	0.0479	1						
Income Class	0.5212	-0.2406	-0.1034	-0.2873	1					
Transaction Year	0.09	-0.0071	0.0129	0.0492	-0.0667	1				
Education Score	-0.4319	0.2141	0.1343	0.132	-0.6159	0.0537	1			
Living Environment Score	-0.5213	0.2333	0.0794	0.3261	-0.5066	0.0642	0.2249	1		
Employment Score	-0.5149	0.1782	0.088	0.1345	-0.6142	0.0545	0.7894	0.3515	1	
Share of Kids	-0.0679	0.2153	0.0556	0.0792	-0.0941	0.0277	0.2654	0.0048	0.2228	c

Appendix D; STATA

```
clear

cd "C:\Users\yves-\OneDrive\Documenten\Master Thesisi"

import excel "Brighton_Sunderland", firstrow clear


// ENCODE

encode property_type, gen(PropCode)

encode new_build, gen(new_build_code)

encode estate_type, gen(estate)

encode town, gen(city)

encode county, gen(counties)


// create year date, time fixed effect

generate date = date(deed_date, "DMY")

generate year = yofd(date)


tab new_build_code
```

```
label define newbuil 1 "NO" 2 "YES"

label values new_build_code newbuil


tab PropCode

recode PropCode 3=1

label define typepro 1 "Detached" 2 "Flat/Maisonettes" 5 "Semi-Detached" 4 "Terraced"

label values PropCode typepro


// REMOVE DUPLICATES

gen combinedaddres= street + " " + saon + " " + paon

duplicates list combinedaddres

duplicates report combinedaddres date price_paid

duplicates list combinedaddres date price_paid

duplicates drop combinedaddres date price_paid, force

// Check

regress price_paid i.PropCode

predict r, resid

kdensity r, normal

histogram price_paid

generate lnprice=ln(price_paid)

predict r1, resid

kdensity r1, normal

sktest lnprice

correlate lnprice PropCode new_build_code



// drop outliers
```

```
summarize lnprice, d

drop if lnprice <= 10.30895

drop if lnprice >= 13.99783


histogram price_paid

histogram lnprice


regress lnprice i.PropCode


*** WITH SPATIAL DUMMIES

summarize Dummy_100 Dummy_250 Dummy_500 Dummy_750 Dummy_1000 Dummy_2000

tab Dummy_100


recode Dummy_100 . = 0

recode Dummy_250 . = 0

recode Dummy_500 . = 0

recode Dummy_750 . = 0

recode Dummy_1000 . = 0

recode Dummy_2000 . = 0


generate spatial_ring_100_250 = .

replace spatial_ring_100_250 = 1 if Dummy_250 == 1 & Dummy_100 == 0

replace spatial_ring_100_250 = 0 if Dummy_250 == 0 | Dummy_100 == 1

summarize spatial_ring_100_250


generate spatial_ring_250_500 = .

replace spatial_ring_250_500 = 1 if Dummy_500 == 1 & Dummy_250 == 0
```

```
replace spatial_ring_250_500 = 0 if Dummy_500 == 0 | Dummy_250 == 1
summarize spatial_ring_250_500

generate spatial_ring_500_750 = .
replace spatial_ring_500_750 = 1 if Dummy_750 == 1 & Dummy_500 == 0
replace spatial_ring_500_750 = 0 if Dummy_750 == 0 | Dummy_500 == 1
summarize spatial_ring_500_750

generate spatial_ring_750_1000 = .
replace spatial_ring_750_1000 = 1 if Dummy_1000 == 1 & Dummy_750 == 0
replace spatial_ring_750_1000 = 0 if Dummy_1000 == 0 | Dummy_750 == 1
summarize spatial_ring_750_1000

generate spatial_ring_1000_2000 = .
replace spatial_ring_1000_2000 = 1 if Dummy_2000 == 1 & Dummy_1000 == 0
replace spatial_ring_1000_2000 = 0 if Dummy_2000 == 0 | Dummy_1000 == 1
summarize spatial_ring_1000_2000

gen dist_childcare = .
replace dist_childcare = 0 if Dummy_100 == 1
replace dist_childcare = 1 if spatial_ring_100_250 == 1
replace dist_childcare = 2 if spatial_ring_250_500 == 1
replace dist_childcare = 3 if spatial_ring_500_750 == 1
replace dist_childcare = 4 if spatial_ring_750_1000 == 1
replace dist_childcare = 5 if spatial_ring_1000_2000 == 1
replace dist_childcare = 6 if dist_childcare == .
```

```
reg lnprice ib(#1).dist_childcare

* 2097 values dropped

tab dist_childcare, missing

drop if dist_childcare == .


label define distance 0 "0-100m" 1 "100-250m" 2 "250-500m" 3 "500-750m" 4 "750-1000m" 5 "1000-2000m" 6 ">2000m"

label values dist_childcare distance


// income classes

list INCOME

tab INCOME, missing

drop if INCOME ==.

tab INCOME

recode INCOME 24500/37000 = 1 38100/44200 = 2 4/61900 = 3, generate(income_class)

tab income_class

label define incomeclass 1 "lower" 2 "middle" 3 "higher"

label values income_class incomeclass



// population of area in percentages

gen Per_below_15 = Age015/AllAges

gen Per_16_29 = Age1629/AllAges

gen Per_30_44 = Age3044/AllAges

gen Per_45_64 = Age4564/AllAges

gen Per_above_65 = Age65/AllAges
```

```
tab Per_below_15, missing

recode Per_below_15 .0366056/.1278255 = 1 .1317273/.1745623 = 2 .1751874/.2855306 = 3, gen(share_kids)

tab share_kids

label define kidsshare 1 "low" 2 "average" 3 "high"

label values share_kids kidsshare

histogram share_kids



// FINAL MODEL //

tab county dist_childcare

tab district dist_childcare

tab city dist_childcare


reg lnprice ib(#1).dist_childcare if county == "BRIGHTON AND HOVE"

reg lnprice ib(#1).dist_childcare if county == "TYNE AND WEAR"

reg lnprice ib(#1).dist_childcare

predict xr

summarize xr


reg lnprice ib(#2).dist_childcare

reg lnprice ib(#2).dist_childcare

reg lnprice ib(#3).dist_childcare

reg lnprice ib(#4).dist_childcare

reg lnprice ib(#5).dist_childcare

reg lnprice ib(#6).dist_childcare
```

```
reg lnprice ib(#7).dist_childcare

// Summarize Variables of interest

summarize lnprice i.dist_childcare i.PropCode i.new_build_code i.income_class i.share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS i.year

correlate lnprice PropCode new_build_code dist_childcare income_class year EducationSkillsandTrainingS LivingEnvironmentScore EmploymentScore share_kids

pwcorr lnprice PropCode new_build_code i.dist_childcare i.income_class year EducationSkillsandTrainingS LivingEnvironmentScore EmploymentScore share_kids

est store correlationmatrix

outreg2 using myreg.doc, replace ctitle (correlationmatrix) label

// Model 1

reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if county == "BRIGHTON AND HOVE", r

r2_a

outreg2 using myreg.doc, replace ctitle (Model 1) label

vif

est store model1vif

predict r2, resid

histogram r2, normal

// MODEL 2
```

```
reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if county == "TYNE AND WEAR", r

outreg2 using myreg.doc, append ctitle (Model 2) label

vif

est store model2vif

// Model 3

reg lnprice ib(#7).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year, r

outreg2 using myreg.doc, append ctitle (Model 3) label

predict r3, resid

histogram r3, normal

vif

estat imtest

estat hettest

rvfplot, yline (0)

// _pctile price_paid, p(33.333, 66.667)

// return list

// 176000

// 307000

// sum price_paid, d

// ROBUSTNESS CHECK 1/3
```

```
// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if price_paid <= 176000 , r

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if price_paid > 176000  & price_paid <= 307000 , r

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if price_paid > 307000 , r



// Robustness Check 1/2  // CHECKED

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if price_paid < 240000 , r



// outreg2 using myreg.doc, replace ctitle (Model 4) label

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if price_paid >= 240000 , r

// r2_a

// outreg2 using myreg.doc, append ctitle (Model 5) label



// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year, r

// correlate lnprice PropCode dist_childcare



// Check for property typepro

// reg lnprice ib(#7).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if PropCode == 1, r

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if PropCode == 2, r
```

```
// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code i.estate ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if PropCode == 4, r

// reg lnprice ib(#4).dist_childcare ib(#2).PropCode i.new_build_code ib(#2).income_class ib(#1).share_kids EmploymentScore LivingEnvironmentScore EducationSkillsandTrainingS ib(#4).year if PropCode == 5, r


// r2_a


// predict price

summarize price if (dist_childcare ==  0)

summarize price if (dist_childcare == 1)

summarize price if (dist_childcare == 2)

summarize price if (dist_childcare == 3)

summarize price if (dist_childcare == 4)

summarize price if (dist_childcare == 5)

summarize price if (dist_childcare == 6)


// area effects

tab oa11cd

encode(oa11cd), gen(output_area)


reg lnprice i.PropCode i.new_build_code ib(#3).dist_childcare output_area

regcheck


tab lsoa11cd

encode(lsoa11cd), gen(lsoutput_area)

reg lnprice i.PropCode i.new_build_code lsoutput_area ib(#3).dist_childcare
```

```
tab msoa11cd

encode(msoa11cd), gen(msoutput_area)

reg lnprice i.PropCode i.new_build_code ib(#3).dist_childcare msoutput_area ib(#3).year

regcheck

// significant




// break up between dummy_250 // chow -test

// reg lnprice i.PropCode i.new_build_code i.estate msoutput_area ib(#2).income_class ib(#3).year Per_below_15 Per_16_29 Per_30_44 Per_above_65 CrimeDeprivationScore EducationDeprivationScore LivingEnvironmentDeprivation Employment if dist_childcare == 2

// reg lnprice i.PropCode i.new_build_code i.estate msoutput_area ib(#2).income_class ib(#3).year Per_below_15 Per_16_29 Per_30_44 Per_above_65 CrimeDeprivationScore EducationDeprivationScore LivingEnvironmentDeprivation Employment if dist_childcare == 2

// include density, instead of population distribution

// reg lnprice i.PropCode i.new_build_code i.estate ib(#3).dist_childcare msoutput_area ib(#2).income_class ib(#3).year PopulationDENSITYperKM CrimeDeprivationScore EducationDeprivationScore LivingEnvironmentDeprivation Employment



// panel data ?



// help panel

// encode unique_id, generate(id)

// encode street, generate(streets)

// encode paon, generate(PAON)

// encode postcode, generate(post_code)

// encode lsoa11cd, generate(lsoa)

// didregress (lnprice msoutput_area i.PropCode) (Dummy_250), group(post_code) time(year)

// xtset id date, daily
```

```
// xtset unique_id

// xtset id date

// xtline  y

// xtset streets date

// rvfplot, yline (0)

// estat imtest

// estat hettest

// repeated sales /////////

// voorbeeld // transaction number 1

// sort combinedaddres date

// by combinedaddres: gen dup = cond(_N==1,0,_N)

// drop if dup==0

// drop dup


// quietly by combinedaddres: gen dup = cond(_N==1,0,_n)

// egen soldgood=group(combinedaddres)

// keep if dup==1                          /*Keep only the first transaction*/

// rename dup numsale                      /*Identify the number of sale (first)*/

// label variable numsale "Number of the transaction occurring over time"

// label variable soldgood "Unique ID for transaction of the same good (house)"

// save "C:\Users\yves-\Downloads\Example-RepeatedSales.dta", replace



// voorbeeld // transaction number 2


// cd "C:\Users\yves-\OneDrive\Documenten\Master Thesisi"

// import excel "Brighton_ppd (1)", firstrow clear
```

```
// sort combinedaddres date
// by combinedaddres: gen dup = cond(_N==1,0,_N)
// drop if dup==0
// drop dup

// quietly by combinedaddres: gen dup = cond(_N==1,0,_n)
// egen soldgood=group(combinedaddres)
// keep if dup==2			/*Keep only the second transaction*/
// rename price_paid price_Paid2
// rename date TransactionDate2
// rename dup numresale
// save "C:\Users\yves-\Downloads\Example-RepeatedSalesSecondTransaction.dta", replace

// combine both repeated sales files
// clear
// cd "C:\Users\yves-\Downloads\"
// use "C:\Users\yves-\Downloads\Example-RepeatedSales.dta", replace
// merge 1:1 soldgood using "C:\Users\yves-\Downloads\Example-RepeatedSalesSecondTransaction.dta"
// drop if _merge!=3
// drop _merge
// save "C:\Users\yves-\Downloads\RepeatedSales.dta", replace

// generate dependent/independent variables
// generate dprice = ln(price_Paid2) - ln(price_paid)
// gen YearSale = year(date)
```

```
// gen YearReSale = year(TransactionDate2)

// generate d2010 = (YearReSale==2010) - (YearSale==2010)
// generate d2011 = (YearReSale==2011) - (YearSale==2011)
// generate d2012 = (YearReSale==2012) - (YearSale==2012)
// generate d2013 = (YearReSale==2013) - (YearSale==2013)
// generate d2014 = (YearReSale==2014) - (YearSale==2014)
// generate d2015 = (YearReSale==2015) - (YearSale==2015)
// generate d2016 = (YearReSale==2016) - (YearSale==2016)
// generate d2017 = (YearReSale==2017) - (YearSale==2017)
// generate d2018 = (YearReSale==2018) - (YearSale==2018)
// generate d2019 = (YearReSale==2019) - (YearSale==2019)
// generate d2020 = (YearReSale==2020) - (YearSale==2020)

// estimating model
// reg dprice d2013- d2020 Dummy_100 spatial_ring_100_250 spatial_ring_250_500 spatial_ring_500_750 spatial_ring_750_1000 spatial_ring_1000_2000, r
// regcheck
```