Do good schools influence property prices? Disentangling school and neighbourhood effects with empirical evidence from Brighton.

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A perception that proximity to good schools pushes house prices up is common and one factor which contributed to a shift in the secondary-school admissions policy away from proximity-based criteria in Brighton, England, in 2008. This decoupling of proximity was expected to reduce perceived house price inflation near good schools. But is this link as strong as many believe or are other factors more important? We examine 81,000 residential transactions in Brighton between 2000 and 2019, assessing the effect of schools alongside other contextual factors such as building attributes, accessibility to jobs, deprivation, and macro price trends, as well as the impact of the policy change in 2008. We find that after accounting for local neighbourhood confounders and a general upward drift in property prices, proximity to good schools has only a limited impact on house prices, with other local factors playing an often more important role. The admissions policy reform has little discernible impact on prices.

Keywords: word; house prices; schools, accessibility, hedonic models, Brighton and Hove

Word Count – 9,329

Github Repository (all analysis code and data)

Introduction

In popular media and marketing narratives as well as the field of housing research, the theory that proximity to good schools makes housing more expensive is widely accepted as something approaching an unassailable fact. The causal pathways appear obvious to anyone with even a rudimentary understanding of economic theory – in a system where resource scarcity (good, free-to-access schools) can be high, and access to that limited resource is determined, frequently, by geographic residential proximity, then competition for that residential proximity will increase. As demand and competition rises and the and the route to winning is through paying more, then prices will naturally increase in this classical supply and demand scenario.

The literature from across the world is full of evidence that this theory holds in many different contexts (see, amongst other studies, Bonilla-Mejía et al., 2020; Chin and Foong, 2006; Fack and Grenet, 2010; Haurin and Brasington, 1996; Cheshire and Shepard, 2004; Kane et al., 2005; Wen et al., 2017; and Rosiers et al. 2001). However, despite the headlines of these papers boosting the narrative, the strength of the association can sometimes be quite weak (for example Wen et al., 2017) with other factors (such as accessibility to urban centres) playing an equal if not more important role.

Some of the work in this area has had the advantage of longitudinal data and clear policy shifts at particular times (see Bonilla-Mejía et al., 2020) which have allowed for natural experiments to be conducted with treatment and control groups to help determine the potential impact of policy changes and the size of the school effect, but these studies are in the minority. And in the case of the Bonilla-Mejía et al. paper specifically, while spatial catchment covariates were tested, they failed to account for other local spatial factors which might be playing an important role in the story.

In this paper we address these issues through taking a more critical approach to the way the influence of schools on house prices has, to date, been conceived. Schools may well play a role in the decisions that some home-buyers make – indeed it can feature prominently in the marketing materials of estate agents – but can we say for certain that the presence of a good school is any more important, than access to employment opportunities or other neighbourhood factors, especially where good schools, good neighbourhoods and good employment opportunities might often overlap? We explore this question through a detailed analysis of house prices in Brighton, England. Brighton makes for a particularly interesting case study as in 2008, the admissions policy for its secondary schools was altered, if not primarily – as social mixing was a priority – partially in response to a perceived house price premium near some of the more popular secondary schools. (Allen et al., 2010). We carry out a detailed spatial and temporal analysis which examines the sale prices of homes across the city between 2000 and 2019 – crucially either side of the admissions policy change – and relate these prices to school performance, proximity to those schools and a basket of other potentially influential variables.

Our analysis is facilitated though the use of a detailed linked dataset created by Chi et al. (2020) which links Land Registry Price Paid data to detailed property attributes contained within the Department for Levelling Up, Housing and Communities (DLUHC) Energy Performance Certificate dataset. These data are further enhanced through attaching school performance and travel-time / accessibility data for the city centre and major railway stations, as well as contextual neighbourhood and deprivation data.

The main research question of this study is thus:

"How strong is the effect of proximity to good schools on house prices in Brighton and did the 2008 secondary school admissions reform have any impact on prices?"

Our findings in this paper are important for a number of reasons: There is of course academic merit in contributing to the evidence base in this popular area of housing research; however, the relevance of this work to sound policymaking, particularly around school admissions, is key. Any policy formulated using poor evidence or 'received wisdom' runs the risk of being a poor policy. Where policies are implemented that disconnect pupils from their local schools, then the resulting impacts on the social welfare of pupils or on the transport systems of cities need to be balanced against the positive impacts intended, such as increased social mixing and housing affordability. If some of these positive impacts don't exist, then the policy is on weaker foundations.

Brighton's admissions reforms were implemented to promote equity with a secondary benefit of combatting the phenomenon of expensive housing near popular schools (Allen et al., 2013). Over a decade after these changes were made, we are now able to review the house price dimension of this story, with potentially significant relevance for other geographical contexts. The rest of this paper proceeds with a review of the relevant contextual literature relating to house prices and school proximity, followed by an exploration of the local Brighton setting before detailing data used, methodology employed and our results. We conclude with a discussion of our findings.

Review

Examining the relationship between schools and house prices

A large body of international work exists which makes a causal link between proximity to good schools and higher house prices. In the United States (US), the link between residential choice and school choice has been established through qualitative (Lareau & Goyette, 2014) and quantitative studies in Boston, Massachusetts (Black, 1999) and Chicago (Bonilla-Mejía et al., 2020). In Paris, France, there is evidence that a standard deviation increase in public school performance raises housing prices by 1.4 to 2.4 percent (Fack & Grenet, 2010) while in Singapore where primary school admissions are dependent on proximity, distance to schools can explain a large amount of the variation in house price differences (Chin & Foong, 2006). In Japan, Kuroda (2018) demonstrated that proximity to better schools increased rents for family dwellings.

In England, proximity to state-funded schools is an established admission criterion (UK Government, 2023) and research to date suggests a straightforward link between this and house prices. Gibbons and Machin (2006) for example, showed that a 10 percent increase in children reaching their expected grades at Key Stage 2 (ages 7-11) increases house prices by 3 percent, and that each 100m distance increase from a school lowers the premium by 8.4 percent relative to the original level. That said, it was also found that only those schools in the top performance deciles had a positive influence on house prices - most schools depress house prices in their vicinity as ‘average schools are not desirable local amenities’ (Stephen Gibbons & Machin, 2006, p. 90).

While a large body of quantitative evidence has emerged in this area, many of the studies feature methodological limitations. For example, data samples that are either relatively small (Black, 1999; Cheshire & Sheppard, 2004; Steve Gibbons & Machin, 2003; Leech & Campos, 2003), do not account for property-level characteristics (Stephen Gibbons & Machin, 2006), or cover a short period of time (Cheshire & Sheppard, 2004; Steve Gibbons & Machin, 2003; Leech & Campos, 2003). The outcome of any of these limitations is the inferential certainty of the results is called into question.

An established methodology for examining the factors that influence house prices is the hedonic regression model. Based on the Rosen model (Rosen, 1974), it theorises that house prices demonstrate consumer choice as an optimal balance of bundled attributes. With the appropriate data inputs the hedonic price model can be a powerful explanatory tool and illustrate that property prices are a predictable function of property-level and neighbourhood-level attributes. A major challenge with this model, however, is dealing with omitted variable and endogeneity problems (Gibbons & Machin, 2008) which could lead to upwardly biased estimates if confounding variables are not recognised (Black, 1999). In order words, should the effects of schools on house prices be confounded by other, unaccounted for, neighbourhood factors, then their influence may be exaggerated.

Sometimes absolute distance is less important than being within a school's catchment boundary and some research designs that use boundary discontinuities are well-documented in the existing literature. These focus on house-price differentials between houses separated by catchment area boundaries (Cheshire & Sheppard, 2004; Davidoff & Leigh, 2007; Fack & Grenet, 2010; Stephen Gibbons & Machin, 2006). These studies also mostly report a 2-4 percent increase in house prices for a one-standard-deviation increase in school performance for a given catchment. However, this approach does not account for varying neighbourhood-level attributes within school catchment boundaries.

Where distinct changes in policy or school availability have occurred at particular times points, another approach is to use "natural experiments" which look at before and after 'treatment' effects. In our context the 'treatment' could be opening or closing of schools or changes in admissions policies, with the effect measured in house price changes. This approach was used in the US by Reback (2005) and Kane et al. (2005) that capitalised on school policy changes, and could be similarly applied to Brighton's admissions reforms where one approach could be to explore comparable housing and other contextual data have been collated for local authorities where admissions policies have not been altered like Brighton's. Directly relevant to this work, Shah (2018) studies the effect of Brighton's reforms on house prices for a small sub-set of repeat sales, and found that a 10 percent increase in the GCSE pass rate of a secondary school increased house prices in that sample by 2.38 percent. Shah analysed treatment and control samples affected by Brighton's 2008 reforms using a difference-in-difference approach. However, the study has limitations as property-level attributes are not accounted for, and only limited sample of repeat sales data of same houses pre- and post- reform between the years 1995-2017 is used. Furthermore, their definition of treatment and control groups could be questioned as their control groups were still subject to the same policy changes as the treatment groups.

Other Contextual Influences on House Prices

While proximity to good schools is important, it is not the only consideration for home buyers. Housing is often characterised as a "bundled good" in economic discourse (Goodman, 1978) as home buyers pay for the property's intrinsic attributes and its neighbourhood-level utilities such as school quality, transport links, and accessibility to the city centre – a proxy for employment opportunities and other services. A classically economically rational home buyer (Huu Phe & Wakely, 2000) would be aiming to optimise their housing investment with respect to other amenities such as public goods, proximity to urban centres, and other spatial factors (Alonso, 1964; Cho, 2001). Services like rail connectivity (Du & Mulley, 2007; Stephen Gibbons & Machin, 2005), distance to city centre (McCord, M. et al., 2014), and travel time to London (Chi et al., 2020), are key considerations in residential choice in the UK context. Other neighbourhood factors that could potentially be considered include local rates of crime (McIlhatton et al., 2016)) and access to green spaces (McCord, J. et al., 2014).

School admissions in Brighton

Before the school admissions reform was announced in 2007, Brighton's admissions criteria were similar to most English Local Authorities (LAs). Parents expressed their preferences for any state school and schools admitted students until their published capacity was reached. Schools and students were then matched using a priority-matching mechanism which considered only the first choice, then using oversubscription criteria to rank and allocate remaining students where necessary (Allen et al., 2013). Under the UK national School Admissions Code, 2007, distance between home and school is cited as a 'clear and objective criterion' for oversubscription that ensures students do not have overly long journeys to and from the school (School Admissions Code, 2007) – and indeed is used as the primary tie-breaker in many local authorities. However, the Code was also cognisant of how this could advantage families who can afford properties near the school, so a range of other suitable decision criteria are listed – including random (lottery) allocation. While the national code serves as a guide, the decision on which criteria are applied rests with local admissions authorities.

Brighton's authorities recognised the problem of fair access to popular secondary schools (Eastwood & Turvey, 2008) and consequently, in 2008, introduced a lottery system, alongside new catchment areas[1] to its secondary school admissions process (distance was retained as a criteria for primary schools). The reform was designed to improve equitable access to secondary schools and stop the creation of 'golden halos' of housing premiums near oversubscribed schools (Allen et al., 2013, p.152). Interviews with parents in the city (Robinson et al. 2016) confirmed that this perception of higher house prices in the proximity of popular schools was well established.

In the post-reform admissions process, a lottery was used first to select applicants within the catchment areas and then, if places were still available, applied once more for applicants living outside the catchment area who had expressed a preference for that school. While this meant that families living in the catchment areas for less popular secondary schools lacked choice, the policy reform transformed the chances of families getting a place at their preferred school within a catchment, especially those within dual catchment areas. Dual catchment areas (e.g. Blatchington Mill and Hove Park, Dorothy Stringer and Varndean) give children in the catchment an equal probability of admission, with a place at either school virtually guaranteed. This means that composition of student populations in both single and dual school catchments would be changed post-reform – with those within the catchment but living a relatively long way from the school, given equal probability of admission to those living next door.

While the Dorothy Stringer/Varndean (DS/V) catchment area is relatively affluent with both schools being popular, the Blatchington Mill/ Hove Park catchment area is interesting because Blatchington Mill performed significantly better than Hove

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[1] https://applyforaschool.brighton-hove.gov.uk/p/schoolsmap

Park in the post-16 General Certificate of Secondary Education (GCSE) examination, with Hove Park having a higher proportion of students eligible for free school meals (FSM) – a marker of social deprivation within the school cohorts (Allen et al., 2013). The reform, thus, somewhat delinks proximity to a popular school from probability of access. In the Blatchington Mill/ Hove Park catchment area, houses previously guaranteed a place by virtue of proximity now having to enter a lottery with all the families in the catchment area. It is also important to note that the equitable access to popular schools in Brighton also now depends on the drawing of catchment areas, which are devised by the Local Authority. Nonetheless, proximity still matters as being within a catchment area with good schools (e.g. DS/V) virtually guarantees a place at either school, just that it should have a weaker effect.

Study Design

To investigate the school effect on property prices, we use an established hedonic regression modelling framework, with some adjustments for spatial and temporal elements. We incorporate both structural/building-level attributes alongside locational attributes as advocated by Orford (2002), but unique in this study relative to others is the detailed linkage of school quality via realistic walking and public transport journey times along the road network to home locations – this allows for a much more accurate representation of proximity/accessibility than crude distance buffers. We are also cognisant of the perceptions of school quality changing over time, so every sale is linked to the perceived quality of the nearest primary and secondary school when the sale occurred. Also, conscious that grouping variables like school catchment areas might be unwittingly capturing general area effects, we include alternative area groupings to control for erroneous associations. To explore the impact of the 2008 admissions policy change, the final model splits the data into two panels of pre- and post- reform sales.

Data

House Prices and Structural Attributes

The spine of our research dataset is the new linked House Price (HP) dataset for England and Wales (1995-2021), created by Chi et al. (2022). This dataset covers more than 18 million transactions from the Land Registry Price Paid dataset (LR-PPD) between 1995 and 2021 and links these transactions with key building attribute data from the Department for Levelling Up, Housing and Communities' (DLUHC) Energy Performance Certificates (EPCs) dataset. From this we select 7 structural variables including price paid, construction year, year of sale, property type, floor area, number of rooms, energy efficiency rating and postcode, for 81,652 sales transactions in Brighton between 2000 and 2020, spatially joining them with our own neighbourhood, accessibility and school quality perception variables.

The full research dataset and associated code are available on an online repository. All data were obtained from open and publicly-available repositories, including but not limited to: the London Datastore, Ofsted Online Reports, Department for Education (DfE) Archives, and the Office for National Statistics (ONS).

Locational Attributes – Local Schools Data

Perceptions of school quality amongst homebuyers are subjective but using information from a range of school-related datasets, we hope to derive categorical composite 4-level indicator of perceived school quality, using the Ofsted terminology of: Outstanding, Good, Satisfactory and Poor. Ofsted ratings are only factored in from the year 2007 as archived data was patchy until then. Ratings persist between inspections, so a school rated "Outstanding" in 2007 maintains that rating until a new inspection is carried out. Past Ofsted reports for Academies (a new class of state school, partially funded from private investment and exempt from local authority control) are also wiped 5 years after academisation (a controversial process occasional forced upon under-performing state schools), which means useful data was lost for schools such as Portslade Aldridge and Brighton Aldridge. This denies the historicity of their school quality, as they might have been rated ‘good’ or better in many of the years prior but only deemed inadequate for a short period before academisation. Hence, we adopt a ‘business-as-usual’ approach, continuing the last recorded rating where data is lacking, assuming that school ratings, the demography of their cohorts and local perceptions do not change rapidly over short periods of time. An example of this is using the previous year’s data for St Joseph’s Primary School and Balfour Primary School when they had no data for specific years.

The DfE Archives were a rich resource, with data available on key school information (school names and postcodes), Key Stage 2 and 4 results, Free School Meals (FSM) and pupil destinations. We recognise that including FSM in a perceptions variable could erroneously link deprivation with quality, so give it a low weighting in the mix. However, the link between FSM and attainment levels might be relevant in perceptions. Key Stage 2 (KS2) results were available from 2003 while Key Stage 4 (KS4) results (GCSEs) were available from 2000, and FSM and Pupil Destination (for secondary school) information was available from 2012. The availability of datasets shapes the ranking of schools, with variables only being factored in and weighted from the year they are available. The process of ranking and categorising perceived school quality is summarised in the appendix.

Other Locational Attributes and Proximity Calculations

To calculate proximity/accessibility to schools and other relevant services, the ONS

Postcode Directory (ONSPD) was used to add latitude and longitude coordinates to the postcodes in the HP and schools datasets. Coordinates for the Brighton, Hove and Preston Park rail stations were obtained using their coordinates on Google Maps. These stations were chosen as they are the key stations that are connected to London via the Thameslink/Southern Rail/Gatwick Express network (Thameslink, 2023) and service Brighton's substantial London commuter population – particularly those "employed full-time in manager, director and senior official, professional and associate professional and technical occupations"[2] which have the highest salaries and which may add to the pool of available property purchasing capital in the city. A general catch-all for other services and local employment services was the city centre of Brighton. The point used as the city centre reference was obtained by calculating the centroid of the Brighton and Hove Regional Centre polygon as determined by the Consumer Data Research Centre's (CDRC) dataset on retail centres in the UK (Consumer Data Research Centre, 2022).

Accessibility to these important services and opportunities was calculated using the Rapid Realistic Routing with R5 (r5r) package (Pereira et al., 2021). This uses the road network from OpenStreetMap alongside public transport schedules and elevation to generate realistic travel times between all residential postcodes, schools, railway stations and the city centre. These were calculated for both walking and taking the bus. The bus schedules used are from 2021, and while these may not accurately represent bus routes and timetables for the full 2000-2019 period, in the UK, bus routes and schedules do not undergo drastic changes over time.

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[2] See - https://www.commute-flow.net/classification.html#g9 – for a map demonstrating how closely linked Brighton is to London for "Techs & the City Types" commuters.

Bands of 5 minutes, up to 30 minutes were generated for walk times, while for bus times it was up to 45 minutes with maximum 20 minutes walking. Transactions outside these bounds were labelled “Not near” whichever service. Variables representing walk times to the nearest rail stations, and primary and secondary schools (regardless of quality) were also generated for all postcodes in Brighton to provide insights into the baseline effects of schools on property prices and a comparable variable for rail stations. For proximity to schools and rail stations, walk times up to 30 minutes were with anything beyond that classed as ‘not near’. Bus time to city centre was used in preference to car travel times as the 2021 Census found 37.4 percent of Brighton households had no cars or vans – much higher than the English average of 23.5 percent (ONS, 2023) – which means walking or public transport are the main forms of transport in the city.

To explore local neighbourhood effects, we used the 2019 Index of Multiple Deprivation (IMD) ranks and deciles, as well as 2011 Output Area Classification (OAC) supergroups, school catchment areas and electoral ward boundaries. With the IMD we do not account for changes in relative deprivation and demographic profiles over time and just use the latest iteration. While it might have been preferable to try and match deprivation profiles temporally to house sales, studying the evolution of the Index of Multiple Deprivation over time from 2010 via the CDRC Map Maker the general drift within Brighton is towards being less-deprived, with relative geographic positions remaining quite constant between 2010 and 2019. If anything, any associations between higher price and affluence or lower price and deprivation might be underplayed at the beginning of the study period.

Given the potential importance of secondary school catchment areas post reform, we include these as area dummy variables in the analysis. To deal with the possibility of erroneous neighbourhood effects being ascribed to catchment boundaries, we also include electoral wards as a comparison grouping (or random effect using statistical terminology) variable.

Data Pre-Processing

Constructing the dataset involved three main steps: the first being the categorisation of schools according to their perceived quality; the second generating variables for geographical proximity of the city centre, rail stations and schools perceived as 'outstanding/good'; the third merging all of these new derived variables with the transactions in the HP dataset and cleaning (removing incomplete records or extreme values) before analysis.

All variables were combined into one dataset, with code adapted from (Chi et al., 2021) being used to clean the dataset of missing or overly high or low sale price values. The top and bottom 5 percent of transactions in terms of prices for each year (2000-2019) were also excluded from the dataset to account for outliers which are common in house-price datasets. More information on the data cleaning process can be found in the supplementary material.

Explaining House Prices – The Hedonic Price Model

The general hedonic price model (Freeman, 1979; Rosen, 1974) we use can be written as follows:

$$P_{it} = f(X_{ht}, X_{gt}, X_s, e_t)$$

where:

P_{it} = price of transaction i in period t

X_{ht} = a vector of property-level characteristics at the time of transaction

X_{gt} = a vector of neighbourhood-level contextual variables at the time of transaction

X_s = a vector of socio-economic characteristics of the neighbourhood assumed to be persistent over time.

For P_{it}, the element of time is factored in by using the year of transaction as a categorical variable to control for year-on-year variations in price, and coefficient changes are interpreted as percentage change in price from the reference year (Fleming & Nellis, 1985). We could have attempted to standardise prices across years using national information on inflation, but in retaining year as a dummy variable, we are able to compare these annual inflationary effects with those of the other variables. X_s does not have a time element to it as we just use 2019 IMD data as an approximation of relative deprivation / affluence within the city.

Exploratory Analysis

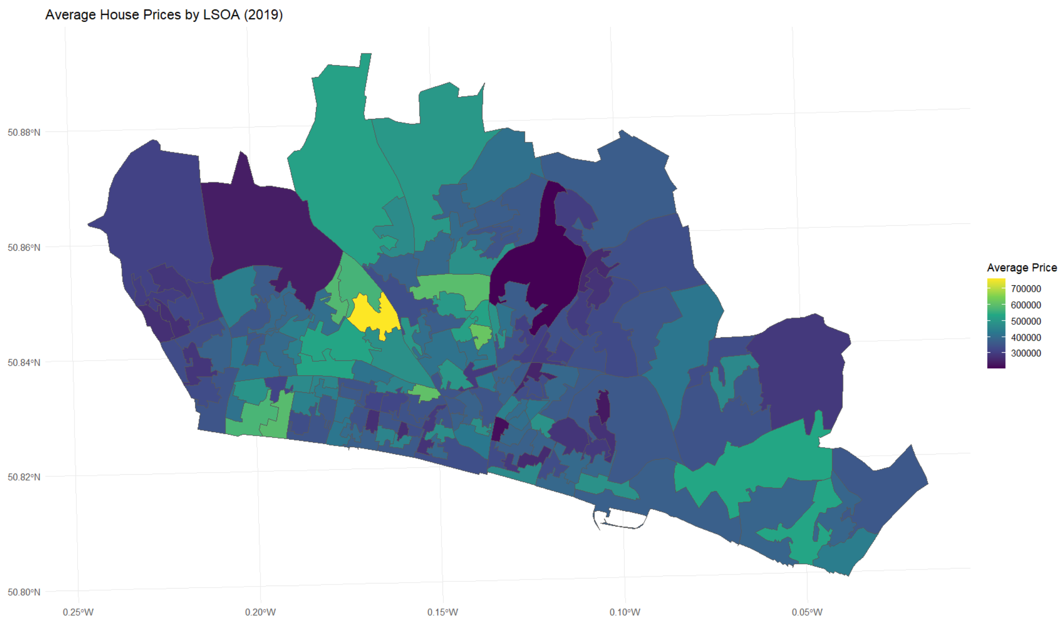
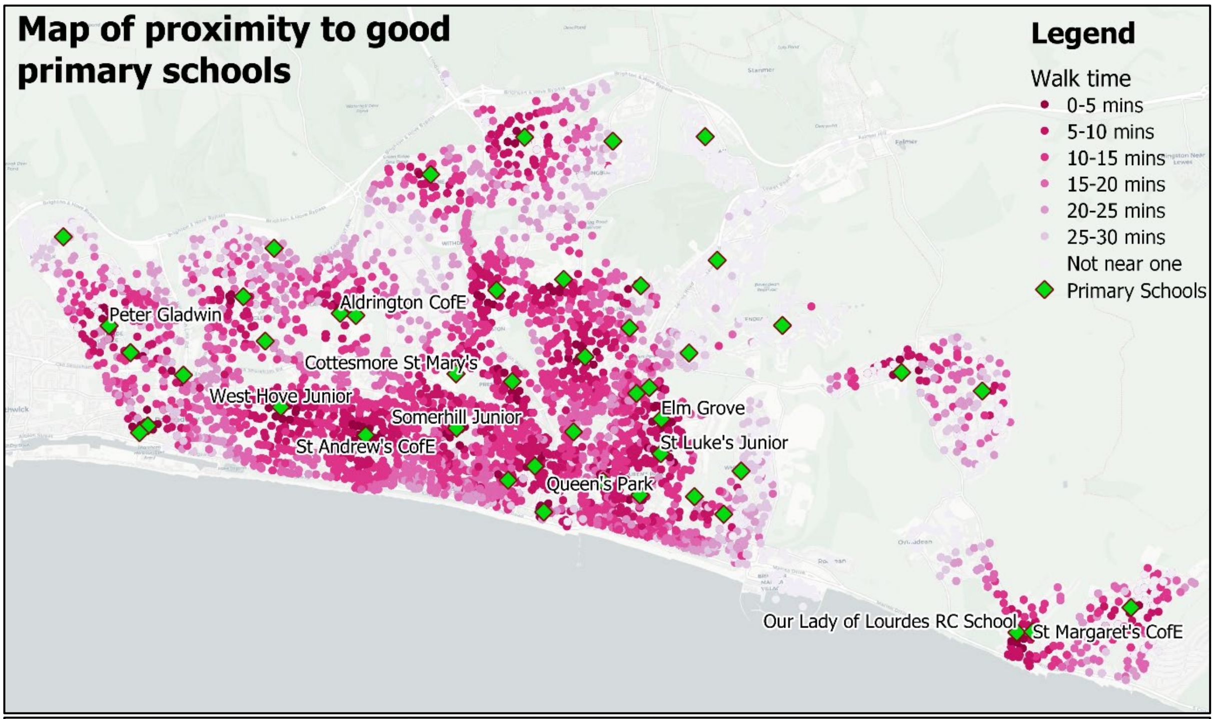
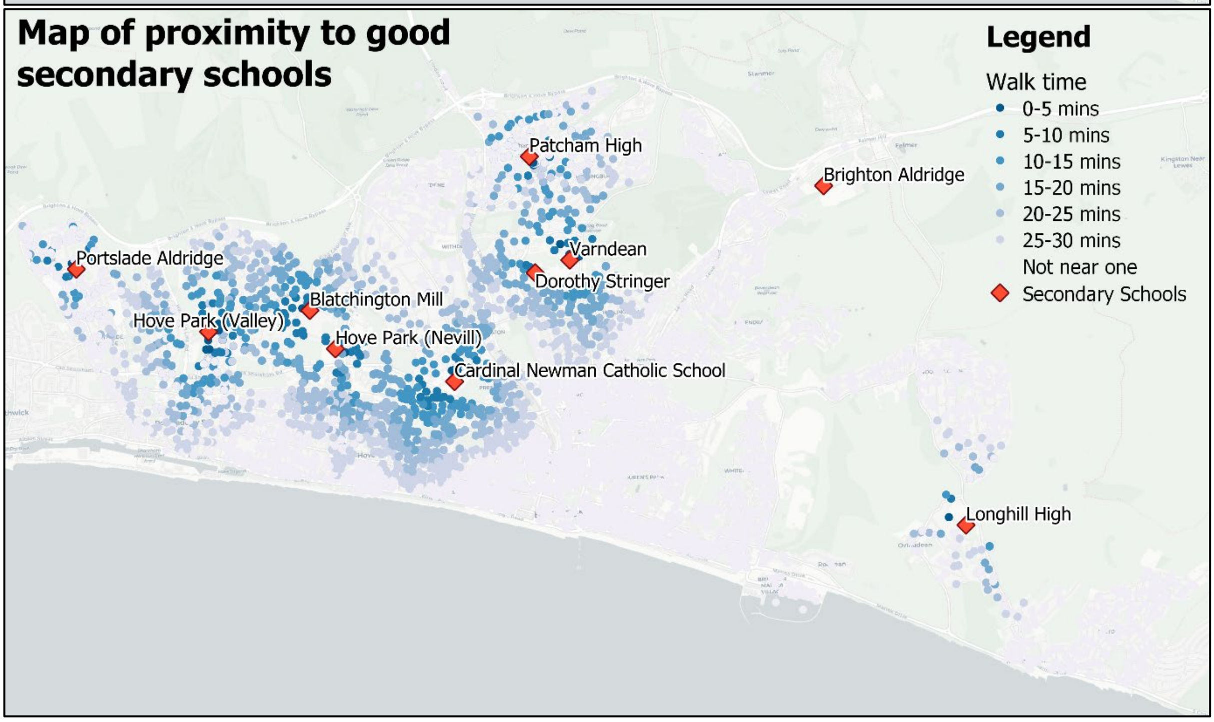


Figure 1: Map showing average house prices in Brighton and Hove by LSOA (2019)

The map above (Figure. 1) illustrates the spatial distribution of the house prices analysed in this report, aggregated to Lower Level Super Output Areas (LSOAs) in 2019 (the geographical variation in house prices does not change much year-by-year). Higher prices tend to be seen in the North and East of the City Centre, with the LSOAs with the highest prices near Preston Park and Hove rail stations (Figure 2c) and also near in-demand schools such as Blatchington Mill, Dorothy Stringer and Varndean. Proximity to good primary schools (Figure 2a) seems centred near the city centre and rail stations, with good secondary schools being located more towards the west (Figure 2b). However, Whitehawk and Mouselcoomb (red areas eastward of Brighton station are deprived in terms of both IMD and a lack of good schools (Figure 2c).





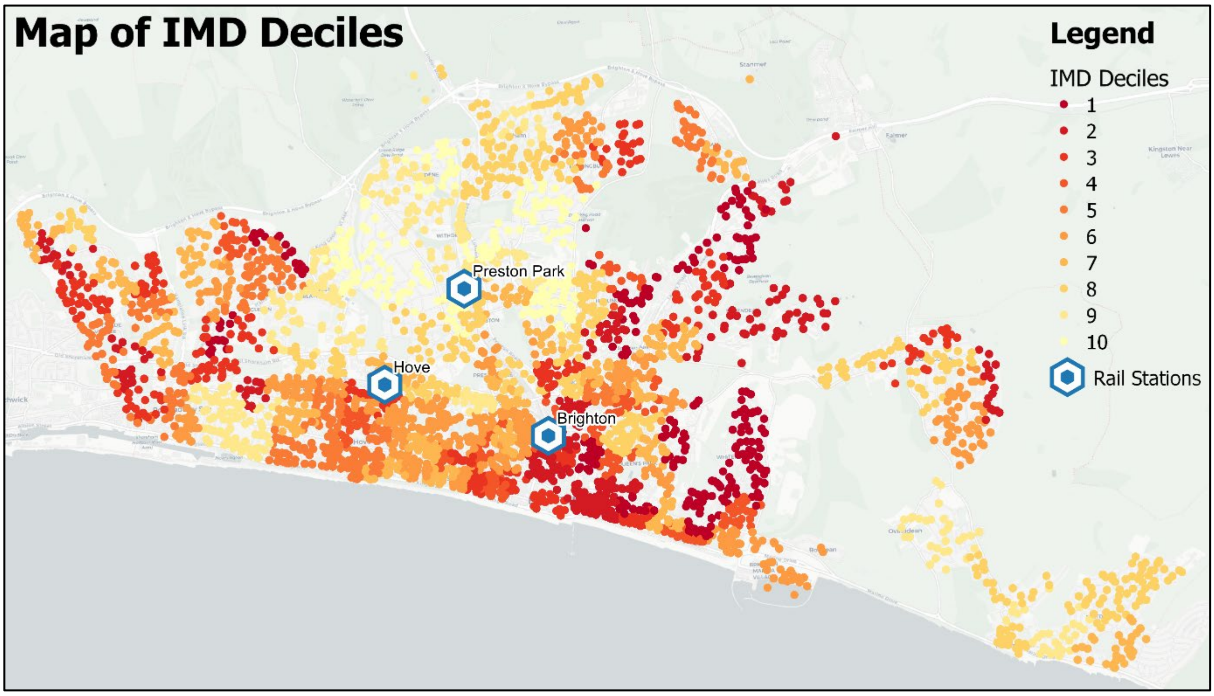


Figure 2: Maps of proximity to good primary (a), and secondary schools (b) (selected good schools labelled), and IMD deciles (c).

The dataset contains data on price per square metre, but our experiments found that using price per square metre as the dependent variable resulted poorer models fits compared to raw price, and size moved to the explanatory side of the model. Price per square metre also made some variables such as number of rooms difficult to interpret. Examining the frequency distribution of price (Figure 1), we can observe that the data are right-skewed – a long-tail of fewer, more expensive properties shifting the mean value to the right of the modal property price. To correct this skew we transform it by taking the natural logarithm (Box & Cox, 1964) and use that as the dependent variable (Figure 3). The explanatory variables total floor area and walk time to the nearest train station are transformed in the same way to correct a similar positive skew. The distributions of each explanatory variable are illustrated through histograms (continuous variables) and barplots (categorical variables) in the Appendix.

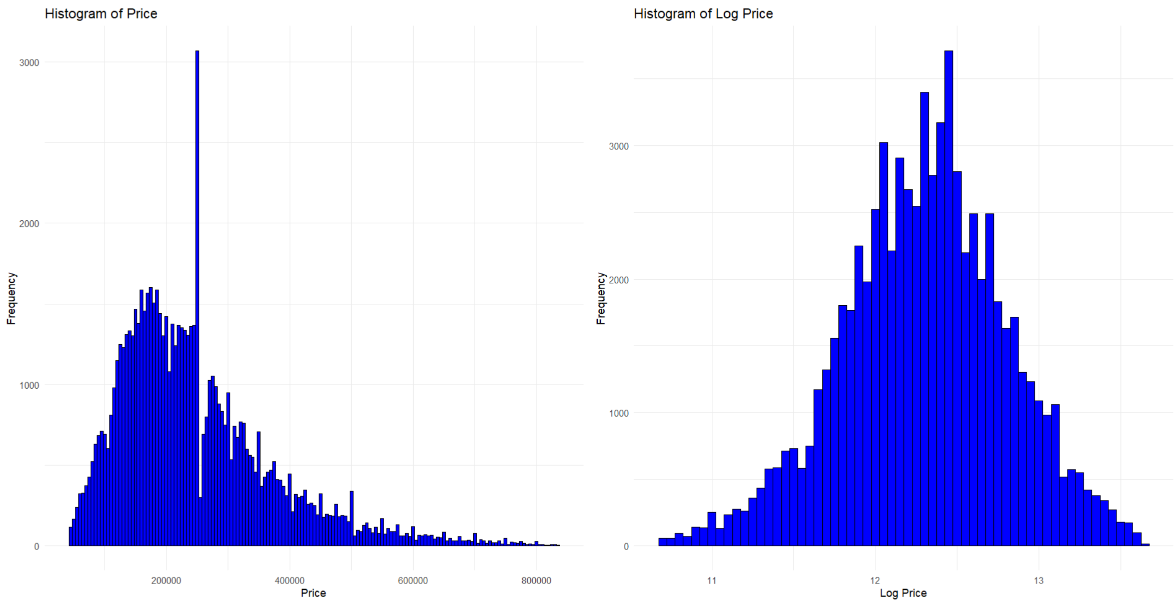


Figure 3*:* Distribution of dependent variable before-after natural log transformation

The correlation matrix (Figure 4) reveals the correlations between all explanatory variables. The coefficients for price, total floor area and number of rooms are moderately high, while some groups of variables such as those related to the accessibility of rail or schools are only moderately correlated. Electoral wards are highly correlated with rail and secondary school variables, but this is understandable as it is a categorical geographical variable that covers the entire study area.

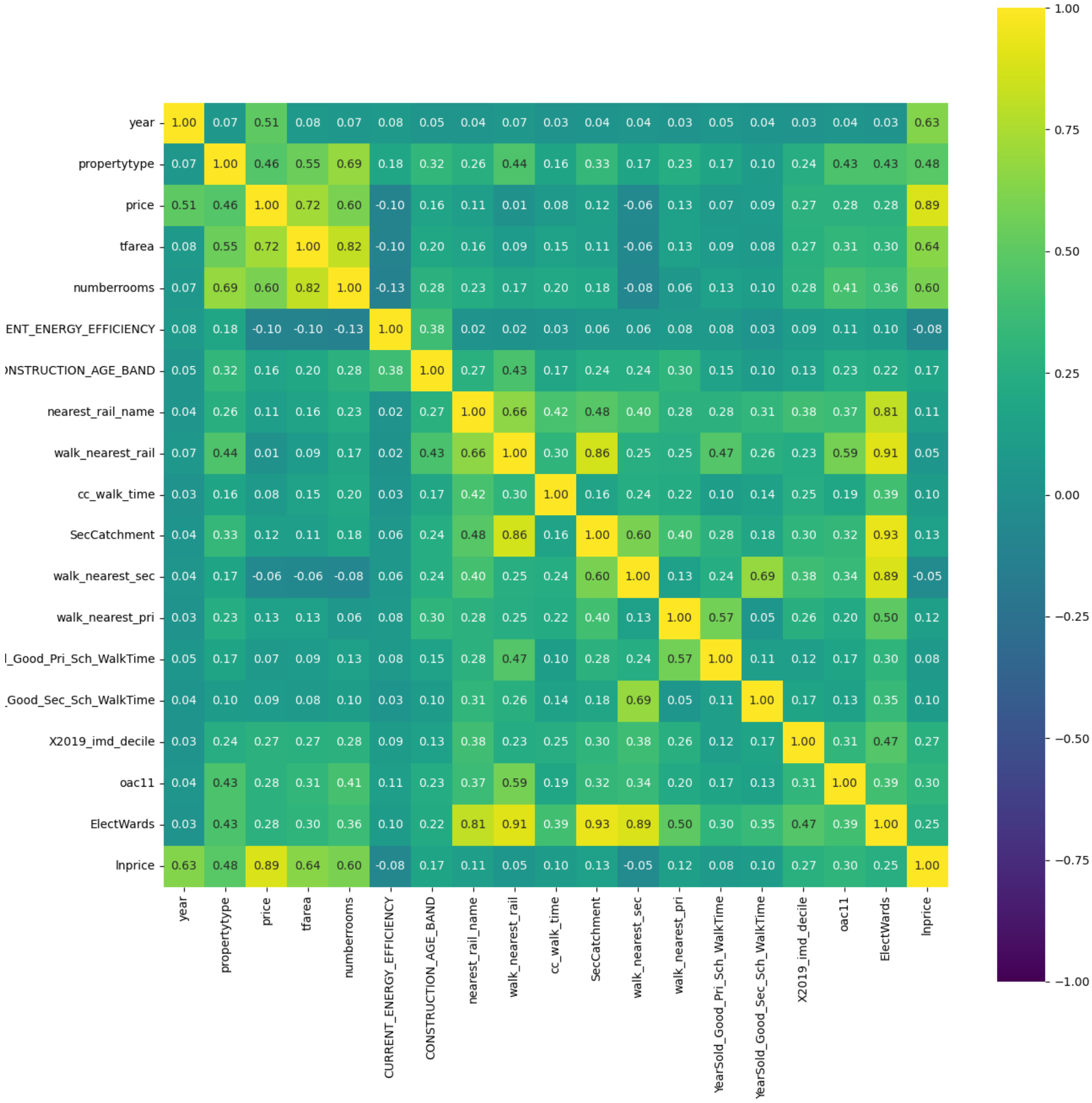


Figure 4: Correlation matrix for the dataset

Generalised VIF (GVIF) values were used to check for multicollinearity since there are both numerical and categorical variables. $GVIF^{1/2 \cdot Df}$, where D_f is the number of coefficients in the subset (or categories), is an equivalent to Variance Inflation Factor (VIF) to check for multicollinearity (Fox & Monette, 1992). The $GVIF^{1/2 \cdot Df}$ values were all below 5 (available in appendix) which is an acceptable threshold for multicollinearity (Hair, 2009).

Results

The final hedonic price model models (the natural log of) house price-paid, as a function of property type, total floor area, proximity to services (including schools and employment through mainline rail and the town centre), and 2019 IMD deciles. The model is first run on the whole dataset spanning the years 2000-2019, then, to observed differences before and after the admissions policy change in 2008, the data are split into two panels; the first containing transactions from 2000 to 2007, second spanning 2008 to 2019. We were unable to carry out a classical difference-in-differences analysis as all houses within the Brighton and Hove study area were subject to the policy change, so defining clear treatment and control groups was not feasible.

The coefficient associated with each variable in the model is an implicit indicator of importance, but where these are dependent of the original scale of measurement, their standardised t-values provide insights into their relative importance with each other. The model 1 baseline model investigates just the contribution that building level characteristics and year sold make to price variations in the city.

Model 1 – Baseline Model

In model 1 (Table 1), 83.1 percent of the variation in price paid in Brighton across the 19 year study period can be explained by sale year, property type, total floor area, number of rooms, energy efficiency, and construction age band, with the most important physical characteristic being floor area. However, relentless year-on-year price increases (except for a short period immediately after the global financial crisis in 2008) since 2000 mean that when a property was sold has the most influence on the price, over and above all other factors. Detached properties are 22.7 percent more expensive than flats, on average, while a 1 percent increase in floor area is associated with a 0.57 percent increase in house price and more rooms generally mean higher prices. Energy efficiency has a negligible (and slightly negative) effect while buildings built between 1900-1990 have a negative effect on price as compared to buildings built after.

Table 1: Baseline Model 1

	Full dataset; property-level	
Variable	Coefficient	T-value
Constant	9.002**	591.83
Year (2000)		
2001	0.176**	40.43
2002	0.371**	85.29
2003	0.493**	110.49
2004	0.587**	131.21
2005	0.629**	136.30
2006	0.708**	162.45
2007	0.825**	186.32
2008	0.777**	136.49
2009	0.725**	143.07
2010	0.848**	175.26
2011	0.847**	176.63
2012	0.878**	182.95
2013	0.911**	194.68
2014	1.01**	224.37
2015	1.10**	236.78
2016	1.18**	249.13
2017	1.23**	254.68
2018	1.238**	247.65
2019	1.223**	242.21
Property Type (Flat/Maisonette)		
Detached	0.205**	56.02
Semi-detached	0.091**	31.78
Terrace	0.076**	33.57
Number of rooms	0.021**	21.08
Log Total floor area	0.571**	167.61
Energy Efficiency	-0.0002**	-2.83
Construction Age		
Before 1900	0.030**	3.95
1900-1929	-0.012	-1.61
1930-1949	-0.080**	-10.32
1950-1966	-0.158**	-20.39
1967-1975	-0.119**	-14.98
1976-1982	-0.096**	-10.62
1983-1990	-0.043**	-4.90
1991-1995	0.035**	3.57
1996-2002	0.128**	14.68
2003-2006	0.145**	15.22
2007 onwards	0.088**	7.80
Sample Size	73,559	

Adjusted R^2	0.831
F-statistic	9540**

**p<0.05 - Notes: T-values are in parentheses.

Model 2 – Baseline + Contextual Variables

In model 2 we compare three variants of a model containing property-level *and* additional contextual variables. Over repeated iterations of experimentation, three contextual variables proved the most interesting: secondary school catchment areas, proximity to good schools in the year sold, and electoral wards. These variables plus the Index of Multiple Deprivation in 2019 were added to the baseline model (Table 2). The additional contextual variables are helpful in explaining house prices, with the adjusted R^2 increasing from 83.1% to > 86%.

Table 2: Model 2 - Baseline + Contextual Variables Model

Variable (Reference)	a) Main model with school catchment areas	b) Main model with proximity to schools	c) Main model with electoral wards	d) Main model with all variables of interest
	Coefficients (t-value)			
Constant	8.882** (536.13)	8.903**(543.04)	9.139** (516.03)	9.085** (367.60)
Year (2000)				
2001	0.179** (45.78)	0.180**(45.63)	0.179** (46.25)	0.180** (46.55)
2002	0.374** (95.70)	0.374** (95.07)	0.374** (96.73)	0.374** (97.03)
2003	0.498** (124.19)	0.500** (123.76)	0.499** (125.67)	0.500** (126.11)
2004	0.591** (146.96)	0.592** (146.07)	0.591** (148.55)	0.592** (149.09)
2005	0.631** (152.24)	0.633** (151.71)	0.630** (153.70)	0.632** (154.32)
2006	0.712** (181.83)	0.713** (180.88)	0.711** (183.49)	0.712** (184.00)
2007	0.835** (210.02)	0.834** (208.31)	0.835** (211.89)	0.835** (212.44)
2008	0.786** (153.77)	0.786** (152.67)	0.786** (155.35)	0.787** (155.78)
2009	0.728** (160.01)	0.729** (159.08)	0.726** (161.34)	0.727** (161.70)
2010	0.847** (196.76)	0.846** (193.42)	0.846** (196.75)	0.846** (197.23)
2011	0.847** (196.76)	0.846** (195.01)	0.847** (198.51)	0.846** (198.89)
2012	0.877** (203.63)	0.876** (201.66)	0.875** (205.30)	0.875** (205.36)
2013	0.914** (217.33)	0.912** (215.40)	0.913** (219.38)	0.912** (219.62)
2014	1.015** (250.41)	1.016** (248.84)	1.014** (252.72)	1.014** (253.16)
2015	1.103** (265.40)	1.103** (263.47)	1.102** (267.98)	1.103** (268.41)
2016	1.187** (279.96)	1.187** (277.94)	1.186** (282.61)	1.186** (283.28)
2017	1.236** (284.92)	1.234** (282.52)	1.235** (287.53)	1.234** (288.08)
2018	1.242** (276.58)	1.238** (273.88)	1.241** (279.21)	1.241** (279.75)
2019	1.229** (270.88)	1.228** (268.83)	1.230** (273.84)	1.230** (274.47)

	a) Main model with school catchment areas	b) Main model with proximity to schools	c) Main model with electoral wards	d) Main model with all variables of interest
Property Type (Flat/Maisonette)				
Detached	0.299** (79.58)	0.301** (80.58)	0.307** (81.77)	0.310** (82.65)
Semi-detached	0.216** (73.34)	0.213** (72.20)	0.226** (76.43)	0.229** (77.20)
Terrace	0.175** (77.33)	0.169** (74.14)	0.192** (82.91)	0.192** (83.04)
Number of rooms	0.028** (30.84)	0.027** (29.85)	0.029** (32.46)	0.029** (32.55)
Log Total floor area	0.497** (158.08)	0.504** (159.46)	0.490** (156.56)	0.488** (156.30)
Energy Efficiency	0.0001** (2.28)	0.0001** (2.14)	0.0003** (4.03)	0.0003** (4.24)
Construction Age (NA)				
Before 1900	-0.013 (-1.88)	-0.011 (-1.52)	-0.012 (-1.75)	-0.012 (-1.84)
1900-1929	-0.025** (-3.62)	-0.027** (-3.79)	-0.022** (-3.23)	-0.023** (-3.32)
1930-1949	-0.051** (-7.30)	-0.051** (-7.18)	-0.052** (-7.39)	-0.050** (-7.15)
1950-1966	-0.097** (-13.88)	-0.091** (-12.98)	-0.094** (-13.60)	-0.091** (-13.20)
1967-1975	-0.087** (-12.16)	-0.083** (-11.59)	-0.087** (-12.26)	-0.086** (-12.11)
1976-1982	-0.065** (-8.00)	-0.066** (-8.01)	-0.067** (-8.26)	-0.066** (-8.20)
1983-1990	-0.033** (-4.22)	-0.034**(-4.23)	-0.032** (-4.09)	-0.033** (-4.18)
1991-1995	0.031** (3.53)	0.018** (1.99)	0.021** (2.43)	0.025** (2.83)
1996-2002	0.099** (12.47)	0.084** (10.52)	0.090** (11.43)	0.091** (11.49)
2003-2006	0.136**(15.84)	0.129** (14.92)	0.135** (15.80)	0.139** (16.25)
2007 onwards	0.086** (8.44)	0.081** (7.91)	0.079** (7.80)	0.084** (8.30)
Bus time to city centre (Not near)				
0-5 minutes	0.326** (13.77)	0.352** (14.79)	0.306** (12.86)	0.229** (11.19)
5-10 minutes	0.237** (34.37)	0.285** (41.81)	0.243** (31.57)	0.216** (27.50)
10-15 minutes	0.181** (35.07)	0.232** (47.19)	0.188** (30.21)	0.159** (24.35)
15-20 minutes	0.148** (31.82)	0.183** (40.08)	0.152** (28.31)	0.125** (21.87)
20-25 minutes	0.092** (20.31)	0.119** (26.93)	0.098** (19.79)	0.075** (14.62)
25-30 minutes	0.079** (19.18)	0.102** (25.20)	0.076** (16.84)	0.057** (12.19)
30-35 minutes	0.035** (9.55)	0.044** (12.30)	0.042** (10.43)	0.031** (7.57)
35-40 minutes	-0.011** (-3.11)	-0.011** (-3.26)	0.004 (1.19)	-0.005 (-1.41)
40-45 minutes	-0.018** (-5.43)	-0.014** (-4.09)	-0.008** (-2.23)	-0.011** (-3.15)
Rail Station (None)				
Brighton	-0.020** (-7.10)	-0.009** (-3.20)	-0.039** (-12.10)	-0.027** (-8.01)
Hove	-0.011**(-3.30)	0.003 (1.01)	-0.056** (-13.98)	-0.047** (-11.57)
Preston Park	0.038**(9.39)	0.038** (9.66)	-0.009** (-1.96)	-0.016** (-3.08)
Log Walk time to nearest rail	-0.027** (-13.66)	-0.033** (-18.82)	-0.045** (-17.89)	-0.038** (-14.36)
Walk time to nearest secondary school	0.0004** (6.16)	0.0004** (6.21)	0.0004** (4.04)	0.0007** (6.36)
Walk time to nearest primary school	0.005** (35.60)	0.007** (41.90)	0.004** (29.74)	0.005** (30.11)
IMD Deciles (Decile 1)				
Decile 2	0.098** (20.22)	0.073** (15.00)	0.107** (20.89)	0.100** (19.17)
Decile 3	0.132** (28.75)	0.115** (25.08)	0.119** (24.67)	0.116** (23.18)
Decile 4	0.137** (29.37)	0.138** (29.53)	0.144** (30.72)	0.138** (28.82)
Decile 5	0.145** (30.59)	0.147** (31.22)	0.123** (23.85)	0.122** (23.06)
Decile 6	0.162** (37.45)	0.164** (38.00)	0.161** (34.51)	0.155** (32.10)
Decile 7	0.183** (41.86)	0.169** (38.59)	0.174** (38.45)	0.169** (36.23)
Decile 8	0.194** (42.95)	0.186** (41.24)	0.191** (40.04)	0.183** (36.84)
Decile 9	0.231** (46.66)	0.235** (47.32)	0.210** (38.96)	0.204** (36.70)
Decile 10	0.290** (51.92)	0.288** (51.22)	0.249**(41.08)	0.241** (38.49)

	a) Main model with school catchment areas	b) Main model with proximity to schools	c) Main model with electoral wards	d) Main model with all variables of interest
Catchment areas (Aldridge)				
Blatchington and Hove	0.153** (33.58)			0.026 (1.58)
Stringer and Varndean	0.118** (28.87)			0.016 (1.04)
Longhill	0.085** (17.85)			-0.060** (-3.58)
Patcham	0.082** (16.56)			-0.039** (-2.48)
Portslade	0.034** (6.94)			-0.122** (-6.87)
Proximity to good secondary school in year sold				
0-5 minutes		0.064** (4.81)		0.030** (2.20)
5-10 minutes		0.064** (10.93)		0.037** (5.85)
10-15 minutes		0.032** (8.21)		0.016** (3.81)
15-20 minutes		0.023** (7.28)		0.008** (2.23)
20-25 minutes		0.016** (5.69)		-0.003 (-1.04)
25-30 minutes		0.008** (3.15)		-0.009** (-3.63)
Proximity to good primary school in year sold				
0-5 minutes		0.097** (19.88)		0.052** (10.37)
5-10 minutes		0.057** (15.75)		0.020** (5.14)
10-15 minutes		0.041** (12.63)		0.007** (2.14)
15-20 minutes		0.042** (13.29)		0.012** (3.44)
20-25 minutes		0.044** (12.70)		0.020** (5.41)
25-30 minutes		0.025** (6.58)		0.012** (3.10)
Electoral Wards (Goldsmid)				
Brunswick and Adelaide			0.003 (0.50)	0.005 (0.99)
Central Hove			0.046** (10.08)	0.046** (9.65)
East Brighton			-0.054** (-6.84)	-0.049** (-5.01)
Hangleton and Knoll			-0.016** (-2.44)	-0.045** (-6.67)
Hanover and Elm Grove			-0.089** (-15.59)	-0.091** (-11.81)
Hollingdean and Stanmer			-0.116** (-17.92)	-0.105** (-12.20)
Hove Park			0.018** (3.07)	-0.008 (-1.30)
Moulsecoomb and Bevendean			-0.171** (-25.29)	-0.162** (-9.34)
North Portslade			-0.119** (-16.56)	0.005 (0.79)
Patcham			-0.064** (-10.31)	-0.021** (-2.03)
Preston Park			0.019** (3.72)	0.022** (2.85)
Queen's Park			-0.052** (-8.26)	-0.052** (-6.04)
Regency			-0.001 (-0.24)	-0.002 (-0.34)
Rottingdean Coastal			-0.007 (-1.02)	0.036** (3.45)
South Portslade			-0.128** (-18.76)	NA (NA)
St. Peter's and North Laine			-0.058** (-11.53)	-0.053** (-7.92)
Westbourne			0.046** (9.27)	0.042** (8.07)
Wish			-0.012** (-2.12)	-0.023** (-3.89)
Withdean			-0.013** (-2.01)	0.004 (0.38)
Woodingdean			-0.130** (-17.74)	-0.072** (-6.64)
Sample Size	73,559	73,559	73,559	73,559
Adjusted R^2	0.864	0.862	0.867	0.868
F-statistic	6980**	6230**	5840**	4920**

**$p<0.05$ - Notes: T-values are in parentheses.

Taking catchment areas, proximity to schools and electoral wards separately, they all add a similar amount of explanatory power to the model. Combining them offers no perceptible advantage in explanatory power, but we do see a noticeable confounding effect on school catchment areas from electoral wards. This suggests it is not being in a catchment per se that can affect house prices, rather that some neighbourhoods are more preferable than others and these can be home to particular schools and catchments then overlap. The importance of a house being in the two most important catchment areas (Blatchington and Hove, and Dorothy Stringer and Varndean) virtually disappears when electoral wards / neighbourhoods are included. On their own, electoral wards also add more to the adjusted R2 than catchment areas. Good schools do appear to be part of this mix in local area effects that improve the desirability of housing, but the neighbourhoods they are in appears to be even more important. The best model for Brighton includes proximity to good schools in the year sold, electoral wards but not catchment areas.

Model 3 – The Pre- and Post-Admissions Reform Panel Model

This study then runs the optimised model for the whole period alongside pre- and post-reform periods. Pre-reform refers to the years 2000-2007, and post-reform refers to 2008-2019.

Table 3: Model 3 - whole period (a) and pre (b)-post (c)-reform comparison

	a) Whole period	b) Pre-reform	c) Post-reform
Variable (Reference)		Coefficients (t-value)	
Constant	9.103** (491.80)	9.289** (337.26)	9.715** (400.34)
Year (2000/2008)			
2001	0.180** (46.51)	0.180** (44.37)	
2007	0.835** (212.20)	0.833** (201.10)	
2009	0.726** (161.48)		-0.060** (-11.91)
2019	1.230** (274.03)		0.439** (86.88)
Property Type (Flat/Maisonette)			
Detached	0.307** (81.95)	0.271** (43.51)	0.336** (73.93)
Semi-detached	0.226** (76.46)	0.207** (45.72)	0.246** (65.21)
Terrace	0.192** (82.70)	0.179** (51.67)	0.206** (68.33)
Number of rooms	0.029** (32.51)	0.025** (18.14)	0.032** (28.35)
Log Total floor area	0.489** (156.47)	0.465** (99.99)	0.514** (126.13)
Energy Efficiency	0.0003** (4.05)	-0.00008 (-0.76)	0.0007** (8.57)
Construction Age (NA)			
Before 1900-1990	-0.022** (-3.17) to -0.093** (-13.36)	-0.023** (-2.04) to -0.102** (-9.89)	-0.030** (-3.28) to -0.083** (-8.98)
1991-2007 onwards	0.020** (2.34) to 0.136** (15.92)	0.055** (4.30) to 0.186** (14.77)	0.029** (2.72) to 0.085 (7.66)
Bus time to city centre (Not near)			
0-5 minutes	0.283** (11.87)	0.242** (7.67)	0.312** (8.57)
25-30 minutes	0.067** (14.72)	0.036** (4.90)	0.087** (15.35)
40-45 minutes	-0.007** (-1.98)	-0.019** (-3.31)	-0.002 (-0.45)
Rail Station (None)			
Brighton	-0.030** (-9.09)	-0.019** (-3.94)	-0.038** (-8.95)
Hove	-0.054** (-13.30)	-0.051** (-8.41)	-0.052** (-10.07)
Preston Park	-0.007 (-1.36)	-0.011 (-1.31)	-0.002 (-0.34)
Log Walk time to nearest rail	-0.044** (-17.12)	-0.048** (-12.48)	-0.041** (-12.04)
Walk time to nearest secondary school	0.0007** (6.49)	0.0008** (4.74)	0.0003** (2.05)
Walk time to nearest primary school	0.005** (29.37)	0.005** (19.21)	0.005** (22.49)
IMD Deciles (Decile 1)			
Decile 2	0.104** (20.34)	0.114** (14.90)	0.096** (14.46)
Decile 10	0.241 (39.21)	0.248** (25.61)	0.229** (29.79)
Proximity to good secondary school in year sold			
0-5 minutes	0.034** (2.55)	0.030 (1.20)	0.027 (1.81)
5-10 minutes	0.043** (6.74)	0.027** (2.51)	0.040** (5.09)
20-25 minutes	0.0009 (0.32)	-0.016** (-3.56)	0.005 (1.38)
25-30 minutes	-0.007** (-2.65)	-0.012** (-3.30)	-0.005 (-1.67)

	a) Whole period	b) Pre-reform	c) Post-reform
Proximity to good primary school in year sold			
0-5 minutes	0.055** (10.83)	0.054** (6.63)	0.062** (9.63)
5-10 minutes	0.023** (5.96)	0.017** (2.64)	0.040** (8.10)
20-25 minutes	0.026** (7.38)	0.019** (3.33)	0.041** (8.91)
25-30 minutes	0.018** (4.66)	0.010 (1.76)	0.028** (5.82)
Electoral Wards			
	-0.165** (-23.58) to 0.052** (10.30)	-0.151** (-13.91) to 0.045** (5.75)	-0.178** (-19.90) to 0.051** (7.83)
Sample Size	73,559	35,256	38,303
Adjusted R^2	0.867	0.800	0.816
F-statistic	5110**	1720**	1980**

**p<0.05 - Notes: T-values are in parentheses. Range of values presented for electoral wards are smallest and largest range of significant values. Full results available in appendix.

General Observations

Model assumptions

This final model was then checked if it fits the assumptions for linear regression which are that errors are independent and normally-distributed, and if there is equal error variance (Harris, 2016). The residual plot (Figure 5) shows that the variance is largely consistent with no distinct patterning. The Q-Q plot and histogram show that the residuals are close to being normally distributed, although there is evidence for positive kurtosis meaning there are more observations in the tails of the distribution than a true normal distribution would expect. These plots are after dropping the top and bottom 5 percent of transactions in terms of price, so the upper tail of the Q-Q plots would have been more pronounced without the filtering; although none of this invalidates the analysis.

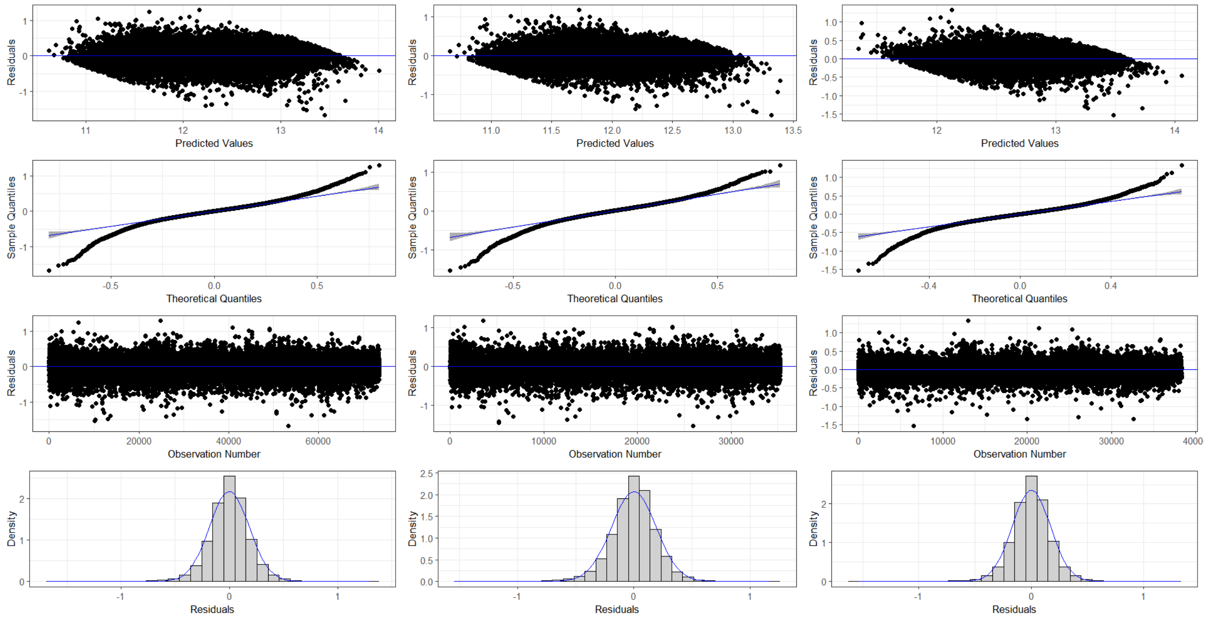


Figure 5: Residual, Q-Q, Index and Histogram plots (from top to bottom) of models in Table 3 (L: full period, C: pre-reform, R: post-reform)

Analysis Observations

The general trends in the directions and magnitudes of the effects of the explanatory variables are similar both pre- and post-admissions reform. The full model with electoral ward dummy variables (Model 3a – almost identical to Model 2c) seems to explain house prices well, with a high adjusted R^2 of 86.7 percent for the whole period and 80.0 and 81.6 percent for pre- and post-reform periods respectively. Year-on-year variation is important, with 2009 house prices being -6.0 percent lower than 2008, on average, being explained by delayed effects of the Global Financial Crisis in 2008. Property-level effects are also important, with semi-detached and terrace properties being on average 23.0 and 19.6 percent more expensive than flats respectively (Table 1). This increase in coefficients and t-values, even after including contextual variables, confirms what all home-buyers already know - that property-level variables are key determinants of prices, and more important than contextual variables. No matter where they are, bigger houses are almost always more expensive than smaller ones; but this is often ignored when studies fail to adjust for dwelling mix in their analysis.

Across the three regressions, IMD deciles have relatively high t-values suggesting that ambient levels of deprivation around properties matters. Decile 2 (second most-deprived) is associated with a 10.5-12.1 percent increase in price relative to Decile 1, with Decile 10 (least deprived) associated with a 25.7-28.1 percent increase. The other variable for socio-economic context, OAC supergroups, was confounded by IMD data hence dropped from the model.

Looking at locational factors, proximity to the city centre (and its associated employment and service opportunities) has a clear positive effect on prices, with houses within a 5-minute bus journey of the centre being associated with a 27.4-36.6 percent increase in prices. This positive effect decreases as houses become more distant from the city centre, turning into a slight negative effect of 0.7 percent for the whole period when houses are 40-45 minutes away from the city centre relative to houses not near city centre at all. As walk-time from a rail station increases by 1 percent, prices fall by 4.4 percent – a logical effect given the association with access to higher paid jobs in London. However, this contrasts with the categorical variable for houses near Brighton, Hove and Preston Park rail stations. For the whole period, Brighton and Hove stations are respectively associated with a -3.0 and -5.4 percent effect on house prices relative to houses not near stations, while Preston Park's coefficient is statistically insignificant.

Zooming in on school proximity effects, as walk-time to the nearest secondary school (regardless of quality) increases, prices *increase* by 0.03-0.08 percent this is counter to the expected direction of the relationship. Speculatively we might hypothesise an association with increased noise and traffic associated with the schools being a dis-amenity to home buyers, however a more likely interpretation school proximity is only important for a sub-section of home-buyers and for those that it is, there may not be value in locating near an *average* school. With the inclusion of electoral ward dummy variables, the coefficients for proximity to a *good* secondary school in year sold are statistically significant and positive up to a walk-time of 20 minutes away.

Over the whole study period, walking proximity to a good secondary school does increase prices, but this should be contextualised by acknowledging the effect is considerably smaller than walking proximity to the mainline railway stations. Furthermore, when decomposed into pre- and post-reform datasets, there is limited statistical significance for the school proximity variable pre-reform, with houses between 5-10 minutes distance being 2.7 percent more expensive, but statistically insignificant for the other distance bands and a negative effect when more than 20 minutes away. Post-reform, proximity only has a statistically significant positive effect on houses 5-15 minutes away. To be clear, this is the opposite effect to the one expected by bringing in the lottery for over-subscription – with the small proximity effect *increasing* after the link between admissions and distance was abolished.

Interestingly, the primary school effect is larger than the secondary school effect. There is a clear positive and statistically significant effect for proximity to good primary schools in the year sold. Being within 5 minutes of walking distance from a good primary school is associated with a 5.5 percent increase in prices relative to being more than 30 minutes away from one. This positive effect gradually decreases to 1.8 percent for the 25-30 minutes distance band for 2000-2019. This causal pathways for this could be associated with distance proximity still mattering as an admission criterion at Primary level, but also with the fact that at Primary School age, parents will frequently accompany their children to school, adding to their daily duties in a way that doesn’t occur at secondary school. Combined, these two factors may make proximity a desirable quality that does not exist for secondary schools. Another result of note, but one without causal explanation, is that this effect appears stronger after the secondary schools admissions reform, with the effect of the 0-5 minutes distance band increasing from 5.4 to 6.2 percent post-reform, and the 25-30 minutes band associated with a 2.8 percent increase as compared to a statistically insignificant effect pre-reform.

Electoral wards effects vary considerably, but with some effects of note. For example, those with the largest negative coefficients (relative to the reference central Ward of Goldsmid to the West of the Main railway station and spanning the Brighton/Hove border) were Hanover and Elm Grove and Hollingdean and Stanmer – these areas are notable for high levels of ‘Studentification’ (see Sage et al. 2012 for a detailed account in this area).

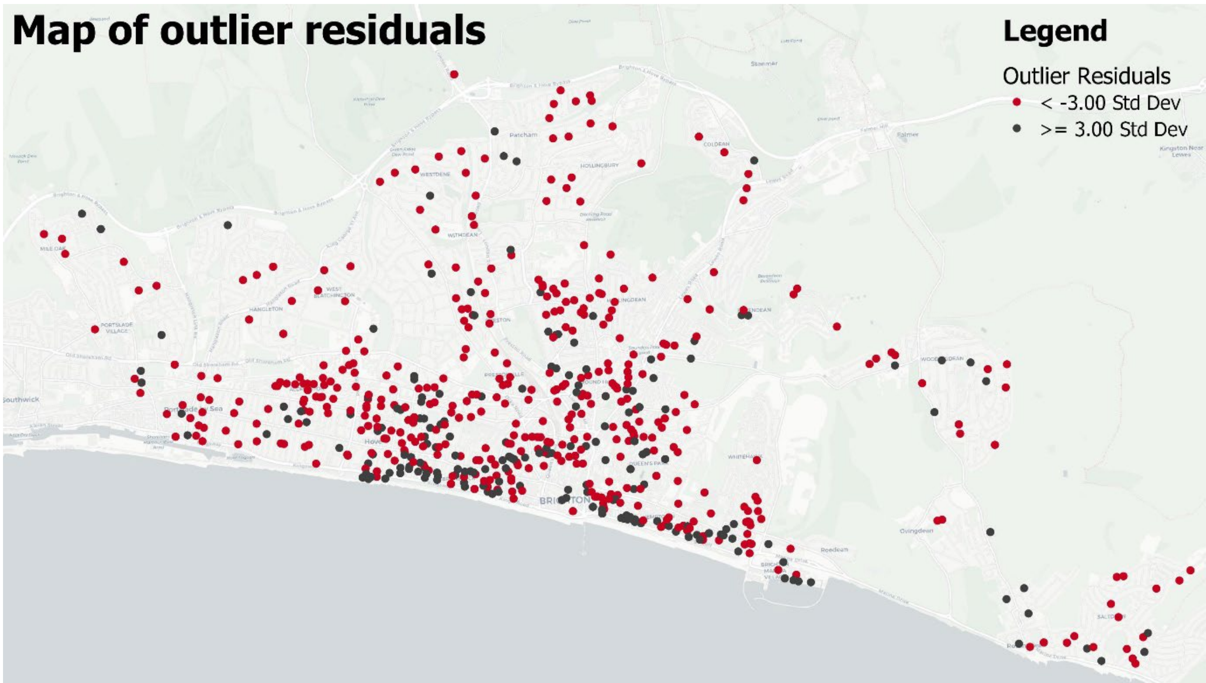


Figure 6: Map of outlier residuals (model 3a)

Mapping the residuals from the final model (Figure 6) shows us the properties that either cost far more (positive residuals) or far less (negative residuals) than what the model predicts. The negative outliers are mostly transactions before 2010, in IMD deciles above 5 (more deprived), and more than 30 minutes away from the city centre, although a number do occur more centrally. Some of these extreme negative residuals are transactions are in the central and Hanover areas, where the "studentification" and "touristification" in the city is concentrated. Noise and anti-social behaviour from both activities (Sage *et al*., 2012, Prosser, 2022) can be higher in these areas, with the proliferation of short-term holiday let homes fuelled by websites like AirBnB, potentially dampening the sale values of neighbouring properties. As for the few positive outliers, most are also before 2010, but they also exhibit a clear spatial patterning – mainly concentrated in a thin band which runs East to West along the seafront. This is clearly a 'sea view' or accessibility to the beach and seafront premium which was not captured as a variable in the model.

Discussion

This study sought to shed new light on the established perception that proximity to schools pushes up house prices. Our case study area in Brighton is a particularly interesting study due to the change in secondary school over subscription criteria in 2008, which many believed would impact a perceived 'golden halo' effect around some of the city's best schools. We were able to carry out a detailed analysis in finer spatial and temporal resolution than has been attempted before, with detailed measurements of geographical proximity and accessibility at the postcode-level and accounting for temporal changes in school quality.

We found that contrary to expectations, *increasing* the walk-time to a nearest school (ignoring its perceived quality) *increases* house prices by 0.07 and 0.5 percent for secondary and primary schools respectively. This echoes the earlier noted Gibbons and Machin findings (2006, p. 90) that 'average schools are not desirable local amenities', and that only the top schools have a positive effect on house prices. In Brighton, while *good* school proximity has some effect on house prices, the effect is small when compared to proximity to the mainline train stations and the accessibility to higher paying jobs in London that these offer; small compared to general neighbourhood deprivation/affluence effects; small compared to accessibility to the City Centre; and small compared to the relentless upward drift of house prices in the UK over the last 20 years. If Brighton's admissions reforms were in any way influenced by this perception of 'golden halos' recounted by Allen *et al*. (2013), then we can now say definitively that the empirical evidence does not back this perception up. Examining the sales that occurred both before and after the 2008 policy change confirms that the effect did not exist in a big way before the reform, and the decoupling of proximity from school admission at secondary level had no dampening effect on prices near schools. Given the negative impacts on pupils of not attending their nearest school and on the increased pressure on the City's transport infrastructure for those having to travel long distances to access their education, without a compelling house price case underpinning the reform, the policy itself may need revisiting.

In this analysis, rather than standardising our dependent price variable to account for on-going inflationary trends in the housing market – for example by selecting a base year and adjusting by the consumer price index (CPI) or the retail price index (RPI), we chose to account for inherent inflation in the system by including a dummy variable for the sale year. This had the benefit of allowing us to compare standardised coefficients across variables and see to what extent simply buying a house later would have, compared to being close to a school or any other hedonic variable.

This is important as many of the perceptions of school proximity price inflation have been made against a backdrop of a long-term trend of house price inflation. Anyone living in a city and seeing price inflation might be forgiven for attaching any number of plausible reasons to the increase, but in Brighton we now have definitive evidence that proximity to good schools has only a small impact on house prices and is less important than other contextual factors.

Study Limitations

It could always be argued that we could have taken the modelling analysis further than we have to try and account for even more of the unexplained variation in the model – the inclusion of a coastal location variable or attempts to match more closely school quality to when house purchase offers were made rather than taking the date at when entries make it onto the land registry database. It is also true that our metric for determining perceived school quality which was based primarily on Ofsted ranking and exam performance could easily be critiqued – particularly where some measure of 'value added' (outcomes relative to cohort composition) might be a more nuanced measure and one which some parents may prioritise.

Another direction we could have explored in more detail is spatial or temporal non-stationarity (where relationships may not hold in the same way over space or time), particularly with differences between school catchment areas – something which we could have achieved through using the catchments or sale years as additional panels or levels in the data, adopting a multi-level or linear mixed-effects framework. These options are still open for future research – and something we experimented with in earlier iterations of this research. At this time we found that given our primary objective was to ascertain how strong the effect of good school proximity is on house prices in Brighton and whether the 2008 secondary school admissions reform had any impact on prices; and little evidence of a strong link was found at any point; we can be satisfied that the analysis we carried out in its present form and the methods we used worked, were easy to interpret, and allowed us to draw useful conclusions.

We have not in this study attempted to account for the deeper structural, social and spatial forces interacting to reproduce geographies of educational advantage and housing market affordability that clearly intersect in ways that can be profoundly problematic when discussing equitable access to both. To an extent this was beyond the scope of what we were trying to achieve, however within our current analysis framework, interacting the index of multiple deprivation with good school proximity variables might have revealed more about how deprivation and distance factors can work both together and in opposition to one-another in different parts of the city to have variegated influences on price.

Conclusions

Referring back to our primary research question, we can conclude that good schools may play a small part pushing house prices up, but their influence should not be overstated compared with other contextual factors. Consequently, because the effect was already small, changes to the secondary school admissions policy in 2008 had very little impact on house prices near the most popular schools, contrary to some expectations.

To unearth this finding, we studied the spatial and temporal dimensions of the housing market context at a level of detail rare in the existing literature. Our use of the r5r algorithm in estimating detailed walking and public transport journey times from homes to schools, railway stations and the city centre meant we were able to generate a highly nuanced representation of proximity to these services in the city. Examining Ofsted and DfES data on school performance over a twenty-year period meant that we were able to attach plausible quality perceptions to schools at the time when houses in the dataset were sold, giving a level of temporal resolution to the analysis also rarely seen.

In incorporating detailed time and dwelling attribute data to our price analysis – thanks to the pioneering work of Chi et al. (2022) and their unique linked dataset – and bringing in both deprivation and important catchment and confounding neighbourhood/electoral ward random effects, we were able to fully disentangle different type of influence on the sale prices of properties sold. It would have been very easy to claim a clear school catchment area effect had we not fully tested other spatial groupings at the Ward level and discovered the catchment effect disappears when we do. It helps prove that the neighbourhood context of a school is important but not necessarily a result of the school on its own – this challenges work that has been carried out in other UK studies and shows while Brighton might be a unique case, merit may be found in adopting this approach in studies elsewhere.

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Appendix

Appendix 1

Process for deriving perceived school quality scores:

For primary schools, more weight was given to KS2 academic results and Ofsted ratings where data was available. KS2 results were used from 2003-2006, with KS2 results and Ofsted ratings weighted at 50 percent each from 2007-2011, and 45 percent each from 2012-2019 with percentage of students on FSM weighted at 10 percent.

For secondary schools: from 2003-2006 categories were similarly dependent on just KS4 results, but from 2007-2011 rankings were derived from an equal weighting between academic results (KS4) and Ofsted ratings. From 2012-2019 they were weighted as 30 percent each for academic results, Ofsted ratings and pupil destination, with 10 percent given to percentage of students on FSM. The metric for academic results is the percentage of 15 year old pupils achieving 5 or more grades A*-C (GCSE/GNVQ) and similar metrics as it is a common indicator of secondary school performance (Cheshire & Sheppard, 2004; Glen & Nellis, 2010), with the equivalent metric after the 2017 curriculum change (Ofqual, 2017) being used too. For pupil destination, the total percentage of students from each school going to a Sixth Form School or College is computed and ranked, with the highest percentage school ranked 1. This assumes that parents link progression to post-16 education with academic quality which could be contested, but we still think a justifiable metric when raw exam results are also used.

After accounting for all the variables in both primary and secondary school datasets, all schools were ranked and classified into one of four bands (Outstanding, Good, Satisfactory and Poor), with each band comprising their respective quantiles. Secondary schools are given one of three bands (Outstanding, Good, Poor) as there only 9 state secondary schools within the city (Brighton & Hove City Council, 2023). The Cardinal Newman Catholic School (CNCS) has autonomy over its admissions and prioritises Catholic children (CNCS, 2023), but after this priority, other priority categories still apply (Brighton & Hove City Council, 2023) and on this basis we still include it in our analysis. Hove Park School also has 2 campuses, Valley campus and Nevil campus, and both locations were used to determine proximity to good schools. It was assumed that both locations would have been used for admissions, as is the policy for King's School in Brighton. Finally, the primary school rankings for 2003 are extended to cover 2000-2002 as well on the assumption that school quality does not change rapidly. While a time lag between school ranking and transaction year could have been included, it is also difficult to estimate an ideal time lag, hence the same years were used as an approximation.

Appendix 2 – Variable frequency distributions

Figure 1: Histograms of continuous independent variables

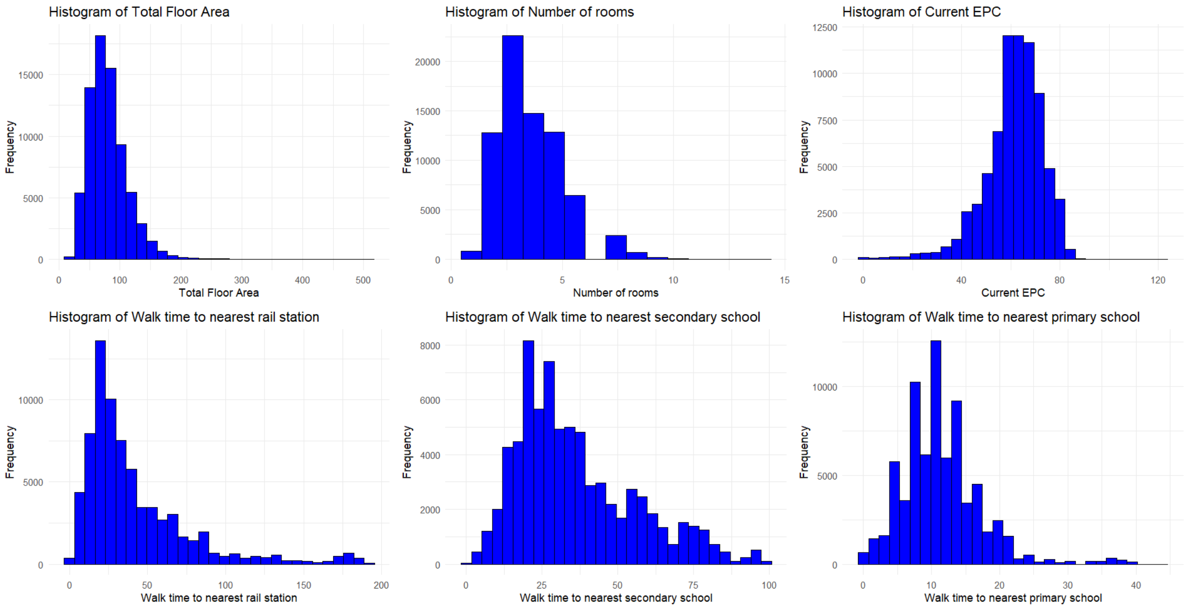


Figure 2: Barplots of categorical independent variables

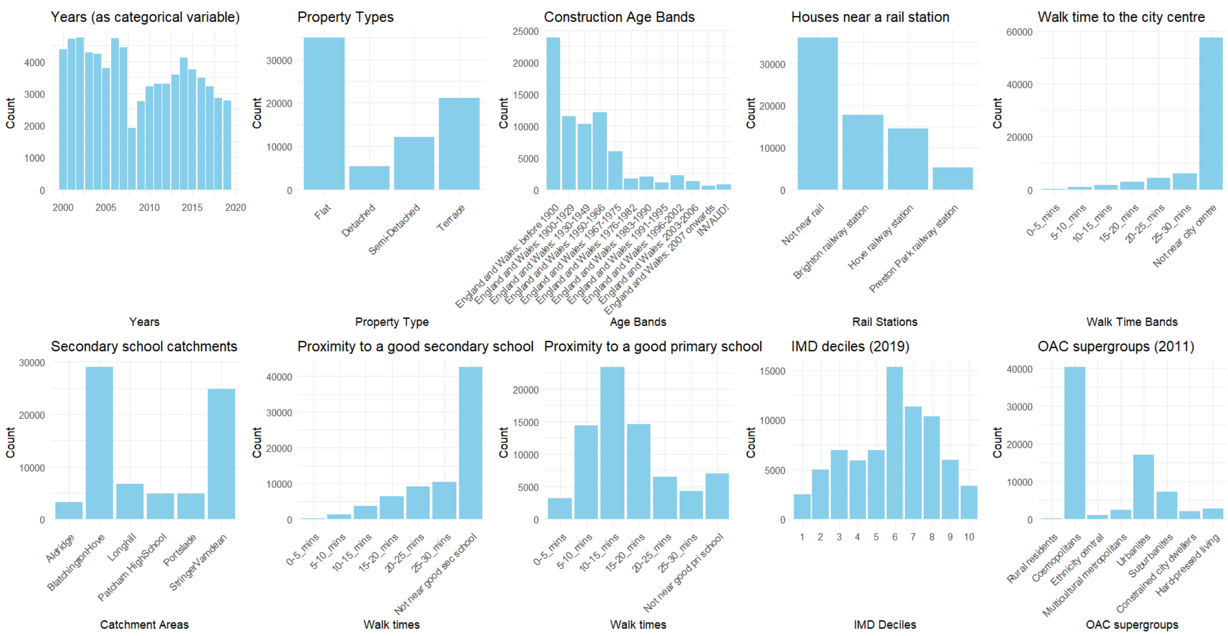
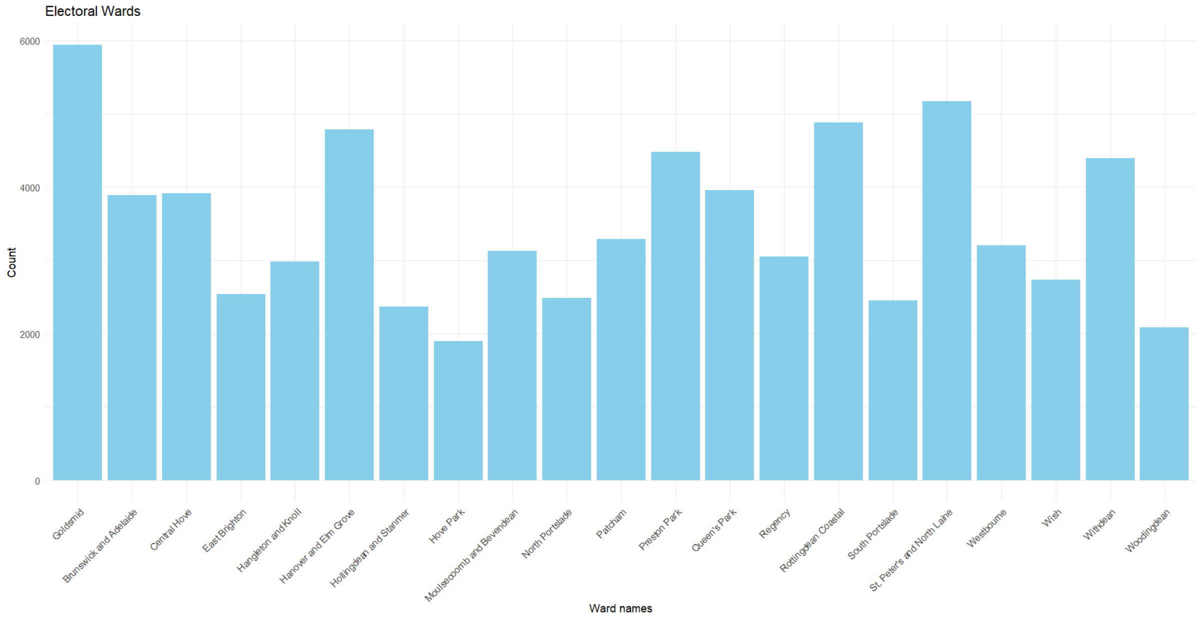


Figure 3: Barplots of Brighton's electoral wards


Electoral Wards
Count
6000
4000
2000
0
Goldsmid
Brunswick and Adelaide
Central Hove
East Brighton
Hangleton and Knoll
Hanover and Elm Grove
Hollingdean and Stanmer
Hove Park
Moulsecoomb and Bevendean
North Portslade
Patcham
Preston Park
Queen's Park
Regency
Rottingdean Coastal
South Portslade
St. Peter's and North Laine
Westbourne
Wish
Withdean
Woodingdean
Ward names

Appendix 3

Table 1: GVIF values of variables

	GVIF	D_f	$GVIF^{1/(2\cdot Df)}$
Years (as factors)	1.120	19	1.003
Property type	4.962	3	1.306
Number of rooms	3.691	1	1.921
Construction age band	4.394	12	1.064
Energy efficiency	1.216	1	1.103
Log Total floor area	3.051	1	1.747
Bus time band to city centre	79.282	9	1.275
Nearest rail station name	56.541	3	1.959
Log Walk time to nearest rail	8.599	1	2.932
Walk time to nearest primary school	2.274	1	1.501
Walk time to nearest secondary school	8.660	1	2.943
IMD decile	29.066	9	1.206
Proximity to good primary school (year sold)	5.552	6	1.154
Proximity to good secondary school (year sold)	4.156	6	1.126
Electoral wards	68,969	20	1.321

Appendix 4

Table 2: Whole period and pre-post-reform regressions full results

	Whole period	Pre-reform	Post-reform
Variable (Reference)	Coefficients (t-value)		
Constant	9.103** (491.80)	9.289** (337.26)	9.715** (400.34)
Year (2000/2008)			
2001	0.180** (46.51)	0.180** (44.37)	
2002	0.374** (96.97)	0.375** (92.55)	
2003	0.500** (126.05)	0.499** (119.58)	
2004	0.592** (148.82)	0.591** (141.22)	
2005	0.632** (154.22)	0.632** (146.66)	
2006	0.712** (183.89)	0.710** (174.22)	
2007	0.835** (212.20)	0.833** (201.10)	
2008	0.786** (155.57)		*(Reference)*
2009	0.726** (161.48)		-0.060** (-11.91)
2010	0.846** (196.97)		0.059** (11.91)
2011	0.846** (198.53)		0.058** (11.89)
2012	0.874** (205.02)		0.086** (17.53)
2013	0.912** (219.33)		0.124** (25.80)
2014	1.014** (252.86)		0.227** (48.26)
2015	1.102** (268.00)		0.315** (66.04)
2016	1.186** (282.83)		0.399** (82.49)
2017	1.234** (287.71)		0.445** (90.65)
2018	1.240** (279.35)		0.451** (89.89)
2019	1.230** (274.03)		0.439** (86.88)
Property Type (Flat/Maisonette)			
Detached	0.307** (81.95)	0.271** (43.51)	0.336** (73.93)
Semi-detached	0.226** (76.46)	0.207** (45.72)	0.246** (65.21)
Terrace	0.192** (82.70)	0.179** (51.67)	0.206** (68.33)
Number of rooms	0.029** (32.51)	0.025** (18.14)	0.032** (28.35)
Log Total floor area	0.489** (156.47)	0.465** (99.99)	0.514** (126.13)
Energy Efficiency	0.0003** (4.05)	-0.00008 (-0.76)	0.0007** (8.57)
Construction Age (NA)			
Before 1900	-0.011 (-1.58)	-0.028** (-2.83)	0.009 (1.02)
1900-1929	-0.022** (-3.17)	-0.048** (-4.70)	0.005 (0.51)
1930-1949	-0.051** (-7.34)	-0.072** (-6.96)	-0.030** (-3.28)
1950-1966	-0.093** (-13.36)	-0.102** (-9.89)	-0.079** (-8.76)
1967-1975	-0.086** (-12.16)	-0.086** (-8.23)	-0.083** (-8.98)
1976-1982	-0.067** (-8.31)	-0.060** (-4.96)	-0.073** (-6.97)
1983-1990	-0.033** (-4.21)	-0.023** (-2.04)	-0.050** (-4.80)
1991-1995	0.020** (2.34)	0.055** (4.30)	-0.021 (-1.82)
1996-2002	0.086** (10.92)	0.126** (11.05)	0.029** (2.72)
2003-2006	0.136** (15.92)	0.186** (14.77)	0.085** (7.66)
2007 onwards	0.080** (7.86)	0.109** (5.41)	0.082** (6.95)
Bus time to city centre (Not near)			
0-5 minutes	0.283** (11.87)	0.242** (7.67)	0.312** (8.57)
5-10 minutes	0.234** (30.25)	0.216** (18.61)	0.226** (22.11)
10-15 minutes	0.179** (28.57)	0.145** (14.95)	0.199** (25.03)
15-20 minutes	0.146** (26.77)	0.116** (13.56)	0.164** (23.97)
20-25 minutes	0.090** (17.93)	0.058** (7.32)	0.110** (17.60)
25-30 minutes	0.067** (14.72)	0.036** (4.90)	0.087** (15.35)

30-35 minutes	0.037** (9.12)	0.026** (3.86)	0.044** (8.84)
35-40 minutes	0.0007 (0.21)	-0.003 (-0.53)	0.002 (0.57)
40-45 minutes	-0.007** (-1.98)	-0.019** (-3.31)	-0.002 (-0.45)
Rail Station (None)			
Brighton	-0.030** (-9.09)	-0.019** (-3.94)	-0.038** (-8.95)
Hove	-0.054** (-13.30)	-0.051** (-8.41)	-0.052** (-10.07)
Preston Park	-0.007 (-1.36)	-0.011 (-1.31)	-0.002 (-0.34)
Log Walk time to nearest rail	-0.044** (-17.12)	-0.048** (-12.48)	-0.041** (-12.04)
Walk time to nearest secondary school	0.0007** (6.49)	0.0008** (4.74)	0.0003** (2.05)
Walk time to nearest primary school	0.005** (29.37)	0.005** (19.21)	0.005** (22.49)
IMD Deciles (Decile 1)			
Decile 2	0.104** (20.34)	0.114** (14.90)	0.096** (14.46)
Decile 3	0.116** (23.95)	0.128** (17.63)	0.108** (17.21)
Decile 4	0.141** (30.04)	0.150** (21.22)	0.133** (22.08)
Decile 5	0.122** (23.66)	0.137** (17.48)	0.109** (16.63)
Decile 6	0.158** (33.77)	0.167** (23.70)	0.150** (24.92)
Decile 7	0.171** (37.64)	0.171** (24.85)	0.172** (29.52)
Decile 8	0.185** (38.17)	0.193** (26.14)	0.175** (28.32)
Decile 9	0.203** (37.36)	0.215** (25.54)	0.187** (27.17
Decile 10	0.241 (39.21)	0.248** (25.61)	0.229** (29.79)
Proximity to good secondary school in year sold			
0-5 minutes	0.034** (2.55)	0.030 (1.20)	0.027 (1.81)
5-10 minutes	0.043** (6.74)	0.027** (2.51)	0.040** (5.09)
10-15 minutes	0.021** (4.96)	0.006 (0.89)	0.019** (3.36)
15-20 minutes	0.012** (3.63)	0.004 (0.73)	0.007 (1.65)
20-25 minutes	0.0009 (0.32)	-0.016** (-3.56)	0.005 (1.38)
25-30 minutes	-0.007** (-2.65)	-0.012** (-3.30)	-0.005 (-1.67)
Proximity to good primary school in year sold			
0-5 minutes	0.055** (10.83)	0.054** (6.63)	0.062** (9.63)
5-10 minutes	0.023** (5.96)	0.017** (2.64)	0.040** (8.10)
10-15 minutes	0.012** (3.52)	0.004 (0.74)	0.029** (6.52)
15-20 minutes	0.017** (5.12)	0.016** (2.93)	0.030** (6.96)
20-25 minutes	0.026** (7.38)	0.019** (3.33)	0.041** (8.91)
25-30 minutes	0.018** (4.66)	0.010 (1.76)	0.028** (5.82)
Electoral Wards			
Brunswick and Adelaide	0.006 (1.22)	0.006 (0.82)	0.004 (0.57)
Central Hove	0.050** (10.74)	0.044** (6.22)	0.049** (7.98)
East Brighton	-0.063** (-7.91)	-0.055** (-4.47)	-0.062** (-6.04)
Hangleton and Knoll	-0.026** (-3.98)	-0.002 (-0.15)	-0.051** (-6.09)
Hanover and Elm Grove	-0.094** (-16.39)	-0.086** (-9.96)	-0.099** (-13.34)
Hollingdean and Stanmer	-0.110** (-16.95)	-0.114** (-11.39)	-0.110** (-13.24)
Hove Park	0.009 (1.47)	0.008 (0.85)	0.003 (0.40)
Moulsecoomb and Bevendean	-0.165** (-23.58)	-0.151** (-13.91)	-0.178** (-19.90)
North Portslade	-0.114** (-15.68)	-0.090** (-7.83)	-0.145** (-15.83)
Patcham	-0.064**(-10.18)	-0.049** (-4.74)	-0.084** (-10.63)
Preston Park	0.019** (3.54)	-0.005 (-0.70)	0.035** (5.14)
Queen’s Park	-0.060** (-9.32)	-0.067** (-6.91)	-0.049** (-5.94)
Regency	-0.002 (-0.37)	-0.033** (-3.80)	0.026** (3.23)
Rottingdean Coastal	-0.015** (-2.05)	0.023** (2.08)	-0.038** (-4.18)

South Portslade	-0.129**(-18.78)	-0.124** (-11.65)	-0.145** (-16.71)
St. Peter's and North Laine	-0.060** (-11.63)	-0.076** (-9.94)	-0.050** (-7.26)
Westbourne	0.052** (10.30)	0.045** (5.75)	0.051** (7.83)
Wish	-0.007 (-1.28)	-0.023** (-2.61)	-0.004 (-0.49)
Withdean	-0.014** (-2.05)	-0.18 (-1.70)	-0.016 (-1.85)
Woodingdean	-0.130** (-17.58)	-0.089** (-7.64)	-0.162** (-17.56)
Sample Size	73,559	35,256	38,303
Adjusted R^2	0.867	0.800	0.816
F-statistic	5110**	1720**	1980**