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Re-Examining the Property Price Premium Around ‘Better’ Schools

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Re-Examining the Property Price Premium Around ‘Better’ Schools*

Abstract

The established consensus from a large worldwide literature is that access to a ‘better’ school increases local property prices, which is typically interpreted as reflecting parents’ demand for school quality. We show that this relationship does not hold universally. Using data on English secondary schools, we show that price premiums are concentrated in the minority of areas where the difference in quality between schools is large, and weak or absent elsewhere. Exploring other dimensions of heterogeneity, we find that households pay comparable premiums to avoid schools at the bottom of the quality distribution as to reach the top, conditional on the size of the quality gap. A sufficiently affluent school peer group is a necessary condition for higher attainment to raise prices, suggesting that households value a bundle of school attributes.

JEL classification

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Keywords

school quality, property prices, boundary discontinuity design

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1 Introduction

Parents’ residential location affects either their child’s default allocation to school, or the probability of admission to their chosen school, in many parts of the world. This incentivises parents to choose their residential location with school access in mind. Indeed, an established literature finds evidence of higher property prices linked to ‘better’ schools, typically defined by academic performance. For example, in their widely cited literature review, Black and Machin (2011) state, “A one standard deviation increase in school test scores seems to generate house price increases on the order of around 3–4%”. Published estimates of this relationship are remarkably consistent across contexts, in settings with and without school choice systems, and high and low levels of school accountability.¹ While there is broad agreement on average premiums across contexts, there has been limited study of heterogeneity within contexts. Understanding nuances in the relationship between local school quality and property prices is important given the growing policy debate around reforming geographic school admissions criteria, where the consequences for housing markets will depend on the precise nature of the school quality premium. Admission to school has become less dependent on residential location in Barcelona (Spain), Brighton and Hove (England) and Cambridge (US), for example.

We study the conditions under which school quality is capitalised into property prices by asking three questions. First, is capitalisation observed throughout the quality distribution, or concentrated where differences in school quality are largest? More general hedonic and sorting models predict that equilibrium prices may be nonlinear in amenities because they reflect equilibrium sorting among heterogeneous households (Rosen, 1974; Epple and Sieg, 1999), with endogenous neighbourhood peers potentially amplifying these effects in nonlinear ways (Bayer et al., 2007; Caetano, 2019). Second, do premiums reflect competition for the best schools, avoidance of the worst schools, or both? Evidence from school peer effects suggests that conditions at the bottom of the distribution are important, with the harm from disruptive peers exceeding the benefit from high-quality ones (Lavy et al., 2012). On the residential choice side, local complementarities imply that declines in school quality may trigger self-reinforcing deterioration in neighbourhood quality through sorting and peer effects (Bénabou, 1993; Durlauf, 1996). Third, how do multiple dimensions of school quality jointly determine property price premiums?² The school choice literature is clear that parents make trade-offs between school characteristics when choosing schools, conditional on location, and similar trade-offs are likely to shape residential location decisions.

We study these questions using the boundary discontinuity design (Black, 1999) in the context of English secondary schools, where catchment areas give pupils priority access to their local school. The design compares property prices on either side of a catchment area boundary: properties on one side have priority access to a higher-performing school, while other neighbourhood attributes do not jump discontinuously. In most aspects we follow the existing literature, for example excluding boundaries where the identifying assumptions are less likely to hold (those coinciding with major roads, rivers and railways). We innovate by defining a binary treatment indicator for being on the higher-quality side. This specification, combined with our rich national data, allows us to present a nuanced picture of heterogeneity. We interact the treatment indicator with measures of the quality gap across the boundary and the absolute position of the two schools in the national distribution.

¹Even in Finland, where school performance is not publicly available, the premium attached to the ‘better’ school side is around 3% (Harjunen et al., 2018).

²Our primary measure of school quality is pupil attainment (which combines school effectiveness and pupil intake), but we also consider pupil progress (value-added, or school effectiveness net of intake) and pupil socioeconomic composition (SES). We recognise SES is not a measure of school ‘quality’, but from the discrete choice literature, it is a school characteristic parents care about and may therefore be willing to pay for through the housing market (Hastings et al., 2009; Borghans et al., 2015; Burgess et al., 2015; Denice and Gross, 2016; Glazer and Dotter, 2017; Akyol and Krishna, 2017; Beuermann et al., 2018; Fack et al., 2019; Harris and Larsen, 2019; Ruijs and Oosterbeek, 2019; Abdulkadiroğlu et al., 2020; Bertoni et al., 2020; Walker and Weldon, 2020)

We have three main findings. First, the relationship between school quality differences and property prices is concentrated where the difference between schools either side of the boundary is large. Consistent with previous literature, the average premium is around 2.5%, but this masks substantial concentration. Premiums are around 6.5% where the quality gap between the pair of schools is in the top quartile of the distribution, and weak or absent elsewhere. This changes the interpretation of households’ willingness to pay, from proportional across the distribution and relatively low compared to household income, to concentrated and relatively high compared to household income.

Second, premiums arise at both ends of the school quality distribution. Price premiums imply sorting towards the best-performing schools (‘reaching the top’) and sorting away from the worst-performing schools (‘escaping the bottom’). On average, the premium for marginally ‘escaping the bottom’ (‘better’ schools in the second quartile of school quality relative to the first quartile) is similar to the premium for marginally ‘reaching the top’ (‘better’ schools in the top quartile relative to the third), 2.1% compared to 2.3%, respectively. Premiums are stronger when the difference in quality across the boundary is large. In this case, even at boundaries where both schools are below the national median, the side with the ‘better’ school commands a premium of around 7–8%, comparable to the premium at boundaries where both schools are above the national median.

Third, premiums arise only when observable dimensions of school quality align. When the same school in the pair has higher attainment and socioeconomic composition, premiums are relatively large (2.6–3.2%). When one school has higher attainment but lower socioeconomic composition, premiums vanish. Value-added (school effectiveness net of intake) has no independent pricing power. Households price the combination of school characteristics, not any single dimension in isolation.

Our paper contributes to a large literature estimating the effect of school quality on property prices using the boundary discontinuity design, pioneered by Black (1999). Typical estimates of the premium per standard deviation of school quality range from 1–4% for primary schools to 3–7% for secondary schools across a wide range of settings.³ These estimates are remarkably consistent but nearly all assume a log-linear relationship between school quality and prices.

A small number of papers have allowed for heterogeneity. Gibbons and Machin (2006) explore interactions between school quality, over-subscription and distance, finding that premiums occur around very high-performing schools, particularly if they are over-subscribed. Fack and Grenet (2010) show that private school outside options dilute the premium. Bibler and Billings (2020), Chan et al. (2020) and Caetano (2019) all find premiums that are larger around the highest-performing schools. In England, Hussain (2023) uses Ofsted inspection timing as information shocks and finds a convex price response: large effects near schools serving advantaged pupils, but little impact in disadvantaged neighbourhoods. However, Greaves and Hussain (2023) show that school *choice* responses to the same Ofsted information are similar for low and higher-income households. This suggests that the asymmetric price response in Hussain (2023) reflects housing market frictions or credit constraints in disadvantaged areas, rather than asymmetric preferences for school quality. Our boundary design captures the long-run sorting equilibrium, and finds comparable premiums at both ends of the quality distribution.

A large literature studies parents’ preferences for multidimensional school quality through school choice models (Hastings et al., 2009; Borghans et al., 2015; Burgess et al., 2015; Denice and Gross, 2016; Glazerman and Dotter, 2017; Akyol and Krishna, 2017; Beuermann et al., 2018; Fack et al., 2019; Harris and Larsen, 2019; Ruijs and Oosterbeek, 2019; Abdulkadiroğlu et al., 2020; Bertoni et al., 2020; Walker and Weldon, 2020). On the housing market, Imberman and Lovenheim (2016) show that value-added is not capitalised into property prices after being made public, although Gibbons et al.

³For primary/elementary schools: 1.8% in the San Francisco Bay Area (Bayer et al., 2007); 2.4% in Shanghai (Chan et al., 2020); 2–4% in Boston (La, 2015); 3% in Helsinki (Harjunen et al., 2018); 3.5% in England (Gibbons and Machin, 2003; Gibbons et al., 2013). For secondary schools: 3.5% in Australia (Davidoff and Leigh, 2008); 6% in Auckland (Cheung et al., 2022); 7% in Charlotte (Bibler and Billings, 2020). See Black and Machin (2011) for a review.

(2013) find that school value-added has an independent effect on local premiums, over and above the peer group. We connect these literatures by testing whether households bundle dimensions of school quality, rather than one measure having an independent effect. Our findings suggest that higher attainment is not a sufficient condition for property prices to rise, as the premium only occurs when the school also has a relatively high socioeconomic composition.

Our findings have important implications for the general equilibrium consequences of reforms to school choice and admissions criteria, which will depend on the precise relationship between school quality and prices (demand). This is important to consider in the context of calls to reform school admissions (Burgess et al., 2020) and recent implementation in some schools and areas (Brighton and Hove, 2024; Sutton Trust, 2024) due to the concern that poorer households are priced out of ‘good’ schools and that catchment areas contribute to residential segregation of cities (Davidoff and Leigh, 2008; Hamnett and Butler, 2013; Bernelius and Vilkama, 2019; Oberti and Savina, 2019). Our findings show that some areas are currently disproportionately affected by residential sorting for schools, and so would therefore be disproportionately affected by school admissions reform which partially breaks the link between residential location and school access.

The rest of the paper is structured as follows. Section 2 describes the education system in England and the residential incentives created for parents through commonly used over-subscription criteria. Section 3 details the data used, including construction and summary statistics. Section 4 outlines the methodology to identify the causal effect of local school quality on property prices (including, in our interpretation, the effect of endogenous neighbourhood characteristics that arise due to school quality). Section 5 presents the results for the role of geographic admissions on neighbourhood sorting, before Section 6 concludes.

2 Context

Our context is admission to state-funded secondary schools in England, where school choice has been enshrined nationwide since the Education Reform Act of 1988. Everywhere in the country, parents must submit a ranking of preferred schools to their Local Authority (LA) of residence in the year before their child starts secondary school. These rankings can be informed by school league tables of school performance, and a wide array of indicators for pupil composition, in addition to information gathered through informal local networks. If a school becomes over-subscribed, then school admissions criteria are used to rank pupils according to their characteristics. This Section describes each of these features of the English state school admissions system in detail.

Information available to parents: Parents have access to copious information about school composition and performance. For example, the Department for Education maintains two websites that make it easy for parents to find their local school options and the characteristics of these schools.⁴ Characteristics include pupil performance (the share of pupils achieving the benchmark standard of performance, and specifically in English and Maths, and the ‘English Baccalaureate’), pupil progress (a measure of value-added, or school effectiveness), pupil absence, and pupil composition. Pupil composition includes, for example, the percentage of pupils whose first language is not English, and those eligible for free school meals at any point in the past six years. In addition, schools are ranked by Ofsted periodically, and this information is publicly and widely available (Hussain, 2023; Greaves et al., 2023).

Parents’ school choices: Pupils begin secondary school in September of the academic year in which they turn 12 years old.⁵ Parents must submit their rank-ordered list of secondary school

⁴Get Information about Schools and School Performance Tables.

⁵The academic year runs from September until mid-July. Pupils born in September are therefore the oldest in the

choices before the deadline of 31st October in the previous academic year. These school choices are submitted to their LA of residence. Parents can choose schools in other LAs by including them on the rank-ordered list submitted to their LA.

Schools’ over-subscription criteria: If a school has more places than applicants, all applicants are admitted. When a school becomes over-subscribed, the over-subscription criteria are used to rank pupils in priority order, to determine which pupils are admitted. For example, a ‘sibling’ criterion would give applicants with a sibling at the school priority above applicants without. These criteria must be pre-defined and published in advance. Over-subscription criteria must abide by the Government’s School Admissions Code (2021), which prohibits using specific criteria likely to favour advantaged groups in society, such as interviews with parents.

The most common over-subscription criterion (aside from the sibling criteria) is geographic. Burgess et al. (2023) show that around 90% of secondary schools in England have some form of geographic school admissions criteria. Around 53% have a pre-defined catchment area, which gives pupils who live inside priority above those who live outside. Almost all schools with geographic criteria use the distance between home and school as a tie-breaker between pupils with otherwise equivalent priority.

Other common admissions criteria include special needs (used by 48% of secondary schools), a child of staff (used by 44%), feeder primary schools (used by 38%) and religious observance (used by 15%) (Burgess et al., 2023). Around 11% of schools use pupil ability or aptitude as an admissions criterion. Approximately half of these schools are ‘selective’ or ‘grammar’ schools, which select all pupils according to ability. Pupils must pass an entry test to gain admission to these prestigious schools.⁶ The other half of schools are partially selective - permitted to admit up to 10% of their intake according to aptitude in the school’s specialist subject, for example, music, languages and sport.

School assignment: Given parents’ school choices and schools’ admissions criteria, each LA then runs a truth-revealing allocation mechanism to allocate pupils to schools. Overall, the allocation mechanism allows parents to make multiple school choices with few strategic distortions. Pupils are assigned to their most preferred school at which they gain admission according to the schools’ capacity and (if applicable) over-subscription criteria.

More formally, the allocation mechanism is known as ‘equal preferences’ and is equivalent to the school-proposing Gale-Shapley deferred acceptance mechanism with a short list length (between 3 and 6 choices, depending on the LA), see Pathak and Sönmez (2013), Burgess et al. (2025) and examples within.⁷ This short list length means some parents are incentivised to misreport their true preferences to include a safe rather than ambitious school choice, coined “skipping the impossible” by Fack et al. (2019). This is because, if they are unassigned to any of their ranked schools, they would be allocated to a school with spare places (by definition, unpopular).

3 Data

3.1 Data sources

This Section describes the publicly available data used to estimate the relationship between local school quality and property prices, and variation according to market characteristics. Further details about data construction are given in Appendix A.1.

cohort, while pupils born in August are the youngest.

⁶In these areas, pupils who do not pass the test, known as the ‘11-plus’, attend ‘comprehensive’ schools (previously called ‘secondary modern’ schools). These pupils are typically around 80% of those in the area.

⁷Terrier et al. (2021) describe the algorithm as ‘student-proposing’ rather than ‘school-proposing’, but this is inconsistent with the description of the process from LAs in England.

Property prices: We take property prices from the [Price Paid Data from HM Land Registry](#), covering all property sales in England and Wales that are sold for full market value and lodged with HM Land Registry for registration. These are linked to data from the Energy Performance Certificate database to observe more property details, such as the floor area (Chi et al., 2025). Properties are geolocated within postcodes, small geographic areas containing typically 15 addresses.

Catchment areas (school zones): We use catchment areas collected for a related project on schools’ admissions arrangements in England, from the 2021/2022 academic year. We use catchment areas from 50 LAs, where Geographic Information System (GIS) files were publicly available or requested by the research team through a ‘Freedom of Information’ request to the LA.⁸ We include catchment boundaries only where the catchments are not overlapping, which implies that a property is in the catchment area for one rather than multiple schools.

The data collection exercise yields 957 catchment areas.⁹ These are around 52% of secondary schools that use a catchment area in their admissions criteria in England ($N = 1,827$), and around 29% of the total number of secondary schools ($N = 3,249$). Appendix Figure B.1 maps LAs in England according to the use of catchment areas and inclusion in our sample. LAs included in our sample are shaded in dark blue. LAs where a sizeable share of secondary schools (more than 17%, with an average of 68%) have a catchment area are shaded in light blue. LAs where catchment areas are uncommon (most notably in London) are transparent.

Our results are generalisable to areas where the majority of schools currently use catchment areas, and not the wider country. This is because catchment areas are used more in rural areas, and almost absent in London, so that our sample is not representative of England as a whole. Our sample is representative of the LAs which use catchment areas, however. Appendix Table A.1 provides the detail of the sample selection relative to all LAs with catchment areas.

Similarly, schools in our sample are representative of schools in areas of England which use catchment areas, but not of schools in England more generally. Appendix Table A.2 contains characteristics of pupils in terms of gender (and attendance, panel A), free school meals (panel B), ethnicity and language (panel C) and school quality (panels D and E), averaged across academic years 2016/17, 2017/18 and 2018/19.

School quality and composition: Publicly available information on secondary school performance is from the official statistics available on the [‘Find and compare schools in England’](#) website. We use the percentage of pupils that achieve at least 5 GCSEs at grades 9 to 5 (including English and Maths), and the schools’ value-added measure (known as Progress 8). For school composition, we use the percentage of pupils eligible for free school meals. For each of these measures, we take the average across 2017/2018 and 2019/2020 academic years.¹⁰ Each continuous measure is standardised to have a mean of zero and a standard deviation of one, according to the national distribution of secondary school performance.

Appendix Figure B.2 shows the variation in school quality and composition across catchment areas in England. Appendix Figure B.3 repeats this for one LA in England, demonstrating the local variation across catchment area boundaries. There are neighbouring catchment areas with large differences in school quality/composition according to each measure.

Resident population: We retrieve publicly available information about the composition of resi-

⁸An additional 15 LAs provided information in excel or pdf format, which we choose not to incorporate as the boundaries we can construct are less precise than the boundaries provided in GIS format.

⁹Not all of these enter the analysis. We keep only catchment areas with an immediately neighbouring catchment that shares a clean common boundary, and apply further geometric and data-availability filters. Appendix A.1 details the full sequence of restrictions.

¹⁰Our data construction accounts for changes in school identifiers over time, for example, changes occurring due to conversion to academy status.

dents from the 2021 [UK Census](#) wave. Information is retrieved at the output area level, which is the most granular geographic disaggregation available: on average, one output area contains around 11 postcodes. We use information about the housing arrangement (tenure, accommodation type, number of rooms, bedroom occupancy), demographic characteristics (gender, age, ethnicity, migration status, dependent children), economic activity (employment, student share, job classification) and education/job specialisation (highest qualification).

Income: We also retrieve estimates of net income at the MSOA (Middle layer Super Output Area) level, which is a less granular geographic disaggregation than output areas. The Office for National Statistics (ONS) published [estimates for fiscal year 2018](#) at the MSOA level, but due to the coarseness of the geographic units, we are unable to precisely produce average figures for each catchment area. We choose to produce average income figures for each *boundary* between two neighbouring catchment areas as described in Appendix A.1.

Final sample: Our analysis sample consists of property sales assigned to boundaries between two neighbouring schools’ catchment areas: each transaction is first assigned to a catchment area by its postcode, and subsequently to the boundary between its assigned school’s catchment area and a neighbouring one. Neighbouring catchments are paired within the same LA and we retain pairs sharing a clean common border. Appendix A.1 describes the pairing rules and the filters applied to obtain the final set of boundaries. This yields 1,260 boundary pairs from 750 schools.

Appendix Table A.3 shows the full sample of prices paid by bandwidth specification, which is roughly £300,000, on average.

3.2 Boundary classification

For each boundary b we observe its two schools and their three quality measures j , introduced in Section 3.1: attainment (*att*), value-added (*vadd*) and socioeconomic composition (*ses*).

Denoting s_i and s_{-i} for the two catchment areas that form b , and SQ_s^j for the standardised quality of school s on measure j , we construct two boundary-level variables that we use throughout the analysis. The first boundary-level variable is the size of the gap in quality across the boundary, $\Delta SQ_b^j = |SQ_{s_i}^j - SQ_{s_{-i}}^j|$.

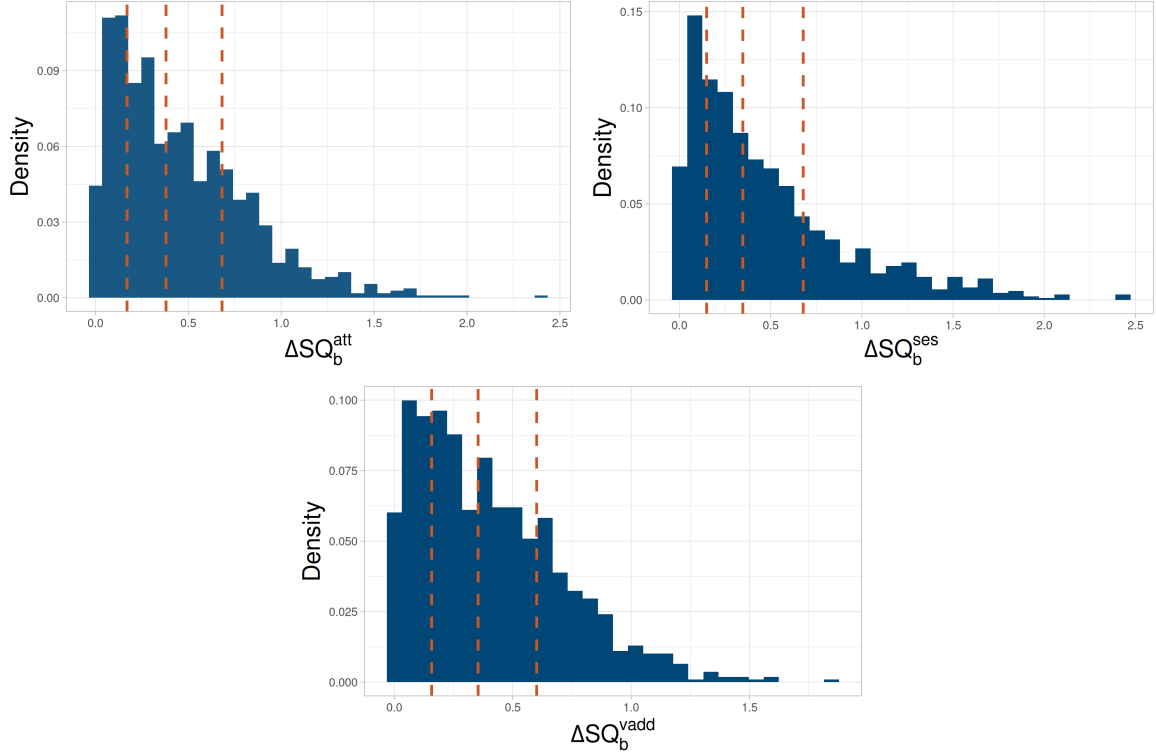
Figure 1 shows the distribution of the school quality difference, ΔSQ_b^j , across catchment area boundaries, as defined by attainment, value-added and socioeconomic composition. For attainment, the median difference is around 0.4 of a standard deviation (see also Appendix Table A.4). Only around 10% of school pairs have a difference of more than one standard deviation, which is the metric commonly reported in the literature to present the relationship between school quality and prices.

We group ΔSQ_b^j into quartiles, $\Delta SQ_b^{j,Q}$, with $Q1$ including boundaries where school quality for the pair of schools is most similar and $Q4$ for pairs of schools with the largest difference in school quality. The orange vertical lines in Figure 1 show the quartiles.

School pairs can vary in the level of school quality in addition to the difference in school quality. Figure 2 illustrates the variation in the quality of the treated (or higher-performing) school within quartiles of $\Delta SQ_b^{j,Q}$, as measured by attainment. The boxes show the 25th, 50th and 75th percentiles, while the dots represent outlier schools with particularly high or low quality. There is variation in the absolute ‘quality’ of the ‘better’ school, which can even be below the national median.

The second boundary-level variable therefore represents the level of school quality according to the national quality distribution. This allows us to capture whether premiums vary according to the absolute level of the ‘better’ or ‘worse’ school. Letting $SQ_s^{j,Q}$ denote the national quartile rank of

Figure 1: Distribution of school ‘quality’ differences across catchment area boundaries in England



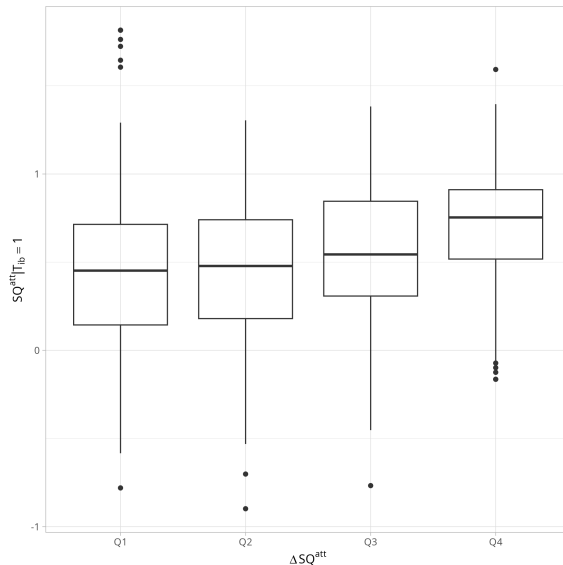
Source: DfE School Performance Tables and catchment areas collected by the authors. Notes: Orange dashed lines represent the quartiles of each distribution, where the cutoff values are: for attainment $\{0.17, 0.39, 0.68\}$; for socioeconomic composition $\{0.15, 0.36, 0.71\}$; for value-added $\{0.16, 0.35, 0.62\}$.

school s on measure j , we record the pair $SQ_b^{comb} = (SQ_{s_i}^{j,Q}, SQ_{s-i}^{j,Q})$, to differentiate between schools with the same ΔSQ_b^j , but at different positions in the national distribution. For instance, $Q1-Q2$ is a boundary between a bottom-quartile and a second-quartile school, while $Q3-Q4$ is a boundary between a third-quartile and a top-quartile school.

3.3 Descriptive statistics

Table 1 shows the residential composition of boundaries across the distribution of attainment difference (columns (1)-(4)) and the relative position of schools in the full quality distribution on either side of the boundary (columns (5)-(8)). The most noticeable differences are in net income, which are higher for schools to the right of the attainment distribution (higher $SQ_s^{j,Q}$). Columns (5)-(8) also highlight some compositional differences depending on where in the absolute quality distribution the alternatives are. Column (5) shows that in neighbourhoods where the ‘jump’ in school quality is from the bottom of the quality distribution ($Q1$) to the middle ($Q2$) the population is on average poorer, less educated and less likely to own a house. They are more likely to live in a rented property, to live in a flat and in smaller properties.

Figure 2: Distribution of school ‘quality’ for treated schools by ΔSQ attainment quartile



Source: DfE School Performance Tables and catchment areas collected by the authors. Notes: This figure shows the school quality of the treatment school for all pairs of schools with a boundary in our final sample, where school quality is defined by attainment. The box and whisker plots represent the 25th, median and 75th percentiles for the school quality of the treatment school, with outliers represented by the dots in the whiskers. The four columns split the sample by quartiles for the difference in school quality across the boundary. For example, $Q4$ has the largest difference in school quality across the boundary.

Appendix Tables A.5 and A.6 show the same statistics using socioeconomic composition and value-added as quality measures. Overall, the patterns are similar for socioeconomic composition but more muted for value-added.

Figure 3 shows the correlation between the school quality measures. While each pair of measures is strongly positively correlated, there are schools with high performance and a less advantaged intake, and vice versa. We will exploit this variation to test whether households value individual dimensions of school quality independently or, alternatively, as a bundle.

4 Methodology

The relationship between local school quality and property prices is challenging to estimate, as many observable and unobservable neighbourhood characteristics could influence both school quality and local prices. For example, an area might attract higher-income households due to quality housing stock or local amenities, such as parks. This sorting could then influence school quality (as defined by attainment) due to the positive correlation between parents’ income and pupil ability. This means that the higher property prices around good schools are likely to be driven partly by unobservable neighbourhood characteristics.

Table 1: Sample description, attainment difference

	ΔSQ				SQ^{comb}			
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q1-Q2 (5)	Q2-Q3 (6)	Q3-Q4 (7)	Q1-Q4 (8)
Net income, 2018 £	34955.88	34942.77	35118.85	35178.33	32816.48	34570.17	37954.55	35435.49
% Flat	0.08	0.08	0.09	0.10	0.10	0.08	0.08	0.10
% House	0.88	0.88	0.88	0.87	0.87	0.89	0.89	0.87
% Employed	0.56	0.56	0.56	0.56	0.55	0.56	0.57	0.56
% Unemployed	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.02
% White	0.92	0.91	0.90	0.89	0.89	0.91	0.92	0.89
% Lv. 4 highest qualification	0.33	0.32	0.32	0.32	0.27	0.32	0.39	0.33
% Stayers	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
% 1 room	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01
% 2 rooms	0.07	0.06	0.07	0.07	0.07	0.06	0.06	0.07
% 3 rooms	0.20	0.20	0.21	0.21	0.22	0.20	0.19	0.20
% 6 rooms	0.11	0.11	0.10	0.10	0.08	0.11	0.13	0.11
% High managerial job	0.14	0.13	0.13	0.13	0.10	0.13	0.17	0.13
% Homeowners	0.69	0.69	0.68	0.67	0.64	0.70	0.73	0.67
% Social rent	0.13	0.13	0.14	0.14	0.17	0.13	0.11	0.15
% Private rent	0.17	0.17	0.17	0.17	0.18	0.16	0.15	0.17
N. residents	46592	44929	46621	47335	46904	44164	44033	47741
N. boundaries	273	274	271	263	142	129	144	77

Source: Census 2021 at output area level (ONS), net income at MSOA level (ONS), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Descriptive statistics for boundaries characterised by small (Q1) to large (Q4) differences in pupil attainment and boundaries with different relative position in the attainment distribution. Net income, number of residents and number of boundaries reported in levels, the remaining variables represent shares of resident population. ‘Lv. 4 highest qualification’ is the share of residents whose highest qualification is at Level 4 or above (degree level or equivalent, such as a bachelor’s degree, Certificate of Higher Education, or HNC/HND). ‘Stayers’ is the share of residents who lived at the same address one year before the Census.

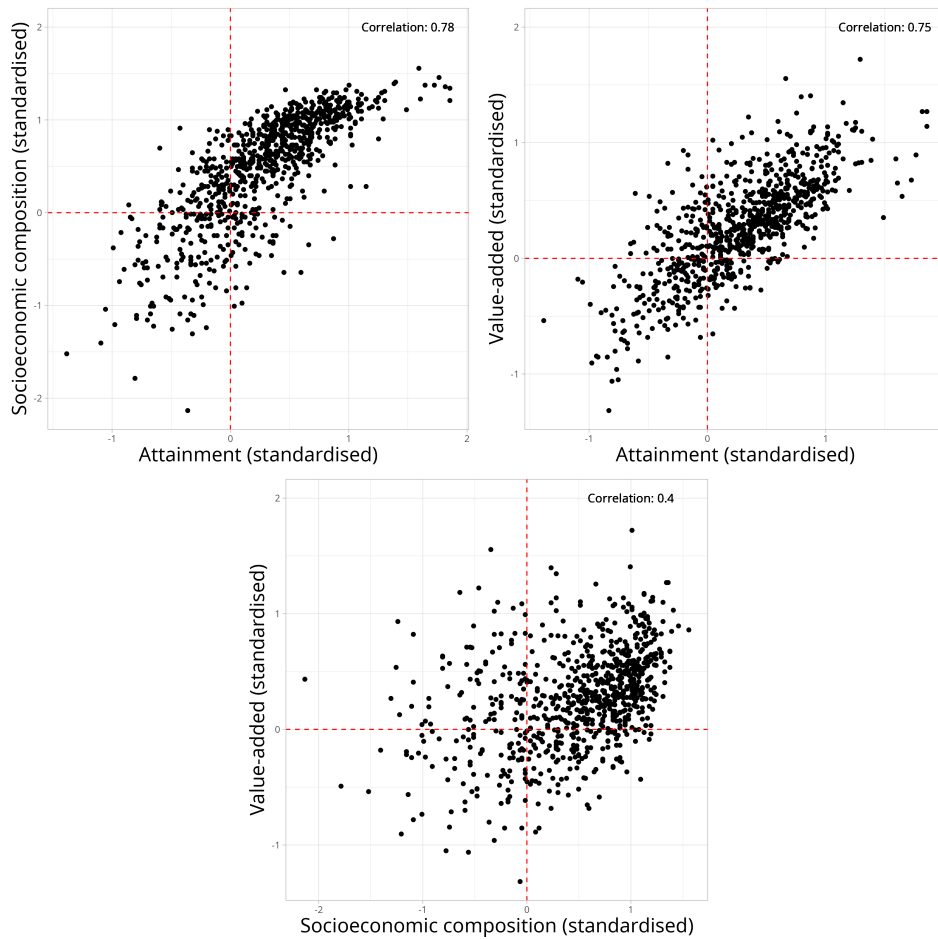
This Section presents the boundary discontinuity design, which is one widely used empirical strategy to overcome this identification challenge. We then outline how we adapt the traditional specification to explore heterogeneity in multiple dimensions.

4.1 Boundary discontinuity design

One solution to the empirical challenge described above, originally established by Black (1999), is to focus on properties around a catchment (or school zone) boundary, known as the boundary discontinuity design. Within a small geographical area around the boundary, property characteristics and local amenities can plausibly be assumed to be constant. The only discontinuous jump on either side of the boundary is access to a higher-quality school. Comparing prices on either side of the boundary therefore isolates the effect of access to that higher-quality school.

In most aspects, we follow the methodology from the boundary discontinuity design literature. First, we exclude catchment boundaries that coincide with administrative boundaries, as all comparisons across catchment boundaries are within LA. Also, boundaries that coincide with physical boundaries such as large rivers, main roads and railway tracks (Black, 1999; Gibbons and Machin, 2003; Bayer et al., 2007; Davidoff and Leigh, 2008). We take school quality as an average over multiple years (Black, 1999; Kane et al., 2006; Gibbons and Machin, 2006; Bayer et al., 2007; Fack and Grenet, 2010; Ries and Somerville, 2010; Gibbons et al., 2013; Chung, 2015; La, 2015; Harjunen et al., 2018;

Figure 3: The correlation between school quality measures



Source: DfE School Performance Tables. Notes: This figure shows the correlation between school-level attainment, pupil socioeconomic composition and value-added. Each dot represents a secondary school in our sample.

Bibler and Billings, 2020) and use log property prices, as is standard in the literature.

We adapt the traditional boundary discontinuity design by defining a binary treatment indicator for being on the higher-quality side of the boundary, rather than entering school quality as a continuous regressor. We do so for three reasons. First, fewer than 10% of boundaries in our data show quality differences exceeding one standard deviation, so the conventional per-standard-deviation interpretation describes a margin that few boundaries actually reach. Second, a binary indicator maps directly to the policy-relevant question of whether the discrete jump in school priority at the catchment boundary is priced. Third, the relationship between school quality differences and prices need not be log-linear, as equilibrium prices depend on the distribution of preferences and incomes. Our formulation allows us to interact the treatment indicator with measures of the quality gap and the absolute position of schools in the national distribution, to study where premiums arise without imposing a functional form.

Using the notation introduced in Section 3.2, we define treatment as a binary indicator for being

on the side of the boundary with the higher school quality (SQ), where the definition of school quality varies by j :

$$T_{ib}^j = \begin{cases} 1 & \text{if } SQ_i^j > SQ_{-i}^j \\ 0 & \text{if } SQ_i^j < SQ_{-i}^j \\ \text{NA} & \text{otherwise} \end{cases} \quad (1)$$

We use three measures of school quality: attainment ($j = att$), value-added ($j = vadd$) and socioeconomic composition (SES, $j = ses$), which are defined fully in Section 3.1. We recognise SES is not a measure of school ‘quality’, but from the discrete choice literature, it is a school characteristic parents care about and may therefore be willing to pay for through the housing market (Hastings et al., 2009; Borghans et al., 2015; Burgess et al., 2015; Denice and Gross, 2016; Glazerman and Dotter, 2017; Akyol and Krishna, 2017; Beuermann et al., 2018; Fack et al., 2019; Harris and Larsen, 2019; Ruijs and Oosterbeek, 2019; Abdulkadiroğlu et al., 2020; Bertoni et al., 2020; Walker and Weldon, 2020). For conciseness, we focus on attainment for our main analysis.

The estimating equation is:

$$y_{ibt} = \tau^j T_{ib}^j + \beta H_{ibt} + d_{ib} + \theta^b + \theta^t + \epsilon_{ibt} \quad (2)$$

where y_{ibt} is the log property price for property i near boundary b at time t , T_{ib}^j is the treatment indicator based on measure j , H_{ibt} are property characteristics (type, construction period, distance from the assigned school, and floor area), d_{ib} is the distance from boundary b , θ^b are boundary fixed effects, and θ^t are year fixed effects. The boundary fixed effects account for all neighbourhood characteristics common to properties on both sides, such as housing stock, proximity to transport, and local amenities.

Our main specification restricts the sample to properties within an optimal bandwidth, computed following Calonico et al. (2014). Robustness checks vary the bandwidth around the catchment area boundary (100m, 200m, 320m, 500m and 800m).¹¹

Our main specification controls for property characteristics that are plausibly exogenous to the school admissions system and household sorting. Appendix Table A.7 shows that these property characteristics are largely balanced across the boundary.¹² The only exception is distance from the assigned school, which is systematically further on the higher-quality side of the boundary. We present alternative specifications with no property controls and with a fuller set of property characteristics that may be endogenous to sorting. For example, more affluent households could be more likely to install double-glazed windows.

The identifying assumption for the boundary discontinuity design is that the neighbourhoods on either side of the boundary (within the close range defined by the optimal bandwidth selection) would be similar in the absence of the school system. For example, exogenous neighbourhood characteristics, such as access to public transport and the age of the housing stock, are assumed to be constant across the boundary.¹³

¹¹This is a typical approach in the existing literature. For example, Black (1999) uses bandwidths of 0.15, 0.2 and 0.35 miles. Similarly, Kane et al. (2006) use 0.4, 0.2 and 0.1 miles. Bayer et al. (2007) use 0.2 and 0.1 miles. Davidoff and Leigh (2008) use 600m, 500m and 200m, while Fack and Grenet (2010) use 250m, 300m and 350m. At the higher end, Gibbons and Machin (2003) use 1000m, although properties are matched to the nearest property on the other side of the boundary, and Cheung et al. (2022) use 500m, 800m and 1000m.

¹²See the online appendix for balance when treatment status is defined by socioeconomic status and value-added (Online Appendix Tables OA.1 and OA.2).

¹³Appendix Table A.7 shows that exogenous properties of the housing stock we can observe are balanced.

Despite relying on the same identifying assumption, our interpretation of the estimated effect differs from previous literature in this field. We interpret the price premium on the higher-quality side as the total effect of school quality, including both the direct valuation of school access and the endogenous neighbourhood composition that arises from sorting. Previous work has either assumed or provided evidence of little sorting across boundaries. However, as Kane et al. (2006) note, even if neighbourhoods are initially similar on either side of a boundary, “the similarity may not last long as properties are bought and sold, as neighbours change, and as houses depreciate and are improved.” Our interpretation follows the equilibrium sorting framework of Bayer et al. (2007), who show that the total capitalisation effect of school quality includes both a direct preference channel and a social multiplier from the re-sorting of higher-income households. Appendix A.4 shows that sorting is primarily according to socioeconomic status, with more high managerial workers on the higher-quality side of the boundary.

4.2 Heterogeneity in the relationship between school quality differences and price premiums

To explore the potential for heterogeneity in the relationship between school quality differences and property prices, we use the quartiles of the quality gap $\Delta SQ_b^{j,Q}$ defined in Section 3.2. We test the hypothesis that there are heterogeneous effects of school quality differences on property prices by estimating the following equation:

$$y_{ibt} = \tau^{j,Q} T_{ib}^j \times \Delta SQ_b^{j,Q} + \beta H_{ibt} + d_{ib} + \theta^b + \theta^t + \varepsilon_{ibt} \quad (3)$$

Equation 3 includes the full set of interactions between the treatment indicator and the quartile of the quality gap: $\tau^{j,1}$ estimates the premium at boundaries where neighbouring schools are very similar, and $\tau^{j,4}$ at boundaries where they are very different. If premiums are concentrated where the quality gap is large, $\tau^{j,4}$ should be proportionately larger than the other estimates.

4.3 ‘Reaching the top’ or ‘escaping the bottom’?

The heterogeneity analysis in Section 4.2 explores whether premiums depend on size of the quality gap, but not on the absolute quality of the school pair. A large gap could arise between a top school and an average school, or between an average school and a bottom school. We distinguish between these cases to study whether price premiums are driven by ‘reaching the top’, ‘escaping the bottom’, or both.

Using the national position combinations SQ_b^{comb} defined in Section 3.2, we estimate Equations 2 and 3 within subsamples defined by this pair. For example, boundaries where the lower-ranked school is in Q1 and the higher-ranked school is in Q2 (‘escaping the bottom’), or where the lower-ranked school is in Q3 and the higher-ranked school is in Q4 (‘reaching the top’).

4.4 Multidimensionality of school quality

School performance and socioeconomic composition are both important factors in parents’ school choices (see the references in Section 4.1), but are often highly correlated. Although the correlation is positive for secondary schools in England, there are boundaries where the higher-performing school has a less advantaged intake, and vice versa (see Figure 3). We exploit this variation to test whether premiums require alignment across quality dimensions.

For each pair of quality measures (j, k) , we split the sample of boundaries according to whether the side of the boundary with higher measure j also has a higher measure k (i.e. the two treatments agree) or the side with higher measure j has instead a lower k (i.e. the two treatments disagree). We then estimate Equation 2 within each of the samples to test whether premiums arise only when both measures being considered are higher on one side, which suggests that the quality dimensions are jointly taken into account. Alternatively, the extent to which premiums also arise where the two treatments disagree, suggesting some trade-offs between quality measures.

5 Results

We first present our main heterogeneity results, together with a comparison which most closely replicates the existing results in the boundary discontinuity design literature (Section 5.1). We then turn to our remaining two extensions which explore heterogeneity in the effect of school quality differences across the boundary in price premiums. First, in Section 5.2, how the premium responds at different points of the school quality distribution, for example moving from a low to average-performing school, or average to high-performing school. Finally, in Section 5.3, we show how combinations of school quality measures influence premiums.

5.1 Heterogeneity in price premiums

Table 2 shows that, in general, our results follow those from the previous literature. Panel A shows estimates of $\widehat{\tau^{att}}$ from Equation 2: there is around a 2.5% increase in property prices for properties on the side of the boundary with the high-performing school when the measure of school quality is defined by attainment. Panel B instead shows estimates (one per row) of $\widehat{\tau^{att,Q}}$ for quartiles of ΔSQ^{att} : we see that across all columns the largest estimated premium arises in Q4 of the attainment difference distribution.

We conclude that the price premium is larger where the difference in school quality is sufficiently large through a statistical test. Appendix Table A.8 shows the pairwise test for coefficient equality for all the estimated premiums within each ΔSQ quartile, where column (1) refers to Panel B of Table 2. The pairwise tests show how estimates for Q4 are significantly higher than all other premiums within other difference quartiles.

The results are sensitive to the set of covariates included in the estimation. Our preferred specification is column (3) as it is the one least likely to suffer from a ‘bad control’ issue: we only include dwelling characteristics that owners cannot reasonably modify and omit any of the Census covariates so as to minimise confounding our effect with school quality induced relocation (i.e. the composition of neighbourhoods changes because specific types of households relocate *in order to* access higher-quality schools).¹⁴

¹⁴The advantage of adding more controls is to capture more differences across the boundary apart from school quality. The disadvantage is that some of these variables might be endogenous - affected by residential sorting for school quality - and therefore a ‘bad control’. Columns (1)-(5) show estimates for progressively larger sets of covariates. ‘Dist. school’ enters in column (2) and refers to distance (in meters) from the assigned school, included linearly in the model. EPC covariates are property-level characteristics from Energy Performance Certificates which we split in two subsets. ‘Exogenous’ (column (3)) are those which are not easily modifiable in response to sorting, including floor area, construction age band and property type (i.e. a detached house/a flat,...). ‘Full’ (column (4)) includes attributes which are more potentially endogenous to household sorting, including energy rating, energy efficiency, energy consumption, lighting, heating and hot water costs, main fuel, CO2 emissions, number of rooms, number of fireplaces and type of window glazing. We also add shares of population living in the assigned output area (from the Census). The ‘Restricted’ set (column (5)) includes shares of people living in flats/houses/shared accommodation, the share of employed people, shares of people employed in high managerial occupations, share of students, share of families with dependent children

Table 2: Estimation results for the relationship between the difference in local school quality (defined by attainment) and property prices

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
τ^{att}	0.033*** (0.009)	0.027*** (0.009)	0.025*** (0.005)	0.025*** (0.005)	0.013*** (0.003)	0.009*** (0.003)
Panel B: ΔSQ quartiles						
$\tau^{att,1}$	-0.014 (0.016)	-0.013 (0.016)	-0.013 (0.009)	-0.012 (0.008)	-0.004 (0.006)	-0.003 (0.005)
$\tau^{att,2}$	0.036 (0.024)	0.030 (0.021)	0.028*** (0.011)	0.026*** (0.009)	0.017** (0.007)	0.012** (0.005)
$\tau^{att,3}$	0.007 (0.017)	-0.002 (0.017)	0.020** (0.009)	0.024** (0.009)	0.008 (0.007)	0.003 (0.006)
$\tau^{att,4}$	0.108*** (0.018)	0.098*** (0.017)	0.065*** (0.010)	0.063*** (0.010)	0.035*** (0.007)	0.025*** (0.006)
Border FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dist. school	No	Yes	Yes	Yes	Yes	Yes
EPC covariates	No	No	Exogenous	Full	Full	Full
Census covariates	No	No	No	No	Restricted	Full
Observations	431857	431857	366761	324075	324075	324075

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***, 0.01, **, 0.05, *: 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The full set of EPC covariates, as well as the restricted and full sets of Census covariates are described in Appendix A.1. All specifications control linearly for distance to the boundary.

The main takeaway is that, while larger sets of covariates dampen the estimated premiums (variation in property prices is explained by both dwelling characteristics and residential composition) the main qualitative result survives this exercise: premiums are disproportionately larger in areas where the difference in attainment between schools is very large.

To demonstrate disproportionately large premiums where the difference in school quality is largest, we conduct two alternative specifications. First, Appendix Table A.9 replaces quartiles of ΔSQ with equally spaced bins of 0.2 standard deviations each: column (1) is the equivalent of column (3), Panel B, in Table 2. While the point estimates vary, the conclusion is the same: boundaries with larger attainment differences disproportionately drive estimated premiums. Second, Appendix Figure B.4 plots estimated marginal effects from two models, where the treatment effect is defined as a flexible function of the continuous quality gap ΔSQ using, respectively, a cubic polynomial and natural spline interactions. A Wald test strongly rejects linearity in the spline specification ($F = 12.38$, $p < 0.001$). The estimated marginal effect is near zero for quality gaps below 0.4 standard deviations and rises steeply beyond that threshold. This confirms that the concentration of premiums in $Q4$ reflects a genuine feature of the data rather than an artefact of the quartile discretisation.

We perform a series of robustness checks for these results. First, to assess robustness to the econometric specification, Appendix Table A.10 shows estimates of Panel B above where we fully control for the share of families living in one-room dwellings and five-room dwellings. The full set of Census covariates is listed in Appendix A.1.

saturate the model with interactions between the quartile indicators and the included covariates.¹⁵ The results for columns (2)-(4) remain virtually unchanged, although results including Census covariates do not show a noticeably larger premium in Q4 of ΔSQ .

Second, to explore the spatial dimension of the score function, Appendix Table A.11 displays estimates of our preferred specification using either a different polynomial of distance from the boundary (columns (1)-(3)) or different polynomials of the coordinates of each unit (columns (4)-(6)).¹⁶ The results remain practically unchanged. Appendix Table A.12 instead uses different combinations of kernel and distance polynomials to weight observations, with results stable in this case too.

Third, to explore sensitivity of the results to the bandwidth, Table A.13 presents results using bandwidths of 100, 200, 320, 500 and 800m instead of the optimally computed CCT. Overall, the qualitative implications for our preferred specification (column (3) of Table 2) remain, although the magnitude of the estimated premiums varies: the smaller the bandwidth, the smaller the premium. For bandwidths of 320m upwards, the magnitudes are very similar to those in Table 2.

Finally, Appendix Table A.14 shows that both the average premium and its concentration in Q4 are stable across Pre-COVID, COVID and Post-COVID periods, ruling out the concern that the results are driven by pandemic-era housing market distortions.

Overall, these results demonstrate that the effect of school quality on property prices is driven by contexts where the difference in school quality across catchment area boundaries is largest. The standard interpretation of previous estimates, which implies a log-linear effect by school quality difference, therefore requires more nuance. The capitalisation gradient varies across the quality distribution because the marginal willingness to pay depends on the income and preferences of the marginal household at each boundary (Epple and Sieg, 1999).

Appendix Tables A.15 and A.16 replicate this analysis using alternative measures of school quality: socioeconomic composition (SES) and value-added (Progress 8). The SES results display a similar pattern to attainment. The average premium is around 2.5% and is concentrated in Q4 of ΔSQ^{ses} , where it reaches 6.8% in our preferred specification. This is expected, given the strong correlation between attainment and socioeconomic composition. The value-added results are qualitatively similar but smaller in magnitude: the average premium is 1.6% and the Q4 premium is 3.0%. Moreover, the value-added premiums are more evenly distributed across quartiles, with Q3 also showing significant effects (2.6%***). Pairwise Wald tests (Appendix Table A.8) confirm that the Q4 value-added premium is not statistically distinguishable from Q2 or Q3, in contrast with attainment and SES where Q4 is significantly larger than all other quartiles. The weaker concentration of value-added premiums in Q4 is consistent with some evidence that value-added is not independently capitalised into property prices (Imberman and Lovenheim, 2016), although for primary schools in England there is a price premium for higher value-added (Gibbons et al., 2013).

We contextualise these magnitudes in Section 5.4 by comparing implied premiums to local median incomes across different subsamples.

5.2 ‘Reaching the top’ or ‘escaping the bottom’?

Price premiums could arise in competition for ‘superstar’ schools, as is typically implied and studied in previous literature. In contrast, price premiums could also arise to avoid the ‘worst’ schools, which would have different important implications for policy.

¹⁵Note: column (1) from Table 2 is omitted as it includes no covariates. Therefore the correspondence between the columns is lagged by 1.

¹⁶Note: we do not have the precise location of each building but rather the postcode it is located in.

Table 3 presents the estimates of equations 2 (Panel A) and 3 (Panel B), to explore whether price premiums are observed only to access the top, or also to ‘escape the bottom’. Panel A shows average premiums across the sample, while Panel B shows premiums within different ΔSQ bins to address the concern that estimates in Panel A may entirely be driven by the difference in school quality rather than the relative position in the absolute distribution.

Table 3: Estimation results for price premiums across boundaries with varying levels of school quality

	Below med. - Above med. (1)	Q1 - any other (2)	Q1 - Q2 (3)	any other - Q4 (4)	Q3 - Q4 (5)
Panel A: Average effect					
τ^{att}	0.042*** (0.008)	0.028*** (0.007)	0.021* (0.012)	0.029*** (0.007)	0.023** (0.010)
Panel B: ΔSQ quartiles					
$\tau^{att,1}$	-0.041 (0.032)	-0.022 (0.017)	-0.074** (0.031)	-0.024 (0.018)	-0.003 (0.019)
$\tau^{att,2}$	0.055** (0.021)	0.017 (0.012)	0.012 (0.018)	0.018 (0.016)	0.033* (0.019)
$\tau^{att,3}$	0.019 (0.015)	0.009 (0.012)	0.029* (0.017)	0.038*** (0.014)	-0.002 (0.013)
$\tau^{att,4}$	0.064*** (0.012)	0.065*** (0.012)	0.082** (0.034)	0.060*** (0.010)	0.088*** (0.024)
Border FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Observations	147385	165813	54117	126118	45201

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Column (1) shows premiums estimated from boundaries where the treated school sits above the median of the national attainment distribution and the control school sits below. Column (2) shows the estimated premiums for moving from Q1 of the attainment distribution (the control school) to anywhere else in the distribution. Columns (3)-(5) follow the same logic. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The full set of EPC covariates, as well as the restricted and full sets of Census covariates are described in Appendix A.1. All specifications control linearly for distance to the boundary.

Panel A of Table 3 shows remarkably stable premiums for both ‘escaping the bottom’ (column (2), leaving Q1 for anywhere else and column (3), leaving Q1 for a below-median school) and ‘reaching the top’ (column (4), reaching Q4 from anywhere and column (5), reaching Q4 from an above-median school). While the ‘reaching the top’ result is expected and consistent with existing literature, the robustness of the ‘escaping the bottom’ premium challenges the conventional focus on competition for the best schools: households also pay significant premiums to avoid the worst available option, even when the alternative school is itself below the median.

Panel B shows that premiums are disproportionately larger when the pair of schools have very different school quality, such that the heterogeneity evident in Table 2 is also present in this case. Conditional on a large quality gap (Q4 of ΔSQ^{att}), the premiums for Q1→Q2 (8.2%***) and Q3→Q4 (8.8%***) are comparable in magnitude. Appendix Table A.9 confirms this at finer resolution using 0.2 s.d. bins: within the (0.8–1.0] bin, escaping (7.3%***) and reaching (8.0%***) premiums are again comparable; at (0.6–0.8], the reaching premium is larger (4.4%***) vs 10.9%***). At very large gaps (above 1.0 s.d.), only the ‘escaping the bottom’ subsample has sufficient observations, because Q3→Q4 boundaries with such large differences are rare.

Balance tests for the Q1→Q2 and Q3→Q4 subsamples (Appendix Table A.7) show that the key

property characteristics are balanced across the boundary in both subsamples, supporting the validity of the RDD at both ends of the quality distribution.

We interpret these findings as evidence that households pay substantial premiums to escape the worst available schools, comparable to the premiums paid to access the best. This extends the existing literature, which has focused on competition for top schools (Bibler and Billings, 2020; Chan et al., 2020), by showing that the same mechanism operates in disadvantaged contexts where both schools are below the national median.

Appendix Tables A.17 and A.18 present the analogous decomposition for SES and value-added. When school quality is defined by socioeconomic composition, the broad comparisons in Panel A of Appendix Table A.17 show that both directions are priced: ‘escaping the bottom’ (column (3): 3.6%^{***}) and ‘reaching the top’ (column (5): 1.7%^{**}). Panel B shows similar patterns to Table 3 for heterogeneity by ΔSQ defined by socioeconomic composition, although these results should be interpreted with caution due to small sample sizes in some cells. For value-added, Appendix Table A.18 shows similar patterns, although not all premiums are statistically significant, and are limited by small sample sizes in some cells.

5.3 Multidimensionality of school quality

This Section explores how households respond to multiple dimensions of school quality. As described in Section 3.3, school-level attainment, socioeconomic composition and value-added are positively correlated, but the correlation is far from perfect. Some schools with higher attainment than their neighbour ($T^{att} = 1$) will have lower socioeconomic composition ($T^{ses} = 0$) and vice versa.

Table 4 presents estimates of equation 2 for the pairwise combinations of our three quality measures. Each column displays one of these combinations, while each panel subsets the data according to whether the two treatment indicators agree (i.e. one school is the treated school with respect to both, in Panel A) or disagree (i.e. one school is the treated school according to one measure, but the control according to the other, in Panel B).

The estimates suggest premiums arise for a bundle of school characteristics, rather than one dimension of school quality alone. When the two measures agree (Panel A), we estimate positive premiums of around 3% in all three pairings, each significant at the one percent level. When they disagree (Panel B), the premiums are smaller and mostly insignificant. The premium falls to zero when attainment and SES disagree (column (1)), and the pairings that involve value-added retain only small premiums. This suggests that households do not price attainment and SES separately, and that households are less responsive to value-added measures than the other two measures. The marginally significant premium in Panel B, column (2) shows that premiums arise for schools with higher attainment but lower value-added than the neighbouring school.

Appendix Table A.19 explores heterogeneity in premiums by the size of the quality gap. As for our main results in Table 2, the premium is disproportionately larger around boundaries where the difference in school quality is large ($Q4$), where treatment status for both measures agrees. In contrast, where treatment status for the two measures disagree, the estimates are typically smaller and largely insignificant. For the case where treatment status is defined by attainment, compared with SES, the average premium is a precise zero where the treatments disagree. The top quartile has a coefficient of 4.0%, consistent with higher premiums where the difference in school quality is large, but it is not statistically significant. As in Table 4, lower value-added does not depress premiums as much as lower socioeconomic composition. Overall, we interpret these findings as suggestive that households bundle some school quality measures (attainment and socioeconomic composition) but value-added is separated.

Table 4: Estimation results for price premiums across treatments’ alignment

	ATT - SES	ATT - VADD	SES - VADD
Panel A: Treatments agree			
τ	0.032*** (0.005)	0.026*** (0.005)	0.032*** (0.006)
Panel B: Treatments disagree			
τ	0.000 (0.010)	0.020* (0.012)	0.010 (0.009)

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Each column refers to a different pair of treatments being compared. The top panel refers to boundaries where both treatment variables equal one on the same side of the boundary, the bottom panel refers to boundaries where treatment variables equal one on different sides. The specification includes the same set of covariates and fixed effects as that of column (3) in Table 2: the covariates include distance from the assigned school, construction age band, floor area and property type. We control linearly for distance to the boundary and include year and boundary fixed effects.

5.4 Premiums in context

Table 5 contextualises the estimated premiums by comparing them to average property prices and median income across different subsamples. The average premium of 2.5% (column (1)) translates to roughly £8,000, or just under three months of median income for households living near catchment area boundaries.

In contrast, if we focus on boundaries in the top quartile of ΔSQ^{att} (column (3)) the size of premiums paid to access a better school reaches almost 7 months of median income. This underlines that the heterogeneous relationship between school quality and property prices has noticeably different implications depending on the local context. The premiums represent an even larger share of median income, between 7.5–11 months of median income, for households living in areas at the top and bottom of the school quality distribution where the difference in quality across the boundary is large (columns (6) and (7)).

Overall, this exercise highlights how heterogeneously premiums arise across the school quality distribution. While the average premium is modest, the implied cost of school quality sorting in areas with large quality gaps is substantial relative to local incomes. These back-of-the-envelope calculations illustrate how the effect of reforming school admissions criteria, reducing the reliance on catchment areas, will have a heterogeneous impact on the housing market and households’ wealth and income.

6 Conclusion

This paper uses the boundary discontinuity design to study how property prices respond to differences in school quality across catchment area boundaries in England. The existing literature has largely estimated average effects, finding a consistent premium of around 3–4% per standard deviation of school quality. We extend this literature along three dimensions.

First, we show that the relationship between school quality differences and property prices is heterogeneous. The average premium of 2.5% masks substantial variation: premiums are concentrated at boundaries where the quality gap is in the top quartile of the distribution (6.5% in our preferred

Table 5: Estimated premiums in context: implied magnitudes across subsamples

	All CA (1)	ΔSQ Q1 (2)	ΔSQ Q4 (3)	Q1–Q2 borders (4)	Q3–Q4 borders (5)	Q1–Q2, ΔSQ Q4 (6)	Q3–Q4, ΔSQ Q4 (7)
N. boundaries	1,086.0	273.0	263.0	142.0	144.0	22.0	17.0
Avg. residents per boundary	45,879.7	46,215.8	46,900.5	46,288.0	43,709.3	47,937.8	43,851.2
Median income (£)	35,033.7	35,055.5	35,198.3	33,150.1	37,930.3	31,672.5	38,239.9
Avg. house price (£)	320,959.3	326,468.2	314,160.4	261,763.5	391,669.8	240,004.6	411,756.6
Estimated effect (%)	2.5	-1.3	6.3	2.1	2.3	8.3	8.4
Implied premium (£)	8,024.0	-4,172.3	19,774.4	5,470.3	9,129.7	19,876.0	34,619.5
Share of median income (%)	22.9	-11.9	56.2	16.5	24.1	62.8	90.5
Months of median income	2.7	-1.4	6.7	2.0	2.9	7.5	10.9

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Each column refers to a different subsample of catchment area boundaries. Median income is the average of output-area-level median net income (2018) across output areas in the subsample. The estimated effect in column (1) is set at 2.5%; effects in the remaining columns are estimated via OLS with exogenous EPC covariates, boundary and year fixed effects, using the CCT optimal bandwidth. The implied premium is the product of the estimated effect and the average property price. Months of median income is the implied premium divided by monthly median income.

specification), while boundaries with smaller gaps show weak or no effects. This pattern is robust to alternative bandwidth choices, covariate specifications, distance polynomials, and finer discretisations of the quality gap. A flexible spline specification strongly rejects linearity ($F = 12.38$, $p < 0.001$): the marginal effect is near zero for gaps below approximately 0.4 standard deviations and rises steeply above.

Second, we show that premiums arise at both ends of the school quality distribution. Households pay substantial premiums to escape the worst accessible schools, comparable to the premiums paid to access the best. This is true on average, and also conditional on a large quality gap. The existing literature has focused on competition for top schools (Bibler and Billings, 2020; Chan et al., 2020), and recent evidence from England using Ofsted information shocks finds larger price effects in affluent areas than in disadvantaged ones (Hussain, 2023). Our cross-sectional boundary design captures the long-run sorting equilibrium, where the accumulated residential choices of households generate premiums wherever quality gaps are large, including in disadvantaged contexts where both schools are below the national median.

Third, we show that premiums require alignment across observable dimensions of school quality. When the same school in the pair has higher test scores and peer composition, premiums are relatively large (2.6–3.2%), but when one school has higher test scores but lower peer composition, premiums vanish. Value-added has no independent pricing power once attainment and pupil socioeconomic composition are accounted for. Households seem to price the combination of school characteristics, not any single dimension in isolation.

Using simple back-of-the-envelope calculations, we show that while the average premium translates to roughly three months of median income, in areas where sorting is most prevalent the implied cost reaches 7.5–11 months of median income. These magnitudes apply at both ends of the quality distribution.

Our results have implications for the general equilibrium effects of reforming school admissions criteria. Where quality gaps between adjacent schools are small, which is the case for the majority of boundaries in England, the price effects of geographic admissions are relatively muted. Reforms to school admissions in these areas would produce limited housing market disruption. In contrast, at boundaries with large quality gaps, estimated premiums are around 6.5% and residential sorting by occupation is substantial. These are the areas where admissions reform would most affect the housing market. The concentration of premiums and sorting at a minority of boundaries suggests

that the welfare effects of geographic admissions are heterogeneous and that reforms would produce concentrated rather than widespread disruption.

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A Appendix

A.1 Data sources and construction

This appendix describes the data sources, variable construction and sample restrictions underlying the analysis. All data are publicly available under the Open Government Licence v3.0 or equivalent open licences.

A.1.1 Property transactions

We use the Price Paid Data from HM Land Registry, which records all residential property sales in England and Wales that are sold for full market value and lodged with the Land Registry. Each record contains the sale price, date, postcode, property type (detached, semi-detached, terraced, flat), tenure (freehold or leasehold) and new-build status. We restrict to transactions from 2019 onwards to align with the school quality measures described below. Properties are geolocated to postcode centroids using the ONS Postcode Directory (February 2023 edition), which provides Ordnance Survey grid references at 1m resolution.

A.1.2 Energy Performance Certificates

We link property transactions to Energy Performance Certificates (EPCs) using the unique transaction identifier provided by the EPC-Land Registry linked dataset (Chi et al., 2025). EPCs provide detailed property characteristics including total floor area (m²), construction age band, current energy rating (A–G), energy efficiency score, energy consumption, CO₂ emissions, heating, hot water and lighting costs, number of habitable rooms, number of fireplaces, main fuel type, glazing type and main heating system efficiency. We classify these into two groups for the regression analysis:

- *Exogenous EPC covariates*: property type, total floor area and construction age band. These are structural characteristics that owners cannot readily modify and are unlikely to be affected by school quality through sorting.
- *Full EPC covariates*: the exogenous set plus energy rating, energy efficiency, energy consumption, lighting cost, heating cost, hot water cost, main fuel, CO₂ emissions, number of rooms, number of fireplaces and glazing type.

A.1.3 School catchment areas

Catchment areas (school zones) for English secondary schools are collected for the 2021/2022 academic year from 50 Local Authorities (LAs) where Geographic Information System (GIS) shapefiles were publicly available or obtained through Freedom of Information requests. Our initial sample contains 957 catchment areas. We apply the following restrictions:

1. Schools with multiple catchment areas are combined into a single polygon (2 cases).
2. One school with no location within its catchment area is dropped.
3. Catchment areas with substantial overlap (>0.5% of the smaller catchment area) are removed, so that each postcode maps to a single school. This leaves 817 schools.

A.1.4 School boundary pairs

We create pairs of neighbouring catchment areas within the same LA that share a boundary (using rook contiguity with a 10m tolerance). Our initial sample is 1,550 boundary pairs from 797 schools. We apply the following additional restrictions:

1. Remove boundaries where the catchment area overlap exceeds 0.5% of the smaller area (leaves 1,430 pairs from 785 schools).
2. Remove boundaries with relatively short shared border lines (leaves 1,301 pairs from 762 schools).
3. Remove boundaries that intersect with a third school’s catchment area for more than 5% of their length (leaves 1,265 pairs from 750 schools).
4. Remove boundaries where both schools lack all three quality measures (leaves 1,260 pairs).

Appendix Figure B.5 illustrates the construction of neighbouring school pairs for one LA, and Appendix Figure B.6 shows the postcode centroids that fall within different bandwidths from one boundary.

A.1.5 School quality measures

Publicly available school performance data are taken from the Department for Education’s “Find and compare schools in England” website. We construct three measures of school quality, each standardised to mean zero and standard deviation one in the national distribution of secondary schools:

- *Attainment (att)*: the percentage of pupils achieving at least 5 GCSEs at grades 9 to 5, including English and Maths.
- *Socioeconomic composition (ses)*: the percentage of pupils *not* eligible for free school meals (so that higher values indicate a more advantaged intake).
- *Value-added (vadd)*: the Progress 8 score, which measures school effectiveness net of pupil ability. Progress 8 is an average of pupil progress between the end of primary and the end of secondary school.

For each measure, we take the average across the 2017/2018 and 2019/2020 academic years to reduce noise from year-to-year fluctuations.

A.1.6 Treatment definition

For each boundary pair and quality measure $j \in \{\text{att}, \text{ses}, \text{vadd}\}$, we define a binary treatment indicator $T_{ib}^j = 1$ if the property i is on the side of boundary b assigned to the higher-quality school, and $T_{ib}^j = 0$ otherwise. We also compute the school quality difference ΔSQ_b^j (in standard deviations) and classify it into quartiles. Boundaries where the two schools have identical quality on measure j receive no treatment assignment for that measure.

A.1.7 Bandwidth selection

For each boundary and quality measure, we compute the optimal bandwidth using the Calonico, Cattaneo and Titiunik (2014) procedure (`rdbwselect` with the “`msetwo`” method), which selects asymmetric bandwidths for the treated and control sides. The running variable is signed distance from the boundary (positive on the treated side). Covariates used in bandwidth selection are property type, total floor area and construction age band. We also report results using fixed symmetric bandwidths of 100m, 200m, 320m, 500m and 800m.

A.1.8 Census data (2021)

Resident population characteristics are taken from the 2021 UK Census at the output area (OA) level, the most granular geographic unit available (each OA contains approximately 11 postcodes on average). We retrieve variables in the following categories:

- *Accommodation*: share in houses, flats, shared or mobile accommodation.
- *Tenure*: share owning outright, share in social rent, share in private rent.
- *Occupation (NS-SEC)*: share in higher managerial/professional, lower managerial/professional, intermediate, small employers, lower supervisory/technical, semi-routine and routine occupations.
- *Qualifications*: share with Level 4+ (degree), no qualifications, and intermediate levels.
- *Demographics*: share by ethnicity (White, Asian, Black, Mixed, Other), share of dependent children by age band (0–4, 5–9, 10–15, 16–18), share with no dependent children.
- *Economic activity*: share employed, share unemployed, share students.
- *Migration*: share who stayed in the same area, share who moved from within the UK, share who moved from outside the UK.
- *Rooms*: share of households by number of rooms (1–9+).

Census variables are linked to postcodes through the OA–postcode mapping in the ONS Postcode Directory.

The “restricted” set of Census covariates used in some specifications includes shares of people living in flats, houses and shared accommodation, the share employed, share in high managerial occupations, share of students, share of families with dependent children aged 10–15 and 16–18, share of families with no dependent children, and the share living in one-room and five-room dwellings.

A.1.9 Income

Estimates of net household income at the Middle layer Super Output Area (MSOA) level are taken from ONS experimental statistics for fiscal year 2018.¹⁷ MSOAs are a less granular geographic unit than output areas: each MSOA contains approximately 30 output areas and may intersect with more than one catchment area. We are therefore unable to assign income precisely to individual catchment areas or postcodes. Instead, we compute average income figures for each *boundary* between two neighbouring catchment areas using the following procedure:

¹⁷Source: ONS, “Exploring the use of admin data to derive small area income estimates.”

1. We define a buffer around each boundary, using the CCT optimal bandwidth as the preferred distance.
2. We compute the spatial intersection between the buffer area and all neighbouring MSOAs using GIS overlay analysis.
3. We compute the share that each intersection represents of the total buffer area.
4. We use these shares as weights in a weighted mean of the net income of all MSOAs overlapping with the buffer.

This procedure requires the assumption that income is uniformly distributed within each MSOA. The resulting boundary-level income estimates are used in the back-of-the-envelope calculations (Table 5) to contextualise the estimated premiums relative to local incomes. They are not used as covariates in the main regressions.

A.2 Additional tables

Table A.1: Residents' composition from 2021 Census, in sample and out of sample

	CA, in sample (1)	CA, not in sample (2)	Difference (3)
% Flat	0.11	0.1	-0.000
% House	0.86	0.86	0.000
% Employed	0.56	0.57	-0.004***
% Unemployed	0.02	0.02	-0.000***
% White	0.88	0.89	-0.000
% Lv. 4 highest qualification	0.32	0.33	-0.002***
% Stayers	0.89	0.9	-0.001*
% 1 room	0.01	0.01	0.000
% 2 rooms	0.07	0.07	0.000
% 3 rooms	0.21	0.21	-0.001
% 6 rooms	0.1	0.1	-0.001
% High managerial job	0.13	0.13	0.001
% Homeowners	0.67	0.67	-0.003**
% Social rent	0.15	0.14	0.005***
% Private rent	0.18	0.18	-0.004***
% Youngest child: 10-15	0.08	0.08	-0.002***
% Youngest child: 16-18	0.03	0.03	-0.000**
N. residents	16128197	12369385	
Net income, 2018 £	34176.89	34331.7	-155***

Source: Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: The table shows the share of residents within (column 1) and outside (column 2) our sample for selected resident characteristics. Numbers are aggregated from the 2021 Census output area figures. The figures shown are population-weighted averages. Differences (column 3) are from a two-sample t-test. Signif. codes: ***: 0.01, **: 0.05, *: 0.1. 'Lv. 4 highest qualification' is the share of residents whose highest qualification is at Level 4 or above (degree level or equivalent, such as a bachelor's degree, Certificate of Higher Education, or HNC/HND). 'Stayers' is the share of residents who lived at the same address one year before the Census.

Table A.2: Pupil composition and school quality, in sample and out of sample secondary schools

	CA, in sample (1)	CA, not in sample (2)	Difference (3)
<i>Panel A: gender composition</i>			
Girls	0.5 (0.03)	0.5 (0.12)	0.008*
Boys	0.5 (0.03)	0.5 (0.12)	-0.008*
<i>Panel B: free school meals</i>			
FSM uptake	0.09 (0.03)	0.08 (0.05)	0.009***
FSM eligibility	0.12 (0.04)	0.1 (0.06)	0.014***
<i>Panel C: ethnicity and language</i>			
White	0.85 (0.09)	0.86 (0.14)	0.001
Black	0.03 (0.02)	0.03 (0.03)	0.002
Asian	0.03 (0.01)	0.03 (0.02)	-0.000
English language	0.89 (0.07)	0.9 (0.11)	-0.005
<i>Panel D: school quality (raw measures)</i>			
Attainment	58.58 (12.1)	61.49 (14.75)	-2.91**
% FSM	25.4 (13.23)	20.94 (10.61)	4.46***
Value added	-0.07 (0.34)	-0.03 (0.37)	-0.04
<i>Panel E: school quality (standardised)</i>			
Attainment	0.25 (0.48)	0.37 (0.58)	-0.11**
% FSM	-0.41 (0.66)	-0.63 (0.53)	0.22***
Value added	0.26 (0.43)	0.32 (0.47)	-0.06

Source: DfE School Performance Tables, and catchment areas collected by the authors. Notes: The table compares schools in and out of our sample, conditional on the usage of catchment areas. Panels A to C show the composition of pupils (averages of within-school shares of all pupils). Panels D and E report school quality measures (pupil attainment, value-added, and the share of pupils eligible for free school meals), in raw and standardised form respectively. % FSM is the inverse of our measure of socioeconomic composition. Column (3) reports the in-sample minus out-of-sample difference, with stars from a two-sample t-test. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.3: Summary statistics for property prices and sales, by bandwidth

Bandwidth	Price (£) (1)	Log(price) (2)	N. sales (3)	Dist. to school (4)	N. obs (5)
100 (m)	275298.07 (187976.59)	12.36 (0.55)	212.08 (132.72)	1903.11 (1493.7)	47578
200 (m)	274937.51 (181669.33)	12.37 (0.55)	431.62 (281.63)	1879.8 (1496.16)	107147
320 (m)	275905.73 (183667.69)	12.37 (0.55)	649.99 (419.54)	1875.55 (1564.01)	179376
500 (m)	277152.9 (187559.69)	12.37 (0.55)	944.85 (595.83)	1857.41 (1616.2)	293251
800 (m)	279832.27 (191984.28)	12.38 (0.56)	1336.75 (816.53)	1852.49 (1700.17)	486249
CCT optimal (att)	320460.05 (230184.08)	12.5 (0.58)	961.42 (676.68)	2942.82 (2835.67)	431857
CCT optimal (ses)	319244.11 (228077.42)	12.5 (0.57)	961.69 (675.77)	2959.34 (2845.02)	425043
CCT optimal (vadd)	320828.52 (230457.87)	12.51 (0.58)	958.95 (672.64)	2976.11 (2869.55)	433716

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Summary statistics for property prices at different bandwidths around the catchment area boundary. Columns (1)-(4) show averages (standard deviations in parentheses) for each variable, computed from the sample restricted according to the 'Bandwidth' column.

Table A.4: ΔSQ distribution by quartile, across quality measures

School quality measure	Quartile	Mean (1)	s.d. (2)	Min (3)	p25 (4)	Median (5)	p75 (6)	Max (7)
Attainment	Q1	0.09	0.05	0.00	0.05	0.09	0.13	0.17
	Q2	0.27	0.06	0.17	0.22	0.26	0.31	0.39
	Q3	0.53	0.09	0.39	0.46	0.52	0.62	0.68
	Q4	0.99	0.28	0.69	0.77	0.90	1.13	2.57
Value added	Q1	0.08	0.05	0.00	0.04	0.08	0.12	0.16
	Q2	0.25	0.05	0.16	0.20	0.25	0.29	0.35
	Q3	0.48	0.08	0.35	0.41	0.47	0.54	0.62
	Q4	0.88	0.23	0.62	0.70	0.83	0.98	1.85
Socioeconomic Composition	Q1	0.07	0.04	0.00	0.03	0.07	0.12	0.15
	Q2	0.25	0.06	0.15	0.20	0.25	0.30	0.36
	Q3	0.51	0.10	0.36	0.43	0.50	0.60	0.71
	Q4	1.13	0.36	0.71	0.84	1.03	1.34	2.43

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Mean, standard deviation and selected percentiles for the school quality differences across boundaries, by quartile and measure. ΔSQ is computed from standardized quality measures.

Table A.5: Sample description, SES difference

	ΔSQ				SQ^{comb}			
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q1-Q2 (5)	Q2-Q3 (6)	Q3-Q4 (7)	Q1-Q4 (8)
Net income, 2018 £	36014.38	35443.88	34658.95	33978.67	32579.70	34674.98	37484.38	35920.42
% Flat	0.09	0.08	0.08	0.11	0.10	0.08	0.08	0.11
% House	0.88	0.88	0.89	0.85	0.86	0.89	0.89	0.85
% Employed	0.57	0.56	0.56	0.56	0.55	0.56	0.57	0.57
% Unemployed	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.02
% White	0.91	0.92	0.91	0.88	0.87	0.95	0.95	0.88
% Lv. 4 highest qualification	0.34	0.34	0.31	0.31	0.27	0.31	0.38	0.33
% Stayers	0.90	0.90	0.91	0.89	0.90	0.90	0.90	0.89
% 1 room	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01
% 2 rooms	0.06	0.06	0.06	0.08	0.07	0.06	0.06	0.07
% 3 rooms	0.20	0.20	0.20	0.22	0.22	0.21	0.19	0.20
% 6 rooms	0.11	0.11	0.10	0.09	0.08	0.11	0.13	0.11
% High managerial job	0.15	0.14	0.13	0.12	0.10	0.13	0.17	0.14
% Homeowners	0.69	0.70	0.69	0.64	0.64	0.71	0.73	0.67
% Social rent	0.13	0.13	0.13	0.16	0.17	0.12	0.11	0.15
% Private rent	0.16	0.16	0.16	0.18	0.19	0.16	0.15	0.17
N. residents	47405	44033	44418	49728	48438	43990	44088	50203
N. boundaries	285	266	276	254	132	160	154	54

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Descriptive statistics for boundaries characterised by small (Q1) to large (Q4) differences in pupil socioeconomic composition (SES) and boundaries with different relative position in the SES distribution. Net income, number of residents and number of boundaries reported in levels, the remaining variables represent shares of resident population.

Table A.6: Sample description, value-added difference

	ΔSQ				SQ^{comb}			
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q1-Q2 (5)	Q2-Q3 (6)	Q3-Q4 (7)	Q1-Q4 (8)
Net income, 2018 £	35103.07	35278.20	35001.84	34795.77	34166.37	35736.37	36344.20	34645.69
% Flat	0.08	0.09	0.09	0.10	0.09	0.08	0.09	0.09
% House	0.89	0.87	0.88	0.87	0.88	0.88	0.88	0.88
% Employed	0.56	0.56	0.56	0.56	0.56	0.56	0.56	0.56
% Unemployed	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
% White	0.92	0.91	0.91	0.89	0.92	0.91	0.90	0.90
% Lv. 4 highest qualification	0.32	0.33	0.32	0.32	0.29	0.33	0.36	0.32
% Stayers	0.90	0.90	0.90	0.90	0.90	0.90	0.89	0.90
% 1 room	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.01
% 2 rooms	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07
% 3 rooms	0.20	0.21	0.20	0.21	0.21	0.20	0.19	0.21
% 6 rooms	0.11	0.11	0.11	0.10	0.09	0.11	0.12	0.10
% High managerial job	0.13	0.14	0.13	0.13	0.12	0.14	0.16	0.13
% Homeowners	0.69	0.69	0.69	0.67	0.68	0.70	0.70	0.68
% Social rent	0.14	0.13	0.14	0.15	0.15	0.13	0.13	0.14
% Private rent	0.16	0.17	0.16	0.17	0.16	0.16	0.16	0.17
N. residents	45495	46737	45871	47396	46249	46320	45836	46840
N. boundaries	275	272	275	259	147	131	154	84

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Descriptive statistics for boundaries characterised by small (Q1) to large (Q4) differences in pupil value-added and boundaries with different relative position in the value-added distribution. Net income, number of residents and number of boundaries reported in levels, the remaining variables represent shares of resident population.

Table A.7: Balance test, attainment

Characteristic	Full sample (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)	Q1-Q2 (6)	Q1-Q4 (7)	Q2-Q3 (8)	Q3-Q4 (9)
Dist. to school (m)	128.81 (2757.08)	-29.72 (3160.07)	55.56 (3223.18)	217.81** (2457.95)	258.09* (2250.77)	97.81 (1941.7)	260.5 (2164.47)	347.26 (2816.01)	-100.43 (4027.74)
Floor area (sqm)	2.39*** (95.02)	0.86 (97.3)	2.32 (97.48)	0.18 (92.33)	6.31*** (93.37)	1.14 (87.32)	8.15*** (91.23)	2.34 (97.5)	1.19 (105.81)
Energy efficiency	-0.12 (61.96)	-0.27 (61.71)	-0.44 (61.6)	0.44 (62.29)	-0.25 (62.2)	-0.01 (62.19)	0 (62.72)	0.54 (61.4)	-0.36 (61.77)
CO2 emissions	0.11** (4.47)	0.07 (4.56)	0.18 (4.6)	-0.02 (4.34)	0.24*** (4.38)	0.07 (4.16)	0.26** (4.24)	0.07 (4.68)	0.13 (4.84)
N. rooms	0.07*** (4.71)	0.06 (4.78)	0.04 (4.79)	0 (4.65)	0.18*** (4.63)	0.09** (4.5)	0.22** (4.58)	0.02 (4.84)	-0.01 (5.02)
Detached house	0.02** (0.27)	0 (0.29)	0 (0.29)	0.03** (0.24)	0.04*** (0.26)	0.01 (0.19)	0.09** (0.27)	0.03 (0.31)	0 (0.36)
Flat	0.01 (0.15)	-0.02* (0.13)	0.02 (0.12)	0.02 (0.14)	0.01 (0.18)	-0.01 (0.13)	0.01 (0.18)	0.04* (0.11)	0.02 (0.14)
Semi-detached house	-0.01 (0.29)	0.01 (0.29)	-0.01 (0.3)	-0.02* (0.3)	0 (0.28)	0.01 (0.31)	-0.04 (0.27)	-0.04** (0.32)	0 (0.27)
Terraced	-0.02** (0.29)	0.01 (0.29)	-0.01 (0.29)	-0.02 (0.32)	-0.04** (0.27)	-0.01 (0.36)	-0.06 (0.28)	-0.02 (0.26)	-0.02 (0.22)
Energy rating: A-C	0 (0.31)	-0.01 (0.31)	-0.01 (0.31)	0.01 (0.31)	0 (0.31)	-0.01 (0.3)	0.01 (0.35)	0.01 (0.29)	-0.01 (0.33)
Energy rating: D-G	0 (0.69)	0.01 (0.69)	0.01 (0.69)	-0.01 (0.69)	0 (0.69)	0.01 (0.7)	-0.01 (0.65)	-0.01 (0.71)	0.01 (0.67)
Construction: 1900-1949	-0.01 (0.23)	0.01 (0.22)	0.01 (0.2)	-0.03** (0.25)	-0.02 (0.25)	-0.01 (0.28)	-0.03 (0.21)	-0.03 (0.23)	-0.02 (0.16)
Construction: 1950-1982	0.01 (0.35)	0.01 (0.34)	0 (0.36)	0 (0.35)	0.03 (0.34)	-0.02 (0.36)	0.02 (0.31)	0 (0.37)	0.04 (0.34)
Construction: 1983-2007	0 (0.28)	-0.01 (0.29)	-0.02 (0.29)	0.03* (0.26)	-0.01 (0.26)	0.02 (0.23)	0.04 (0.31)	0.01 (0.26)	-0.02 (0.35)

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: The table shows estimated differences in property characteristics, with the boundary average in parentheses. Differences are estimated via OLS, regressing each characteristic on a treatment indicator and boundary and year fixed effects. Signif. codes ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the boundary level.

Table A.8: Pairwise Wald tests of ΔSQ quartile equality

	Attainment (1)	SES (2)	Value-added (3)
Q4 = Q1	0.078*** (0.013)	0.068*** (0.014)	0.036** (0.014)
Q4 = Q2	0.037** (0.015)	0.060*** (0.014)	0.017 (0.014)
Q4 = Q3	0.045*** (0.014)	0.047*** (0.014)	0.004 (0.011)
Q3 = Q2	-0.008 (0.014)	0.013 (0.012)	0.013 (0.013)
Q3 = Q1	0.033*** (0.013)	0.021* (0.013)	0.032** (0.014)
Q2 = Q1	0.041*** (0.014)	0.008 (0.013)	0.019 (0.016)

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Each row tests the null hypothesis that the price premiums associated with the indicated ΔSQ quartiles are equal. The underlying estimates come from the interaction specification with exogenous EPC covariates and the optimally computed CCT bandwidth.

Table A.9: Effect on property prices by ΔSQ bins, attainment (0.2 s.d.)

	Full sample (1)	Below med. - Above med. (2)	Q1 - any other (3)	Q1 - Q2 (4)	any other - Q4 (5)	Q3 - Q4 (6)
$T_{i,b}^{att} \times \Delta SQ = [0, 0.2]$	0.004 (0.028)	0.004 (0.028)	-0.011 (0.014)	-0.047** (0.023)	-0.021 (0.015)	0.004 (0.016)
$T_{i,b}^{att} \times \Delta SQ = (0.2, 0.4]$	0.043* (0.023)	0.043* (0.023)	0.012 (0.013)	0.013 (0.017)	0.028* (0.016)	0.032* (0.019)
$T_{i,b}^{att} \times \Delta SQ = (0.4, 0.6]$	0.014 (0.022)	0.014 (0.022)	0.006 (0.017)	0.030 (0.022)	0.026* (0.016)	-0.011 (0.014)
$T_{i,b}^{att} \times \Delta SQ = (0.6, 0.8]$	0.036** (0.014)	0.036** (0.014)	0.034** (0.014)	0.044** (0.018)	0.064*** (0.018)	0.109*** (0.040)
$T_{i,b}^{att} \times \Delta SQ = (0.8, 1]$	0.044*** (0.017)	0.044*** (0.017)	0.047*** (0.016)	0.073** (0.032)	0.047*** (0.013)	0.080*** (0.017)
$T_{i,b}^{att} \times \Delta SQ = (1, 1.2]$	0.109*** (0.029)	0.109*** (0.029)	0.105*** (0.030)	0.065*** (0.006)	0.070*** (0.018)	0.002 (0.033)
Border FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Observations	147385	147385	165813	54117	126118	45201

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The chosen bandwidth is the optimally computed CCT one. Each of the bins within which the premiums are estimated measures 0.2 s.d. of the difference in standardised attainment.

Table A.10: Effect on property prices by ΔSQ quartile, attainment: covariates interaction

	(1)	(2)	(3)	(4)	(5)
$\tau^{att,1}$	-0.013 (0.016)	-0.013 (0.008)	-0.012 (0.008)	-0.004 (0.006)	-0.003 (0.005)
$\tau^{att,2}$	0.030 (0.021)	0.030*** (0.011)	0.027*** (0.010)	0.017** (0.007)	0.013** (0.005)
$\tau^{att,3}$	-0.002 (0.017)	0.020** (0.009)	0.023** (0.009)	0.008 (0.007)	0.004 (0.006)
$\tau^{att,4}$	0.098*** (0.017)	0.062*** (0.009)	0.060*** (0.009)	0.032*** (0.007)	0.023*** (0.005)
Border FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Dist. school	Yes	Yes	Yes	Yes	Yes
EPC covariates	No	Exogenous	Full	Full	Full
Census covariates	No	No	No	Restricted	Full
Observations	431857	366761	324075	324075	324075

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***, 0.01, **, 0.05, *, 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The bandwidth around the boundary is the CCT optimally computed one. The specifications show results for specifications interacting the set of covariates with the ΔSQ indicator.

Table A.11: Robustness: attainment, distance polynomial

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
τ_{att}	0.025*** (0.005)	0.025*** (0.005)	0.025*** (0.005)	0.026*** (0.005)	0.026*** (0.005)	0.026*** (0.005)
Panel B: ΔSQ quartiles						
$\tau_{att,1}$	-0.013 (0.009)	-0.013 (0.009)	-0.013 (0.009)	-0.013 (0.009)	-0.013 (0.009)	-0.013 (0.009)
$\tau_{att,2}$	0.028*** (0.011)	0.028*** (0.011)	0.028*** (0.010)	0.028** (0.011)	0.028** (0.011)	0.028** (0.011)
$\tau_{att,3}$	0.020** (0.009)	0.020** (0.009)	0.020** (0.009)	0.021** (0.009)	0.021** (0.009)	0.021** (0.009)
$\tau_{att,4}$	0.065*** (0.010)	0.065*** (0.010)	0.065*** (0.010)	0.067*** (0.010)	0.067*** (0.010)	0.067*** (0.010)
Dist. boundary	Linear	Quadratic	Cubic	No	No	No
Latitude	No	No	No	Linear	Quadratic	Cubic
Longitude	No	No	No	Linear	Quadratic	Cubic
Observations	366761	366761	366761	366761	366761	366761

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***, 0.01, **, 0.05, *, 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The chosen bandwidth is the optimally computed CCT one. Each column shows estimated premiums using different functions of distance from the boundary or latitude and longitude.

Table A.12: Robustness: attainment, distance weights

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
τ_{att}	0.025*** (0.005)	0.019*** (0.005)	0.021*** (0.005)	0.025*** (0.005)	0.019*** (0.005)	0.021*** (0.005)
Panel B: ΔSQ quartiles						
$\tau_{att,1}$	-0.013 (0.009)	-0.016* (0.009)	-0.015* (0.009)	-0.013 (0.009)	-0.016* (0.009)	-0.015* (0.009)
$\tau_{att,2}$	0.028*** (0.011)	0.028** (0.011)	0.029*** (0.011)	0.028*** (0.011)	0.028** (0.011)	0.029*** (0.011)
$\tau_{att,3}$	0.020** (0.009)	0.010 (0.009)	0.012 (0.009)	0.020** (0.009)	0.010 (0.009)	0.012 (0.009)
$\tau_{att,4}$	0.065*** (0.010)	0.054*** (0.010)	0.057*** (0.010)	0.065*** (0.010)	0.054*** (0.010)	0.057*** (0.010)
Kernel	Uniform	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov
Polynomial order	1	1	1	2	2	2
Observations	366761	366761	366761	366761	366761	366761

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***, 0.01, **, 0.05, *, 0.1. Standard errors are clustered at the boundary level. Each column estimates the same specification as column (3) of table A.10 using different distance weights and polynomials of distance from the boundary. Column (1) is exactly equivalent to column (3) of Table A.10, while columns (2)-(6) show varying combinations of weights and polynomials.

Table A.13: Bandwidth sensitivity: attainment

	(1)	(2)	(3)	(4)	(5)
Panel A: Average effect					
τ^{att}	0.002 (0.007)	0.015** (0.006)	0.022*** (0.006)	0.027*** (0.006)	0.039*** (0.005)
Panel B: ΔSQ quartiles					
$\tau^{att,1}$	-0.036*** (0.013)	-0.017 (0.013)	-0.016 (0.012)	-0.012 (0.010)	-0.004 (0.010)
$\tau^{att,2}$	0.006 (0.012)	0.020* (0.012)	0.013 (0.011)	0.012 (0.009)	0.018** (0.009)
$\tau^{att,3}$	0.003 (0.014)	0.007 (0.011)	0.015 (0.010)	0.023** (0.010)	0.039*** (0.009)
$\tau^{att,4}$	0.028* (0.016)	0.045*** (0.012)	0.065*** (0.011)	0.075*** (0.011)	0.088*** (0.011)
Bandwidth (m)	100	200	320	500	800
Border FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Dist. school	Yes	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Census covariates	No	No	No	No	No
Observations	40514	90990	152337	249878	417086

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the boundary level. Each column is the preferred specification (column 3 of Table A.10) at the indicated fixed bandwidth.

Table A.14: Price premiums by time period: Pre-COVID, COVID and Post-COVID

	Pre-COVID (1)	COVID (2)	Post-COVID (3)
Panel A: Average effect			
τ^{att}	0.025*** (0.006)	0.030*** (0.005)	0.021*** (0.005)
Panel B: ΔSQ quartiles			
$\tau^{att,1}$	-0.020* (0.010)	-0.011 (0.009)	-0.012 (0.009)
$\tau^{att,2}$	0.028** (0.012)	0.036*** (0.012)	0.024* (0.012)
$\tau^{att,3}$	0.026*** (0.010)	0.023** (0.010)	0.016* (0.009)
$\tau^{att,4}$	0.067*** (0.011)	0.073*** (0.011)	0.058*** (0.010)
Border FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous
Observations	60531	141474	164756

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the boundary level. Pre-COVID: transactions up to 2019. COVID: 2020–2021. Post-COVID: 2022 onwards. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. The bandwidth is the CCT optimally computed one.

Table A.15: Effect on property prices, socioeconomic composition: average and by ΔSQ quartile

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
τ^{ses}	0.033*** (0.010)	0.022** (0.009)	0.025*** (0.005)	0.025*** (0.005)	0.011*** (0.004)	0.007** (0.003)
Panel B: ΔSQ quartiles						
$\tau^{ses,1}$	-0.015 (0.019)	-0.015 (0.018)	-0.001 (0.009)	-0.004 (0.009)	-0.005 (0.007)	-0.003 (0.006)
$\tau^{ses,2}$	0.021 (0.018)	0.007 (0.018)	0.008 (0.009)	0.012 (0.009)	0.002 (0.006)	0.003 (0.006)
$\tau^{ses,3}$	0.017 (0.019)	0.008 (0.019)	0.021** (0.009)	0.021** (0.009)	0.011* (0.007)	0.007 (0.006)
$\tau^{ses,4}$	0.103*** (0.020)	0.085*** (0.018)	0.068*** (0.011)	0.066*** (0.010)	0.034*** (0.007)	0.022*** (0.006)
Border FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dist. school	No	Yes	Yes	Yes	Yes	Yes
EPC covariates	No	No	Exogenous	Full	Full	Full
Census covariates	No	No	No	No	Restricted	Full
Observations	425043	425043	360834	318484	318484	318484

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. All specifications control linearly for distance to the boundary.

Table A.16: Effect on property prices, value-added: average and by ΔSQ quartile

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
τ^{vadd}	0.017*	0.013	0.016***	0.016***	0.009***	0.007**
	(0.010)	(0.009)	(0.005)	(0.005)	(0.003)	(0.003)
Panel B: ΔSQ quartiles						
$\tau^{vadd,1}$	-0.022	-0.027	-0.006	-0.002	-0.000	-0.005
	(0.023)	(0.021)	(0.012)	(0.011)	(0.008)	(0.006)
$\tau^{vadd,2}$	0.034*	0.027	0.013	0.012	0.008	0.011
	(0.018)	(0.017)	(0.011)	(0.011)	(0.008)	(0.007)
$\tau^{vadd,3}$	0.025	0.023	0.026***	0.021***	0.010*	0.010*
	(0.017)	(0.016)	(0.007)	(0.008)	(0.006)	(0.006)
$\tau^{vadd,4}$	0.030*	0.027	0.030***	0.032***	0.018***	0.011**
	(0.017)	(0.017)	(0.008)	(0.008)	(0.005)	(0.005)
Border FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dist. school	No	Yes	Yes	Yes	Yes	Yes
EPC covariates	No	No	Exogenous	Full	Full	Full
Census covariates	No	No	No	No	Restricted	Full
Observations	433716	433716	367910	324931	324931	324931

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level (ONS), net income at MSOA level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. All specifications control linearly for distance to the boundary.

Table A.17: Escaping the bottom and reaching the top, socioeconomic composition

	Below med. - Above med. (1)	Q1 - any other (2)	Q1 - Q2 (3)	any other - Q4 (4)	Q3 - Q4 (5)
Panel A: Average effect					
τ^{ses}	0.043*** (0.009)	0.040*** (0.008)	0.036*** (0.014)	0.031*** (0.008)	0.017** (0.009)
Panel B: ΔSQ quartiles					
$\tau^{ses,1}$	0.041 (0.072)	-0.022 (0.016)	-0.006 (0.027)	-0.002 (0.014)	0.021* (0.012)
$\tau^{ses,2}$	-0.010 (0.012)	0.031 (0.021)	0.089** (0.035)	0.006 (0.013)	0.009 (0.013)
$\tau^{ses,3}$	0.015 (0.013)	0.019 (0.013)	0.025 (0.019)	0.032** (0.012)	0.038* (0.020)
$\tau^{ses,4}$	0.084*** (0.012)	0.063*** (0.011)	0.041* (0.024)	0.096*** (0.017)	0.029 (0.032)
Border FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Observations	137088	150558	52328	133424	52041

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Column (1) shows premiums estimated from boundaries where the treated school sits above the median of the national attainment distribution and the control school sits below. Column (2) shows the estimated premiums for moving from Q1 of the attainment distribution (the control school) to anywhere else in the distribution. Columns (3)-(5) follow the same logic. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. All specifications control linearly for distance to the boundary.

Table A.18: Escaping the bottom and reaching the top, pupil value-added

	Below med. - Above med. (1)	Q1 - any other (2)	Q1 - Q2 (3)	any other - Q4 (4)	Q3 - Q4 (5)
Panel A: Average effect					
τ^{vadd}	0.026*** (0.007)	0.027*** (0.007)	0.016 (0.012)	0.027*** (0.008)	0.019* (0.011)
Panel B: ΔSQ quartiles					
$\tau^{vadd,1}$	0.029 (0.050)	0.028 (0.020)	-0.008 (0.027)	-0.017 (0.024)	0.026 (0.030)
$\tau^{vadd,2}$	0.012 (0.016)	0.014 (0.018)	0.021 (0.023)	0.037* (0.021)	0.022 (0.016)
$\tau^{vadd,3}$	0.016 (0.011)	0.024** (0.011)	0.029 (0.018)	0.033*** (0.009)	0.038*** (0.012)
$\tau^{vadd,4}$	0.036*** (0.009)	0.035*** (0.009)	-0.027 (0.028)	0.034*** (0.012)	-0.070* (0.039)
Border FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Observations	147527	155488	50916	146286	52106

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Column (1) shows premiums estimated from boundaries where the treated school sits above the median of the national attainment distribution and the control school sits below. Column (2) shows the estimated premiums for moving from Q1 of the attainment distribution (the control school) to anywhere else in the distribution. Columns (3)-(5) follow the same logic. Standard errors are clustered at the boundary level. The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school. All specifications control linearly for distance to the boundary.

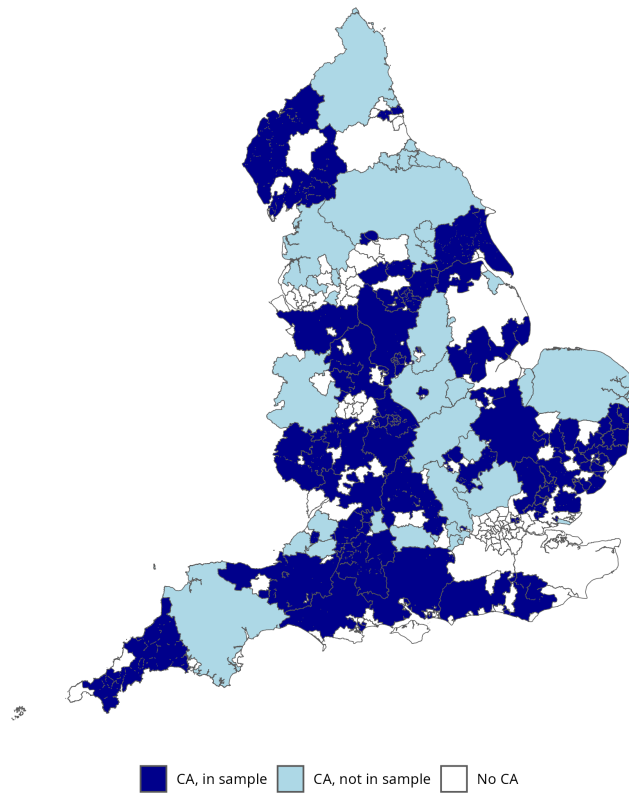
Table A.19: Multidimensionality: attainment premium by school quality gap

	ATT-SES, agree (1)	ATT-SES, disagree (2)	ATT-VADD, agree (3)	ATT-VADD, disagree (4)
Panel A: Average effect				
τ^{att}	0.032*** (0.005)	0.000 (0.010)	0.026*** (0.005)	0.020* (0.012)
Panel B: ΔSQ quartiles				
$\tau^{att,1}$	-0.018 (0.011)	0.001 (0.015)	-0.012 (0.011)	-0.016 (0.014)
$\tau^{att,2}$	0.037*** (0.013)	0.001 (0.015)	0.017* (0.010)	0.059*** (0.022)
$\tau^{att,3}$	0.023** (0.010)	-0.011 (0.023)	0.018** (0.009)	0.026 (0.032)
$\tau^{att,4}$	0.067*** (0.010)	0.040 (0.054)	0.065*** (0.010)	0.076 (0.067)
Border FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dist. school	Yes	Yes	Yes	Yes
EPC covariates	Exogenous	Exogenous	Exogenous	Exogenous
Census covariates	No	No	No	No
Observations	304464	52726	294997	70389

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the boundary level. Columns split the sample by whether attainment agrees or disagrees with SES (columns 1–2) or with value-added (columns 3–4) about the higher-quality side. Panel A reports the average premium; Panel B reports separate premiums by quartile of the attainment gap ΔSQ^{att} . The exogenous set of EPC covariates includes floor area, property type, construction age band and distance from assigned school.

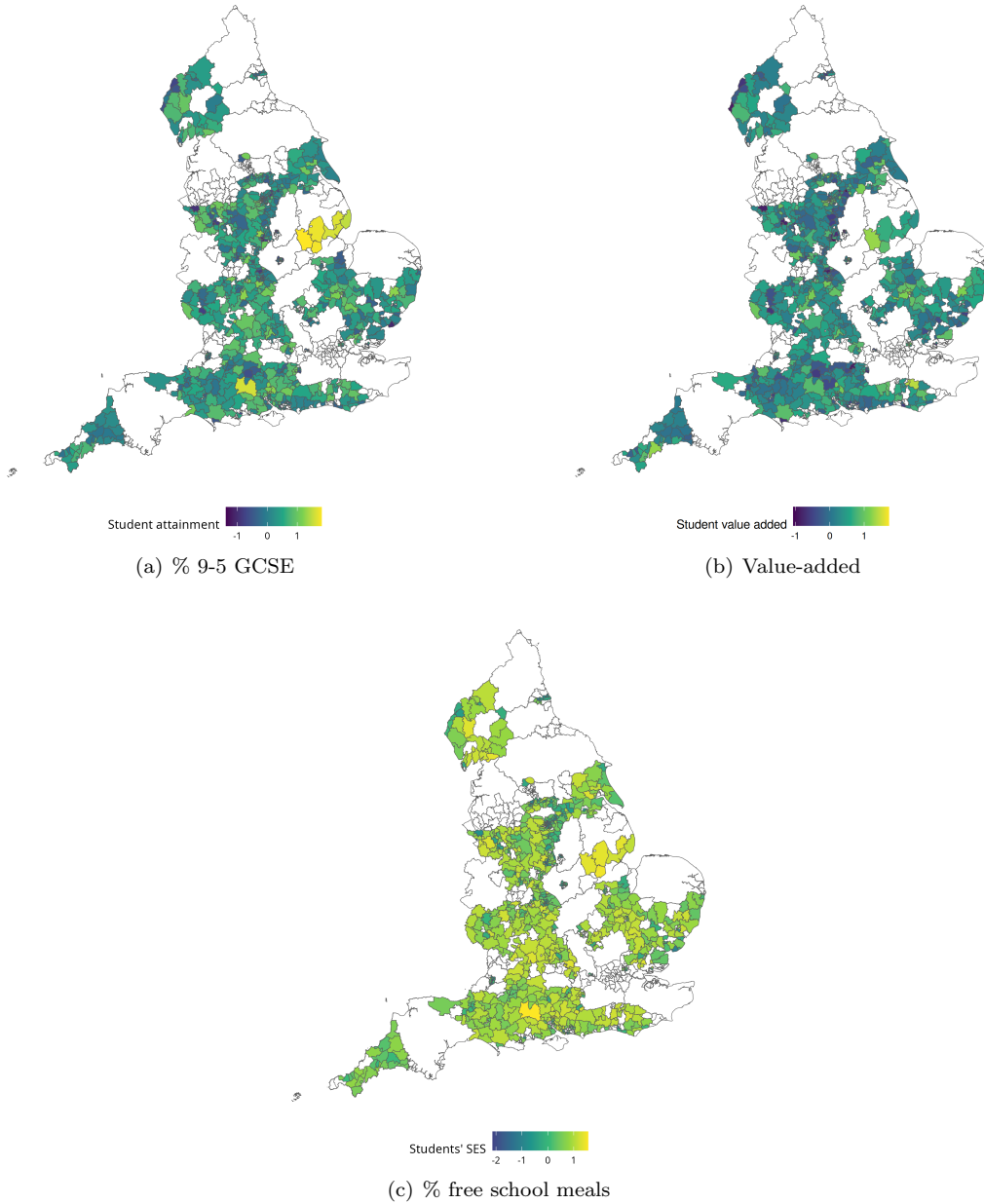
A.3 Additional figures

Figure B.1: Local Authorities (LAs) in England, by use of catchment areas



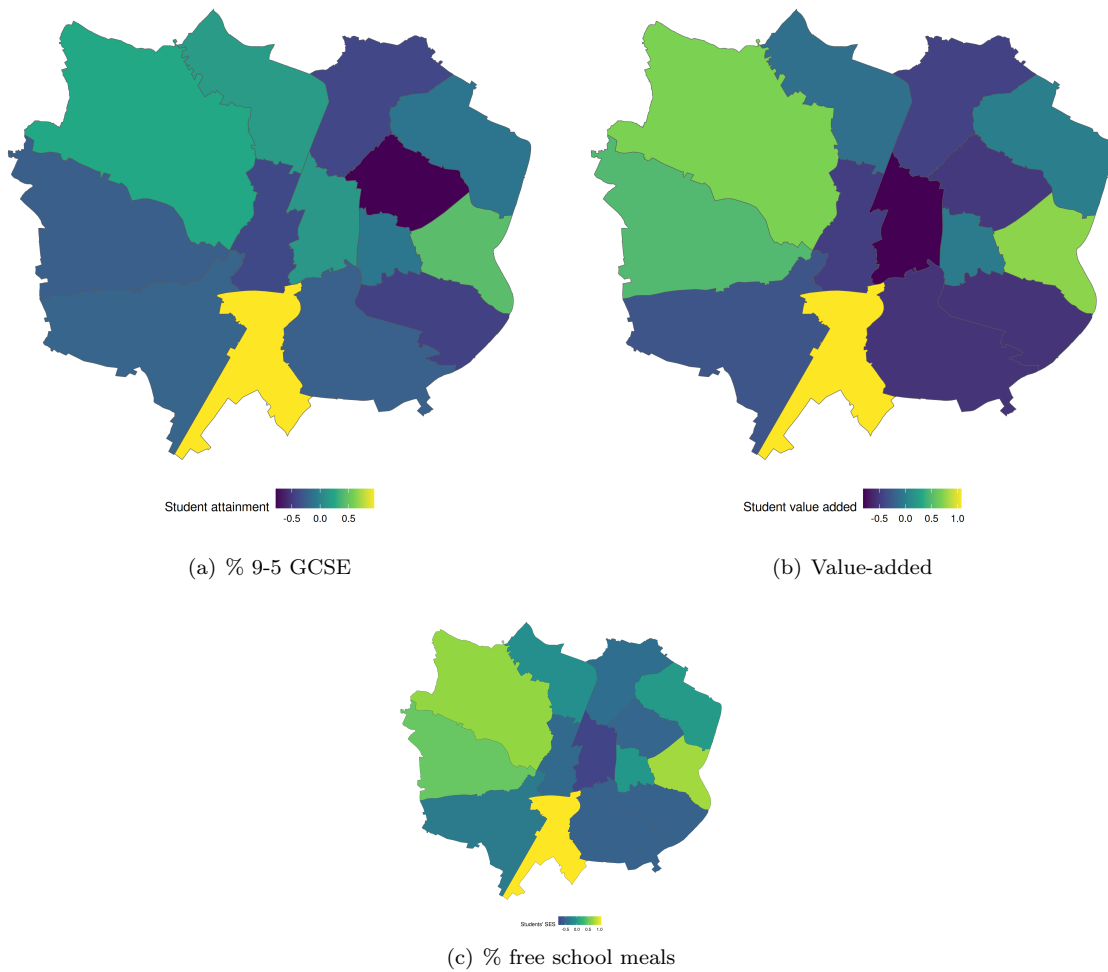
Source: catchment areas collected by the authors and school admissions criteria collected by Burgess et al. (2023).

Figure B.2: School 'quality' across catchment areas in England



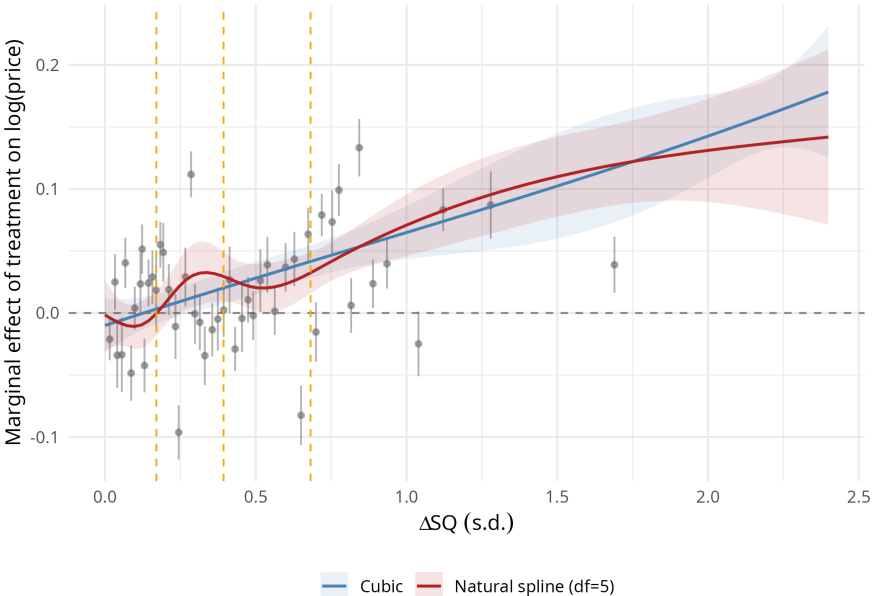
Source: DfE School Performance Tables and catchment areas collected by the authors.

Figure B.3: School 'quality' across catchment areas in one Local Authority



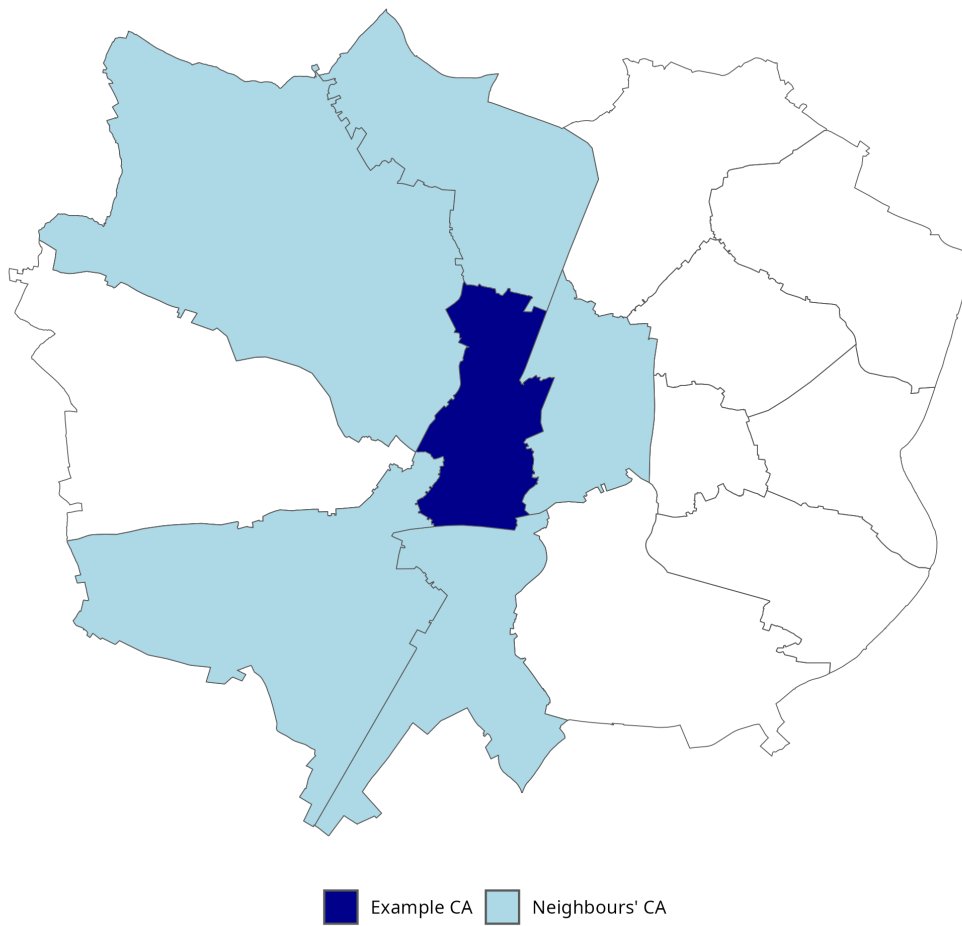
Source: DfE School Performance Tables and catchment areas collected by the authors.

Figure B.4: Marginal effect of treatment on log(price) as a function of the school quality gap (ΔSQ^{att})



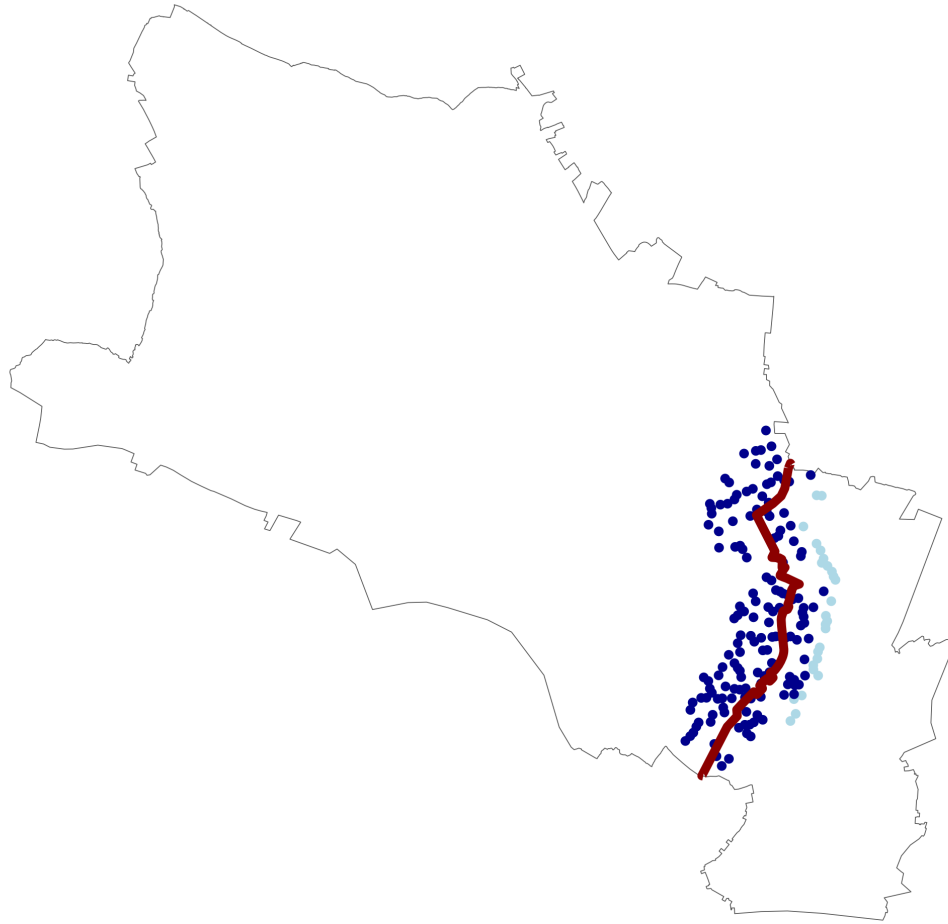
Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, and catchment areas collected by the authors. Notes: The figure shows the estimated marginal effect of being on the higher-quality side of the boundary, as a function of the continuous school quality difference (ΔSQ). Blue line: cubic polynomial interaction. Red line: natural spline (df=5) interaction. Shaded areas: 95% confidence intervals. Grey points: boundary-level treatment effects from 50 equal-frequency bins. Orange dashed lines: quartile cutoffs of ΔSQ^{att} . All specifications include boundary and year fixed effects, exogenous EPC covariates, and distance to the boundary.

Figure B.5: Example of construction of neighbouring catchment areas



Source: catchment areas collected by the authors.

Figure B.6: Example of construction of postcodes close to catchment area boundaries



Bandwidth • 320 m • Optimal CCT

Source: catchment areas collected by the authors and ONS Postcode Directory.

A.4 Residential sorting

This Section presents evidence on which households sort across catchment area boundaries. The outcome in each regression is a Census 2021 share at the output area level, regressed on the treatment indicator with boundary fixed effects, replicating equation 2 with Census characteristics as the dependent variable, rather than log prices. Values in brackets are control-side means.

Sorting is primarily according to socioeconomic status. The better-school side has a higher share of managerial/professional workers, degree holders and outright homeowners, and a lower share of routine workers, social renters and residents with no qualifications (not shown). The share of White residents is not significantly different for attainment boundaries (Table A.20), though it is for SES boundaries (Table A.21), which could reflect the correlation between FSM eligibility and ethnicity.

These sorting patterns support the interpretation that Census covariates are endogenous to school quality through residential sorting, justifying our preferred specification that excludes them (column 3 in the main tables), and our interpretation that the property price premium is the total effect of demand for school quality and endogenous characteristics of the very local neighbourhood.

A.4.1 Main sorting variables

Table A.20: Residential sorting: pupil attainment

	High managerial (1)	Unemployed (2)	White (3)	Private rent (4)	Mortgage (5)	Degree educated (6)	Dependent children, 16-18 (7)	No dependent children (8)	Stayers (9)
Panel A: Average									
r^{att}	0.008*** [0.139]	-0.001*** [0.023]	0.002 [0.876]	-0.002 [0.184]	-0.002 [0.303]	0.013*** [0.336]	0.001*** [0.028]	0.003 [0.725]	0.002 [0.894]
Panel B: ΔSQ quartiles									
$r^{att,1}$	-0.003 [0.146]	-0.000 [0.022]	0.002 [0.903]	0.001 [0.180]	-0.001 [0.303]	-0.005 [0.345]	0.000 [0.028]	-0.001 [0.731]	0.003 [0.894]
$r^{att,2}$	0.006* [0.139]	-0.000 [0.022]	-0.004 [0.873]	0.006 [0.178]	-0.007 [0.305]	0.011** [0.334]	0.001 [0.028]	0.004 [0.723]	-0.005 [0.894]
$r^{att,3}$	0.011*** [0.133]	-0.001** [0.025]	0.005 [0.866]	-0.003 [0.184]	-0.000 [0.308]	0.018*** [0.325]	0.002*** [0.028]	0.008* [0.714]	0.004 [0.897]
$r^{att,4}$	0.020*** [0.139]	-0.003*** [0.024]	0.005 [0.862]	-0.011** [0.194]	0.002 [0.295]	0.028*** [0.340]	0.003*** [0.027]	0.002 [0.732]	0.005* [0.891]
Border FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT
Observations	40015	40015	40015	40015	40015	40015	40015	40015	40015

Source: DfE School Performance Tables, Census 2021 at output area level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Each column is a separate regression with a Census 2021 share as outcome. Control-side means in brackets. Bandwidth: CCT optimal.

Table A.21: Residential sorting: pupil socioeconomic composition

	High managerial (1)	Unemployed (2)	White (3)	Private rent (4)	Mortgage (5)	Degree educated (6)	Dependent children, 16-18 (7)	No dependent children (8)	Stayers (9)
Panel A: Average									
r^{ses}	0.010*** [0.139]	-0.001*** [0.023]	0.005** [0.877]	-0.005* [0.184]	0.003 [0.303]	0.015*** [0.335]	0.001*** [0.028]	0.004* [0.726]	0.004*** [0.894]
Panel B: ΔSQ quartiles									
$r^{ses,1}$	0.002 [0.150]	0.000 [0.022]	-0.001 [0.877]	-0.002 [0.172]	0.003 [0.306]	0.004 [0.349]	0.001 [0.029]	-0.005 [0.721]	0.004 [0.895]
$r^{ses,2}$	0.008*** [0.146]	-0.001 [0.022]	-0.002 [0.893]	-0.004 [0.180]	0.000 [0.304]	0.012*** [0.345]	-0.001 [0.029]	0.007* [0.727]	0.002 [0.897]
$r^{ses,3}$	0.009*** [0.129]	-0.000 [0.024]	-0.003 [0.884]	-0.002 [0.178]	0.003 [0.303]	0.016*** [0.316]	0.003*** [0.027]	-0.000 [0.727]	0.002 [0.903]
$r^{ses,4}$	0.022*** [0.132]	-0.004*** [0.026]	0.026*** [0.857]	-0.012** [0.206]	0.007 [0.299]	0.029*** [0.334]	0.003*** [0.027]	0.014*** [0.728]	0.009*** [0.882]
Border FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT
Observations	39204	39204	39204	39204	39204	39204	39204	39204	39204

Source: DfE School Performance Tables, Census 2021 at output area level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Each column is a separate regression with a Census 2021 share as outcome. Control-side means in brackets. Bandwidth: CCT optimal.

Table A.22: Residential sorting: value-added

	High managerial (1)	Unemployed (2)	White (3)	Private rent (4)	Mortgage (5)	Degree educated (6)	Dependent children, 16-18 (7)	No dependent children (8)	Stayers (9)
Panel A: Average									
r^{vadd}	0.005*** [0.139]	-0.000 [0.023]	-0.006** [0.875]	-0.001 [0.185]	-0.004* [0.302]	0.008*** [0.337]	0.001*** [0.028]	-0.002 [0.725]	0.000 [0.893]
Panel B: Δ SQ quartiles									
$r^{vadd,1}$	0.002 [0.145]	0.000 [0.022]	-0.004 [0.888]	-0.001 [0.180]	0.001 [0.306]	0.003 [0.344]	0.001* [0.028]	-0.005 [0.723]	0.001 [0.891]
$r^{vadd,2}$	0.005 [0.143]	0.000 [0.023]	-0.003 [0.887]	-0.003 [0.187]	-0.004 [0.301]	0.004 [0.344]	0.001 [0.027]	-0.005 [0.730]	-0.000 [0.893]
$r^{vadd,3}$	0.007*** [0.140]	-0.001* [0.023]	-0.005 [0.881]	0.001 [0.175]	-0.001 [0.309]	0.012*** [0.332]	0.002** [0.028]	0.000 [0.724]	0.002 [0.897]
$r^{vadd,4}$	0.007** [0.129]	-0.000 [0.026]	-0.012* [0.844]	0.001 [0.200]	-0.014** [0.292]	0.012** [0.327]	0.001 [0.028]	0.002 [0.722]	-0.001 [0.892]
Border FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT	Optimal CCT
Observations	40107	40107	40107	40107	40107	40107	40107	40107	40107

Source: DfE School Performance Tables, Census 2021 at output area level (ONS), and catchment areas collected by the authors. Notes: Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Each column is a separate regression with a Census 2021 share as outcome. Control-side means in brackets. Bandwidth: CCT optimal.

B Online Appendix

Table OA.1: Balance test, socioeconomic composition (full sample)

Characteristic	Full sample (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)	Q1-Q2 (6)	Q1-Q4 (7)	Q2-Q3 (8)	Q3-Q4 (9)
Dist. to school (m)	272.69*** (2773.36)	-143.48 (3431.57)	473.45*** (3179.07)	255.29* (2590.27)	487.46*** (1987.53)	157.95 (1900.24)	983.33** (2099.55)	436.24* (3186.49)	490.78** (3945.8)
Floor area (sqm)	2.15*** (94.98)	-0.61 (99.48)	1.96 (97.71)	0.58 (93.05)	6.18*** (90.37)	1.88 (87.08)	15.26*** (98.11)	-0.21 (95.89)	2.97 (103.47)
Energy efficiency	-0.05 (61.93)	0.21 (61.93)	0.06 (61.66)	0.06 (61.75)	-0.48 (62.37)	-0.07 (62.27)	-1.97 (62.2)	0.44 (61.02)	-0.19 (62.2)
CO2 emissions	0.1** (4.47)	-0.04 (4.61)	0.09 (4.6)	0.04 (4.44)	0.28*** (4.27)	0.08 (4.15)	0.85** (4.6)	-0.04 (4.62)	0.15 (4.73)
N. rooms	0.06** (4.7)	0 (4.85)	0.04 (4.78)	0.02 (4.67)	0.16*** (4.54)	-0.01 (4.48)	0.46*** (4.77)	-0.05 (4.71)	0.09 (4.98)
Detached house	0.02*** (0.27)	0.01 (0.31)	0.03* (0.3)	0.01 (0.26)	0.05*** (0.21)	0 (0.19)	0.19*** (0.26)	0.01 (0.31)	0.02 (0.35)
Flat	0.01 (0.15)	-0.01 (0.13)	0.02 (0.14)	0.01 (0.13)	0.01 (0.18)	0.02 (0.15)	-0.02 (0.18)	0.04 (0.13)	0 (0.12)
Semi-detached house	-0.01 (0.29)	-0.01 (0.29)	-0.02 (0.29)	-0.01 (0.3)	-0.01 (0.29)	-0.01 (0.33)	-0.05 (0.28)	-0.04 (0.29)	0.01 (0.28)
Terraced	-0.02** (0.29)	0.01 (0.27)	-0.03** (0.28)	0 (0.31)	-0.05*** (0.31)	-0.01 (0.33)	-0.12*** (0.28)	-0.02 (0.27)	-0.03* (0.25)
Energy rating: A-C	0 (0.31)	0 (0.32)	0.02 (0.32)	0 (0.3)	-0.01 (0.31)	-0.01 (0.3)	-0.07 (0.31)	0.02 (0.3)	0 (0.34)
Energy rating: D-G	0 (0.69)	0 (0.68)	-0.02 (0.68)	0 (0.7)	0.01 (0.69)	0.01 (0.7)	0.07 (0.69)	-0.02 (0.7)	0 (0.66)
Construction: 1900-1949	-0.02** (0.23)	-0.02** (0.18)	-0.02 (0.2)	-0.02 (0.24)	-0.02 (0.3)	-0.02 (0.32)	-0.04 (0.21)	-0.02 (0.18)	0 (0.14)
Construction: 1950-1982	0.01 (0.35)	0.02 (0.36)	0.01 (0.35)	0.02 (0.36)	0.01 (0.32)	0.01 (0.32)	0.02 (0.35)	-0.01 (0.38)	0.03 (0.35)
Construction: 1983-2007	0 (0.27)	0.01 (0.31)	0 (0.29)	0 (0.26)	0 (0.24)	0 (0.24)	0.03 (0.27)	0.03 (0.28)	-0.01 (0.35)

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level, net income at MSOA level, and catchment areas collected by the authors. Notes: The table shows estimated differences in property characteristics, with the boundary average in parentheses. Differences are estimated via OLS, regressing each characteristic on a treatment indicator and boundary and year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the boundary level.

Table OA.2: Balance test, value-added (full sample)

Characteristic	Full sample (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)	Q1-Q2 (6)	Q1-Q4 (7)	Q2-Q3 (8)	Q3-Q4 (9)
Dist. to school (m)	96.51 (2791.46)	140.23 (3168.28)	288.21* (2946.41)	-43.42 (2604.39)	-28.02 (2433.86)	-156.59 (2018.65)	88.11 (2190.43)	585.46* (3434.46)	-90.33 (3234.28)
Floor area (sqm)	1.18* (95.1)	-1.28 (97.48)	2.47* (95.5)	1.16 (95.54)	1.97* (91.68)	1.15 (90.32)	4.41* (91.94)	3.92* (98.28)	0.29 (100.98)
Energy efficiency	0.05 (61.95)	-0.1 (61.93)	-0.07 (62.14)	0.07 (61.69)	0.33 (62.03)	0.42 (62.4)	1.03 (61.83)	-0.59 (61.62)	0.08 (61.48)
CO2 emissions	0.05 (4.47)	0.01 (4.56)	0.12* (4.44)	0.04 (4.53)	0.03 (4.36)	0.01 (4.29)	0 (4.4)	0.28** (4.64)	-0.02 (4.73)
N. rooms	0.03 (4.71)	-0.02 (4.78)	0.08* (4.69)	0.03 (4.74)	0.03 (4.61)	0.03 (4.58)	0.13 (4.63)	0.08 (4.85)	0.03 (4.87)
Detached house	0.01 (0.27)	-0.01 (0.3)	0.01 (0.27)	0.02 (0.28)	0.02 (0.25)	0.02 (0.22)	0.04 (0.27)	0.02 (0.3)	0.02 (0.3)
Flat	0.01 (0.15)	0.01 (0.13)	0 (0.16)	0 (0.13)	0.03** (0.16)	0 (0.15)	0.02*** (0.14)	0.04** (0.11)	-0.01 (0.16)
Semi-detached house	-0.01 (0.29)	0 (0.29)	0 (0.28)	-0.01 (0.29)	-0.02 (0.3)	-0.02 (0.32)	-0.05 (0.32)	-0.02 (0.31)	-0.01 (0.27)
Terraced	-0.01* (0.29)	0 (0.28)	-0.01 (0.29)	-0.01 (0.3)	-0.03* (0.29)	0 (0.31)	-0.01 (0.27)	-0.04* (0.28)	0.01 (0.26)
Energy rating: A-C	0 (0.31)	0 (0.32)	0 (0.32)	0 (0.3)	0.01 (0.31)	0.01 (0.31)	0.05* (0.3)	0 (0.3)	-0.01 (0.3)
Energy rating: D-G	0 (0.69)	0 (0.68)	0 (0.68)	0 (0.7)	-0.01 (0.69)	-0.01 (0.69)	-0.05* (0.7)	0 (0.7)	0.01 (0.7)
Construction: 1900-1949	-0.01* (0.23)	0.01 (0.19)	-0.02* (0.23)	-0.01 (0.24)	-0.02 (0.26)	-0.01 (0.27)	0.01 (0.24)	-0.01 (0.21)	-0.01 (0.22)
Construction: 1950-1982	0.01 (0.35)	0.01 (0.35)	0.01 (0.35)	0.02 (0.35)	0.01 (0.32)	0.03 (0.36)	-0.06 (0.35)	-0.03 (0.37)	0.01 (0.33)
Construction: 1983-2007	0 (0.28)	-0.02 (0.3)	0.01 (0.27)	-0.01 (0.26)	0.01 (0.27)	-0.02 (0.24)	0.03 (0.28)	0.01 (0.27)	0.01 (0.28)

Source: Price paid and EPC from the EPC-Land Registry linked dataset (Chi et al., 2025), DfE School Performance Tables, Census 2021 at output area level, net income at MSOA level, and catchment areas collected by the authors. Notes: The table shows estimated differences in property characteristics, with the boundary average in parentheses. Differences are estimated via OLS, regressing each characteristic on a treatment indicator and boundary and year fixed effects. Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the boundary level.