The Ofsted effect: a hedonic regression study examining the impact of school ratings on house prices across Northwest England

Elle Brown

Professional Economist BSc and Apprenticeship Level 6

School of Economics

University of Kent, July 2024

Abstract

This study examines the relationship between Ofsted ratings and property prices across Northwest England, between 2016 and 2019. Ratings are often perceived as an indicator of educational 'quality', which many parents consider when buying a property. Pre-requisites including proximity to the school, form part of pupil admission criteria, so properties in this study are matched to the closest school using longitude and latitude. A hedonic price model is employed, using OLS methodology. Findings indicate a statistically significant, positive correlation exists between prices and association with a Key-Stage Four (KS4) school rated 'outstanding' or 'good', and negative correlation between prices and association with a KS4-school rated 'inadequate'. These results highlight the need for policymakers to assess whether distributional impacts exist that particularly affect the proportion of individuals from low socio-economic backgrounds attending 'outstanding' or 'good' schools, if they cannot afford to live near these schools.

Acknowledgements

I would like to express my deepest gratitude to everyone who helped to support me through this process, including the staff at the University of Kent Business School and my colleagues in DEFRA. This endeavour would not have been possible without the Government Economic Service, who funded my degree apprenticeship.

Additionally, I could not have undertaken this journey without my parents Jackie and Stephen, my sister Faith and my rabbit Lionel. Their motivation, support and encouragement has been steadfast and unwavering throughout the course of my studies. I am incredibly grateful to them.

1. Introduction and rationale

This paper examines the relationship between Ofsted ratings of state schools and property prices in the Northwest of England. Since Ofsted's creation in 1992, schools across the country have faced regular inspection, to ensure the 'quality' of education provided meets expected national standards. 'Quality' education provides individuals the human capital to access long-term employment opportunities and improve living standards. A perceived measure of 'quality' for many parents are Ofsted ratings, which alongside metrics including GCSE-results, inform the decision to buy a property close to a school with the specific characteristics aligning to their preferences, within their budget constraint. Other property-specific characteristics reflected within the 'consumption-bundle' include physical structure, neighbourhood demographics, and local service proximity.

This research extends beyond previous studies, which typically focus on examination-performance or property attributes, by modelling the impact of ratings on prices. Statistically significant results could be used by policymakers to inform investment in '*inadequate'* or '*requires improvement'* schools, to ensure equitable educational outcomes are achieved irrespective of property proximity. The study offers new insight by utilising the latest pre-pandemic data. The pandemic represented a structural break in the collection of Ofsted data, as inspections were immediately stopped, and schools moved to online teaching, so is not suitable for analysis.

To identify whether a statistical relationship exists, Ordinary Least Squares (OLS) methodology has been applied to Northwest property transactions between 1st January 2016 and 31st December 2019. Each property was assigned to the closest school, using longitude and latitude, and data pertaining to property-specific characteristics have been matched to each property using its LSOA-code. A 60-day lag is assumed to exist between publication of the latest inspection results. Transactions below this threshold use previous inspection results to inform whether the school matched to the property meets their educational preferences.

2. Economic theory

Consumers have heterogenous preferences: reflecting varying levels of utility derived from purchasing properties with different characteristics. Each house comprises of a specific bundle of “property characteristics” (z) and quantity of “other goods” (x), determined by “household characteristics” (s)[1]. These factors combined define the utility function:

U(z,x:s) (a)

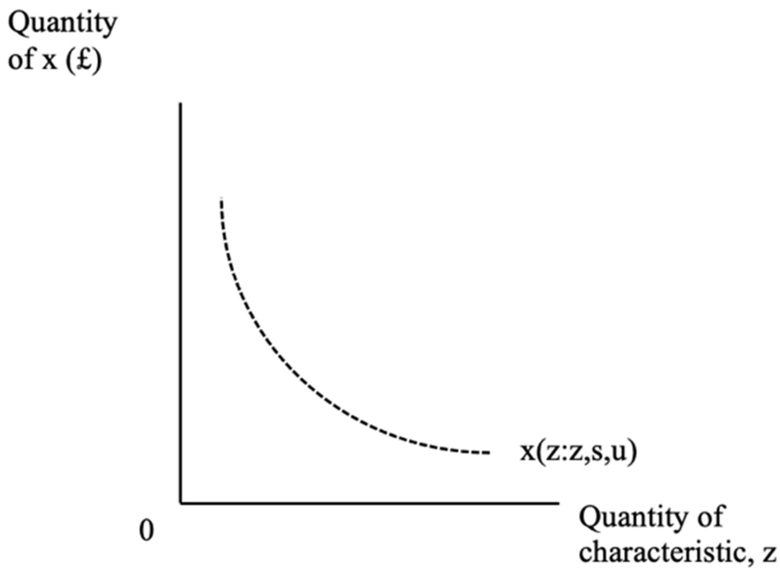
Demand theory states rational consumers aim to maximise utility and minimise opportunity costs. Under the assumption of rationality and perfect information, consumers have reflexive, monotonic, complete, and transitive preferences, which are applicable to the housing market. Consumers rank preferences based on utility derived from consuming a specific bundle of ‘goods’ and ‘characteristics’. Day (2001) includes

Figure 1 in their study, which shows an indifference curve reflective of different ‘consumption-bundles’ combinations, equivalent to x(z:zs,s,u).

Figure 1, therefore, reflects potential quantity of consuming attribute (z) along the horizontal-axis and quantity of the ‘composite good’ along the vertical-axis (the monetary value of housing). Consumption utility is constant along the curve, meaning buyers prefer all curve points equally. *De facto*, finite resources including time and income introduce budgetary constraints to consumption.

Figure 1 Indifference curve

[1] Day, B.H. (2001). ‘*The theory of hedonic markets: obtaining welfare measures for changes in environmental quality using hedonic market data’*. London, UK: Centre for Social and Economic Research on the Global Environment. Available at: https://www.researchgate.net/publication/39065598_The_theory_of_hedonic_markets_Obtaining_welfare_measures_for_changes_in_environmental_quality_using_hedonic_market_data



Rosen (1974)[2] proposed household indifference curves can be inverted to understand how specific locational, neighbourhood and structural characteristics interact to determine property price. This is represented by the 'bid function':

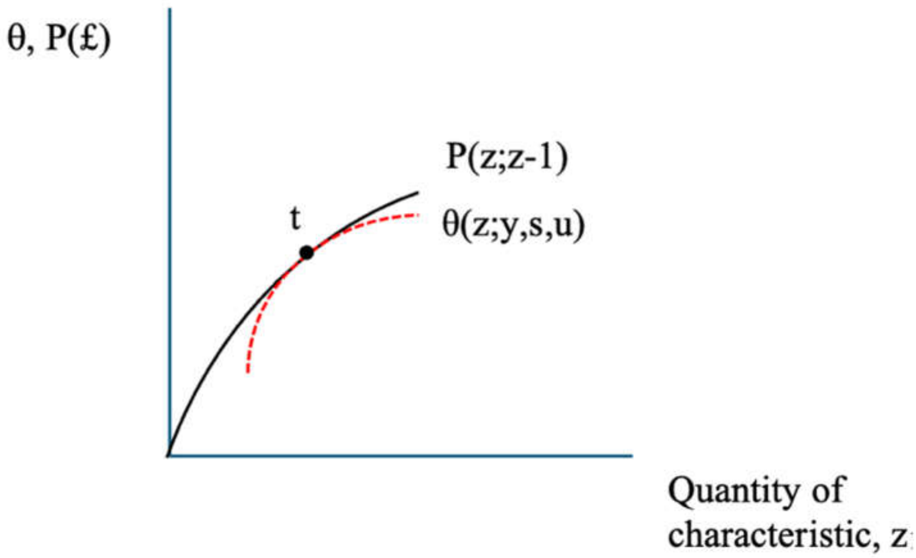
$$\theta(z;y,s,u) \qquad \text{(b)}$$

The bid function (Figure 2), similarly derived from Day (2001), highlights a buyer's maximum 'willingness-to-pay' for a property possessing specified characteristics (z), on the conditions of income (y), household characteristics (s) and utility derived from the property (u). Combinations along the bid 'curve' reflect different preference combinations. Like the constraint imposed upon the indifference curve by budget constraints, the bid curve is constrained by the 'hedonic price function', or market prices:

$$P(z;z-1). \qquad \text{(c)}$$

Figure 2 Hedonic Price Function and the Bid Curve

[2] Rosen (1974). *Hedonic prices and implicit markets: product differentiation in pure competition.* Journal of Political Economy, 82(1), pp.34-55. doi:10.1086/260169.



Tangency (t) of the hedonic and bid functions indicates the market equilibrium property price: derived from consumer willingness to pay for (z) at a specific price.

Rosen's contribution to hedonic theory is underpinned by several assumptions, including perfect competition in the housing market and the 'product' of housing is homogenous. Using large volumes of standardised transaction data provides assurance this can be met, as it indicates existence of significant numbers of buyers and sellers within the market. Each household is assumed to be a price-taker and there is full market clearing at the equilibrium between demand and supply. Consumers are assumed to have perfect information on property characteristics. Information asymmetries on housing characteristics are likely to persist in the 21st Century but is less problematic than encountered in older studies, due to widespread popularity of online-property websites, providing evidence on characteristics including room size and council tax. It is assumed characteristics can be quantified and monetised to extract willingness-to-pay for a one-unit increase in a specific attribute, *ceteris paribus*.

3. Literature Review

Research on the relationship between Ofsted ratings and property prices is limited. Hussain (2023)[3] employed a difference-in-difference approach to assess whether price differentials exist between properties associated with Key-Stage 2 schools that underwent a rating change between inspections compared to schools whose rating was maintained. Hussain found

[3] Hussain, I. (2023). *'Housing Market and School Choice Response to School Quality Information Shocks'.* Journal of Urban Economics', 138, 103606. doi:10.1016/j.jue.2023.103606

evidence a one-unit rating improvement resulted in a 0.46% increase in prices ($p<0.05$), accounting for property and school controls.

Buyers are likely to consider other educational indicators, including examination-results and school demographics, to make school 'quality'[4] inferences. In hedonic literature, examination-results are the most predominant measurement of 'quality'. Exploring the relationship between GCSE examination-results and house prices in seven major English cities, between 2001-2007, Glen and Nellis (2010)[5] found every 10% improvement in students achieving 5A*-C GCSEs, commanded a 1-3% increase in prices. Similar conclusions were attained by Orford (2018)[6], who found houses located in the catchment-area of higher-than-average pass-rates were £2,700 and £13,500 more expensive. Similar conclusions on 'quality' and prices are consistently found across international literature (Figlio and Lucas, 2004[7]). Challenges exists making inferences using international findings because heterogeneity exists between standardised testing methods across countries and societal preferences on the importance of 'quality' in consumption decisions.

School demographics may also be considered as a contributor to 'quality', although Hussain's (2023) failed to establish a significant relationship between prices and ratings of schools with significant proportions of free-school-meal eligible students (used as a proxy for socio-economic background). The paper also found households with English as an additional language do not respond in the short-term to rating changes.

Hedonic studies highlight the importance of accounting for neighbourhood, structural and locational characteristics in determining prices. Evidence exists to suggest neighbourhood characteristics, including inhabitant education-level achieved, crime and income, impact

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[4] Clapp, J.M., et al. (2008) *'Which school attributes matter? the influence of school district performance and demographic composition on property values'*, Journal of Urban Economics, 63(2), pp. 451–466. doi:10.1016/j.jue.2007.03.004.
[5] Glen, J. and Nellis, J. (2010) *'"The price you pay": The impact of state-funded secondary school performance on residential property values in England'*, Panoeconomicus, 57(4), pp. 405–428. doi:10.2298/pan1004405g.
[6] Orford, S. (2018) *'The capitalisation of school choice into property prices: A case study of grammar and all ability state schools in Buckinghamshire, UK',* Geoforum, 97, pp. 231–241. doi:10.1016/j.geoforum.2018.09.009.
[7] Figlio, D.N. and Lucas, M.E. (2004) *'What's in a grade? school report cards and the Housing Market'*, American Economic Review, 94(3), pp. 591–604. doi:10.1257/0002828041464489.

prices. Gibbons et al. (2012)[8] highlighted positive correlation between areas with higher prices, income, and educational performance. Income data is not readily available at an LSOA-aggregated level. As a solution, Turnbull et al. 2018[9], suggests socio-economic classification and education-level achieved can be used to approximate income.

The role of structural attributes is routinely assessed across existing research, with particular emphasis placed on bedroom quantity. The *a priori* expectation for rational consumers with monotonic preferences would be to purchase a property with the greatest number of bedrooms, providing it resides within budgetary constraint. Fletcher et al. (2000)[10] found evidence from data on 19,951 sold properties in the Midlands on property type to indicate the existence of higher consumer willingness to pay a 'premium' to purchase a 'detached' property. Fletcher builds upon these findings in later research (2004)[11], where authors gave the premium as £17,002, in contrast to a mid-terrace property of £6,262 in a sample of 1,600 Midlands properties. Tenure longevity may also influence willingness to pay and was included in Hussain (2023).

Proximity to local services introduces time-cost savings: increasing willingness-to-pay a higher price if individuals derive significant utility from ease of access to healthcare, employment, and supermarkets. Due to heterogenous preferences across regions[12], the literature often reports conflicting results in respect to statistical significance and the direction of the relationship between characteristics and prices. Chin and Chau (2003)[13] argue some consumers value hospital proximity to mitigate emergency consequences, whereas others would consider noise and traffic to be a dis-amenity. Existing studies typically have not

[8] Gibbons, S., et al. (2013) *'Valuing school quality using boundary discontinuities'*, Journal of Urban Economics, 75, pp. 15–28. doi:10.1016/j.jue.2012.11.001.
[9] Zahirovic-Herbert, V. and Turnbull, G.K. (2009) *'Public School Reform, expectations, and capitalization: What signals quality to homebuyers?'*, Southern Economic Journal, 75(4), pp. 1094–1113. doi:10.1002/j.2325-8012.2009.tb00948.x.
[10] Fletcher, M., et al. (2000) *'The modelling of housing submarkets'*, Journal of Property Investment & Finance, 18(4), pp. 473–487. doi:10.1108/14635780010345436.
[11] Fletcher, M., et. al. (2004*) 'Comparing hedonic models for estimating and forecasting House prices'*, Property Management, 22(3), pp. 189–200. doi:10.1108/02637470410544986.
[12] Aziz, A., et al. (2020) *'The impact of neighborhood services on land values: An estimation through the hedonic pricing model'*, GeoJournal, 86(4), pp. 1915–1925. doi:10.1007/s10708-019-10127-w.
[13]Chin, T. L. and Chau, K. W. (2003). '*A critical review of literature on the hedonic price Model'*, International Journal for Housing and Its Applications 27 (2), pp. 145-165.

accounted for proximity to general practitioners (GPs), although ongoing NHS pressures indicate potential inclusion suitability. Supermarket proximity is not widely explored, although one study[14] found it to have a statistically significant ($p<0.05$), positive impact on prices: a one-unit increase in nearby supermarkets led to a 0.039-unit price increase. Proximity to employment opportunities may increase utility when individuals value in-person employment. Variation exists in its reported impact on prices on across international literature, due to lack of perfect information on societal attitudes towards work-life balance and country-specific economic conditions (Turnbull et al. 2018).

The impact of interest rates, affecting mortgage and loan rates, is less widely explored within hedonic studies, but may affect property-market dynamics from a supply and demand perspective. This study encompasses a period of historically 'low' interest rates, improving buyer affordability. Rates, therefore, impact the hedonic function, because it affects consumer demand behaviour by altering the ability to purchase a property representative of specific characteristics. A significant caveat is the period assessed was subject to relatively marginal rate changes, meaning statistical significance may be harder to detect.

4. Methodology

a. Hypothesis

The null (H0) and alternative (H1) hypothesis are as follows:

- H0: The rating of the closest school associated with a property does not have a statistically significant effect on its price.
- H1: The rating of the closest school associated with a property has a statistically significant effect on its price.

[14] Heyman, A.V. and Sommervoll, D.E. (2019) *'House prices and relative location'*, Cities, 95, p. 102373. doi:10.1016/j.cities.2019.06.004.

b. Empirical strategy

Hedonic literature is inconclusive as to the most appropriate technique for estimating property prices. This section provides a comprehensive overview of common approaches adopted and their strengths and limitations.

A methodology consistently employed across hedonic studies is OLS: reliant on the assumption of linearity between property prices and characteristics. To obtain unbiased estimates exhibiting minimum variance relative to other estimators, according to the Gauss-Markov theorem, estimates must not be subject to exogeneity, heteroskedasticity, multicollinearity and error term dependence. OLS has several advantages over alternative methodologies, including ease of coefficient interpretation to identify how specific characteristics determine overall price, according to Taylor (2008)[15]. OLS models typically have adaptable functional forms. Nellis and Glen (2011)[16] employed OLS and undertook specification sensitivity analysis to explore the relationship between prices in two U.K. cities and educational 'quality' (defined by percentage of students receiving 5 A*-C GCSEs). This provided additional validation to their main model findings: evidence of a statistically significant relationship ($p<0.05$). The strengths highlighted provide justification of its widespread utilisation across hedonic studies. OLS is subject to several limitations, which often arise due to difficulties acquiring quality, publicly available data. Large datasets, in contrast, have a higher likelihood of multicollinearity[17] as data exhibits strong heterogeneity and often, heteroskedasticity - violating the Gauss-Markov Theorem. Misspecification is also common, due to challenges determining relevance of certain structural, neighbourhood or locational variables. To prevent incorrect inference of biased and inconsistent estimates arising due to misspecification, analysis across sub-samples within the housing market should be undertaken (Chin and Chau, 2003). Several studies[18], including Zahirovic-Herbert and

[15] Taylor, L.O. (2008) *'Theoretical Foundations and empirical developments in hedonic modelling',* Hedonic Methods in Housing Markets, pp. 15–37. doi:10.1007/978-0-387-76815-1_2.
[16]Nellis, J. and Glen, J. (2011) '*The impact of published school performance results on Residential Property Prices: A Comparative Study of two UK cities'*, Global Business and Economics Review, 13(2), p. 168. doi:10.1504/gber.2011.040730.
[17] Day, B., et al. (2003). *'What price peace? A comprehensive approach to the specification and estimation of hedonic housing price models'.* Working Paper EDM, No. 03-08, University of East Anglia, The Centre for Social and Economic Research on the Global Environment, Norwich. Available at: https://www.econstor.eu/bitstream/10419/80269/1/36778145X.pdf.
[18] Fack, G. and Grenet, J. (2010a) '*When do better schools raise housing prices? evidence from Paris public and private schools'*, Journal of Public Economics, 94(1–2), pp. 59–77. doi:10.1016/j.jpubeco.2009.10.009.

Turnbull (2009) explore the relationship between property prices and school quality have utilised this approach, by conducting research at regional or city-level, because it minimises spatial variation and heterogeneity.

Difference-in-difference technique is another approach popular in hedonic studies. It traditionally compares a group subject to ‘treatment’ within a population, and a ‘control’ group not subject, to capture the ‘average treatment effect’ of an intervention. Hussain (2023) utilised this approach to capture the price effect revealed between properties associated with a school that underwent an Ofsted rating change and schools experiencing no change. The paper identified a significant limitation of this methodological approach: strong reliance on assumptions, including parallel trends[19], which *de facto,* are hard to satisfy. Violation of difference-in-difference assumptions results in multicollinearity, although as noted in the previous section, is not an exclusive threat to difference-in-difference research.

‘Instrumental variables’ can be utilised in hedonic studies but are often subject to challenges concerning incorrect instrument identification, resulting in inefficient and biased estimates and without guarantee that results are unaffected by omitted-variable bias. Fixed-Effects modelling may also be used to control for unobserved heterogeneity across location, time, or groups, but is not appropriate for this study, due to employment of cross-sectional data rather than panel.

The final OLS log-linear model specification is:

$$\text{Ln(price)} = \alpha + \beta_1(S) + \beta_2(E) + \beta_3(N) + \beta_4(L) + \beta_5(C) + \beta_6(B) + \epsilon \qquad (6)$$

This indicates price is determined by covariates of structural (S) educational (E), neighbourhood (N), locational (L) characteristics, as well as local crime rates (C) and the bank rate (B). The iterative model process is documented in the *Results* section.

[19] In the absence of an Ofsted rating changes, both ‘control’ and ‘treated’ properties would experience a similar price ‘trend’.

c. Limitations

This study should be seen in the context of its limitations. Public LSOA-specific data on crime and environment is unavailable, potentially leading to model under-specification. This is compounded by rental data exclusion (Hussain, 2023), as this study focusses solely on price-paid data. In contrast, several included datasets provide detailed insight on property and neighbourhood-specific attributes, which may contribute to over-specification and difficulties obtaining accurate, homoscedastic results. Census data is taken from 2011 and 2021 publications, interpolated, and matched to the transaction year, creating an estimated ‘picture’ of the neighbourhood at the purchase point. Caution should be taken as this approach fails to capture specific year-on-year changes. Interpolation, however, remains the most suitable solution to lack of annual LSOA-specific characteristic data. In other instances, variables have been transformed into percentage-of-LSOA for each specific characteristic, including ‘bedrooms’, to standardise inhabitant numbers between LSOAs, meaning data will be different than if extracted directly from the Census.

The hedonic literature is inconclusive on the most appropriate methodology to employ (Taylor, 2008). The approach taken in this study (OLS) faces several limitations, as highlighted in the *Empirical Strategy* section. To mitigate for this and improve inference, robustness and falsification tests have been undertaken.

Another limitation concerns market segmentation: proximity of the closest school to each property. This assumption fails to acknowledge other implicit boundaries, including catchment areas, which may be an important determinant of school admission. Future studies could assess impacts of defined catchment areas relative to undefined areas across the samples used in this study.

5. Data

a. Property and structural variables (S)

Table 1 shows summary statistics for *price* and *lnprice* of the 604,604 properties sold in Northwest England across the full period.

Table 1 Summary Statistics: price and lnprice

Variable	Observations	Mean	Std. dev.	Min	Max	Kurtosis	Skewness
price	604,604	257,000	1,800,000	1	3.00e+08	12,100	86.2
lnprice	604,604	11.9	.790	0	19.5	15.8	-.571

Nota: all figures in this study are reported to 3s.f.

Price shows evidence of high, positive, right-skewness, indicating a minority of very expensive properties are influencing the mean. To use OLS, the assumption of distribution normality must hold. It is therefore advised to use the natural log of *price (lnprice)* in hedonic studies. Although evidence of skewness persists, the effect is much smaller (-.571) meaning the distribution is more symmetric. There is evidence of kurtosis in both variables as 12,100 and 15.8 show high, positive kurtosis indicating outlier presence in the distribution tails. Price outliers have not been removed from this analysis because observations have been recorded with HM Land Registry: a reputable source with credible data collection methodology. Removal could introduce bias if accurate, extreme observations are excluded.

Lnprice is used as the dependent variable: derived from price estimates in HM Land Registry's Price Paid dataset and transformed to mitigate right-skewness. The dataset includes cross-sectional data on all properties sold and registered in England since 1995. The collection provides data several structural characteristics including property price, type, price, new-build status, address, and transaction date. Specific data including property square-footage is unavailable. The sample includes property transactions across Cumbria, Lancashire, Merseyside, Greater Manchester, and Cheshire, between 1 January 2016 and 31st December 2019. Dummy variables have been created for structural characteristics of the property including for whether it is new, detached, semi-detached, terraced, flat or leasehold. Note only postcodes where a minimum of one transaction occurred in the period are analysed and transactions are not weighted across postcodes.

b. Education variables (E)

School-specific data draws upon two reputable sources: Ofsted and DfE, which are appended to each other using each school's 'unique reference number'. These data sources provide nuanced picture of each school's profile, accounting for the latest Ofsted ratings at the period of property transaction, demographic composition, and examination results of each school. Each property is assigned to the nearest school by kilometre distance using the *geonear* Stata command, which calculates distance based on longitude latitude of each postcode. This data is publicly available online: promoting transparency, accountability and lowers risk of information asymmetries in property buying. As an independent institution undertaking rating inspection without bias, inclusion of Ofsted ratings within this analysis introduces several benefits, including the current system providing sufficient information to plausibly understand ratings differentials between schools (Hussain, 2015)[20]. Assuming consumers are aware and responsive to rating changes, a school's rating provides sufficient information for them to make this distinguishment, feeding into the decision to consume certain characteristics bundle in purchasing a property. Some consumers may be less immediately responsive to ratings changes, which Hussain (2023) suggests can be mitigated for by applying a 60-day lag between the latest inspection result publication and property transaction. This means if less than 60-days exist between these dates, consumers are assumed to use the previous rating result in their decision-making process. This assumption is applied here. DfE data is taken from the previous full academic year, as data is published annually, and current academic year data will not necessarily be available on the transaction date. For example, a house sold in March 2016 will use previous academic year data (2015/16) to inform their understanding of a school's profile.

The following types of state-funded schools without entry requirements are included in analysis: academies (ACC and CY); foundation (FD); free (F); voluntary-aided (AC); and voluntary-controlled (VC). After an inspection, schools are designated '*outstanding'* (1); '*good'* (2*); 'requires improvement'* (3) or '*inadequate'* (4). Table 2 shows summary statistics by school type and Ofsted rating:

Table 2 Summary statistics: school type and rating

School type	**N**	**Mean**	**SD**	**Min**	**Max**
AC	125,372	2.23	.828	1	4
ACC	245,185	1.62	.646	1	4
CY	153,366	2.15	.629	1	4
F	11,694	2.38	.619	2	4
FD	60,364	2.47	.678	1	3
VC	8,623	1	0	1	1
Total	**604,604**	**1.97**	**.766**	**1**	**4**

[20] Hussain,I. (2015). *'Subjective Performance Evaluation in the Public Sector: Evidence from School Inspections*,' Journal of Human Resources, University of Wisconsin Press, vol. 50(1), pages 189-221.

The most common school associated with properties in this study are academies, although within this, schools designated 'ACC' are more often designated 'better' ratings (either '*good'* or '*outstanding'*) than 'CY', as indicated by the lower mean (1.62 compared to 2.15). No voluntary-controlled or foundation schools were deemed '*inadequate'* (max=1 or 3), whilst no 'free' schools were deemed '*outstanding'* (min=2). The range covers all rating types, which should allow for a nuanced exploration of whether different ratings have a statistically significant effect on prices.

c. Neighbourhood (N) and locational (L) variables

Census data is used to understand the effect of neighbourhood and locational attributes on prices. Data is collected every ten years, so interpolation is used to derive annual estimates of each variable in each LSOA. This covers approximately 400-1200 households: representative of homogenous and consistently sized sub-markets. Public Transport Accessibility Indicators are derived from Census data.

The full list of variables assessed, including their description and source, are listed in

Table 3:

Table 3 Variables included in analysis.

Variable name	**Description**	**Source**
lnprice	Natural log of transaction price.	HM Land Registry[21]
new	Dummy variables =1 if equal to variable in 'variable name' column; =0 otherwise.	
detached		
semidetached		
terraced		
flat		
leasehold		
outstanding		Ofsted[22]
good		

[21] HM Land Registry (2024). *'Price Paid Data'*. [online] GOV.UK. Available at: https://www.gov.uk/government/statistical-data-sets/price-paid-data-downloads.
[22] Ofsted (2019). *'State-funded school inspections and outcomes: management information'*. [online] Available at: https://www.gov.uk/government/statistical-data-sets/monthly-management-information-ofsteds-school-inspections-outcomes.

inadequate		
averageattainment8score	Average Attainment-8 score per pupil.	DfE[23]
ks4english_additionallang	Percentage of pupils: • with English as an additional language. • of disadvantaged pupils. • achieving grades 9-4 in GCSE English and Maths.	
ks4disadvantagedpercent		
freeschoolmealpercent		
standard9_4gcsepercent		
sixthformdummy	Dummy=1 if school has a sixth form; =0 otherwise.	
approxsocialgradeDEpercent	Percentage of households in LSOA with: • Social grade: AB (highest), C1, DE (lowest). • Highest educational qualification achieved: one, two, three, four or more. • Bedrooms: one, two, three, four or more.	Office for National Statistics[24][25]
approxsocialgradeC1percent		
approxsocialgradeABpercent		
highestlevelqualonepercent		
highestlevelqualtwopercent		
highestlevelqualthreepercent		
highestlevelqualfourpercent		
numberbedroomstwopercent		
numberbedroomsthreepercent		
numberbedroomsfourormorepercent		
gp_number_30_car	Within 30-minutes travelling distance, by car or public transport(pt):	Urban Big Data Centre[26]
gp_number_30_pt		
employment_30_car		

[23] Department for Education (2023*). ‘Compare school and college performance in England’*. [online] Available at: https://www.compare-school-performance.service.gov.uk/download-data.
[24] Office for National Statistics (2021). ‘*Census 2021 Bulk - Nomis - Official Census and Labour Market Statistics’*. [online] www.nomisweb.co.uk. Available at: https://www.nomisweb.co.uk/sources/census_2021_bulk
[25] Office for National Statistics (2011). *‘Census 2011 Bulk - Nomis - Official Census and Labour Market Statistics’* [online] Available at: https://www.nomisweb.co.uk/census/2011/bulk/r2_2#KeyStatistics 9
[26] Urban Big Data Centre (2023). ‘*Public transport accessibility indicators 2022 metadata (from Public transport accessibility indicators data 2022)’* [Data set resource]. University of Glasgow. Available at: https://data.ubdc.ac.uk/dataset/public-transport-accessibility-indicators-data-2022/resource/cc141d6f-65ad-4204-893a-2dfc99295240

employment_30_pt	• No. GPs. • No. Employment opportunities. • No. Hospitals. • No. Supermarkets.	
hospitals_30_pt		
hospitals_30_car		
supermarket_30_car		
supermarket_30_pt		
total_recorded_crime	Police Force Area annual recorded number of: • Total crime. • Burglary. • Criminal damage and arson. • Sexual offences. • Shoplifting.	Office for National Statistics[27]
burglary		
criminal_damage_and_arson		
sexual_offences		
shoplifting		
boebankrate	Bank Rate on date of transaction.	Bank of England[28]

6. Results

Table 4 presents regression results of several model specifications assessing the relationship between house prices and ratings (using dummy variables), alongside variables highlighted in the *Data* chapter.

[27] Office for National Statistics (2023). '*Crime in England and Wales: Police Force Area data tables - Office for National Statistics*'. [online] Ons.gov.uk. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/policeforceareadatatables.

[28] Bank of England (2024). '*Interest rates and Bank Rate*'. [online] Bank of England.

Available at: https://www.bankofengland.co.uk/monetary-policy/the-interest-rate-bank-rate.

Table 4 OLS regression estimates, Models (1)-(7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
new	0.0344***	0.0252***	-0.0303***	-0.0122***	-0.0184***	-0.0183***	-0.0376***
	(0.00287)	(0.00245)	(0.00319)	(0.00317)	(0.00325)	(0.00324)	(0.00327)
detached	0.354***	0.415***	0.404***	0.399***	0.348***	0.348***	0.364***
	(0.00420)	(0.0112)	(0.0135)	(0.0135)	(0.0136)	(0.0136)	(0.0135)
semidetached	0.0213***	0.0747***	0.0891***	0.0782***	0.0200	0.0198	0.0310**
	(0.00392)	(0.0112)	(0.0134)	(0.0135)	(0.0135)	(0.0135)	(0.0134)
terraced	-0.366***	-0.303***	-0.167***	-0.166***	-0.215***	-0.215***	-0.214***
	(0.00380)	(0.0110)	(0.0131)	(0.0131)	(0.0132)	(0.0132)	(0.0131)
flat	-0.261***	-0.258***	-0.409***	-0.420***	-0.472***	-0.472***	-0.453***
	(0.00433)	(0.0111)	(0.0136)	(0.0136)	(0.0132)	(0.0132)	(0.0132)
leasehold	-0.0540***	-0.0505***	-0.0782***	-0.0847***	-0.0856***	-0.0854***	-0.0882***

	(0.00215)	(0.00274)	(0.00319)	(0.00333)	(0.00334)	(0.00334)	(0.00330)
numberbedroomstwopercent	-0.00448***	-0.00390***	-0.00480***	-0.00459***	-0.00546***	-0.00549***	-0.00596***
	(9.32e-05)	(0.000126)	(0.000150)	(0.000147)	(0.000155)	(0.000155)	(0.000158)
numberbedroomsthreepercent	-0.00618***	-0.00508***	-0.00407***	-0.00346***	-0.00395***	-0.00398***	-0.00458***
	(7.88e-05)	(0.000117)	(0.000144)	(0.000142)	(0.000152)	(0.000152)	(0.000155)
numberbedroomsfourormorepercent	0.00743***	0.00776***	-0.00301***	-0.00167***	-0.00253***	-0.00252***	-0.000547***
	(9.06e-05)	(0.000129)	(0.000180)	(0.000181)	(0.000185)	(0.000185)	(0.000181)
outstanding		0.120***	0.0430***	0.0333***	0.00894*	0.00847*	0.00889*
		(0.00399)	(0.00466)	(0.00457)	(0.00474)	(0.00474)	(0.00471)
good		0.0557***	0.0146***	0.0170***	0.00639*	0.00665*	0.0126***
		(0.00296)	(0.00339)	(0.00335)	(0.00350)	(0.00350)	(0.00349)
inadequate		-0.102***	-0.0447***	-0.00128	-0.00517	-0.00541	-0.0243***
		(0.00634)	(0.00693)	(0.00706)	(0.00754)	(0.00754)	(0.00756)

averageattainment8score	0.00429***	-0.000650**	-0.000203	-9.93e-05	4.84e-05	0.00148***
	(0.000211)	(0.000254)	(0.000260)	(0.000274)	(0.000275)	(0.000254)
ks4english_additionallang	0.00279***	0.00111***	-0.000422***	-0.000436***	-0.000420***	-0.000622***
	(6.58e-05)	(7.24e-05)	(7.55e-05)	(8.07e-05)	(8.06e-05)	(7.91e-05)
ks4disadvantagedpercent	-0.00448***	-0.00319***	-0.00110***	-0.000873***	-0.000857***	
	(0.000197)	(0.000241)	(0.000240)	(0.000243)	(0.000243)	
freeschoolmealpercent	0.0270***	0.0175***	0.00723***	0.00455***	0.00435***	0.00268***
	(0.00114)	(0.00134)	(0.00131)	(0.00134)	(0.00134)	(0.000664)
standard9_4gcsepercent	0.000873***	0.000766***	0.000737***	0.000679***	0.000556***	0.000421***
	(3.29e-05)	(4.48e-05)	(4.42e-05)	(4.83e-05)	(4.95e-05)	(4.85e-05)
sixthformdummy	0.103***	0.0461***	0.0528***	0.0301***	0.0283***	0.0632***
	(0.00249)	(0.00294)	(0.00302)	(0.00325)	(0.00325)	(0.00292)

approxsocialgrade DEpercent	-0.00200***	-0.00236***	-0.00354***	-0.00353***	-0.0130***
	(0.000270)	(0.000285)	(0.000302)	(0.000302)	(0.000250)
approxsocialgrade C1percent	0.00633***	0.00587***	0.00543***	0.00557***	-0.00450***
	(0.000319)	(0.000325)	(0.000344)	(0.000344)	(0.000266)
approxsocialgrade ABpercent	0.0183***	0.0164***	0.0165***	0.0165***	
	(0.000376)	(0.000384)	(0.000399)	(0.000399)	
highestlevelqualon epercent	0.000904***	0.000794***	0.000724***	0.000752***	0.000587***
	(0.000106)	(0.000105)	(0.000123)	(0.000123)	(0.000117)
highestlevelqualtw opercent	-0.00558***	-0.00703***	-0.00727***	-0.00738***	-0.00885***
	(0.000524)	(0.000552)	(0.000547)	(0.000547)	(0.000546)
highestlevelqualth reepercent	0.00163***	0.00126***	0.00204***	0.00181***	0.00272***

	(0.000227)	(0.000225)	(0.000217)	(0.000218)	(0.000217)
highestlevelqualfourpercent	0.00369***	0.00231***	0.00183***	0.00171***	0.00969***
	(0.000280)	(0.000285)	(0.000323)	(0.000324)	(0.000232)
gp_number_30_car		-0.00110***	-0.000962***	-0.00104***	
		(6.53e-05)	(7.56e-05)	(7.61e-05)	
gp_number_30_pt		-0.00859***	-0.00998***	-0.0101***	-0.0119***
		(0.000271)	(0.000299)	(0.000299)	(0.000259)
employment_30_car		1.04e-06***	8.02e-07***	8.04e-07***	
		(2.18e-08)	(2.47e-08)	(2.47e-08)	
employment_30_pt		1.15e-06***	1.22e-06***	1.25e-06***	1.18e-06***
		(4.68e-08)	(5.13e-08)	(5.13e-08)	(5.07e-08)
hospitals_30_pt		0.00288**	-0.00223**	-0.00212*	-0.00142

		(0.00114)	(0.00113)	(0.00113)	(0.00113)
hospitals_30_car		-0.00808***	-0.00837***	-0.00845***	
		(0.000268)	(0.000357)	(0.000357)	
supermarket_30_car		-0.00221***	-0.00130***	-0.00116***	
		(0.000103)	(0.000121)	(0.000121)	
supermarket_30_pt		0.00452***	0.00773***	0.00765***	0.0104***
		(0.000542)	(0.000576)	(0.000576)	(0.000579)
total_recorded_crime			4.87e-06***	5.09e-06***	4.30e-07***
			(1.72e-07)	(1.74e-07)	(1.62e-08)
burglary			4.64e-05***	5.05e-05***	
			(4.33e-06)	(4.35e-06)	
criminal_damage_and_arson			-5.85e-05***	-6.04e-05***	

					(4.73e-06)	(4.74e-06)	
sexual_offences					-0.000121***	-0.000137***	
					(5.85e-06)	(6.09e-06)	
shoplifting					9.60e-06***	9.20e-06***	
					(2.33e-06)	(2.33e-06)	
boebankrate						0.117***	0.0344***
						(0.0108)	(0.0101)
Constant	12.29***	11.78***	11.69***	11.79***	12.19***	12.17***	12.44***
	(0.00737)	(0.0182)	(0.0314)	(0.0325)	(0.0351)	(0.0350)	(0.0319)
Observations	604,604	443,139	292,987	292,987	257,813	257,813	257,813
R-squared	0.238	0.247	0.340	0.355	0.387	0.387	0.373

Standard errors in parentheses, which are heteroskedasticity robust in Models (2) to (7)

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

Results of the modelling process are assessed in this section. Table 4 presents regression results of several model specifications assessing the relationship between house prices and various school, neighbourhood, and locational characteristics, including the role of Ofsted ratings represented by dummy variables. Almost every additional model iteration increased the coefficient of determination, from 0.238 (Model 1) to 0.387 (Model 6), providing reassurance inclusion of additional variables throughout the modelling process improved ability to estimate prices as well as model-fit, given consideration of specific structural locational and neighbourhood characteristics. Model (1) is log-level and specified as:

$$\text{Ln(price)} = \alpha + \beta_1(S) + \epsilon \qquad (1)$$

Model (1) explores how structural characteristics (S) influence price. The p-value (0.000) for every structural characteristic is statistically significant ($p<0.01$), indicating evidence to reject the null hypothesis. Focussing on property type, Table 4 indicates 'detached' prices are 3.50% higher than the reference group property type 'other' (accounting for properties not detached, semi-detached, flat, or terraced), *ceteris paribus*, whilst 'terraced' prices are 30.6% lower. Both property types have a moderate, statistically significant effect on price ($p<0.01$). Note, because a log-linear functional form is used, percentages have been calculated by exponentiating the coefficient, subtracting one, and multiplying by 100. The findings are consistent with theoretical expectations, as it demonstrates consumer rationality to maximise utility given monotonic preferences. With respect to this study, 'detached' may reflect increased space and privacy, which Fletcher et al. (2004) implies is typically more highly-economically valued by homebuyers if the previously mentioned assumption holds, compared to 'terraced' properties, which are often more compact in populous, urban areas. These factors contribute to underlying demand dynamics and price determination, which provide explanation of the positive relationship between prices and 'detached' and the negative relationship with 'terraced'. Model (1)'s coefficient of determination (0.238) is low, suggesting a large proportion of variation in house prices cannot be explained by structural characteristics alone. It also highlights the importance in further model iterations to include other factors including education and neighbourhood attributes. Model (1) uses a very large sample size (n=604,604) of highly varied property transaction datapoints, which hedonic studies suggests is often subject to heteroskedasticity. The Breusch-Pagan test result

(Prob>chi2=0.000) implies evidence to reject the null hypothesis of constant variance, violating the OLS homoscedasticity assumption. This limits the interpretability of Model (1) findings, as estimates may be inefficient, biased, and subject to wide confidence intervals, contributing to misleading inference. To mitigate for homoscedasticity, Model (2) employs robust standard errors:

$$Ln(price)= \alpha + \beta_1(S) + \beta_2(E) + \epsilon \tag{2}$$

Model (2) incorporates a vector of KS4 school-specific educational characteristics (E), including Ofsted rating for the closest state secondary school to the property. The statistically significant ($p<0.01$) results show the largest Ofsted-rating coefficient (0.120) is associated with '*outstanding*', which indicates a one-unit improvement in '*outstanding'* resulted in 12.7% higher property prices than when the closest school was designated the reference category rating of '*requires_outstanding', ceteris paribus*. For '*good'* schools, the average price difference relative to *'requires_outstanding'* was valued at an increase of 5.73% and association with an '*inadequate'*-rated school resulted in a 9.70% decrease in prices relative to the reference category, *ceteris paribus.*

For each rating, the null hypothesis that Ofsted ratings do not have a statistically significant impact on prices is rejected. The coefficient of determination (0.247) indicates a marginal increase in the model's predictive reliability and therefore, an imperative exists for inclusion of additional variables to acquire improved meaningfulness of inferences.

To capture the impact of neighbourhood characteristics (N), including the percentage of the LSOA at each social grade, ONS Census data from 2011 and 2021 is interpolated, matched to the property transaction year, and found as a percentage of the neighbourhood, resulting in Model (3):

$$Ln(price)= \alpha + \beta_1(S) + \beta_2(E) + \beta_3(N) + \epsilon \tag{3}$$

Income data at LSOA-granularity is not available publicly, so the highest education level achieved as a percentage of the neighbourhood is used to approximate for it. The overall findings imply strong evidence of statistically significant, albeit small in magnitude, relationship between prices and neighbourhood attributes as exhibited by high t-values and low p-values reported in Table 4. Neighbourhoods with a greater percentage of highly educated individuals command higher property prices: the *highestlevelqualfourpercent* coefficient (0.00369) implies that a one-unit increase in the percentage of individuals having achieved a Level-4 or above qualification, increases prices by 0.37%. Similar findings are evident in the literature: for example, Orford (2018) argues strong-qualification levels are a form of "cultural capital": used by middle-classes to access professional, well-paid employment and maintain "social status". This means many parents exhibit a strong willingness to pay a premium to live in proximity to "excellent" quality state schools to improve longer-term benefits for their child.

Ofsted ratings continue to have a statistically significantly effect on prices ($p<0.01$), with the direction and magnitude relatively consistent between Model (2) and (3). As in (2), marginally higher premium is placed on properties associated with '*outstanding*' schools compared to '*good'* schools.

$$\text{Ln(price)} = \alpha + \beta_1(S) + \beta_2(E) + \beta_3(N) + \beta_4(L) + \epsilon \tag{4}$$

$$\text{Ln(price)} = \alpha + \beta_1(S) + \beta_2(E) + \beta_3(N) + \beta_4(L) + \beta_5(C) + \epsilon \tag{5}$$

Model (4) includes variables pertaining to local facilities within a 30-minute travelling distance (by car or public transport) from properties. Police-Force-Area-level crime is added to the specification, creating Model (5). Caution should be taken in result interpretation of crime data: it does not account for specific LSOA-differences in crime (which is not publicly available) and a change in Greater Manchester police's IT system in 2019 has reduced the sample size, as the regression cannot be ran for affected households sold within the region for 2019. Given the emphasis placed on crime in hedonic literature, inclusion at Police-Force-Area-level persists as an appropriate solution. It is unexpected *'total_recorded_crime'* and 'burglary' have a positive, significant relationship with prices, although coefficient magnitude (4.87e-06 and 4.64e-05 respectively), is diminutive, meaning constraints exist on practical inferences derived.

$$Ln(price)= \alpha + \beta_1(S) + \beta_2(E) + \beta_3(N) + \beta_4(L) + \beta_5(C)+ \beta_6(B) + \epsilon \quad (6)$$

Model (6) adds the Bank of England bank rate to the previous specification, due to its influence on mortgage rates and gearing ratios (influencing their ability to buy at different prices, given their budgetary constraints and preferences). The results indicate a one-unit increase in the bank rate leads to a positive, increase on prices of 12.4% ($p<0.01$). All three Ofsted ratings regressed appear to be no longer statistically significant at any level, indicating the null hypothesis is not rejected.

Each model iteration increased the number of variables included. It is therefore important to assess whether collinearity exists between independent variables, to prevent unstable, unreliable coefficient estimates. Subjecting each variable in (6) to the Variance Inflation Factor (VIF) highlights specific crime, locational factors and school demographic variables may be collinearly related. Table 5 shows all VIF results above 10, indicating the highlighted variables should potentially be considered for exclusion:

Table 5 Multicollinearity test, (6)

Variable	**VIF**
criminal_damage_and_arson	2680
burglary	1740
total_recorded_crime	218
sexual_offences	182
employment_30_car	116
gp_number_30_car	100
supermarket_30_car	98.6
shoplifting	94.5
hospitals_30_car	25.9
ks4disadvantagedpercent	14.6
freeschoolmealpercent	14.1
approxsocialgradeABpercent	13.5

Although following the same equation specification as (6), fewer covariates are included in vectors (E), (L), (N) and (C) in Model (7). Full breakdown of excluded variables is shown in Table 4, Column 8. Given concerns around heteroskedasticity in previous results, (7) is subject to testing. The null hypothesis that residuals are homoscedastic is rejected, as the plot exhibits 'fanning out' of residual points. Outliers persist in (7), indicating heterogeneity, which is unsurprising given the sample accounts for many buyers (n=257,813), across a wide-geographical region. Outliers and heteroskedasticity alike are commonly reported in hedonic studies and are most often mitigated for through the employment of robust standard errors to obtain unbiased standard errors, fulfilling OLS assumptions.

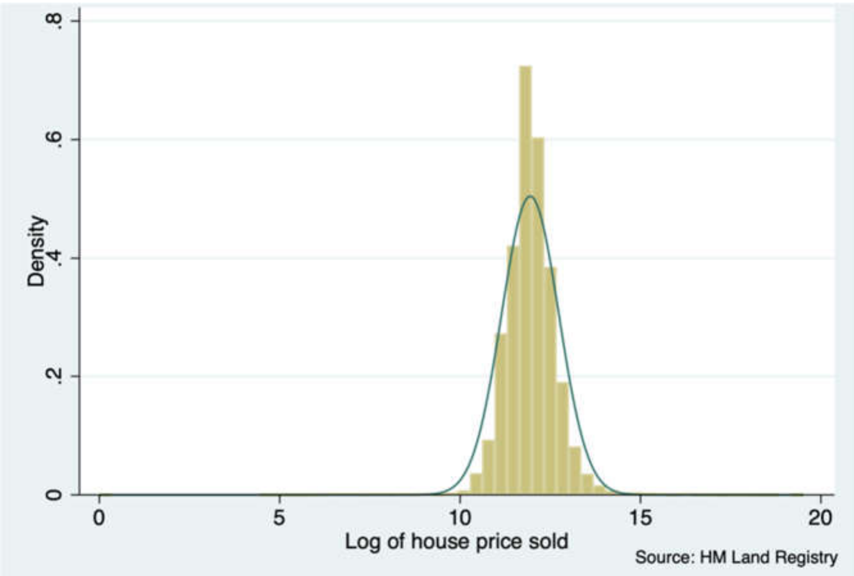
Unlike in Model (6), '*good*' and '*inadequate*' in Model (7) have a statistically significant, yet marginal effect on prices ($p<0.01$), with the direction of relationship with Ofsted variables remaining consistent across all model iterations. Contrary to previous results, the '*inadequate*' coefficient is larger than both '*good*' and '*outstanding*', although this is less important for '*outstanding*' given it no longer holds any significance. Compared to the reference group, a one-unit improvement in '*inadequate*' is therefore expected to result in a decrease in prices of 2.40%, indicating lower demand to live near 'inadequate' schools.

Results for school-specific educational characteristics (E) in Model (7) broadly follow expectations: sixth form and higher GCSE pass-rates are positively associated with prices. Many parents will use these attributes to signal school 'quality' (see *Literature Review* section), because they have the capacity to improve educational outcomes.

Model (7) excludes variables subject to multicollinearity, meaning reported estimates are reliable and stable. The sample residual distribution of *lnprice* appears to be approximately normal:

Figure 3 shows a histogram exhibiting a symmetric 'bell-shape' and limited skewness in the distribution tails.

Figure 3 Histogram of lnprice, (7)



7. Robustness Checks

a. Sensitivity analysis (1): 500m-radius sample

As part of robustness checks, a sample is taken of transactions within a 500m-radius of the school (n=17,533) (Hussain, 2023). Using (7), Table 6 shows an increase in R^2 (0.413) from the full sample (0.373). The decrease in the root-mean-squared error term (0.554 from 0.621) is further evidence of model-fit improvement.

Table 6: Regression summary: 500m property-school radius

F(29, 17503)	=	716
Prob>F	=	0.0000
R-squared	=	0.413
Root-MSE	=	.555

As highlighted in the *Methodology* section, imperative exists to assess OLS specification. Using *linktest* in Stata, the predicted *lnprice* (p=0.024) is not statistically significant at the 1% significance-level, meaning the null hypothesis of no specification error cannot be rejected.

Figure 4 Misspecification test: 500m property-school radius.

lnprice	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
_hat	.183	.361	0.51	0.612	-.525	.891
_hatsq	.0340	.015	2.26	0.024	.00456	.0634
_cons	4.90	2.17	2.26	0.024	.652	9.15

b. Sensitivity analysis (2): Property type

Additional robustness checks are employed by taking four samples pertaining to property types including detached, semi-detached, terraced, and flat to disaggregate property-type effects. The samples are subjected to specification (7), and the results are reported in Table 7:

Table 7 Regression results: Property type

VARIABLES	Detached-only	Semi-detached-only	Terraced-only	Flat-only
leasehold	-0.0539***	-0.0362***	-0.0815***	-0.240***
	(0.00378)	(0.00268)	(0.00292)	(0.0240)
numberbedroomstwopercent	-0.00543***	-0.00703***	-0.0112***	0.00173***
	(0.000389)	(0.000193)	(0.000152)	(0.000149)
numberbedroomsthreepercent	-0.00926***	-0.00585***	-0.00615***	-0.000613***
	(0.000338)	(0.000173)	(0.000147)	(0.000181)
numberbedroomsfourormorepercent	-0.00493***	-0.00365***	-0.00552***	0.00416***
	(0.000367)	(0.000213)	(0.000197)	(0.000259)
outstanding	-0.0392***	0.00611	-0.0137***	0.0420***
	(0.00691)	(0.00437)	(0.00510)	(0.00939)
good	-0.0218***	0.0109***	-0.00788**	0.0283***
	(0.00505)	(0.00312)	(0.00355)	(0.00797)
inadequate	-0.0882***	-0.0473***	-0.0668***	-0.134***
	(0.0113)	(0.00773)	(0.00678)	(0.0183)
averageattainment8score	0.00533***	0.00222***	0.00225***	-0.00405***
	(0.000371)	(0.000219)	(0.000262)	(0.000542)
ks4english_additionallang	-0.00171***	-0.000759***	-0.000218***	-0.00172***
	(0.000119)	(7.25e-05)	(7.53e-05)	(0.000151)

freeschoolmealpercent	0.00311***	0.00120**	0.00357***	-0.00112
	(0.000947)	(0.000585)	(0.000690)	(0.00119)
standard9_4gcsepercent	0.000301***	0.000146***	0.000269***	0.000626***
	(6.55e-05)	(4.18e-05)	(5.06e-05)	(7.79e-05)
sixthformdummy	0.0619***	0.0652***	0.0497***	0.0691***
	(0.00397)	(0.00263)	(0.00319)	(0.00561)
approxsocialgradeDEpercent	-0.00732***	-0.0107***	-0.0127***	-0.0187***
	(0.000391)	(0.000210)	(0.000233)	(0.000366)
approxsocialgradeC1percent	-0.00879***	-0.00566***	-0.00130***	-0.00843***
	(0.000389)	(0.000244)	(0.000293)	(0.000363)
highestlevelqualonepercent	0.00174***	0.000130	0.000454***	-0.000150
	(0.000136)	(0.000124)	(0.000125)	(0.000143)
highestlevelqualtwopercent	-0.00273***	-0.00484***	-0.00123**	-0.00864***
	(0.000816)	(0.000461)	(0.000515)	(0.000888)
highestlevelqualthreepercent	-0.00408***	-0.00107***	-0.000550**	0.00235***
	(0.000371)	(0.000230)	(0.000220)	(0.000230)
highestlevelqualfourpercent	0.0155***	0.0144***	0.0149***	0.00238***
	(0.000324)	(0.000214)	(0.000234)	(0.000299)
gp_number_30_pt	-0.000551	-0.00389***	-0.0114***	-0.0111***
	(0.000561)	(0.000268)	(0.000264)	(0.000312)
employment_30_pt	-1.90e-06***	4.25e-07***	1.49e-06***	1.03e-06***

	(1.66e-07)	(6.26e-08)	(5.57e-08)	(5.29e-08)
hospitals_30_pt	-0.00206	-0.000831	0.00297***	0.00837***
	(0.00209)	(0.00116)	(0.00111)	(0.00143)
supermarket_30_pt	-0.00377***	0.00721***	0.00548***	0.0119***
	(0.00101)	(0.000547)	(0.000613)	(0.000661)
total_recorded_crime	5.06e-07***	4.72e-07***	7.11e-07***	2.74e-07***
	(2.32e-08)	(1.39e-08)	(1.51e-08)	(2.96e-08)
boebankrate	0.101***	0.0350***	-0.0337***	0.0431***
	(0.0148)	(0.00946)	(0.0107)	(0.0159)
Constant	12.86***	12.37***	12.19***	12.50***
	(0.0496)	(0.0285)	(0.0295)	(0.0554)
Observations	48,769	73,690	77,097	37,809
R-squared	0.363	0.484	0.556	0.447

Heteroskedasticity robust standard errors in parentheses

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

Table 7 shows each sub-sample exhibits relatively similar, if not improved R^2 compared to (7): the highest being for 'terraced-only' properties, which at 55.6%, indicates a good level-of-fit. Coefficient magnitude remains low, albeit statistically significant at the 1% level for most Ofsted rating estimates except for '*outstanding'* in the semi-detached sample (p>0.1) and '*good'* in the terraced sample (p<0.05). Table 7 exhibits low standard errors and narrow confidence intervals, providing assurance the true population parameter is close to reported estimates. These findings suggest the specification is robust to sensitivity analysis, providing credibility to overall findings. The relationship direction between independent variables and price remains consistent across samples, although some estimates deviate from expectations. Across each sample, crime has a very small, positive relationship with prices (p<0.01), potentially due to higher police presence in more expensive neighbourhoods, resulting in higher arrests. Higher GP numbers have a negative, small impact on prices (significant for all types except 'detached'), reflecting higher healthcare demand (and supply) in urban areas, which increases noise and traffic congestion. Unexpected findings highlight challenges across hedonic studies in understanding how heterogenous preferences impact prices. Surveys on consumer behaviour and preference could be undertaken to probe these results in future research.

7. Conclusion

The findings indicate Ofsted ratings have statistically significant effects on price across Northwest England over the sample period, suggesting the null hypothesis is rejected: at 1% for '*inadequate'* and '*good'* (p<0.01) and 10% for '*outstanding'* (p<0.1). The estimated property price associated with an '*outstanding'* school is 0.893% higher than the variable reference category '*requires_improvement', cetaris paribus,* whilst *'good'* is 1.27% higher and '*inadequate'* is 2.40% lower. Crime, social-grade, supermarkets, and the bank rate also have a statistically significant effect on price (p<0.01). These conclusions meet theoretical expectations: many consumers strongly value 'quality' education (which many parents interpret '*outstanding'* and '*good'* to reflect), due to its impact on improving social capital, resulting in high-preferential ranking amongst buyers. Elevated demand increases the hedonic price function faced by consumers, making it more expensive for each household to access the characteristic alongside other attributes. Households with the financial resource to be able to pay higher prices do so, meaning under this study's assumptions, become associated with schools expected to deliver ‘quality’ educational outcomes, relative to schools rated ‘*inadequate*’ or ‘*requires_improvement*’.

Policy implications arising are likely to pertain to interventions ensuring children from lower socio-economic backgrounds maintain access to ‘*outstanding*’ or ‘*good*’ schools, when their guardians cannot afford to live in closest proximity. Interventions could include ‘quotas’, to ensure enough children from these backgrounds access ‘quality’ schools. In contrast, policymakers could target specific schools needing improvement: providing additional resource funding to mitigate ‘quality’ disparities.

The coefficient of determination of (7) suggests a moderate level-of-fit (0.373), although robustness checks indicate dis-aggregating the full sample into 500m-radius and property-type samples generally improved fit: likely due to reduced heterogeneity across fewer observations. Further research could explore potential access to paid, restricted datasets, to gain greater understanding of the role of environmental characteristics (including greenspace access by LSOA). Future data collection improvements by HM Land Registry may provide greater nuance on household demographic composition, meaning future research could analyse properties only bought by families, who are directly affected by school admission.

A significant limitation to inference is the assumption that no alternative substitute schools exist for parents to choose, which *de facto*, is unlikely. Factors including catchment-area and sibling-attendance are excluded from analysis, due to data limitations, although are likely to increase school choice. Research could be extended by employing a boundary-discontinuity-design approach, to understand whether imposing geographical constraints on properties, through designated catchment-areas, changes the rating-price effect, by accounting for more than one school per-property sold.

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