Impact of School Quality on House Prices in London and Bristol: Shifts in Urban Housing Dynamics During the COVID-19

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Abstract. This study examines the impact of school quality on house prices in London and Bristol before, during, and after the COVID-19 pandemic. Using cross-sectional data, the analysis highlights the relationship between proximity to high-quality state schools and residential property values, revealing shifts in buyer priorities influenced by pandemic-related factors such as urban exodus and changing educational dynamics. The findings demonstrate that while primary school quality positively correlates with house prices, the strength of this relationship has weakened during the pandemic as buyers increasingly prioritize property-specific characteristics. In contrast, secondary school quality shows varied effects across large and small cities, reflecting differences in school admission criteria and urban characteristics. The persistence of a house price premium near good primary schools suggests ongoing educational inequalities, as access to high-quality education remains limited to wealthier families. These results underscore the need for targeted policy interventions to address the entrenched disparities in educational opportunities and housing affordability in post-pandemic England.

Keywords: School Quality, House Prices, COVID-19 Pandemic, Primary Education, Secondary Education, Urban Housing Market, Educational Inequality, Property Characteristics, London, Bristol, Real Estate Economics.

1. Introduction

Before the COVID-19 pandemic, the relationship between school quality and house prices was well-established, with properties near high-quality state schools in England commanding a premium. This relationship was driven by parents' desire to secure the best educational outcomes for their children, often measured by school ratings, academic results, and attendance rates (Wang & Degol, 2016). However, during and after the pandemic, other factors, such as the urban exodus and the changing dynamics of work-from-home flexibility, have influenced house prices. This shift in priorities potentially altered the established house price premium linked to school quality.

Recent studies have shown a notable shift in the housing market, driven by preferences for properties with more space and in less dense areas, partly due to pandemic-related health concerns and lifestyle changes (Petrosky-Nadeau & Valletta, 2020). This shift was particularly prominent in large cities like London, where house prices experienced volatility due to varying demand factors (Badarinza & Ramadorai, 2018). At the same time, measuring school quality has also evolved. The traditional measures, such as exam performance, have been supplemented by attendance rates, particularly relevant during periods of hybrid or online learning (Bashir et al., 2021; Julaily et al., 2021).

This project aims to explore the effect of the pandemic on the house price premium for properties near good state schools in England, specifically focusing on the variability between and within regions. Using data from London and Bristol, the project assesses the extent to which the pandemic has influenced the correlation between school quality and house prices, accounting for other property and neighbourhood characteristics. By analysing pre-pandemic and post-pandemic periods, this study also evaluates the broader economic and societal impacts, particularly on educational attainment and housing affordability

2. Literature Review

Research consistently shows a positive relationship between school quality and house prices, where properties near high-quality state schools command a premium. Black (1999) addressed the complexities of this relationship by suggesting boundary dummies to control for unobserved factors like neighbourhood characteristics, which can bias the estimation of house price effects. Chiodo et al. (2010) further confirmed that both primary and secondary school quality significantly impacts property values, as families prioritize educational access when buying homes. However, during the COVID-19 pandemic, the dynamics of this relationship were disrupted by shifts in buyer preferences and changes in how school quality is measured.

The pandemic brought about an urban exodus, where buyers moved away from densely populated areas in favour of properties with more space, often in suburban or rural settings (Gallent & Hamiduddin, 2021). This shift altered traditional market conditions, particularly in large cities like London, where demand patterns changed significantly. At the same time, the way school quality was perceived also evolved. Nathwani et al. (2021) highlighted that attendance rates, a key measure of school quality, were significantly affected by health concerns and increased absenteeism during the pandemic. This change in attendance patterns, as noted by Julaily Aida J. et al. (2021), was exacerbated by the transition to remote learning and the use of new technologies like GPS tracking to monitor student engagement, which influenced public perception of school quality.

Moreover, the reliability of attendance rates as a measure of school quality has been increasingly recognized, especially as traditional academic performance metrics were disrupted during the pandemic (Brendan B., 2020). Hill (2012) also emphasized that other property-specific factors, such as the number of bedrooms and bathrooms, play a critical role in determining house prices, further complicating the analysis of the relationship between school quality and property values. These evolving dynamics underscore the importance of re-evaluating whether the traditional house price premium associated with proximity to good schools still holds, especially given the broader economic and societal impacts observed during and after the pandemic. This project aims to assess these changes by focusing on regional variability, particularly in London and Bristol, to better understand the distributional effects on educational outcomes and housing affordability in England.

3. Data

Research consistently shows a positive relationship between school quality and house prices, where properties near high-quality state schools command a premium. Black (1999) addressed the complexities of this relationship by suggesting boundary dummies to control for unobserved factors like neighbourhood characteristics, which can bias the estimation of house price effects. Gibbons et al. (2013) further confirmed that both primary and secondary school quality significantly impacts property values, as families prioritize educational access when buying homes. However, during the COVID-19 pandemic, the dynamics of this relationship were disrupted by shifts in buyer preferences and changes in how school quality is measured.

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Table 1 highlights the variability in house prices and school quality before, during, and after the pandemic across different cities and periods. The table outlines key variables such as house prices before (BP) and during/after the pandemic (AP), as well as attendance rates for primary (ATP) and secondary schools (ATS). The data shows that house prices in London and Bristol were significantly higher during and after the pandemic, reflecting the broader market trends influenced by the exodus from urban centers. Additionally, the variability in ATP and ATS highlights how school quality measures fluctuated, which is crucial in understanding the impact on house price premiums. These shifts underscore the need to critically evaluate how house prices and their affordability around state schools affect educational outcomes, particularly as attendance rates and other factors diverge across regions and time periods.

Table 1. Summary of Variables and Specifications for London and Bristol Housing Market Analysis

Variable	Variable description or specification	Mean (BP/AP)	Min (BP/AP)	Max (BP/AP)	Standard deviation (BP/AP)
AP	The House Price During and After Pandemic in London/Bristol that include the houses from 189/25 districts.	518862.4	110000	1750000	223784.1
BP	The House Price Before Pandemic in London/Bristol that include the houses from 168/25 districts.	425542.8	105000	1270000	193197.5
HP	House price for all periods	484223.5	105000	1750000	217599.2
ATP	The attendance rate of primary school that nearby to the house.	94.09465/ 94.06479	88/88.2	97.9/97.9	1.638875/ 1.759539
ATS	The attendance rate of secondary school that nearby to the house.	91.90172/ 91.95372	83.1/83.1	96.4/97	1.941969/ 2.002135
District	The "District" represents as the district dummies to eliminate the unobserved fix effect like the neighborhood characteristics in each district of London/Bristol	69.67686/ 78.51693	0/0	167/188	43.98686/ 50.92994
$\boldsymbol{X}^*$ BED	There are "NBED", "OBED", "TBED" dummy variables represent the number of bedrooms in each house, the variable represents "1" if the house fitted, "0" if not. (N: No, O: one, T: Two)				
$\boldsymbol{N/O/T}^*$ BATH	There are "NBATH", "OBATH", "TBATH" dummy variables represent the number of bedrooms in each house, the variable represents "1" if the house fitted, "0" if not. (N: No, O: one, T: Two)				
Garden	If the house includes Garden, the variable represents "1", otherwise "0".				
Parking	If the house includes Parking, the variable represents "1", otherwise "0".				
T	Time dummy variable: T=0 if "Before pandemic" period T=1 if "During and After Pandemic" period				

4. Methodology

Traditional models have shown that factors influencing house prices include the physical characteristics of dwellings, such as the number of bedrooms and bathrooms, garden availability, and parking (Hill, 2012). These attributes are represented in the regression model as follows:

$$X_i = \begin{Bmatrix} TOP_i \\ NBED_i \\ OBED_i \\ TBED_i \\ NBATH_i \\ OBATH_i \\ TBATH_i \\ Garden_i \\ Parking_i \end{Bmatrix}, \qquad \beta = \begin{Bmatrix} \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \\ \beta_9 \\ \beta_{10} \\ \beta_{11} \end{Bmatrix}$$

$$\log(HP_i) = \theta_0 + \beta_1 QP_i + \beta_2 QS_i + \boldsymbol{\beta X_i^T} + \eta \tag{1}$$

Where QP_i and QS_i represent the school quality measures for primary and secondary schools, respectively. The correlation of each variable may differ between the "Before Pandemic" and "During and After Pandemic" periods. To accurately evaluate these relationships, this project employs cross-sectional regressions for the two distinct periods.

Directly demonstrating school quality in regression is challenging due to the various ways it can be measured. Bartanen (2020) highlighted that attendance rates have become a key metric for assessing educational success, widely valued by policymakers, with over 72% of U.S. states using attendance as a school quality indicator. Therefore, this project utilizes attendance rates (ATP for primary schools and ATS for secondary schools) as proxies for school quality because of their strong correlation with overall school performance.

$$\log(BP_i) = \beta_0 + \beta_1 ATP_i + \beta_2 ATS_i + \boldsymbol{\beta X_i^T} + \omega_i \tag{2}$$

$$\log(AP_i) = \beta_0 + \beta_1 ATP_i + \beta_2 ATS_i + \boldsymbol{\beta X_i^T} + \pi_i \tag{3}$$

According to Leslie (2003), each district may have unique community factors that influence school quality, leading to omitted variable bias in the coefficients of ATPiATPi and ATSiATSi in regressions (1) and (2). To address this, district dummy variables are introduced, similar to the “boundary dummies” discussed by Black (1999). These district dummies control for unobserved fixed effects, recognizing that distinct districts in cities like London may have unique characteristics that are not easily quantified.

$$\log(BP_i) = \beta_0 + \beta_1 ATP_i + \beta_2 ATS_i + \boldsymbol{\beta X_i^T} + \sigma_1 District_i + \epsilon_i \tag{4}$$

$$\log(AP_i) = \beta_0 + \beta_1 ATP_i + \beta_2 ATS_i + \boldsymbol{\beta X_i^T} + \gamma_1 District_i + \varepsilon_i \tag{5}$$

The choice of Boundary Fixed Effects (FE) estimation over Instrumental Variable (IV) methods stems from the strict requirements of IVs, such as relevance and exclusion, which are difficult to satisfy in this context. IVs can introduce bias when there is even a small correlation between the instruments and error terms, often leading to validity issues, particularly with weak instruments (Edwin, 2006). In this model, potential omitted variables include social and economic background factors that influence both school quality and house prices, making valid IVs challenging to define. Thus, this project emphasizes FE estimation, as recommended by Black (1999).

To evaluate whether the relationship between school quality and house prices remains consistent across periods, a model incorporating time dummy variables (T) and interaction terms with all explanatory variables is used to mitigate omitted variable bias:

$$\mu = \begin{Bmatrix} \mu_3 \\ \mu_4 \\ \mu_5 \\ \mu_6 \\ \mu_7 \\ \mu_8 \\ \mu_9 \\ \mu_{10} \\ \mu_{11} \end{Bmatrix}$$

$$\log(HP_i) = \beta_0 + \beta_1 ATP_i + \beta_2 ATS_i + \boldsymbol{\beta X_i^T} + \sigma_1 District_i + \mu_1 T * ATP_i + \mu_2 T * ATS_i + \boldsymbol{\mu T} * \boldsymbol{X_i^T} + \sigma_2 T * District_i + \vartheta_i \quad (6)$$

The interaction terms allow for assessing whether changes in school quality impact house prices differently across the two periods. If the coefficient estimators for these interaction terms are insignificant, it suggests that the pandemic did not significantly alter the relationship between school quality and house prices.

5. Diagnostic Test

Table 2. Diagnostic Tests for Regression Model Robustness and Validity

Test for	Test	Result of data from BP, AP	Explanation (At 5% significant level)
Heteroskedasticity	Breusch-Pagan test	BP: p=0.0615 AP: p=0.0064	H0: Errors exhibits constant variance BP: Fail to reject H0, we may have homoscedasticity errors. AP: we can reject null, the model has heteroskedasticity, it may not influence the unbiased and consistent of estimator, but the standard error of coefficient estimator will larger. So, we consider robust standard error in Table 4 and 5.
Heteroskedasticity	White test	BP: p=0.1186 AP: p=0.0000	
R2			Value increasing through more variables add in the regression. There might have a better fit of model, but the R2 will not decrease following new variable added, so it might not be highly reliable to describe the quality of prediction of model.
Multicollinearity	Variance Inflation Factor (VIF)	BP: Two has VIF> 10 AP: Three has VIF>10	NBATH, OBATH appear both periods. TBATH appear in AP. The model has variables facing collinearity problem that reduce the estimator efficient for these variables.
Normality of errors	Shapiro Wilk	BP: p=0.00343 AP: p=0.0000	H0: Errors follow a normal distribution we may reject H0 for all BP and AP, however, following the large enough sample size and standardized normal probability plot. We may have an asymptotically normal distribution of errors.
Structure change	Chow test	P=0.000	H0: No structural change We have strong enough evidence to reject H0. Means the pandemic will generate structure change on some of coefficient of variables. But, this test may not show which variables create those changes.
Functional Form Misspecification	Ramsay RESET	BP: p=0.6746 AP: p=0.002	H0: Model has no omitted variable BP: we cannot reject H0, we may not have omitted variables, the model is correctly specified. AP: we can reject H0, we may have omitted variable bias for coefficient. The carefully consider the analysis on AP data.

Table 2 presents the results of various diagnostic tests conducted to assess the validity and robustness of the regression models used in the analysis. These tests include checks for heteroskedasticity using the Breusch-Pagan and White tests, which indicate whether the variance of errors is constant. The results suggest that the model for house prices before the pandemic (BP) does not show significant heteroskedasticity, whereas the model for during and after the pandemic (AP) does, necessitating the use of robust standard errors. The table also highlights multicollinearity issues detected by the Variance Inflation Factor (VIF), normality of errors assessed by the Shapiro-Wilk test, and structural changes confirmed by the Chow test, indicating significant shifts in the impact of variables across periods. The Ramsay RESET test checks for omitted variable bias, showing the AP model may have specification errors. These diagnostics guide adjustments in the analysis to ensure the models' reliability and the robustness of the results.

6. Results

The results presented in Tables 3 and 4 highlight the impact of school quality and other factors on house prices in London, specifically examining the changes before, during, and after the COVID-19 pandemic. The focus is on key variables such as ATP (Attendance Rate for Primary Schools) and ATS (Attendance Rate for Secondary Schools), as well as other property characteristics that influence house prices.

Table 3. Results of London and Bristol (Before Pandemic)

	1	2	3	4	5	6	7*
	log_BP	log_BP	log_BP	log_AP	log_AP	log_AP	log_AP
ATP	0.0416***	0.0257**	0.0266**	0.0192**	0.0148*	0.0154*	0.0154*
	-3.28	-2.14	-2.22	-2.16	-1.88	-1.95	-1.74
ATS	0.000363	-0.00397	-0.00356	0.0049	-0.00214	-0.00166	-0.00166
	-0.03	(-0.40)	(-0.36)	-0.63	(-0.31)	(-0.24)	(-0.23)
TOP		0.118***	0.116***		0.144***	0.144***	0.144***
		-3.38	-3.33		-6.35	-6.35	-7.69
NBED		-0.189*	-0.184*		-0.190***	-0.187***	-0.187***
		(-1.92)	(-1.88)		(-2.72)	(-2.67)	(-2.70)
OBED		-0.346***	-0.346***		-0.350***	-0.346***	-0.346***
		(-3.47)	(-3.47)		(-5.08)	(-5.03)	(-5.63)
TBED		-0.160**	-0.160**		-0.138***	-0.141***	-0.141***
		(-2.23)	(-2.24)		(-2.89)	(-2.95)	(-3.59)
NBATH		-0.0745	-0.0763		-0.529***	-0.531***	-0.531**
		(-0.48)	(-0.49)		(-3.52)	(-3.53)	(-2.14)
OBATH		-0.223	-0.226		-0.685***	-0.683***	-0.683***
		(-1.55)	(-1.58)		(-4.83)	(-4.82)	(-2.84)
TBATH		0.00309	-0.000526		-0.423***	-0.420***	-0.420*
		-0.02	(-0.00)		(-2.95)	(-2.93)	(-1.75)
Parking		-0.074	-0.0679		-0.0798*	-0.0793*	-0.0793**
		(-1.17)	(-1.07)		(-1.85)	(-1.84)	(-2.27)
Garden		0.00511	0.0115		0.0628	0.0647	0.0647*
		-0.09	-0.2		-1.57	-1.62	-1.83
District			0.000793*			0.000498*	0.000498*
			-1.8			-1.84	-1.82
_cons	8.909***	10.91***	10.73***	10.81***	12.36***	12.22***	12.22***
	-6.06	-7.8	-7.67	-10.29	-13.09	-12.92	-11.11
N	523	523	523	888	888	888	888
R^2	0.02	0.163	0.168	0.006	0.229	0.232	0.232
t statistics in parentheses							
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$							
7 robust*							

Table 4. Results of London and Bristol (During and After Pandemic)

	1 (robust)	2 (robust)
	London	Bristol
	log_HP	log_HP
ATP	0.0266**	-0.0500***
	(2.18)	(5.96)
TATP	-0.0115	-0.0151
	(-0.76)	(-1.52)
ATS	-0.00356	0.0198***
	(-0.35)	(4.01)
TATS	0.00152	-0.00255
	(0.12)	(-0.42)
T	1.57	1.999*
	(0.86)	(1.92)
TOP	0.116***	0.0674***
	(3.76)	(3.39)
TTOP	0.0274	0.0659***
	(0.76)	(2.71)
NBED	-0.184*	-0.0265
	(-1.80)	(-0.35)
TNBED	-0.00432	-0.0772
	(-0.04)	(-0.80)
OBED	-0.346***	-0.361***
	(-3.25)	(-4.74)
TOBED	-0.00261	-0.135
	(-0.02)	(-1.39)
TBED	-0.160**	-0.0645
	(-2.33)	(-1.28)
TTBED	0.0217	0.115*
	(-0.27)	(-1.95)
NBATH	-0.0763	-0.207**
	(-0.53)	(-2.07)
TNBATH	-0.452	-0.15
	(-1.56)	(-1.09)
OBATH	-0.226*	-0.249***
	(-1.76)	(-2.80)
TOBATH	-0.457*	0.06
	(1.67)	(-0.49)
TBATH	-0.000526	-0.108
	(-0.00)	(-1.17)
TTBATH	-0.42	-0.01
	(-1.53)	(-0.08)
Parking	-0.0679	-0.0607
	(-1.17)	(-1.56)
Tparking	-0.0129	-0.0292
	(-0.19)	(-0.63)
Garden	0.0115	0.0461
	(0.2)	(1.06)
Tgarden	0.0525	-0.0382
	(0.77)	(-0.73)
District	0.000793*	0.00102
	(1.83)	(0.45)
Tdistrict	-0.000602	(0.00124)
	(-1.17)	(0.44)
_cons	10.73***	5.988***
	(7.4)	(6.79)
N	1411	1471
R^2	0.243	0.43
t statistics in parentheses		
** p < 0.10, ** p < 0.05, *** p < 0.01*		

6.1. Impact of School Quality (ATP and ATS)

Table 3 indicates that in London, ATP (attendance rate for primary schools) significantly influences house prices, particularly before the pandemic. At a 10% significance level, a 1% increase in ATP is associated with a 2.7% increase in house prices predicted before the pandemic. However, during and after the pandemic, the same increase in ATP leads to only a 1.5% increase in house prices, indicating a decreased correlation between school quality and house prices. This change suggests that while school quality remains a factor, its influence has diminished during the pandemic, likely due to shifts in household priorities, such as preferences for larger homes or those located away from urban centres.

Interestingly, the coefficient of TATP (time interaction term with ATP) is not statistically significant in Table 4, implying that the pandemic did not significantly alter the causality between primary school quality and house prices. However, the significant decrease in the impact of ATP suggests other factors might be overriding the influence of school quality during the pandemic. On the other hand, ATS (attendance rate for secondary schools) shows no significant effect on house prices in all periods. This lack of significance suggests that proximity to high-quality secondary schools does not notably affect property values, possibly because secondary school admissions in large cities like London are less dependent on proximity compared to primary schools.

6.2. Impact of Other Variables

The analysis of other variables reveals that property-specific characteristics have gained more importance during the pandemic. Before the pandemic, variables such as TBED (three bedrooms), TOP (property type), and OBED (other bedrooms) were significant alongside ATP. However, during and after the pandemic, almost all property characteristics became significant predictors of house prices except ATS. This shift implies that during the pandemic, buyers placed more emphasis on the physical features of properties—such as the number of bedrooms, type of dwelling, and availability of amenities—rather than the quality of nearby schools. The significance of the District variable in both periods underscores the importance of accounting for unobserved neighbourhood characteristics. The district dummies effectively capture fixed effects that influence house prices beyond observable factors, reaffirming the robustness of the regression model. This highlights that while property-specific attributes became more critical during the pandemic, location-based factors still play a consistent role in determining property values.

Overall, the findings align with the broader question of how the pandemic has affected the traditional house price premium associated with good state schools. The results suggest that while school quality continues to impact house prices, its effect has lessened, with buyers prioritizing property characteristics over proximity to good schools during the pandemic. This indicates a shift in market dynamics, driven by changing lifestyle and space preferences as a response to the pandemic, which could have long-term implications for the housing market and educational access in urban areas like London.

7. Discussion and Evaluation

The results highlight several critical insights into the relationship between school quality and house prices in London and Bristol, particularly before, during, and after the COVID-19 pandemic. The findings illustrate how the pandemic influenced this dynamic and shed light on broader socio-economic implications.

7.1. Impact of Primary School Quality

The coefficient estimator of ATP (attendance rate for primary schools) is less significant and decreased during and after the pandemic compared to the pre-pandemic period. This reduction in significance could be attributed to changes in educational dynamics during the pandemic, such as students preferring to study at home or adopting online learning methods due to school closures and health concerns (Permatasari, 2021). These factors may have created uncertainty in assessing school quality, as highlighted by Shepherd and Mohohlwane (2021), who pointed out that new teaching methods and attendance tracking during the pandemic have further muddled perceptions of school quality. Although the significance of ATP decreased, the positive correlation between primary school quality and house prices still exists, implying that proximity to good primary schools remains important if the "nearest" principle continues to be a key criterion for school admissions.

7.2. Impact of Secondary School Quality (ATS)

The coefficient estimator of ATS (attendance rate for secondary schools) is not significant in any period, which aligns with the differences in admission criteria between primary and secondary schools. Secondary schools tend to prioritize student ability and aptitude over proximity, as noted by West (2011). Additionally, secondary school enrolment often depends on the primary school attended, meaning the effect of primary school quality already captures much of the influence on house prices, rendering the ATS coefficient insignificant.

7.3. Effect of the Pandemic on School Quality and House Prices

Table 4 shows that the coefficients for the interaction terms TATP and TATS are not significant, suggesting that the pandemic did not significantly alter the causal relationship between school quality and house prices. Instead, the focus has shifted towards property-specific characteristics, such as the type and size of the dwelling, as shown in Table 3. This indicates that while the pandemic did not change the underlying effect of school quality on house prices, it made property attributes more critical in housing decisions.

7.4. Comparative Insights between London and Bristol

Both London and Bristol show significant ATP coefficients before the pandemic, suggesting that buyers in both large and smaller cities prioritize proximity to high-quality primary schools to secure better education for their children. This trend could exacerbate income inequality, as only wealthier families can afford homes near the best schools, perpetuating a cycle of limited social mobility and negative impacts on broader societal equity. In contrast, the ATS coefficient is significant in Bristol but not in London, indicating that smaller cities may still rely on proximity for secondary school admissions, unlike larger cities where academic selection is more prevalent. Moreover, the higher coefficient values for ATP in Bristol compared to London suggest that the relationship between primary school quality and house prices is more pronounced in smaller cities. This difference may be due to lower population density and fewer schooling options, making access to quality education more competitive and closely tied to housing location.

7.5. Socioeconomic Implications During and After the Pandemic

The insignificant coefficients for TATP and TATS in both London and Bristol during and after the pandemic imply that the correlation between school quality and house prices remains stable despite the economic challenges posed by the pandemic. This stability highlights that education is seen as a "necessary good" for residents, and families continue to prioritize access to quality schools even in the face of financial hardship (Petrosky-Nadeau, 2020). However, this persistence in the correlation does not mean the broader social conditions remain unchanged. The pandemic-induced economic recession, rising unemployment, and declining GDP per capita have intensified pressures on low-income families, further entrenching income inequality and limiting access to quality education for children from less affluent backgrounds.

The findings underscore that while the pandemic has shifted buyer preferences towards property characteristics, the enduring link between school quality and house prices continues to reflect systemic issues of educational inequality. Addressing these challenges requires targeted policies to improve equitable access to education and mitigate the widening income disparity that restricts social mobility in England.

8. Limitations

8.1. Explanatory Variable Suitability

One key limitation is the potential inadequacy of the attendance rates (ATP and ATS) as explanatory variables, particularly during and after the pandemic. The insignificant coefficients of ATP and ATS in these periods suggest that attendance rates may no longer effectively measure school quality, especially for secondary schools. Schwartz et al. (2021) highlighted improvements in the methods of measuring attendance, which may have weakened the correlation between attendance rates and perceived school quality. Consequently, while house prices may still be influenced by school quality, buyers may no longer rely on attendance rates as a reliable indicator during and after the pandemic. Future research should explore alternative variables that could better capture school quality under these changed circumstances.

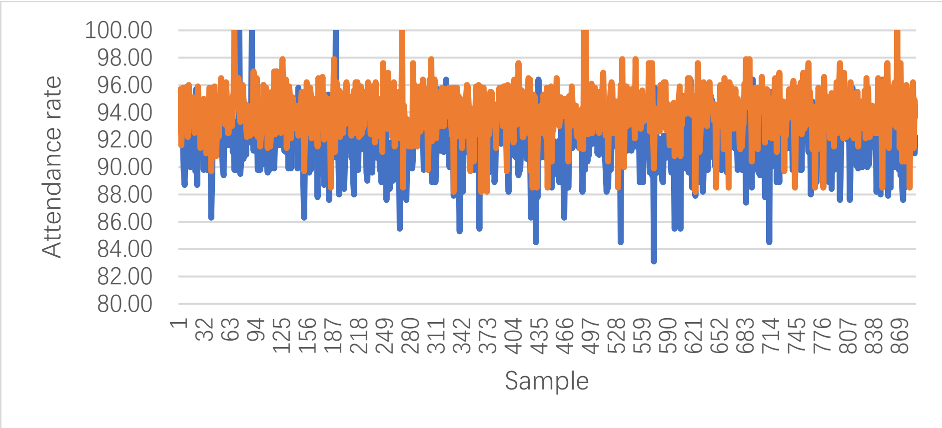

Figure 1. Line chart of ATP and ATS showing attendance rate variability

8.2. Omitted Variable Issues

Another significant limitation involves potential omitted variable biases, as identified in the diagnostic tests, particularly for the during and after pandemic period. High correlation between ATP and ATS, as illustrated in Figure 1, suggests that these variables may not fully capture the relationship between school quality and house prices. Adding interaction terms between ATP and ATS or conducting further tests on their relationship could help mitigate this bias. Additionally, the pandemic has introduced new factors that might influence house prices, such as proximity to industries capable of remote work. Qin et al. (2020) noted that people increasingly prefer neighbourhoods conducive to remote work, which may enhance property values. Future studies should consider these emerging variables to better understand how economic shifts during the pandemic have reshaped the housing market.

8.3. Sample Source and Size

This project relies solely on data from Rightmove, a limitation that could affect the representativeness of the findings. Not all house sales are captured on this platform, potentially leading to selection bias. Expanding the data sources to include other real estate websites or additional channels would provide a more comprehensive dataset, allowing for deeper and more robust analysis. Increasing the sample size and diversity of data would help address this issue, making the results more applicable to the broader market.

These limitations highlight areas where further research and refinement are needed to enhance the understanding of the relationship between school quality and house prices, especially in the context of the evolving economic environment during and after the pandemic. By addressing these issues, future studies can provide more accurate and comprehensive insights into the dynamics of the housing market.

9. Conclusion

This project utilized cross-sectional data to examine the impact of school quality on house prices in London and Bristol, focusing on how these relationships evolved during the COVID-19 pandemic. The findings indicate that primary school quality positively correlates with house prices both before and during the pandemic, although the strength of this relationship has diminished. This suggests that while proximity to high-quality primary schools remains important to homebuyers, the pandemic has slightly weakened its influence as other factors, such as property characteristics, gained prominence.

For secondary schools, the results reveal a contrasting dynamic between large cities like London and smaller cities such as Bristol. In smaller cities, the "nearest" principle still plays a crucial role in school admissions, making school quality a significant factor in determining house prices. However, in larger cities where secondary school admissions prioritize academic ability and other criteria over proximity, school quality has a less pronounced impact on property values. This geographic variation highlights how local education policies and urban characteristics influence the housing market.

In sum, the study underscores the persistence of the poverty cycle, where access to high-quality education remains largely confined to high-income families who can afford homes near better schools. This perpetuates income inequality and limits social mobility, as wealthier families continue to secure educational advantages for their children. The pandemic has not altered this fundamental issue; instead, it has reinforced education as a "necessary good," with families still willing to invest heavily in housing to access better schools, even under economic strain. Addressing these deep-rooted disparities will require targeted policy interventions to improve equitable access to high-quality education and reduce the widening gap between socio-economic groups, ensuring that educational opportunities are not limited by financial means or geographic location.

References

[1] Badarinza, C., & Ramadorai, T. (2018). Home away from home? Foreign demand and London house prices. Journal of Financial Economics, 130(3), 532-555.

[2] Bartanen, B. (2020). Principal quality and student attendance. *Educational Researcher, 49*(2), 101-113.

[3] Bashir, A., Bashir, S., Rana, K., Lambert, P., & Vernallis, A. (2021, August). Post-COVID-19 adaptations; the shifts towards online learning, hybrid course delivery and the implications for biosciences courses in the higher education setting. In Frontiers in education (Vol. 6, p. 711619). Frontiers Media SA.

[4] Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *Quarterly Journal of Economics, 114*(2), 577–599.

[5] Chiodo, A., Hernández-Murillo, R., & Owyang, M. (2010). Nonlinear effects of school quality on house prices. *The Review of Economics and Statistics, 92*(3), 185-204.

[6] Dorn, E., Hancock, B., Sarakatsannis, J., & Viruleg, E. (2021). COVID-19 and education: The lingering effects of unfinished learning. McKinsey & Company, 27.

[7] Edwin, M., Pestman, W., Anthonius, W., Svetlana, B., & Klungel, O. H. (2006). Instrumental variables: Application and limitations. *Epidemiology, 17*(3), 260-267.

[8] Gallent, N., & Hamiduddin, I. (2021). COVID-19, second homes and the challenge for rural amenity areas. Town Planning Review, 92(3), 395-401.

[9] Gallent, N., Stirling, P., & Hamiduddin, I. (2023). Pandemic mobility, second homes and housing market change in a rural amenity area during COVID-19–The Brecon Beacons National Park, Wales. Progress in Planning, 172, 100731.

[10] Gibbons, S. (2003). Valuing English primary schools. *Journal of Urban Economics, 53*(2), 197-219.

[11] Gibbons, S., Machin, S., & Silva, O. (2013). Valuing school quality using boundary discontinuities. Journal of Urban Economics, 75, 15-28.

[12] Hill, R. (2012). Hedonic price indexes for residential housing: A survey, evaluation and taxonomy. *Journal of Economic Surveys, 27*(5), 879-914.

[13] Julaily, J., Ahmad, N., Lowai, A., Abdullah, A., Syarilla, S., Khairi, A., Rajina, R., Ravindran, P., & Yousef, A. (2021). Track student attendance at a time of the COVID-19 pandemic using location-finding technology. *2nd International Conference on Smart Computing and Electronic Enterprise (ICSCEE, 10*, 147-152.

[14] Nathwani, G., Shoaib, A., Shafi, A., Furukawa, T. A., & Huy, N. T. (2021). Impact of COVID-2019 on school attendance problems. *Journal of Global Health, 11*.

[15] Permastasari, A., & Oktiawati, U. (2021). Preferred online learning method during COVID-19 pandemic: A students' perspective. *Journal of Educational and Social Research, 11*(1), 1-9.

[16] Petrosky-Nadeau, N., & Valletta, R. (2020). Unemployment paths in a pandemic economy. *IZA Institute of Labor Economics, No. 13294*.

[17] Qin, B., Peng, Y., & Feng, L. (2023). The impacts of pandemic on urban housing prices: Evidence from the outbreak of COVID-19 in Beijing, 2020. *International Journal of Housing Markets and Analysis, 16*(3).

[18] Rightmove (2020). Available at https://www.rightmove.co.uk/house-prices/london-87490.html?soldIn=5&page=40(Accessed 6 May 2024).

[19] Rosenthal, L. (2003). The value of secondary school quality. *Oxford Bulletin of Economics and Statistics, 65*(3), 329-355.

[20] Santibanez, L., & Guarino, C. M. (2021). The effects of absenteeism on academic and social-emotional outcomes: Lessons for COVID-19. Educational Researcher, 50(6), 392-400.

[21] Schwartz, K. D., Exner-Cortens, D., McMorris, C. A., Makarenko, E., Arnold, P., Van Bavel, M., ... & Canfield, R. (2021). COVID-19 and student well-being: Stress and mental health during return-to-school. Canadian journal of school psychology, 36(2), 166-185.

[22] Shepherd, D., & Mohohlwane, N. (2021). The impact of COVID-19 in education–more than a year of disruption. National Income Dynamics (NIDS)-Coronavirus Rapid Mobile Survey (CRAM) Wave, 5, 1-41.

[23] United Kingdom public sector information website (2012). Available at https://www.gov.uk/?_ga=2.38666339.1304714855.1715459566-425615195.1714775542 (Accessed 6 May 2024).

[24] Wang, M. T., & Degol, J. L. (2016). School climate: A review of the construct, measurement, and impact on student outcomes. Educational psychology review, 28(2), 315-352.

[25] West, A., Barham, E., & Hind, A. (2011). Secondary school admissions in England 2001 to 2008: Changing legislation, policy, and practice. *Oxford Review of Education, 37*(1), 1-20.