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Does Proximity to School Still Matter Once Access to Your Preferred School Zone Has Already Been Secured?

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Abstract
This paper examines the relationship between proximity to secondary schools and property values within three school enrollment zones in Auckland, New Zealand. Results indicate that, in the most sought-after school zone, house prices increase with proximity to school but decrease above 3.664 km. Moreover, we find that the nonlinear effects are most prominent at the lower quantile of the sales price distribution. In the other two school zones, proximity to school reduces house prices. These results demonstrate that distance to school still matters within each school enrollment zone.

Keywords House prices · School proximity · Attendance zone · Hedonic · Quantile

Introduction

In the United States, public schools are free of tuition, but households pay indirectly for higher quality education by bidding up house prices in better quality school districts in real estate markets (Owusu-Edusei et al. 2007). Over the world, many countries have public school enrollment policies that are tied to residential locations. Enrollments at elementary or secondary schools are restricted to students living in a geographically defined area, usually a small neighborhood near the school. As a

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result, households who value a school will be willing to pay a premium to live in the enrollment area defined by that school. Nevertheless, in some areas, the enrollment zone refers to a single school attendance boundary (e.g., School Enrollment scheme in New Zealand), whereas in other areas it means the students living in a specific geographic area have guaranteed enrollment at one of several schools in the zone, not just one particular school (e.g., school district in US). The existing literature abounds with evidence of capitalization of school quality[1]) and school admission[2]) into house prices, typically by comparing property prices on the boundary of the attendance zone (e.g., Black 1999). Proximity to schools, however, is relatively less investigated. On the one hand, proximity to the desired school can be seen as an amenity as it reduces travel time and travel costs (e.g., Weimer and Wolkoff 2001). On the other hand, proximity to schools imposes adverse effects on property prices as a result of increased noise level, traffic congestion, and crime rates (e.g., Guntermann and Colwel 1983).

This paper utilizes the state school enrollment scheme in New Zealand which restricts admissions to families living within a school's delineated boundaries, and develops the existing work on proximity to schools by assessing the role of proximity to a secondary school on housing prices once access to that school has been secured (i.e., being located in that school's enrollment zone). Adopting both the standard hedonic and quantile regression approaches, we find that capitalization of proximity to school is nonlinear, changes across the price distribution, and varies by the popularity of schools. Specifically, in our four-school sample, our results show that house prices increase with proximity to school but decrease above 3.664 km in the most sought-after school zones. On the other hand, house prices decrease with proximity to school in the other two school zones. Moreover, we find that the effects of proximity to school are most prominent at the lower quantile of the sales price distribution in the most sought-after school zone. We also find evidence that the impact of proximity to school is larger in magnitude when measured by driving distance rather than driving time.

The findings in this paper contribute to the body of research that studies proximity to schools and property values (early contributions include Emerson 1972, and Hendon 1973). Several studies evaluate both positive (e.g., safety and shorter travel time) and negative impacts (e.g., noise, traffic jam and trampled lawns) of proximity to primary schools (e.g., primary schools in Lubbock, Texas, studied in Colwell 1983) and find that the positive effect dominates within a closer proximity to schools (e.g., 300 to 500 meters or 9 to 15 minutes walking distance from primary schools in Quebec found by Des Rosiers et al. 2001). More recently, Sah et al. (2016) introduce spatial heterogeneity in the effect of proximity to schools in San Diego County and find a positive (negative) externality of proximity to public (private) primary schools in inland areas but a negative one of both types of schools in

[1]Papers that study school quality include Bayer et al. (2007), Black (1999), Black and Machin (2011), Bogart and Cromwell (1997, 2000), Downes and Zabel (2002), Ferreyra (2007), Gibbons et al. (2013), Nguyen-Hoang and Yinger (2011) and Weimer and Wolkoff (2001).

[2]Papers that evaluate school admission include (Brunner et al. (2012), Epple and Romano (2003), Ferreyra (2007), Machin and Salvanes (2016), Reback (2005), and Schwartz et al. (2014), and Bonilla-Mejía et al. (2020).

coastal areas. However, the authors do not pinpoint the source(s) of this heterogeneity. Another two studies evaluate proximity to all school levels (elementary, middle, and high schools). Owusu-Edusei et al. (2007) suggest that, in general, the house prices in Greenville, South Carolina, are higher within closer proximity to elementary and middle schools. High schools, on the other hand, depress nearby house prices due to more nighttime activity and light. Huang and Hess (2018) use quantile regression and estimate the median marginal effect of distance to schools in Oshkosh, Wisconsin, and conclude that the median sales price decreases with distance to the nearest elementary, middle, and high schools.

This paper extends the current literature and provides evidence on the role of proximity to secondary schools within four state secondary school enrollment zones in Auckland, New Zealand. We acknowledge the nonlinearity of proximity to schools and take advantage of the quantile regression to investigate if school proximity is valued differently in different submarkets (i.e., different points of the distribution of property price) instead of a single expected mean estimation for each school zone.

The rest of the paper is composed as follows: "Auckland Housing Market" describes Auckland's housing market and the selected geographic area of our study. Section "Hedonic Price Model" presents the empirical strategy, the hedonic model, and our quantile regressions. Section "Data" describes the data and their source. Estimation results are presented and discussed in "Empirical Results". The last section summarizes the results and offers some concluding remarks.

Auckland Housing Market

The Economic Outlook (2017) of the Organization for Economic Cooperation and Development (OECD) shows that New Zealand experienced the highest increase in the housing price-to-income ratio index and price-to-rent ratio index since 2013 and 2011 respectively. Indeed, Auckland's property prices have increased by 77.5% between 2011 and 2016, and the average house price reached 1 million New Zealand dollars (NZ$, equivalent to $USD 671,330) for the first time in 2016. Since 2012, the median housing prices in Auckland have inflated from almost 7 times the median household income to 10 times in 2017. As a result, Auckland is now ranked the world's fourth least-affordable housing market with more than one million inhabitants after Hong Kong, Sydney, and Vancouver (Demographia International Housing Affordability Survey, 2017).

New Zealand, like many countries, has public school enrollment policies tied to residential locations. Enrollments at state elementary or secondary schools are restricted to students living in a geographically defined school zone. Within the context of the soaring housing market in Auckland, there are significant neighborhoods such as the "Double Grammar Zone (DGZ)" that have contributed significantly to the inflation of property values. The DGZ references an overlapping area of enrollment zones of Auckland Grammar School (AGS) and Epsom Girl's Grammar School (EGGS). Both schools are prestigious state secondary schools for children aged 13 to 17 but respectively serving boys and girls only. As shown in Fig. 1, AGS enrollment zone (orange) and EGGS enrollment zone (pink) overlap. The overlapped

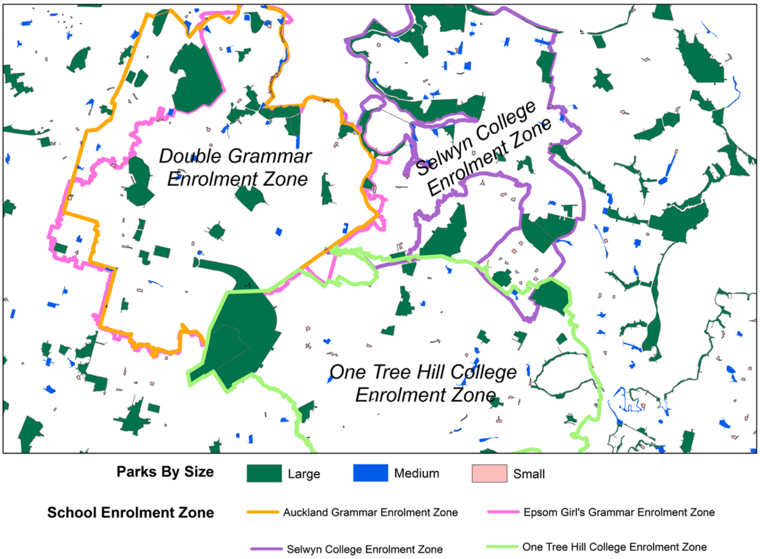

Fig. 1 Study Area – Enrollment Zones and Parks. Note: This figure shows the locations of parks in the study area. In the Auckland region, there are 3,051 parks in total according to Auckland Council's Park Extent Map. Parks are divided into three groups: the bottom third are defined as small parks, the middle third are defined as medium parks, and the top third are defined as large parks. Figure also shows the enrollment zones of four secondary schools in the study are. Information on school zones is from Enrolment Scheme Master downloaded from Education Counts

DGZ is the most sought-after, which is reflected in the mean housing price of at least NZ$225,000, a value 12% higher than the mean housing price in the rest of Auckland. However, it is unlikely that all the houses in DGZ enjoy the same price premium and price appreciation.

Figure 1 also displays two other neighboring school enrollment zones. On the southeastern and northeastern parts of the study area lie One Tree Hill College and Selwyn College respectively. Both are state coeducational secondary schools. The enrollment zone of each of these two schools was defined on January 1, 2015.

Hedonic Price Model

We rely on the theoretical model of Rosen (1974) to estimate the role of the property attributes and their values. Typically, there are three categories of attributes that are evaluated in a hedonic model: 1) structure attributes such as floor area, lot size, number of bedrooms, and housing age; 2) community and amenity attributes such as average neighborhood income and air quality; and 3) locational attributes such as the distance from the Central Business District and proximity to neighborhood parks. In theory, any house can be described as a vector of attributes with values $Z = Z(z_1, z_2, \ldots, z_K)$. In practice, the majority of empirical hedonic studies use the following linear model to be estimated in a single year or over cross-sectional data pooled over time:

$$logP_{it} = \sum_{k=1}^{K} \beta_k z_{it,k} + \sum_{t=1}^{T} \alpha_t D_{it} + \epsilon_{it}, i = 1, \ldots, N, \epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2) \quad (1)$$

where $logP_{it}$ is the logarithm of the sale price of house i at time t ($t = 1, \ldots, T$); $z_{it,k}$ represents observed structure, community, amenity and location attributes k of house i at time t; D_{it} is a time dummy variable with value 1 if house i is sold at time t and 0 otherwise and ϵ_{it} is a random error term. In this specification, the marginal effects of housing attributes (β_k) are constant over time and the quality-adjusted house price indexes can be calculated by taking the exponent of the series of the estimated time dummy variables $\hat{\alpha}_t$.

The location premium of a house is typically represented by accessibility to the central business district (CBD, the primary employment center), schools, shopping centers, parks and other local amenities (e.g., Basu and Thibodeau 1998 and Powe et al. 1995). For instance, Chin and Foong (2006) find that the effect of school accessibility on property values varies with distance to the CBD and the performance of a school. As a result, we control for the first-order interaction of distance to school and distance to CBD. Moreover, we allow the distance to school and the CBD to vary nonlinearly. The latter variable appears in the hedonic models of, among others, Anderson and West (2006) and Halstead et al. (1997) and Rasmussen and Zuehlke (1990).

In addition, studies such as Bolitzer and Netusil (2000) and Lutzenhiser and Netusil (2001) and Voicu and Been (2008) have demonstrated that different open space types, such as natural parks and specialty parks, have different degrees of impact on property values. They also find that there is an optimal open space size that maximizes house prices. In the absence of information about the type and amenities available at each park, we will follow Halper et al. (2015) by grouping parks according to their size and including the accessibility to the nearest park of each of three categories (small, medium and large parks, as defined by each tercile of the size distribution) in our hedonic model:

$$\begin{aligned} logP_{it} = {} & \beta_1 dschool_{it} + \beta_2 dschool_{it}^2 + \beta_3 dcbd_{it} + \beta_4 dcbd_{it}^2 \\ & + \beta_5 (dschool_{it} \times dcbd_{it}) + \beta_6 dshop_{it} + \beta_7 dbeach_{it} + \beta_8 dsmallpark_{it} \\ & + \beta_9 dmediumpark_{it} + \beta_{10} dlargepark_{it} + \sum_{k=1}^{K} \alpha_k S_{it,k} + \sum_{t=1}^{T} \gamma_t DY_{it} \\ & + \sum_{p=1}^{P} \lambda_p DP_{it} + \epsilon_{it}, i = 1, \ldots, N, \epsilon_{it} \sim \mathcal{N}(0,\ \sigma_\epsilon^2) \end{aligned} \quad (2)$$

where $dschool_{it}$ and $dcbd_{it}$ are the driving distances from house i at time t to the school it is associated with and to the CBD respectively. $dshop_{it}$ and $dbeach_{it}$ are the driving distances from each house to the nearest shopping center and the nearest beach, respectively. When it comes to the latter, we select only beaches where swimming is safe. $S_{it,k}$ is a set of observed characteristics of the structure. They include the logarithm of the floor and land areas, the building age, the number of bedrooms, the number of bathrooms, the number of car parks, the types of wall construction, the types of roof, and land slope class. DY_{it} is a year dummy with value 1 if house i is sold at year t and 0 otherwise. DP_{it} is a neighborhood dummy with value 1 if house i is in Postcode zone p and 0 otherwise. Postcode zones in New Zealand do not map precisely to standard geographic classification. In other words, one cannot combine meshblocks, the counterpart of U.S. census blocks, to create a postcode. The study area consists of 9 postcodes. They have an average size of 4.37 square miles. Previous studies, including Des Rosiers et al. (2000) and Nelson (1977) and Ottensmann et al. (2008), demonstrate that models with travel time to employment centers, schools, parks, and transportation stations perform better than simple geographic distance. We will investigate if travel time as the alternative measure of proximity leads to similar results.

With Eq. 2, the marginal effect of driving distance to school on log of house price is obtained as follows:

$$\frac{\partial log P_{it}}{\partial dschool_{it}} = \beta_1 + 2\beta_2 \times dschool_{it} + \beta_5 \times dcbd_{it} \tag{3}$$

It shows that the marginal effect of driving distance to school is a linear function of driving distance to the school itself and driving distance to CBD. That is the marginal effect of $dschool$ depends on $dschool$ and on $dcbd$ too. Suppose $dcbd = 0$, each additional kilometer driven from the school changes the price of a house by $\beta_2\%$. The sign of β_2 determines whether driving distance to school has an increasing or decreasing marginal effect on the log of the sales price. Since $dcbd$ is never 0, the effect of driving distance to school is not constant neither; it changes depending on the driving distance to the CBD at any given driving distance from school.

All the previous specifications assume that the enrollment zones are mutually exclusive. When a house has access to more than one enrollment zone (DGZ in the study sample), we then need to include the accessibility (either driving distance or driving time) to both schools and to allow the first-order interaction between each school and the CBD:[3]

$$\begin{aligned} log P_{it} = {} & \beta_1 dAGS_{it} + \beta_2 dAGS_{it}^2 + \beta_3 dEGGS_{it} + \beta_4 dEGGS_{it}^2 \\ & + \beta_5 (dAGS_{it} \times dcbd_{it}) + \beta_6 (dEGGS_{it} \times dcbd_{it}) + \sum_{a=7}^{13} \beta_a d_{it,a} \\ & + \sum_{k=1}^{K} \alpha_k S_{it,k} + \sum_{t=1}^{T} \gamma_t DY_{it} + \sum_{p=1}^{P} \lambda_p DP_{it} + \epsilon_{it}, i = 1, \dots N, \\ & \epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2) \end{aligned} \tag{4}$$

where $d_{it,a}$ includes the driving distances (or time) to the CBD, its square value, driving distance (time) to the nearest shopping center, to the beach, and to the three

[3] Interaction between the schools was considered initially; however, the empirical model performs better without this interaction. All the results are available from the authors upon request.

types of parks. As a result, in DGZ, the marginal effect of the driving distance to one of the schools, say AGS, has the following form:

$$\frac{\partial log P_{it}}{\partial dAGS_{it}} = \beta_1 + 2\beta_2 \times dAGS_{it} + \beta_5 \times dcbd_{it} \tag{5}$$

In Eqs. 2 to 5 above, the marginal effect of distance to school on the house prices is calculated at the mean. Nevertheless, the mean may mask significant heterogeneity of this marginal effect in price submarkets defined as different points in the price distribution (e.g., McMillen 2012, Liao and Wang 2012, and Zietz et al. 2008). For instance, proximity to school could add a price premium on only a portion of the houses, such as houses in the lower price range. Houses in the higher price range could have attractive features and spacious designs that are more important to the households than proximity to schools. As a result, we complement the results above with the conditional quantile regression techniques introduced by Koenker and Hallock (2001). Quantile regression methods have been widely used in many fields see Fitzenberger et al. 2013, for a review) but, in economics, they have been primarily used in labor economics (e.g., Fitzenberger et al. 2002 and Koenker and Bilias 2002 and education economics e.g., Arias et al. 2002 and Levin 2002).

The conditional quantile regression at the q^{th} quantile, the quantile version of Eq. 1, can be written as:

$$Q_{log P_{it}|z_{it},d_{it}}(q) = \sum_{k=1}^{K} \beta_k(q) z_{it,k} + \sum_{t=1}^{T} \alpha_t(q) D_{it} + \epsilon_{it}, i = 1, \ldots N, \epsilon_{it} \sim \mathcal{N}(0,\ \sigma_\epsilon^2) \tag{6}$$

where $q \in (0, 1)$ denotes a specific quantile level in sales price distribution. In this specification, estimated coefficients vary by quantile levels, i.e. different points of the sales price distribution.

Data

Monthly unit transaction sales data used in this paper were obtained from Quotable Value Limited (QV) powered by CoreLogic NZ Ltd, which is responsible for conducting property market valuations in New Zealand. Purchased monthly data encompasses three neighboring enrollment zones of four state secondary schools in Auckland, AGS, EGGS, Selwyn College and One Tree College, and covers the period from January 2007 to December 2016. Basic QV data used in this paper include the sales prices, the sales date, the property address, the floor area, the land area, various structural characteristics (such as the number of bedrooms and bathrooms), the school zone to which a house is associated. The analytical sample includes all types of houses, apart from apartments. In total, there are 17,966 observations. Dropping observations without sales prices results in 17,796 transactions from 13,284 unique properties. In addition, we exclude 114 observations built on industrial or commercial land, 13 observations (12 unique properties) that are not for residential use. We also exclude properties that are not fully detached or semi-detached units situated on their own clearly defined piece of land, as well as all observations with incomplete information on land and floor area. With all these restrictions, our sample ends up including 10,052 observations.

An examination of the data reveals that sales price, land area, and floor area are all skewed to the right. Hence, the bottom 1% and the top 5% of the sales prices are dropped first. Then the bottom and top 1% of each of the land and floor areas also are trimmed. A further filtering step is taken to drop outliers that we define as houses with more than 5 bathrooms or 5 bedrooms. In the end, the sample reduces to 9,016 observations.

Driving distance and driving time are both calculated via Google Map in R using a pessimist traffic mode. For the driving time, we arbitrarily set the calculation to Monday, March 11th, 2019, with a departure time of 8:00 am (schools start at 8:30 am). This time is chosen as a default to specifically highlight the benefit of living close to a school, i.e. avoiding the morning traffic hours when dropping off children at school. Both driving distance and driving time will be considered because they are not always perfectly collinear. For example, longer driving distance on a highway with high speeds may result in a shorter driving time. Table 1 displays the Pearson correlation test results and associated p-value between driving distance and driving time for each school zone. The results indicate that, while driving distance and time to the schools of interest are very similar (correlation test above 85%),

Table 1 Pearson Product-Moment Correlations of Driving Distance and Driving Time

Variable	1	2	3	4	5	6
(a) Double Grammar Zone ($N = 3,037$)						
1. Driving Distance to AGS	–					
2. Driving Time to AGS	0.870***	–				
3. Driving Distance to EGGS	0.764***	0.851***	–			
4. Driving Time to EGGS	0.769***	0.898***	0.940***	–		
5. Driving Distance to CBD	0.662***	0.467***	0.241***	0.228***	–	
6. Driving Time to CBD	0.601***	0.532***	0.332***	0.348***	0.746***	–
(b) Selwyn College Zone ($N = 3,082$)						
1. Driving Distance to Selwyn College	–					
2. Driving Time to Selwyn College	0.988***	–				
3. Driving Distance to CBD	0.179***	0.227***	–			
4. Driving Time to CBD	-0.448***	-0.369***	0.701***	–		
(c) One Tree Hill College Zone ($N = 2,231$)						
1. Driving Distance to One Tree Hill College	–					
2. Driving Time to One Tree Hill College	0.943***	–				
3. Driving Distance to CBD	0.730***	0.663***	–			
4. Driving Time to CBD	0.844***	0.859***	0.870***	–		

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. These tables present the Pearson Product-Moment correlation coefficients of driving distance and driving time to school and CBD in each of the three school enrollment zones. CBD represents Central Business District. In panel (a), AGS represents Auckland Grammar School. EGGS represents Epsom Girl's Grammar School driving distance and time to the CBD are slightly less so (correlation test is 70% and above).

The list of shopping centers is provided in Appendix Table 7. For each house, the driving distance and driving time to the nearest shopping center is calculated via Google Map in R using a pessimist traffic mode.

When it comes to accessibility to the beach, we rely on Auckland City Council's Safeswim website (https://safeswim.org.nz) to get access to information on water quality and swimming conditions (low, high, very high risks) at each beach. Water quality changes with weather conditions, such as the amount of rainfall, the wind, the tide and sunlight, and the type of beach. As a result, the suitability and safety of a beach to swimmers change with the weather. Therefore, we excluded from our sample all the beaches that have a long-term water quality alert and end up with 17 beaches of which names are provided in Appendix Table 8. Driving distance and driving time between each house and the nearest beach is calculated via Google Map in R using a pessimist traffic mode too.

The driving distance and driving time to the nearest park require to get the location and size of each park from Park Extent, a database from Auckland's City Council. Figure 1 maps the location of the city parks as well as the boundaries of each of the three enrollment zones present in the study area. We assume the level of attractiveness of each park is entirely based on its relative size. As such, we classify them into three groups based on the tercile of the size distribution to which they belong.

Information about land slope is created from a 2013 light detection and ranging (LiDAR) 1-meter resolution digital elevation model (DEM) fitted to the map of New Zealand Primary Land Parcels using ArcGIS. Mean slopes are then divided into six broad groups according to the slope classes from the Land Resource Information System (LRIS): flat to gently undulating (0 - 3°), undulating (4 - 7°), rolling (8 - 15°), strongly rolling (16 - 20°) moderately steep (21 - 25°) and steep (26 - 35°).

Summary statistics for the final analytical sample of 8,386 observations are shown in Table 2. 36.64%, 36.75%, and 26.60% of our observations are from DGZ, Selwyn college, and One Tree Hill college zones respectively. On average, houses in the DGZ are more expensive, older, with larger floors, land areas, and closer to the CBD than elsewhere. Within each school zone, the mean driving distance to school is about 3 km and the mean driving time to school ranges from 5 to 7.6 minutes, which is greater than the mean distance to the nearest school in the aforementioned papers e.g., Des Rosiers et al. (2001), report a mean Euclidean distance of 696 meters to the nearest school. The nearest shopping center is between 2 - 3 km (4.7 - 6.6 mins) drive away on average. The mean driving distances (time) to the nearest small, medium and large parks are about 0.8 km (2 mins), 1.1 km (2.6 mins), and 1.2 km (3 mins). Houses in the Selwyn College zone are in general closer to the beach. 43% of the sample is in the rolling slope range; hence, in the next section, the rolling slope group will be used as the benchmark in the estimation.

While we recognize that other factors such as air quality, neighborhood income, and crime rate are not included in this paper and may affect housing values, this information is not available for our sample. Clark and Herrin (2000) and Chin and Foong (2006) show that households value educational quality more than environmental and safety features. While we do not observe the latter two variables, we make the

Table 2 Summary Statistics

	Double grammar		Selwyn		One tree hill	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Log of Selling Price	14.22	0.40	13.86	0.42	13.45	0.38
Log of Floor Area	5.40	0.34	5.33	0.33	4.95	0.33
Log of Land Area	6.46	0.39	6.30	0.40	6.34	0.36
Decade House Age	6.35	3.75	3.30	3.00	4.58	2.98
Number of Bathrooms	2.16	0.86	1.92	0.84	1.58	0.72
Number of Bedrooms	3.92	0.78	3.78	0.75	3.37	0.72
Number of Carparks	1.77	0.94	1.46	1.09	1.21	0.75
Wall: Brick	0.07	0.25	0.09	0.29	0.19	0.40
Wall: Roughcst	0.13	0.34	0.13	0.34	0.10	0.31
Wall: Iatherboard	0.66	0.47	0.41	0.49	0.51	0.50
Wall: Mixtured Materials	0.10	0.30	0.33	0.47	0.11	0.31
Wall: Other	0.04	0.20	0.04	0.20	0.09	0.28
Roof: Steel	0.41	0.49	0.58	0.49	0.54	0.50
Roof: Tile Profile	0.00	0.05	0.00	0.00	0.00	0.00
Roof: Other	0.59	0.49	0.42	0.49	0.46	0.50
Site Slope:						
Flat to gently undulating (0-3°)	0.10	0.30	0.06	0.23	0.20	0.40
Undulating (4-7°)	0.25	0.43	0.21	0.41	0.41	0.49
Rolling (8-15°)	0.43	0.50	0.50	0.50	0.34	0.47
Strongly rolling (16-20°)	0.12	0.33	0.15	0.35	0.05	0.22
Moderately steep (21-25°)	0.06	0.25	0.06	0.24	–†	–†
Steep (26-35°)	0.04	0.18	0.03	0.16	–†	–†
To Auckland Grammar:						
Driving Distance (Km)	3.41	1.20	–	–	–	–
Driving Time (Mins)	7.52	2.30	–	–	–	–
To Epsom Girl's Grammar:						
Driving Distance (Km)	2.93	0.98	–	–	–	–
Driving Time (Mins)	7.60	1.99	–	–	–	–
To Selwyn College:						
Driving Distance (Km)	–	–	2.87	1.39	–	–
Driving Time (Mins)	–	–	5.16	2.33	–	–
To One Tree Hill College:						
Driving Distance (Km)	–	–	–	–	2.82	1.02
Driving Time (Mins)	–	–	–	–	5.78	1.80
To CBD:						
Driving Distance (Km)	6.17	1.80	9.78	1.79	10.90	1.72
Driving Time (Mins)	15.50	1.83	20.67	1.94	18.33	1.78

Table 2 (continued)

	Double grammar		Selwyn		One tree hill	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
To Nearest Shopping Center:						
Driving Distance (Km)	2.31	0.73	2.03	0.97	2.72	1.06
Driving Time (Mins)	6.56	2.21	4.71	1.83	6.39	1.82
To Nearest Safeswim Beach:						
Driving Distance (Km)	4.30	1.47	3.64	2.03	5.45	1.48
Driving Time (Mins)	9.15	3.54	6.94	3.43	10.93	2.73
To Nearest Small Parks:						
Driving Distance (Km)	0.77	0.51	0.97	0.81	0.77	0.58
Driving Time (Mins)	2.25	1.37	2.32	1.76	1.97	1.36
To Nearest Medium Parks:						
Driving Distance (Km)	0.94	0.50	1.33	1.04	1.30	1.21
Driving Time (Mins)	2.32	1.12	2.96	2.10	2.86	1.90
To Nearest Large Parks:						
Driving Distance (Km)	1.10	0.62	1.17	1.01	1.51	0.96
Driving Time (Mins)	3.01	1.84	2.68	2.12	3.89	2.29
N	3,073		3,082		2,231	

Note: This table presents summary statistics from year 2007 to 2016 by each school zone. † In One Tree Hill College zone, 25 observations with moderately steep slopes and 5 with steep slopes were dropped. Structure characteristics variables are purchased from QV

assumption that their role is absorbed in the neighborhood fixed effects. If it turns out that these variables change in time, then their absence could bias our results even after controlling for neighborhood fixed effects.

Empirical Results

Equation 2 is estimated for Selwyn College and One Tree Hill College zones separately while Eq. 4 is estimated for DGZ. The results are presented in columns (1) to (6) of Tables 3 and 4. As expected, the coefficient estimates associated to the structural and site-specific characteristics (shown in Tables 3) do not differ much in terms of sign and magnitude when one moves from geographic to time distance.

Overall, land area is valued most in DGZ while floor area is valued most in the Selwyn College zone. Across the school zones, we find that the sales price increases by about 0.3 - 0.5% for every 1% increase in square floor area, 0.2 - 0.3% for every 1% increase in square land area, about 1 - 2% for each additional bedroom, and about 3 - 4% for each additional bathroom. These results are in line with the hedonic literature. However, the decade age effect is positive and significant in DGZ,

Table 3 Estimation Results: Structural Attributes

	Double grammar		Selwyn college		One tree hill college	
	Distance	Time	Distance	Time	Distance	Time
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Floor Area	0.465***	0.463***	0.486***	0.496***	0.320***	0.326***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.018)	(0.018)
Log of Land Area	0.314***	0.320***	0.313***	0.301***	0.226***	0.222***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.012)	(0.012)
Decade House Age	0.012***	0.011***	0.001	0.003	-0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Bedrooms	0.022***	0.020***	0.011	0.009	0.021***	0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Number of Bathrooms	0.044***	0.047***	0.031***	0.033***	0.036***	0.037***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Number of Carparks	-0.005	-0.005	-0.011**	-0.003	0.001	0.000
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Wall: Roughcst	-0.043**	-0.039**	0.004	0.005	0.007	0.005
	(0.018)	(0.018)	(0.017)	(0.018)	(0.013)	(0.013)
Wall: Weatherboard	0.010	0.012	0.044***	0.044***	0.035***	0.038***
	(0.017)	(0.017)	(0.014)	(0.014)	(0.009)	(0.009)
Wall: Mixed	-0.030	-0.027	0.058***	0.060***	0.003	0.013
	(0.021)	(0.021)	(0.016)	(0.016)	(0.012)	(0.013)
Wall: Other	0.027	0.032	0.045*	0.032	-0.017	-0.013
	(0.026)	(0.026)	(0.024)	(0.024)	(0.013)	(0.013)
Roof: Tile	0.120**	0.088				
	(0.058)	(0.059)				
Roof: Other	-0.022**	-0.022**	0.016*	0.017*	-0.009	-0.011
	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)
Flat to gently undulating (0-3°)	0.011	0.004	0.047***	0.058***	-0.012	-0.016
	(0.014)	(0.015)	(0.016)	(0.016)	(0.010)	(0.010)
Undulating (4-7°)	0.027***	0.021**	0.050***	0.046***	0.000	-0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)
Strongly rolling (16-20°)	-0.077***	-0.071***	-0.057***	-0.056***	-0.013	-0.007
	(0.014)	(0.014)	(0.012)	(0.012)	(0.015)	(0.015)
Moderately steep (21-25°)	-0.150***	-0.136***	-0.081***	-0.080***		
	(0.018)	(0.018)	(0.018)	(0.018)		
Steep (26-35°)	-0.179***	-0.167***	-0.072***	-0.076***		
	(0.028)	(0.028)	(0.027)	(0.026)		
2008 Sale	-0.035*	-0.036*	-0.067***	-0.072***	-0.068***	-0.069***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.014)	(0.014)
2009 Sale	-0.040**	-0.041**	-0.038**	-0.051***	-0.042***	-0.043***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.014)	(0.014)

Table 3 (continued)

	Double grammar		Selwyn college		One tree hill college	
	Distance	Time	Distance	Time	Distance	Time
	(1)	(2)	(3)	(4)	(5)	(6)
2010 Sale	0.027	0.031*	-0.028	-0.043**	-0.001	0.001
	(0.018)	(0.019)	(0.019)	(0.019)	(0.014)	(0.015)
2011 Sale	0.030	0.034*	0.017	-0.001	0.047***	0.046***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.013)	(0.014)
2012 Sale	0.146***	0.147***	0.095***	0.078***	0.139***	0.136***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.015)
2013 Sale	0.270***	0.267***	0.238***	0.220***	0.277***	0.276***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.014)	(0.014)
2014 Sale	0.416***	0.412***	0.356***	0.339***	0.407***	0.407***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)
2015 Sale	0.562***	0.564***	0.524***	0.507***	0.625***	0.625***
	(0.016)	(0.016)	(0.018)	(0.018)	(0.014)	(0.014)
2016 Sale	0.651***	0.654***	0.689***	0.668***	0.730***	0.731***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.015)	(0.016)
Intercept	9.439***	8.560***	7.933***	8.347***	11.361***	10.910***
	(0.124)	(0.310)	(0.272)	(0.749)	(0.212)	(0.697)
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.709	0.705	0.751	0.744	0.841	0.839
Num. obs.	3,073	3,073	3,082	3,082	2,231	2,231
LogLik	385.449	361.124	459.016	420.277	1055.269	1039.665
AIC	-682.897	-634.248	-842.032	-764.554	-2034.538	-2003.330
BIC	-417.559	-368.910	-612.765	-535.287	-1817.550	-1786.342

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust Standard Errors are reported in brackets. This table presents estimation results for structural attributes and year fixed effects from the standard henodic models. Brick wall, steel roof, rolling slope (8-15°) and year 2007 are set as reference groups

but negative elsewhere. With the highest average age among the three zones, DGZ is the only one to benefit from this vintage effect (Meese and Wallace 1991; Coulson and Lahr 2005). Our results also indicate that sales price decreases with land slope and distance from the beach or large parks while the distance to medium parks as well as shopping centers appreciates a house. This heterogeneity confirms Irwin (2002), Netusil (2005) and Tyrväinen (1997), who find that open space can be positively or negatively valued depending on sizes, uses, and maintenance levels.

When it comes to the effect of proximity to school, the results in column (1) of Table 4 show that, on average, the linear term of driving distances to Epsom Girl's Grammar (EGGS) is statistically different from zero, while the quadratic term is

Table 4 Estimation Results: Proximity Controls

	Double grammar		Selwyn college		One tree hill college	
	Distance (1)	Time (2)	Distance (3)	Time (4)s	Distance (5)	Time (6)
Driving Distance/Time to:						
Epsom Girl's Grammar ($EGGS$)	-0.083**	-0.095**				
	(0.035)	(0.042)				
$EGGS^2$	-0.001	-0.001				
	(0.004)	(0.002)				
Auckland Grammar (AG)	0.014	0.056				
	(0.027)	(0.039)				
AG^2	0.014***	0.003**				
	(0.005)	(0.001)				
Selwyn College (Sel)			0.055	0.049		
			(0.050)	(0.040)		
Sel^2			-0.015***	-0.003***		
			(0.003)	(0.001)		
One Tree Hill College (One)					-0.076	-0.211**
					(0.087)	(0.093)
One^2					0.010	-0.012***
					(0.010)	(0.004)
CBD	0.023	0.097**	0.266***	0.053	-0.177***	0.029
	(0.024)	(0.042)	(0.042)	(0.066)	(0.054)	(0.101)
CBD^2	0.000	-0.002	-0.017***	-0.001	0.006	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
EGGS∗CBD	0.010**	0.006*				
	(0.005)	(0.004)				
AG∗CBD	-0.019***	-0.008**				
	(0.006)	(0.003)				
Sel∗CBD			0.010**	0.001		
			(0.004)	(0.002)		
One∗CBD					0.002	0.022***
					(0.012)	(0.008)
Nearest Small Park	0.061***	0.006	-0.015**	-0.014***	-0.007	-0.007**
	(0.011)	(0.004)	(0.007)	(0.003)	(0.007)	(0.003)
Nearest Medium Park	0.005	0.004	0.006	-0.004	0.013***	0.005**
	(0.010)	(0.004)	(0.008)	(0.004)	(0.003)	(0.002)
Nearest Large Park	-0.028***	-0.006**	0.006	0.006***	0.006	0.006***
	(0.008)	(0.003)	(0.004)	(0.002)	(0.004)	(0.002)
Nearest Shopping Center	0.029***	0.016***	0.022***	0.001	0.012*	0.004
	(0.009)	(0.003)	(0.007)	(0.004)	(0.007)	(0.003)

Table 4 (continued)

	Double grammar		Selwyn college		One tree hill college	
	Distance	Time	Distance	Time	Distance	Time
	(1)	(2)	(3)	(4)s	(5)	(6)
Nearest Beach	-0.043***	-0.015***	-0.040***	-0.012***	-0.004	-0.001
	(0.007)	(0.003)	(0.007)	(0.003)	(0.005)	(0.003)
Structural Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.709	0.705	0.751	0.744	0.841	0.839
Num. obs.	3,073	3,073	3,082	3,082	2,231	2,231
LogLik	385.449	361.124	459.016	420.277	1055.269	1039.665
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BIC	-417.559	-368.910	-612.765	-535.287	-1817.550	-1786.342

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust Standard Errors are reported in brackets. This table presents estimation results for prolixity controls from the standard henodic models. CBD represents Central Business District

not. However, the positive significant interaction of *degg* and *dcbd* suggests that the effect of the average distance to EGGS on sales price is not the same for each distance to CBD. In other words, everything else being equal, an additional km to EGGS increases the house value more for houses that are located further from CBD relative to closer to CBD. As shown in Eq. 5, marginal effect of distance to EGGS depends on the value of distance to EGGS itself and the distance to CBD. At the average driving distances to EGGS (2.93 km), and CBD (6.17 km), one additional km drive from EGGS decreases the house price by about 2.77%. Giving the average sales price in DGZ of NZ$1,498,537, this marginal effect translates into an average decrease of NZ$41,509 per additional km.

In terms of driving distance to Auckland Grammar (AGS), its quadratic term and its interaction with driving distance to CBD are both statistically significant; suggesting the existence of nonlinear effect of distance to AGS. The negative interaction term shows that there is substitutability between distance to AGS and CBD. That is, houses that are far from CBD have quickly decreasing housing price as driving distance to AGS increases. Again, we calculate the marginal effect of distance to AGS using Eq. 5. At the average driving distances to AGS (3.41 km), and CBD (6.17 km), one additional km drive from AGS decreases the house price by about 0.67%. Giving the average sales price in DGZ of NZ$1,498,537, this marginal effect translates into an average NZ$10,040 decrease per additional km. Figure 2a and b show the predicted log of the sales price with the associated 95% confidence intervals for all possible values of driving distance to AGS and EGGS, respectively. Figure 2a indicates that the sales price decreases with the driving distance to AGS until about 3.664 km from the school and increases afterward. In Fig. 2b, the log of sales price appears to decrease with the driving distance to EGGS almost linearly, reflecting that the quadratic term of *degg* is not significant.

Due to the recent increase in population, hence, in driving time, in Auckland, we investigate the marginal effect of driving time as well. Estimation results are presented in column (2) of Table 4. To interpret the results straightforwardly, as before, we calculate the marginal effect of driving time to AGS and EGGS at their mean values, respectively. Based on the average driving time to AGS (7.52 mins), EGGS (7.60 mins), and the CBD (15.50 mins), the results indicate that one more minute drive from AGS and EGGS decreases the house price by about 2.64% and 1.61%, respectively. This corresponds to a decrease in the mean house price of about NZ$39,535 and NZ$24,150 for each additional minute of driving from AGS and EGGS, correspondingly. Figure 2e and f plot the predicted log of sales prices with the associated 95% confidence intervals for all possible values of driving time to AGS and EGGS, respectively, while holding other variables at their mean values. Figure 2e shows that the log of sales price decreases with driving time to AGS with slightly decreasing rate (i.e. decreasing and concave up). In Fig. 2f, the log of sales price also decreases with driving time to EGGS with moderately increasing rate (i.e. decreasing and concave down).

By and large, the above findings suggest a larger price premium of proximity to AGS in the most sought-after DGZ. This is consistent with the results in Hendon (1973) who finds that middle-sized school with an appealing architecture adapted to the neighborhood environment will reflect positively on the price of the nearby homes. Among the four schools in the sample, AGS has two Category I historical places, places of special or outstanding historical or cultural heritage significance or value as defined by Heritage New Zealand Pouhere Taonga, an association advocating for this type of buildings. Therefore, it is likely that higher property prices near AGZ reflect the value of having attractive historical heritages in the neighborhood.

The price-proximity relation in Selwyn College zone is quite a contrast to that in DGZ. The results for Selwyn College zone (Table 4, column 3) shows that everything else being equal, driving distance to Selwyn College increases housing values but at a decreasing rate. Figure 2c plots the predicted log of the sales price at all possible driving distances to Selwyn College with a 95% confidence interval and indicates that it is only above 5 km from the school that distance has a negative marginal effect on housing prices. In other words, proximity to Selwyn College is seen as a “nuisance”. The same pattern is also apparent with the alternative model presented in column (4) and plotted in Fig. 2g.

When it comes to the One Tree Hill College zone, we find that there is an initial price premium for being close to the school (Table 4, column 5, and Fig. 2d). Fig. 2d shows that the log of sales price decreases slightly at a decreasing rate with the driving distance to One Tree Hill College till 2.70 km away and increases afterward. Predicted log of sales prices from the alternative model (column 6) are plotted in Fig. 2h, which show that proximity to One Tree Hill negatively affects house prices within 8.1 minutes’ drive away. Similar to Selwyn College zone, estimation results from both models suggest that proximity to One Tree Hill College is more of a “nuisance.”

In general, our results suggest a price premium of school proximity in DGZ, whereas a price discount in the other two school zones. A possible explanation for the positive relationship between school proximity is that people value transport accessibility too. Traffic jams mostly take place in DGZ. If a shorter driving time to AGS and EGGS means a lower chance of being delayed getting to work, then it is likely that house prices decrease with greater driving time to AGS and EGGS.

Results in Table 4 and plots in Fig. 2 also indicate that the marginal effects of proximity to school can be sensitive to the measures of proximity (driving distance or driving time). A possible explanation is that some people care more about driving distance than driving time and vice versa. For instance, Ottensmann et al. (2008) investigate the role of accessibility to the CBD on property prices in Marion County, Indiana, based on three definitions: i) geographical distance, ii) free-flow travel time, and iii) congested travel time. The authors find that it is only in the models based on free-flow travel time to CBD that accessibility has a statistically significant on prices. Moreover, the travel cost literature (see, among others, Brown and Mendelsohn 1984 and Hellerstein 1991) defines general travel costs as the sum of time costs and distance costs, but it does not have a consensus over the role of time costs on housing prices. In our sample, the BIC statistics (as the models are non-nested) suggest the model with driving distance fits better than the model with driving time in each of the school zones. However, in One Tree Hill school zone the effects of proximity to school are statistically significant when measured by driving time but not driving distance.

Finally, we explore further the heterogeneity present in the magnitude of the marginal effects by re-estimating the model at the 10th, 50th, and 90th percentiles of the price distribution. Results based on defining distance as driving distance and driving time are reported in Tables 5 and 6, respectively. Quantile estimates are also presented in Fig. 3 for each of the school zones. The quantile analysis plotted in Fig. 3a reveals that the nonlinear return of proximity to AGS measured by driving distance is most prominent at the 10th percentile, which means that proximity to AGS increases the sales price more for houses in the lower quantile than in the higher quantile, everything else being equal. In other words, proximity to AGS is a much valuable attribute to houses with relatively lower sales prices. Our results also indicate that proximity to AGS loses its appeal steadily up to 3.864 km, 3.464 km, and 3.464 km in the 10th, 50th, and 90th percentiles respectively (it was 3.664 km in Fig. 2a). An alternative measure of proximity, defined by driving time, affects the rates of nonlinear returns as shown in Fig. 3e. Yet, it is still evident in Fig. 3e that capitalization of proximity to AGS is most prominent at the lower quantile of the sales price distribution.

Figure 3b shows that driving distance to EGGS has a close-to linear effect on housing prices at any chosen quantiles. Proximity to EGGS is positively valued in the 50th, and 90th percentiles of sales price distribution. However, a flat line can almost be fit in the confidence interval at the 10th percentile, which means that there may be no true population distance-to-EGGS effect at the lower end of the housing market in DGZ. Switching from driving distance to driving time does not change the results much, except that there appears to be an initial price discount of proximity to EGGS at the 90th percentile as plotted in Fig. 3f.

Table 5 Quantile Regression Results for Driving Distance Covariates

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Driving Distance to:									
EGGS	-0.065	-0.108**	-0.090						
	(0.067)	(0.045)	(0.059)						
$EGGS^2$	-0.002	0.004	-0.006						
	(0.009)	(0.005)	(0.007)						
AGS	-0.044	0.034	-0.012						
	(0.049)	(0.037)	(0.051)						
AGS^2	0.030***	0.011*	0.004						
	(0.009)	(0.007)	(0.009)						
Sel				0.058	-0.030	0.128*			
				(0.078)	(0.072)	(0.077)			
Sel^2				-0.012**	-0.012***	-0.017***			
				(0.005)	(0.004)	(0.006)			
One							-0.094	-0.144**	-0.106
							(0.113)	(0.069)	(0.132)
One^2							-0.005	-0.007	0.016
							(0.014)	(0.009)	(0.016)
CBD	0.066	0.001	0.017	0.255***	0.222***	0.310***	-0.236***	-0.161***	-0.149
	(0.045)	(0.035)	(0.042)	(0.069)	(0.052)	(0.064)	(0.066)	(0.050)	(0.095)

Table 5 (continued)

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
CBD^2	0.000	0.002	-0.003	-0.015***	-0.016***	-0.020***	0.007	0.003	0.005
	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)	(0.005)	(0.003)	(0.006)
EGGS*CBD	0.012*	0.008	0.009						
	(0.007)	(0.006)	(0.008)						
AGS*CBD	-0.031***	-0.018**	-0.003						
	(0.009)	(0.008)	(0.013)						
Sel*CBD				0.010	0.017***	0.003			
				(0.006)	(0.006)	(0.007)			
One*CBD							0.013	0.017*	-0.000
							(0.017)	(0.010)	(0.018)
Nearest Small Park	0.048**	0.051***	0.052***	-0.024**	-0.009	-0.017	0.006	0.013	0.014
	(0.019)	(0.013)	(0.015)	(0.010)	(0.007)	(0.012)	(0.011)	(0.009)	(0.017)
Nearest Medium Park	0.011	0.001	-0.002	0.019**	0.009	0.005	0.019***	-0.001	-0.019**
	(0.020)	(0.013)	(0.014)	(0.009)	(0.009)	(0.014)	(0.007)	(0.006)	(0.009)
Nearest Large Park	-0.028*	-0.030***	-0.014	0.017***	0.003	0.008	0.000	-0.001	-0.010
	(0.015)	(0.011)	(0.011)	(0.005)	(0.005)	(0.006)	(0.011)	(0.009)	(0.013)
Nearest Shopping Center	0.044**	0.027***	0.051***	0.013	0.006	0.038***	0.007*	0.014***	0.016**
	(0.017)	(0.010)	(0.014)	(0.012)	(0.009)	(0.010)	(0.004)	(0.004)	(0.008)
Nearest Beach	-0.047***	-0.034***	-0.052***	-0.044***	-0.038***	-0.022***	-0.007	0.004	-0.021***
	(0.015)	(0.010)	(0.011)	(0.011)	(0.006)	(0.010)	(0.005)	(0.006)	(0.008)

Table 5 (continued)

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Structural Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	3,073	3,073	3,073	3,082	3,082	3,082	2,231	2,231	2,231

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrap Standard Errors are reported in brackets. This table presents estimation results for prolixity controls (measured by driving distance) from the quantile henodic models. *AGS* represents Auckland Grammar School. *EGGS* represents Epsom Girl's Grammar School. *Sel* represents Selwyn College. *One* represents One Tree Hill College. CBD represents Central Business District

Table 6 Quantile Regression Results for Driving Time Covariates

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Driving Time to:									
EGGS	-0.157**	-0.021	-0.081						
	(0.080)	(0.057)	(0.077)						
$EGGS^2$	-0.001	0.000	-0.007**						
	(0.003)	(0.003)	(0.003)						
AGS	0.126*	-0.001	-0.006						
	(0.070)	(0.048)	(0.063)						
AGS^2	0.007**	0.004**	0.002						
	(0.003)	(0.002)	(0.002)						
Sel				0.081	0.049	0.066*			
				(0.065)	(0.048)	(0.060)			
Sel^2				-0.003*	-0.004***	-0.005***			
				(0.002)	(0.001)	(0.002)			
One							-0.343***	-0.226**	-0.122
							(0.120)	(0.113)	(0.170)
One^2							-0.020***	-0.014***	-0.009
							(0.005)	(0.005)	(0.008)
CBD	0.111	0.064	0.124*	0.188**	0.035	0.059	0.129	0.023	-0.044
	(0.076)	(0.054)	(0.075)	(0.090)	(0.067)	(0.098)	(0.145)	(0.115)	(0.162)
CBD^2	-0.001	0.000	-0.005*	-0.005**	-0.001	-0.001	-0.011**	-0.006	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)

Table 6 (continued)

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
EGGS*CBD	0.012*	-0.000	0.010						
	(0.007)	(0.005)	(0.007)						
AGS*CBD	-0.017***	-0.005	-0.003						
	(0.006)	(0.004)	(0.005)						
Sel*CBD				-0.001	0.001	0.001			
				(0.003)	(0.002)	(0.002)			
One*CBD							0.036***	0.024***	0.014
							(0.009)	(0.009)	(0.014)
Nearest Small Park	-0.000	0.000	0.009	-0.022**	-0.012***	-0.009**	-0.002	-0.002	-0.007
	(0.007)	(0.004)	(0.006)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.006)
Nearest Medium Park	0.002	0.010*	-0.002	0.001	-0.001	-0.008	-0.002	0.003	0.010**
	(0.007)	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)
Nearest Large Park	-0.008	-0.010**	-0.003	0.013***	0.005**	0.005	0.002	0.005**	0.010***
	(0.005)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
Nearest Shopping Center	0.018***	0.014***	0.012***	0.011	-0.005	0.007	-0.004	0.005	0.010*
	(0.006)	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
Nearest Beach	-0.012**	-0.010***	-0.015***	-0.015***	-0.007**	-0.006	0.010***	0.003	-0.010*
	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.007)	(0.003)	(0.004)	(0.005)

Table 6 (continued)

	Double grammar			Selwyn college			One tree hill college		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Structural Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	3,073	3,073	3,073	3,082	3,082	3,082	2,231	2,231	2,231

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrap Standard Errors are reported in brackets. This table presents estimation results for prolixity controls (measured by driving time) from the quantile henodic models. *AGS* represents Auckland Grammar School. *EGGS* represents Epsom Girl's Grammar School. *Sel* represents Selwyn College. *One* represents One Tree Hill College. CBD represents Central Business District

For the Selwyn College zone, our quantile plots in Fig. 3c and g reveal that the positive marginal effects of driving distance/time increase at a decreasing rate for all three percentiles. Therefore, everything else held constant, proximity to Selwyn College appears to be a "nuisance." When it comes to the One Tree Hill College zone, our results in Fig. 3d suggest a milder nonlinear relation beyond the 4 km driving distance at the selected percentiles, whereas the relationship is only statistically significant in the 50th percentile. The nonlinear effects and the negative effects of proximity to school are more noticeable when estimated using driving time (Fig. 3h). That is to say, school proximity is more of a "nuisance" than a "benefit" for houses in One Tree Hill College zone.

Conclusion

While the hedonic literature has extensively focused on membership to a school zone to justify differences in housing prices (Bayer et al. 2007; Black 1999; Black and Machin 2011; Bogart and Cromwell 1997, 2000; Downes and Zabel 2002; Ferreyra 2007; Gibbons et al. 2013), the study of the role of proximity to school on a house's price when the house is already within the chosen school zone has been much less investigated. Yet, proximity to such infrastructures can be both an amenity, when the building's architecture is pleasant and time for driving children to/from school is saved (Owusu-Edusei et al. 2007), and a disamenity when traffic jam and noise accompany drop-offs and pickups (Emerson 1972; Guntermann and Colwell 1983; Hendon 1973; Des Rosiers et al. 2001; Theisen and Emblem 2018).

Based on a sample of housing sales recorded in the most sought-after school zone in Auckland, New Zealand, as well as in its two neighboring school zones, this paper provides evidence that everything else held constant, belonging to a school zone is certainly not the only feature that matters to homeowners. Indeed, our results indicate a nonlinear effect of proximity to secondary schools, which is consistent with previous literature (Hendon 1973; Gibbons and Machin 2006). Our findings indicate also that proximity to school adds a price premium only in the most prestigious school zone (each additional km of driving distance decreases the house price up to 2.77%.) while being perceived as a disamenity in the other two zones.

Next, we adopt a quantile regression approach to explore further the heterogeneity present in our results and to fill the lack of expertise on the relation between proximity to school and housing prices across the distribution of sales prices (Huang and Hess 2018), is the only exception we are aware of and their results are limited to predicting the median effects. Our results show that the positive effect of proximity to the most sought-after school is most prominent in the 10th percentile of the house price distribution. Within the other two secondary school zones, we find again that proximity to school is mostly a disamenity from the 10th to the 90th percentiles.

While we have highlighted several possible sources of amenities and disamenities that explain our results throughout this paper, future work should focus on identifying these attributes more clearly. For instance, if it is the architecture of a school that is seen as the most enjoyable feature whereas poor parking and road structures are the reasons for regular noise and traffic jams, these elements need to be understood clearly. A better design could become a strategy to generate local spatial co-benefits and improve the urban quality of life.

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Appendix

Lists of Shopping Centers and Safe-swim Beaches in Auckland

Table 7 Shopping Centers in Auckland

Shopping centers	Suburb
Atrium on Elliott	CBD
Dress-smart	Central Suburbs
Royal Oak Mall	
Three Kings Shopping Mall	
Westfield Newmarket	
Westfield St Lukes	
Botany Town Center	East Auckland
Meadowbank Shopping Center	
Meadowlands Shopping Plaza	
Eastridge Shopping Center	
Pakuranga Plaza	
Sylvia Park	
Albany Mega Center	North Shore
Glenfield Mall	
Highbury Shopping Center	
Milford Shopping Center	
Pacific Plaza	
Shore City	
Westfield Albany	
Hunters Plaza	South Auckland
Manukau Supa Centa	
Southmall Manurewa	
Westfield Manukau City	
Kelston Shopping Center	Central Suburbs
Lynnmall	
Northwest Shopping Center	
Waitakere Mega Center	
WestCity Waitakere	
Westgate Shopping Center	

Note: This appendix table lists the shopping centers in the city of Auckland

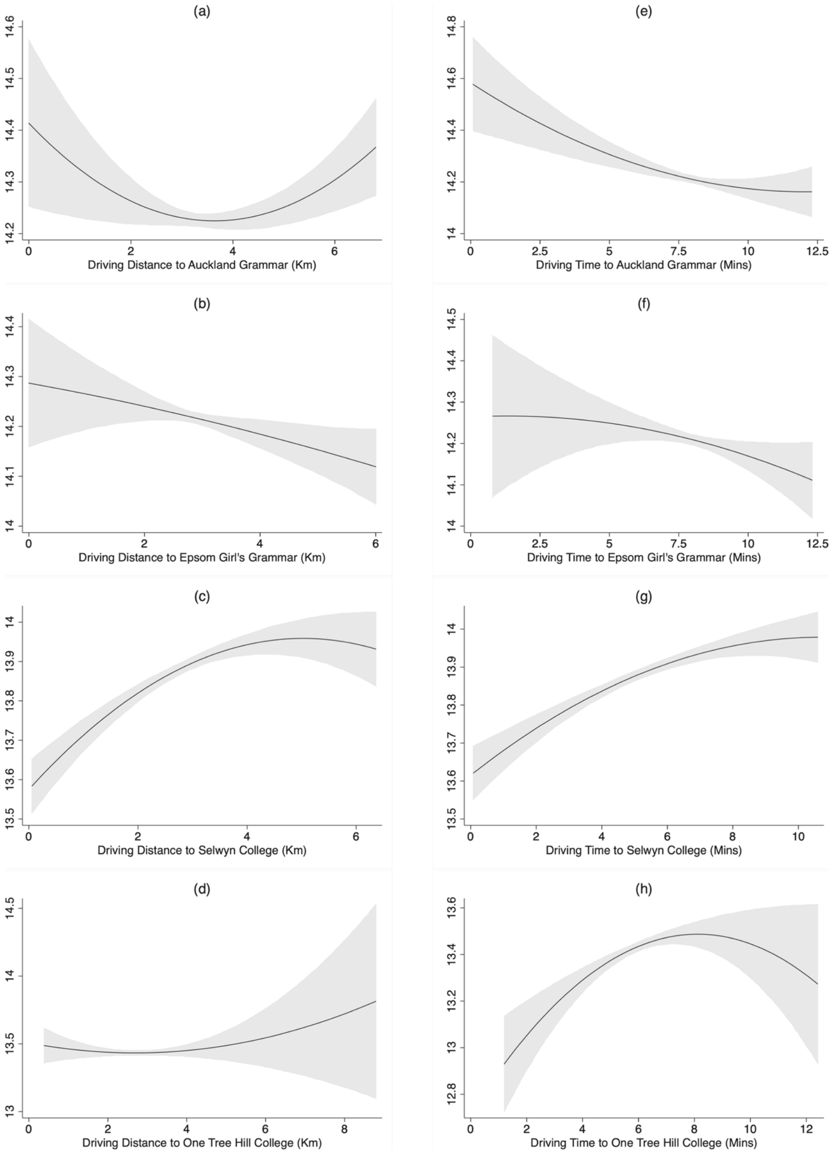

Fig. 2 Predicted Log of Sales Price for Driving Distance(km)/Time(mins) to School. Note: These figures show the predicted values of log of sales price from the standard hedonic models and its 95% confidence band for the sample values of driving distances (km) and time (mins) in each school zone. Other variables were centered at their means for these plots

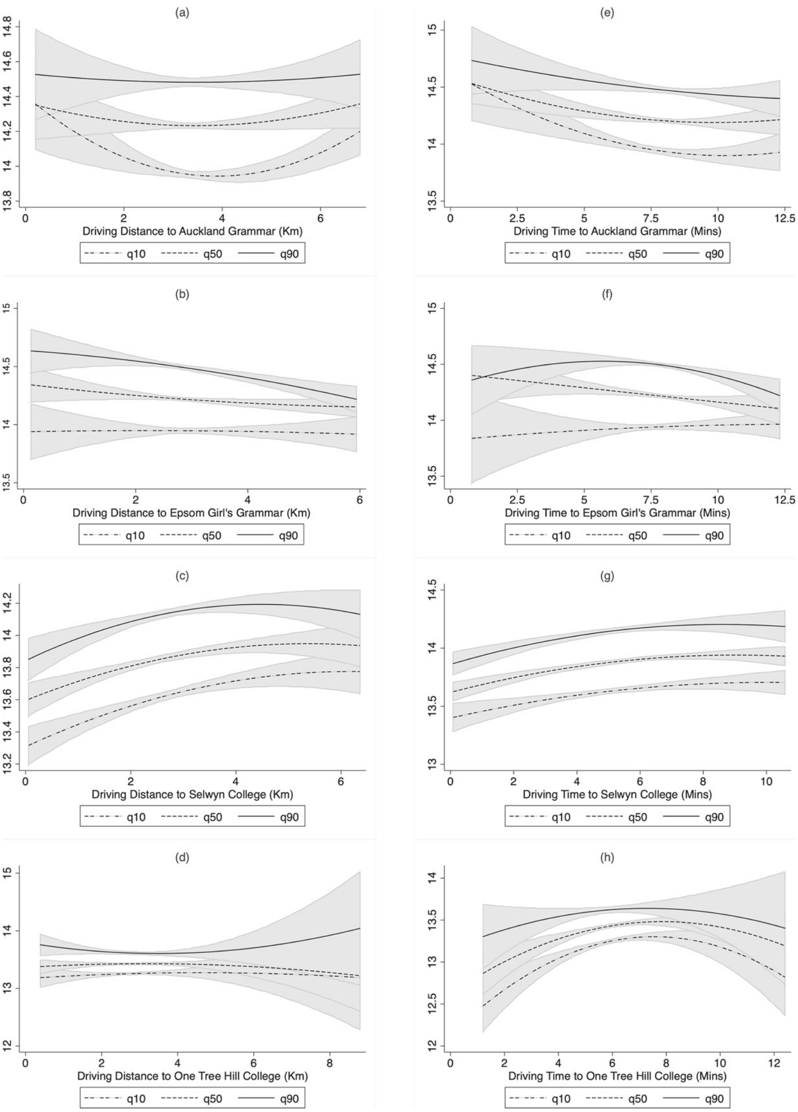

Fig. 3 Quantile Plots - Predicted Log of Sales Price for Driving Distance/Time to Schools. Note: These figures show the predicted values of log of sales price from the quantile hedonic models and its 95% confidence band for the sample values of driving distances and time to the school in each school zone separately at the 10%, 50% and 90% quantiles. Other variables were centered at their mean values for these plots

Table 8 Beaches without Long-term Water Quality Alarm

Name
St Heliers Beach
Kohimarama Beach
Mission Bay Beach
Okahu Bay
Judges Bay
St Marys Bay
Home Bay
Herne Bay
Point Chevalier
Blockhouse Bay
Waikowhai Bay
Granny's Bay
Taumanu West
Onehunga Lagoon
Taumanu Centra
Taumanu East
Point England

Note: This table presents the list of beaches without a long-term water quality alert. This information is accessed from Auckland City Council's Safeswim website (https://safeswim.org.nz)

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