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Does proximity to school still matter once access to your preferred school district has already been secured?

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Abstract

This paper examines the relationship between proximity to secondary schools and property values within four school enrollment zones in Auckland, New Zealand. Results indicate that, in the most desired school zones, house prices increase with proximity to school but decrease above 4 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 reduce the 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

JEL Classification: R29; R30; R31;

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1. 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 which 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 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, 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.

The abundant existing literature, including 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), has extensively focused on school quality or performance effect on housing prices. It shows that school quality, typically measured by the average test score, is capitalized into the house prices. For instance, Black (1999) finds that a 5% increase in elementary test score leads to a 1.8 - 2.1% increase in house value. Gibbons *et al.* (2013) use boundary discontinuity to show that a one-standard deviation increase in either school average value-added or prior achievement increases prices by around 3%. Among the several studies that focus on school admission (Brunner *et al.*, 2012; Epple and Romano, 2003; Ferreyra, 2007; Machin and Salvanes, 2010; Reback, 2005, and Schwartz *et al.*, 2014), Bonilla-Mej´ıa *et al.* (2018) find that the higher probability of admission to Chicago's high-quality magnet schools increases house prices within 1.5 miles of these schools.

One aspect that has been less often investigated in the above literature is the desire for proximity to school once access to the school of choice has been secured. On the one hand, close proximity to the desired school can be seen as an amenity as it reduces less travel time and travel cost. On the other hand, close proximity to schools imposes negative effects on property prices as a result of increased noise level, traffic congestion, and crime rates. The first studies to investigate these issues are Emerson (1972) and Hendon (1973) who demonstrate that house prices in the southern part of Minneapolis and Dallas receptively do decrease with proximity to the nearest school. The latter finds that only a middle-sized school with an appealing architecture adapted to the neighborhood environment will reflect positively on the price of the nearby homes. For Guntermann and Colwell (1983), proximity brings both positive (safety and shorter travel time) and negative (noise and trampled lawns) externalities. Applied to primary schools in Lubbock, Texas, their work shows that the former effect dominates up to 50-400 meters from the school. This threshold is a bit wider than the 300-500 meter (9 to 15 minutes waking distance) tipping point found by Des Rosiers *et al.* (2001) on the impact of primary schools on house prices in Quebec. They too highlight noise and traffic jam as the main disamenity of close proximity. Owusu-Edusei *et al.* (2007) provide a more comprehensive study in that they control not only for the proximity to all school levels (elementary, middle and high schools) but also for the quality of such schools and distance to attributes such as parks and golf courses. Based on Greenville, South Carolina, their results indicate that house prices are in general higher within closer proximity to elementary and middle schools. High schools, on the other hand, have a negative effect on nearby house prices due to more nighttime activity and light. More recently, Sah *et al.* (2016) introduce the idea of spatial heterogeneity in the effect of proximity to schools. They control for school quality and distances to various amenities (freeways, downtown, the coast, library, mall, open space and retail center) to find out that, in San Diego County, there is a positive (negative) externality of proximity to public (private) primary schools in inland areas but a negative one of both types of schools in coastal areas. However, the authors do not pinpoint the source(s) of this heterogeneity. Finally, Huang (2018) uses quantile regression and estimates the median marginal effect of distance to schools in Oshkosh, Wisconsin, and concludes that the median sales price decreases with distances to the nearest elementary, middle and high schools. One advantage of the quantile regression (where median is the 50^{th} percentile) is that it is more robust to the outliers than mean regression models. Nevertheless, the author does not take the advantage of the quantile regression to investigate the marginal effect of proximity to school on the full range of distribution of property price.

This paper develops the existing literature further by assessing the role of proximity to school on housing prices once access to the preferred school has been secured. The major difference with the previous contributions is that it is not the marginal effect of close-range proximity only that is assessed but the entire spectrum of distance within a school’s attendance zone. In addition, we exploit the power of the quantile regression approach more than Huang (2018) by relaxing the assumption of uniform marginal effects of various levels of proximity to school and testing whether proximity is valued the same at the higher and lower end of the housing market.

The rest of the paper is composed as follows: section 2 presents the empirical strategy, the reduced-form hedonic model and our quantile regressions. Section 3 describes Auckland's housing market, the selected geographic area of our study as well as the data and their source. Estimation results are presented and discussed in section 4. The last section summarizes the results and offers some concluding remarks.

2. 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 neighborhood average 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 $Z = Z(z_1, z_2, \dots, z_K)$. 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:

$$\log(P_{it}) = \sum_{k=1}^{K} \beta_k \, z_{it,k} + \sum_{t=1}^{T} \alpha_t \, D_{it} + \varepsilon_{it}, \qquad i = 1, \cdots, N, \;\; \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \tag{1}$$

where $logP_{it}$ is the logarithm of the sale price of house i at time t ($t = 1,..., T$); $z_{it,k}$ 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 central business district (CBD, the major employment center), schools, shopping centers, parks and/or other local amenities (e.g. Basu and Thibodeau, 1998; 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. In addition, we control for the non-linear role of the distance to school and to the CBD. The latter variable appears in the hedonic models of, among others, Anderson and West (2006), Halstead *et al.* (1997), and Rasmussen and Zuehlke (1990).

In addition, studies such as Bolitzer and Netusil (2000), 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 distance 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:

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

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. We will investigate if travel time as the alternative measure of proximity leads to similar results. Previous studies, including Des Rosiers *et al.* (2000), 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. $dshop_{it}$ and $dbeach_{it}$ are the geographical 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 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.

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

$$\frac{\partial logP_{it}}{\partial dschool_{it}} = \beta_1 + 2\beta_2 \times dschool_{it} + \beta_5 \times dcbd_{it} \quad (3)$$

It shows that the marginal effect of driving distance to school is a linear function of driving distance to school itself and driving distance to CBD. The sign of β_2 determines whether driving distance to school has an increasing or decreasing marginal effect on the log of sales price. The sign of β_5 reveals whether driving distance to school and to CBD are complementary (i.e. people prefer to live closer to both) or competitive (i.e. people prefer to live closer to one of them but not both).

All the previous specifications assume that the enrolment zones are mutually exclusive. In the event of a house having access to more than one enrollment zone (DGZ in the study sample), then we need to include accessibility to both schools (in terms of driving distance or time) and to allow the first-order interaction between each school and the CBD as well as between schools:

$$\begin{aligned} logP_{it} = {} & \beta_1 dAGS_{it} + \beta_2 dAGS_{it}^2 + \beta_3 dEGGS_{it} + \beta_4 dEGGS_{it}^2 + \beta_5 (dAGS_{it} \times dEGGS_{it}) \\ & + \beta_6 (dAGS_{it} \times dcbd_{it}) + \beta_7 (dEGGS_{it} \times dcbd_{it}) + \sum_{a=8}^{14} \beta_a d_{it,a} \\ & + \sum_{k=1}^{K} \alpha_k S_{it,k} + \sum_{t=1}^{T} \gamma_t DY_{it} + \sum_{p=1}^{P} \lambda_p DP_{it} + \varepsilon_{it}, \qquad i = 1, \cdots, N, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \end{aligned} \quad (4)$$

where $d_{it,a}$ includes the distances to the CBD, its square value, distance to the nearest shopping center, to the beach and the three 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:

$$\frac{\partial logP_{it}}{\partial dAGS_{it}} = \beta_1 + 2\beta_2 \times dAGS_{it} + \beta_5 \times dEGGS_{it} + \beta_6 \times dcbd_{it} \quad (5)$$

The sign of β_5 informs us about the role of proximity to the other school.

In Eqs. (1) to (5) above, the marginal effect of distance to school on the house prices is calculated at the mean. Yet, the mean may mask significant heterogeneity in the distribution of this marginal effect (McMillen, 2012; Liao and Wang, 2012; Zietz *et al.*, 2007). 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 equation (1), can be written as:

$$Q_{\log(P_{it})|z_{it,d_{it}}}(q) = \sum_{k=1}^{K} \beta_k(q)\, z_{it,k} + \sum_{t=1}^{T} \alpha_t(q) d_{it} + \varepsilon_{it}\,, \qquad i = 1, \cdots, N \tag{6}$$

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 selling price distribution are allowed to evolve differently with covariates.

3. Sample and Data

3.1. 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, 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 that are tied to residential location. Enrollments at elementary or secondary schools are restricted to students living in a geographically defined school zone. There are four of them in Auckland. Two of them, the Auckland Grammar School's enrollment zone (AGS) and Epsom Girl's Grammar School's enrollment zone (EGGS) belong to the so-called Double Grammar Zone (DGZ). They are both 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 DGZ is the most seek 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.

Fig. 1 also displays two other school enrollment zones. On the Southeastern part of the city lies Tree Hill College. It is a state coeducational secondary school. Selwyn College, on the northeast, is a coeducational public secondary school. These two school zones took effect on January 1, 2015.

<Insert Fig.1 here>

3.2. Data

The monthly unit record sales data used in this paper were purchased from Quotable Value Limited (QV) powered by CoreLogic NZ Ltd. which is responsible for conducting property market valuations in New Zealand. Purchased data encompasses school zones of Auckland Grammar School, Epsom Girl's Grammar School, Selwyn College and One Tree Hill College from January 2007 to December 2016.

Basic QV data used in this paper includes 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 a house is associated to. The analytical sample includes all types of houses. Apartments are not included. 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, all 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 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. At 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 8:30am). 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 colinear. For example, longer driving distance on a highway with high speeds may result in 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%), driving distance and time to the CBD are slightly less so (correlation test is 70% and above).

<Insert Table 1 here>

The list of shopping centers is provided in Appendix Table A.1. For each house, the great circle distance to the nearest shopping center is calculated in R.

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 ended up with 17 beaches of which names are provided in Appendix Table B.1. Geographical distance between each house and the nearest beach is calculated in R too.

The distance to the nearest park requires to get the location and size of each park from Park Extent, a database from Auckland's City Council. Fig. 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 proximity and size. As such, we classify them in three groups based on the tercile of the size distribution they belong to.

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 – 35°) and steep (26 - 35°).

Summary statistics for the final analytical sample of 8,507 observations are shown in Table 2. 37.55%, 36.23% and 26.23% 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 floor, 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 7.5 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 Euclidian distance of 696 meter to the nearest school). The nearest shopping center is within 2 km on average. The mean distances to the nearest small, medium and large parks are about 0.35 km, 0.44 km and 0.3 km. Houses in the Selwyn College zone are in general closer to the beach. 41.7% 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.

<Insert Table 2 here>

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 only unavailable for our sample, but it may also not be that crucial. Indeed, Clark and Herrin (2000) and Chin and Foong (2006) show that households value educational quality more than environmental and safety features, even considering that they all are correlated. In addition, these unobserved features will be captured in the fixed effects of our model.

4. Empirical results

Eq. (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 Table 3. As expected, the coefficient estimates associated to the structural and site-specific characteristics do not differ much in terms of sign and magnitude when one moves from geographic to time distance.

<Insert Table 3 here>

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, 0.23 - 0.3% for every 1 % increase in square land area, 2 - 4% for each additional bathroom, and 2 - 2.6% for each additional bathroom. These results are in line with the hedonic literature. However, the decade age effect is positive and significant in DGZ but it is 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 indicate also that sales price decreases with land slope and distance from the beach or from large parks while distance to medium parks as well as shopping centers appreciates a house. This heterogeneity confirms Irwin (2002), Netusil (2005) and Tyrvainen (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) show that the linear and quadratic terms of driving distance to Epsom Girl's Grammar (EGGS) are not different from zero. Yet, an additional km to EGGS increases the price of a house more if the driving distance to CBD is greater. When it comes to Auckland Grammar (AGS), the driving distance does not have a significant effect on the house price initially, but its effect increases and becomes significantly positive at a distance of 3.7km. Moreover, the interaction term shows that there is substitutability between proximity to AGS and to CBD. Indeed, an additional km from AGS decreases the price of a house more if the driving distance to the CBD is greater. In order to quantify the role of driving distance to school in dollar terms, we calculate the marginal effect of distance to AGS using Eq.

(5). At the average driving distances to AGS (3.37 km), EGGS (2.88 km) and CBD (6.16 km), one additional km drive from AGS decreases the house price by about 2.44% (with a p-value of 0.032). Giving the average sales price in DGZ of NZ$ 1,616,496, this marginal effect translates into an average NZ$ 39,443 decrease per additional km. The marginal effect on log of sales price of the driving distance to EGGS is not statistically significant. Fig. 2(a) and Fig. 2(b) show the predicted log of sales price with the associated 95% confidence intervals for all possible values of driving distance to AGS and EGGS respectively. Fig. 2(a) indicates that the sales price decreases with driving distance to AGS until about a 3.764 km drive from the school and increases afterwards. In Fig. 2(b), the log of sales price appears to decrease with driving distance to EGGS almost linearly. However, it also appears that a flat line can be fit within the predicted confidence interval as shown in the non-significant result of the marginal effect calculated in column (1).

<Insert Fig. 2 here>

Due to the recent increase in population, hence in driving time, in Auckland, we investigate the marginal effect of driving time as well. Driving time to EGGS is now significantly affecting housing prices (column 2 of Table 3 and in Fig. 2e and Fig. 2f). Conditional on driving time to EGGS, the effect of driving time to AGS is roughly twice the effect of driving time to CBD. We also find that the marginal effect of driving time to AGS decreases as driving time to CBD increases. Based on the average driving time to AGS (7.45 mins), EGGS (7.51 mins) and the CBD (15.46 mins), the results indicate that one more minute drive from AGS decreases the house price by about 3.26% (with a p-value of 0.000). This result indicates a decrease in the mean house price of about NZ$ 52,698 for each additional minute of driving. Fig. 2(e) and Fig. 2(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. Fig. 2(e) shows that the log of sales price increases moderately with driving time to AGS until about 4.3 minutes from the school and decreases afterwards. In Fig. 2(f), the log of sales price increases with driving time to EGGS until 7.3 minutes and decreases afterwards. A possible explanation for the contrasting results between driving distance and driving time, to AGS in particular, 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 to be delayed to get to work, then it is likely that houses prices decrease with greater driving time to AGS and EGGS.

The price-proximity relation in Selwyn College zone is quite a contrast to that in DGZ. The results for Selwyn College zone (Table 3, column 3) shows that driving distance to Selwyn College exhibits decreasing marginal effects. Fig. 2(c) plots the predicted log of sales price at all possible driving distances to Selwyn College with a 95% confidence interval and indicates that it is only above 4.8 km from the school that distance has a negative marginal effect on housing prices. Yet, very close proximity to Selwyn College is also seen as a "nuisance" (see Fig. 2c). This negative effect of close proximity to school is also apparent with the alternative model presented in column (4) and plotted in Fig. 2(g).

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 3, column 5, and Fig. 2d). Fig. 2(d) shows that log of sales price decreases slightly at a decreasing rate with driving distance to One Tree Hill College till 3.09 km away and increases afterwards. Predicted log of sales prices from the alternative model (column 6) are plotted in Fig. 2(h), which show that proximity to One Tree Hill negatively affect house prices within 8 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".

Results in Table 3 and plots in Fig. 2 indicate that the marginal effects of proximity to school are 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; Hellerstein, 1989) 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. Driving time to school only improves model's fit in DGZ even though the correlation between driving time to AGS and EGGS is as high as 0.9004. However, the improvement is very modest.

Finally, we explore further the heterogeneity present in the magnitude of the marginal effects by calculating the results for the *10th, 50th and 90th* percentiles of the housing distribution. Results are based on defining distance as driving distance and they are reported in Table 4 and in Fig. 3 for each of the school zones. Quantile analysis plotted in Fig. 3(a) reveals that the nonlinear return of proximity to AGS is most prominent at the *10th* percentile, which means that proximity to AGS increases sales price more for houses in the lower quantile than in the higher quantile, everything else equal. Our results indicate also that close proximity to AGS loses its appeal steadily up to 4.7 km, 4 km and 3.6 km in the *10th, 50th and 90th* percentiles respectively (it was 3.7 km in Fig. 2a).

<Insert Fig.3 here>

<Insert Table 4 here>

Fig. 3(b) shows that driving distance to EGGS has a linear effect on housing prices for any quantile; yet, proximity is positively valued in the *90th* percentile of sales price distribution but negatively valued in the *10th* percentile. However, a flat line can be almost fit in the confidence interval at the *10th* percentile, which means that it is possible that there is no true population distance-to-EGGS effect at the lower end of the housing market. Altogether, Fig. 3(a) and Fig. 3(b) indicate that proximity to AGS and EGGS contributes mostly to house prices at the higher end of the price distribution. In addition, the variance of the estimated sales price decreases with greater driving distances to EGGS.

For the Selwyn College zone, our quantile plot in Fig. 3(c) reveals that the positive marginal effects of driving distance are almost linear for all three percentiles. Therefore, everything else held constant, close proximity to Selwyn College appears to be a "nuisance". When it comes to the One Tree Hill College zone (Fig. 3d), our results suggest a nonlinear relation at the *10th* and *50th* percentiles. Proximity to the school is therefore more of a "nuisance" than a "benefit" in these groups whereas the relation is not significant in the *90th* percentile.

5. 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 proximity to school once the preferred school zone membership has been secured 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; Rosiers *et al.,* 2001).

Based on a unique 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 matter to home owners. Indeed, our results indicate a clear nonlinear effect of proximity to secondary schools which is consistent with previous literature (Hendon, 1973; Gibbsons 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 by about 2.44%.) while it is 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 by percentile (Huang, 2018, is the only exception we are aware of and his results are limited to the median marginal return of the distribution). Our results show that the positive effect of proximity to the most prestigious 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 largely a disamenity for all percentiles.

While we have highlighted throughout this paper several possible sources of amenities and disamenities that explain our results, 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 jam, 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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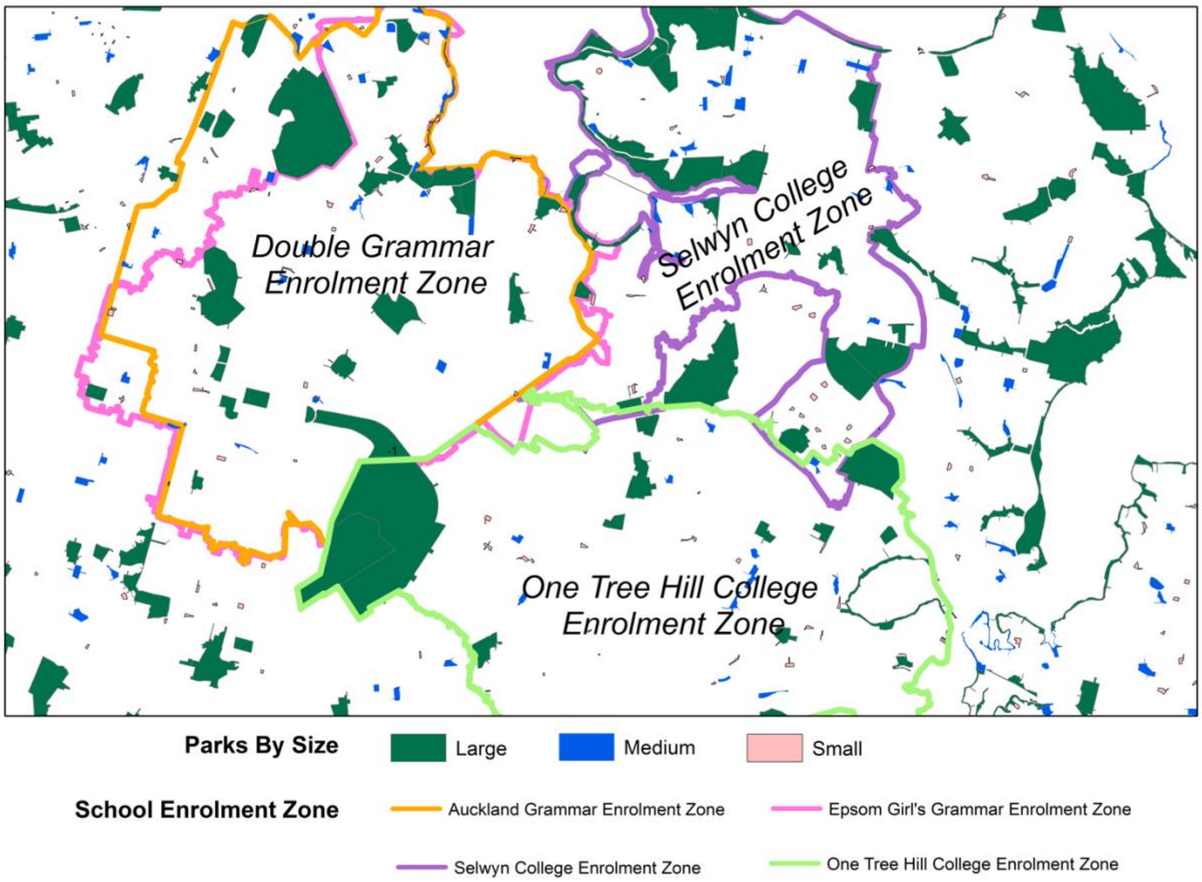
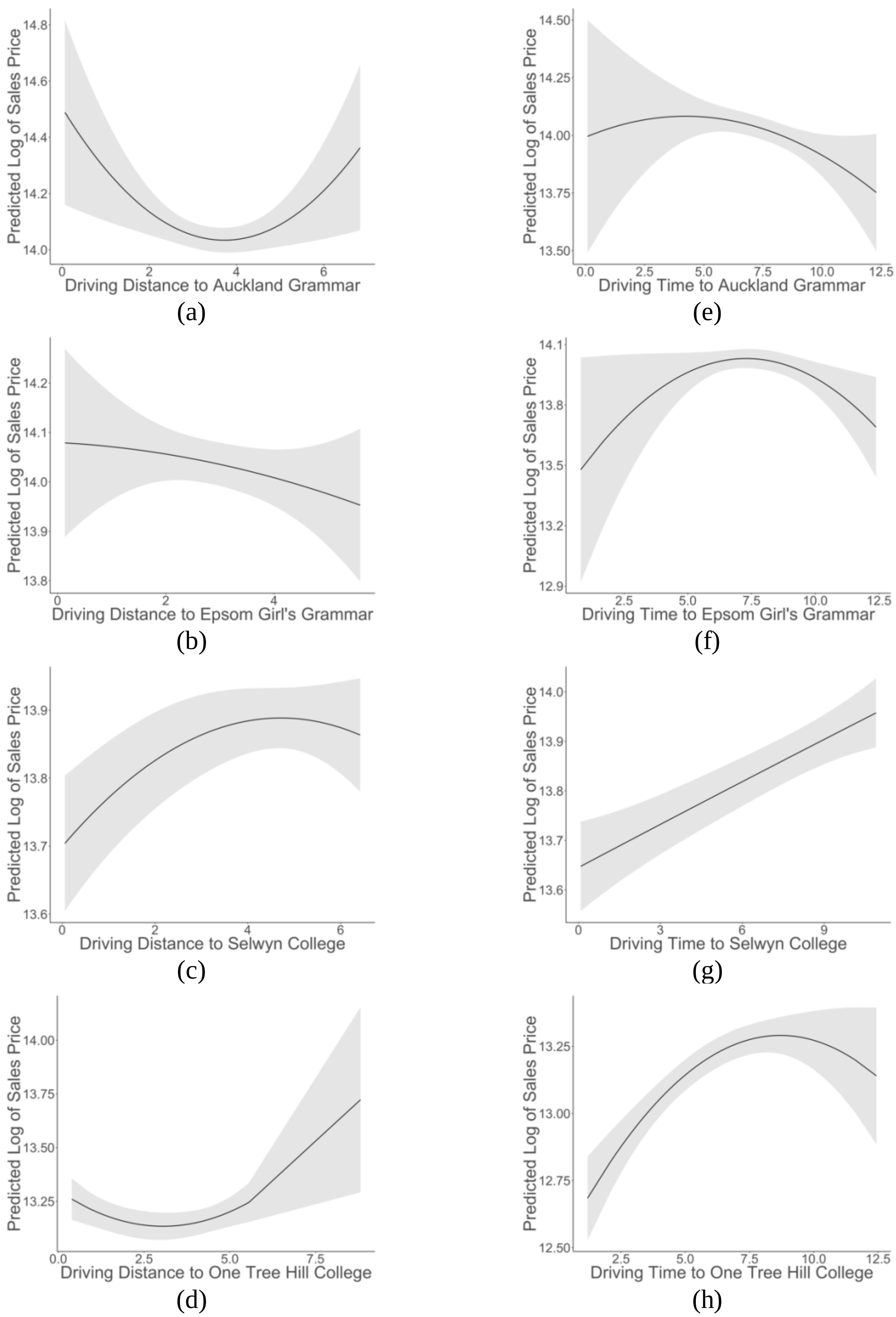
Figures

Figure 1: Study Area – Enrollment Zones and Parks



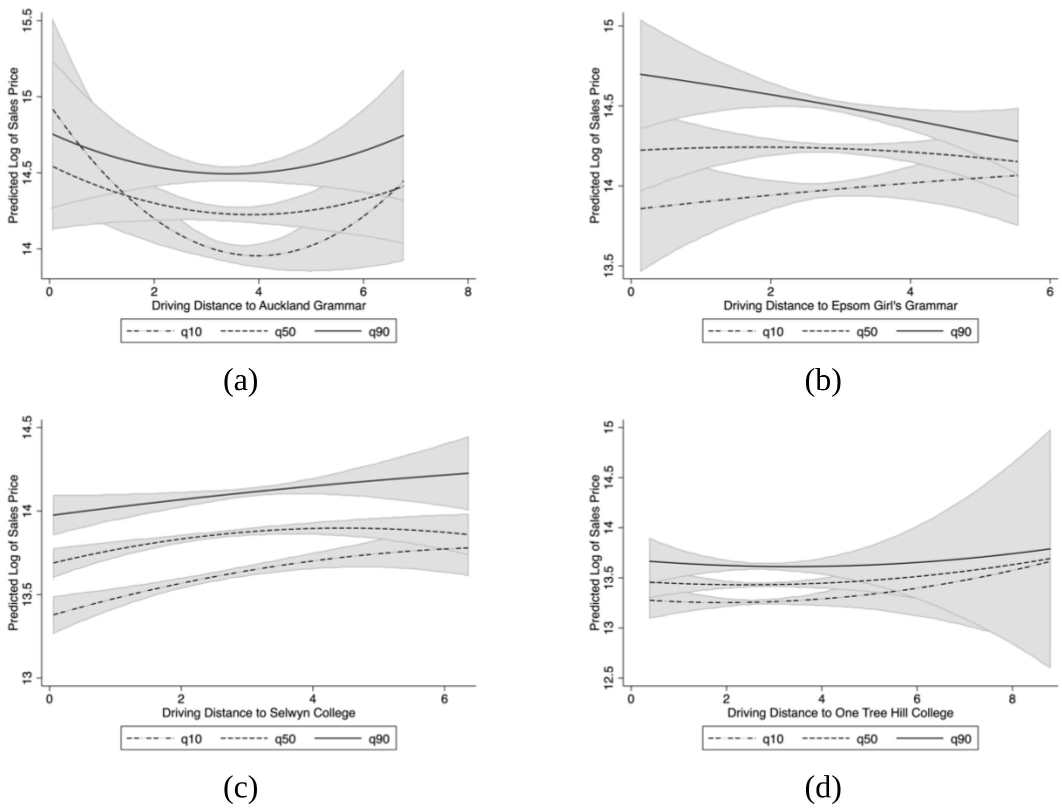
Note: Figure shows the locations of parks in the study area. In the Auckland region, there are 3,051 parks in total according to Auckland Council's Park Extent Map. Parks are divided into three groups: the bottom third are defined as small parks, the middle third are defined as medium parks, and the 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.

Figure 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 and its 95% confidence band for the sample values of driving distances and time in each school zone. Other variables were centered at their means for these plots.

Figure 3: Quantile Plots - Predicted Log of Sales Price for Driving Distance (km) to Schools



Note: These figures show the predicted values of log of sales price 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.

Tables

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

(a) Double Grammar Zone (N=3,194)

Variable	1	2	3	4	5	6
1. Driving Distance to AGS	-					
2. Driving Time to AGS	0.874***	-				
3. Driving Distance to EGGS	0.772***	0.853***	-			
4. Driving Time to EGGS	0.777***	0.900***	0.943***	-		
5. Driving Distance to CBD	0.662***	0.471***	0.251***	0.238***	-	
6. Driving Time to CBD	0.608***	0.542***	0.349***	0.366***	0.745***	-

Note: ***p<0.01, **p<0.05, *p<0.1.

(b) Selwyn College Zone (N=3,082)

Variable	1	2	3	4
1.Driving Distance to Selwyn College	-			
2.Driving Time to Selwyn College	0.988***	-		
3. Driving Distance to CBD	0.179***	0.226***	-	
4. Driving Time to CBD	-0.447***	-0.369***	0.700***	-

Note: ***p<0.01, **p<0.05, *p<0.1.

(c) One Tree Hill College Zone (N=2,231)

Variable	1	2	3	4
1.Driving Distance to One Tree Hill College	-			
2.Driving Time to One Tree Hill College	0.943***	-		
3. Driving Distance to CBD	0.729***	0.662***	-	
4. Driving Time to CBD	0.843***	0.859***	0.869***	-

Note: ***p<0.01, **p<0.05, *p<0.1.

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	5.39	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	0.79	3.78	0.75	3.37	0.72
Number of Carparks	1.78	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	0.33	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°)	0.11	0.31	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°)	0.42	0.49	0.50	0.50	0.34	0.47
Strongly rolling (16-20°)	0.12	0.32	0.15	0.35	0.05	0.22
Moderately steep (21-25°)	0.06	0.24	0.06	0.24	-†	-†
Steep (26-35°)	0.04	0.19	0.03	0.16	-†	-†
To Auckland Grammar:						
Driving Distance (Km)	3.37	1.20	-	-	-	-
Driving Time (Mins)	7.45	2.31	-	-	-	-
To Epsom Girl's Grammar:						
Driving Distance (Km)	2.88	1.00	-	-	-	-
Driving Time (Mins)	7.51	2.02	-	-	-	-
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)	6.14	1.77	9.78	1.79	10.90	1.72
Driving Time (Mins)	15.46	1.81	20.67	1.94	18.33	1.78
Great Circle Distance to:						
Nearest Shopping Center (Km)	1.58	0.56	1.17	0.45	1.79	0.67
Nearest Safeswim Beach (Km)	3.01	1.01	2.14	1.02	3.90	0.76
Nearest Small Parks (Km)	0.39	0.25	0.32	0.22	0.34	0.18
Nearest Medium Parks (Km)	0.44	0.25	0.44	0.26	0.42	0.24
Nearest Large Parks (Km)	0.31	0.21	0.27	0.16	0.34	0.23
Observations	3194		3082		2231	

Note: † 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.

Table 3: Estimation Results

	Double Grammar		Selwyn College		One Tree Hill College	
	Distance	Time	Distance	Time	Distance	Time
	(1)	(2)	(3)	(4)	(5)	(6)
Driving Distance/Time to:						
Epsom Girl's Grammar (EGG)	-0.022 (0.038)	-0.092 (0.053)*				
EGG^2	-0.003 (0.010)	-0.013 (0.006)**				
Auckland Grammar (AG)	-0.008 (0.044)	0.077 (0.050)				
AG^2	0.034 (0.012)***	-0.005 (0.005)				
Selwyn College (Sel)			-0.138 (0.049)***	0.066 (0.038)*		
Sel^2			-0.009 (0.003)***	-0.000 (0.001)		
One Tree Hill College (One)					-0.035 (0.086)	-0.114 (0.088)
One^2					0.018 (0.009)*	-0.011 (0.004)***
CBD	0.053 (0.026)**	0.154 (0.042)***	0.216 (0.038)***	-0.006 (0.067)	-0.243 (0.047)***	-0.018 (0.092)
CBD^2	0.000 (0.003)	-0.003 (0.001)**	-0.017 (0.002)***	0.000 (0.002)	0.010 (0.003)***	-0.004 (0.003)
EGG×AG	-0.021 (0.022)	0.021 (0.010)**				
EGG×CBD	0.014 (0.008)*	0.008 (0.004)**				
AG×CBD	-0.030 (0.010)***	-0.013 (0.003)***				
Sel×CBD			0.022 (0.004)***	-0.002 (0.002)		
One×CBD					-0.007 (0.011)	0.016 (0.007)**
Great Circle Distance to:						
Nearest Small Park	0.144 (0.025)***	0.143 (0.024)***	-0.069 (0.024)***	-0.084 (0.026)***	-0.030 (0.021)	-0.010 (0.023)
Nearest Medium Park	0.050 (0.021)**	0.040 (0.019)**	0.055 (0.023)**	0.074 (0.022)***	0.020 (0.019)	0.059 (0.019)***
Nearest Large Park	-0.089 (0.021)***	-0.080 (0.021)***	-0.017 (0.029)	-0.020 (0.030)	-0.175 (0.019)***	-0.101 (0.019)***
Nearest Shopping Center	0.080 (0.014)***	0.080 (0.013)***	0.125 (0.019)***	-0.002 (0.016)	0.030 (0.016)*	0.080 (0.012)***
Nearest Beach	-0.089 (0.015)***	-0.099 (0.011)***	-0.172 (0.011)***	-0.169 (0.011)***	0.013 (0.013)	0.040 (0.012)***

***$p<0.01$, **$p<0.05$, *$p<0.1$. Robust Standard Errors are reported in brackets.

Table 3 Continued: Estimation Results

	Double Grammar		Selwyn College		One Tree Hill College	
	Distance	Time	Distance	Time	Distance	Time
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Floor Area	0.448 (0.018)***	0.441 (0.018)***	0.484 (0.019)***	0.503 (0.019)***	0.302 (0.018)***	0.315 (0.017)***
Log of Land Area	0.302 (0.013)***	0.304 (0.013)***	0.287 (0.015)***	0.278 (0.015)***	0.238 (0.012)***	0.235 (0.012)***
Decade House Age	0.011 (0.002)***	0.011 (0.002)***	-0.002 (0.002)	-0.000 (0.002)	-0.003 (0.002)**	-0.001 (0.002)
Number of Bathrooms	0.041 (0.006)***	0.044 (0.006)***	0.023 (0.006)***	0.023 (0.006)***	0.032 (0.007)***	0.035 (0.007)***
Number of Bedrooms	0.026 (0.007)***	0.026 (0.007)***	0.026 (0.007)***	0.025 (0.007)***	0.023 (0.007)***	0.019 (0.007)***
Number of Carparks	-0.003 (0.005)	-0.004 (0.005)	-0.014 (0.004)***	-0.014 (0.004)***	0.000 (0.005)	-0.000 (0.005)
Wall: Roughcst	-0.045 (0.018)**	-0.041 (0.017)**	0.001 (0.017)	-0.003 (0.017)	-0.010 (0.013)	-0.010 (0.013)
Wall: Weatherboard	0.009 (0.016)	0.009 (0.016)	0.046 (0.014)***	0.043 (0.014)***	0.029 (0.009)***	0.032 (0.009)***
Wall: Mixed	-0.028 (0.020)	-0.027 (0.019)	0.083 (0.015)***	0.085 (0.016)***	0.003 (0.012)	0.011 (0.012)
Wall: Other	0.036 (0.025)	0.032 (0.025)	0.038 (0.022)*	0.032 (0.023)	-0.034 (0.013)***	-0.024 (0.013)*
Roof: Tile	0.103 (0.060)*	0.102 (0.059)*				
Roof: Other	-0.018 (0.009)**	-0.015 (0.009)*	0.012 (0.008)	0.009 (0.008)	-0.003 (0.007)	-0.006 (0.007)
Flat to gently undulating (0-3°)	0.024 (0.014)*	0.021 (0.014)	0.039 (0.016)**	0.064 (0.016)***	0.002 (0.009)	-0.002 (0.010)
Undulating (4-7°)	0.022 (0.010)**	0.019 (0.010)**	0.056 (0.010)***	0.060 (0.010)***	0.005 (0.008)	0.002 (0.008)
Strongly rolling (16-20°)	-0.077 (0.014)***	-0.077 (0.014)***	-0.056 (0.012)***	-0.063 (0.012)***	-0.004 (0.015)	-0.006 (0.014)
Moderately steep (21-25°)	-0.154 (0.018)***	-0.147 (0.018)***	-0.085 (0.018)***	-0.093 (0.018)***		
Steep (26-35°)	-0.179 (0.026)***	-0.182 (0.026)***	-Q10 (0.025)***	-0.101 (0.025)***		
2008 Sale	-0.038 (0.020)*	-0.038 (0.020)*	-0.068 (0.021)***	-0.071 (0.022)***	-0.065 (0.014)***	-0.067 (0.014)***
2009 Sale	-0.036 (0.017)**	-0.036 (0.017)**	-0.042 (0.016)***	-0.052 (0.017)***	-0.043 (0.013)***	-0.045 (0.014)***
2010 Sale	0.022 (0.018)	0.022 (0.018)	-0.023 (0.018)	-0.040 (0.018)**	-0.003 (0.014)	-0.001 (0.015)
2011 Sale	0.030 (0.019)	0.030 (0.019)	0.032 (0.018)*	0.010 (0.018)	0.046 (0.013)***	0.043 (0.013)***
2012 Sale	0.151 (0.016)***	0.150 (0.016)***	0.095 (0.017)***	0.084 (0.017)***	0.141 (0.014)***	0.137 (0.015)***
2013 Sale	0.272 (0.016)***	0.273 (0.016)***	0.225 (0.017)***	0.214 (0.017)***	0.279 (0.013)***	0.275 (0.014)***
2014 Sale	0.410 (0.016)***	0.408 (0.016)***	0.349 (0.016)***	0.334 (0.016)***	0.411 (0.013)***	0.409 (0.013)***
2015 Sale	0.563 (0.015)***	0.562 (0.015)***	0.517 (0.017)***	0.504 (0.018)***	0.625 (0.014)***	0.624 (0.014)***
2016 Sale	0.652 (0.017)***	0.652 (0.016)***	0.683 (0.017)***	0.668 (0.017)***	0.730 (0.015)***	0.729 (0.016)***
Intercept	9.480 (0.123)***	8.457 (0.312)***	8.965 (0.264)***	9.429 (0.754)***	11.604 (0.256)***	10.596 (0.660)***
Postcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.714	0.715	0.765	0.759	0.847	0.843
Num. obs.	3194	3194	3082	3082	2231	2231
LogLik	442.12	449.30	554.13	511.13	1096.0	1068.5
AIC	-792.2474	-806.5946	-1030.2511	-944.2532	-2114.044	-2059.038
BIC	-513.0721	-527.4193	-794.9511	-708.9532	-1891.346	-1836.340

***$p<0.01$, **$p<0.05$, *$p<0.1$. Robust Standard Errors are reported in brackets.

Brick wall, steel roof, rolling slope (8-15°) and year 2007 are set as reference groups.

Table 4: Quantile Regression Results for Distance Covariates

	Double Grammar			**Selwyn College**			**One Tree Hill College**		
	Q10	Q50	Q90	Q10	Q50	Q90	Q10	Q50	Q90
Driving Distance to:									
EGG	-0.000	-0.019	-0.064						
	(0.071)	(0.053)	(0.071)						
EGG^2	0.000	-0.001	-0.002						
	(0.019)	(0.014)	(0.015)						
AG	-0.028	-0.004	0.019						
	(0.082)	(0.061)	(0.073)						
AG^2	0.062***	0.027*	0.023						
	(0.024)	(0.016)	(0.020)						
Sel				-0.039	-0.136**	-0.056			
				(0.071)	(0.059)	(0.089)			
Sel^2				-0.008	-0.011***	-0.002			
				(0.005)	(0.004)	(0.007)			
One							-0.047	-0.051	-0.024
							(0.112)	(0.083)	(0.135)
One^2							0.008	0.007	0.006
							(0.014)	(0.009)	(0.017)
CBD	0.109**	0.023	-0.001	0.174***	0.174***	0.199***	-0.248***	-0.222***	-0.194**
	(0.044)	(0.035)	(0.038)	(0.058)	(0.044)	(0.059)	(0.065)	(0.054)	(0.090)
CBD^2	0.000	0.002	-0.000	-0.011***	-0.015***	-0.016***	0.009*	0.008**	0.008
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.005)	(0.004)	(0.006)
EGG×AG	-0.043	-0.015	-0.032						
	(0.045)	(0.030)	(0.035)						
EGG×CBD	0.027*	0.010	0.018						
	(0.016)	(0.011)	(0.014)						
AG×CBD	-0.053***	-0.026*	-0.014						
	(0.018)	(0.014)	(0.017)						
Sel×CBD				0.016**	0.024***	0.011			
				(0.006)	(0.005)	(0.008)			
One×CBD							0.001	0.002	-0.002
							(0.017)	(0.011)	(0.019
Great Circle Distance to:									
Nearest Small Park	0.082	0.154***	0.131***	-0.123***	-0.070**	-0.004	-0.035	-0.001	-0.082**
	(0.050)	(0.029)	(0.042)	(0.038)	(0.028)	(0.046)	(0.037)	(0.026)	(0.039)
Nearest Medium Park	0.101**	0.044	0.002	0.102***	0.063**	0.028	0.005	0.025	0.048
	(0.042)	(0.027)	(0.033)	(0.033)	(0.027)	(0.036)	(0.031)	(0.024)	(0.034)
Nearest Large Park	-0.072**	-0.094***	-0.128***	0.056	0.013	-0.178***	-0.145***	-0.160***	-0.129***
	(0.036)	(0.027)	(0.032)	(0.040)	(0.032)	(0.048)	(0.035)	(0.021)	(0.028)
Nearest Shopping Center	0.083***	0.059***	0.098***	0.088***	0.087***	0.063*	0.033	0.046**	0.065**
	(0.026)	(0.017)	(0.023)	(0.032)	(0.023)	(0.034)	(0.022)	(0.020)	(0.027)
Nearest Beach	-0.089***	-0.054***	-0.101***	-0.120***	-0.141***	-0.174***	0.042**	0.030*	-0.016
	(0.027)	(0.020)	(0.022)	(0.017)	(0.013)	(0.020)	(0.020)	(0.016)	(0.023
Num. obs.	3194	3194	3194	3082	3082	3082	2231	2231	2231

***p<0.01, **p<0.05, *p<0.1. Bootstrap Standard Errors are reported in brackets.

Appendix A List of Shopping Centers

Table A.1: 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	
Wsstfield Manukau City	
Kelston Shopping Center	West Auckland
Lynnmall	
Northwest Shopping Center	
Waitakere Mega Center	
WestCity Waitakere	
Westgate Shopping Center	

Appendix B   List of Beaches

Table B.1: Beaches without Long-term Water Quality Alarm

Name	Number
St Heliers Beach	1
Kohimarama Beach	2
Mission Bay Beach	3
Okahu Bay	4
Judges Bay	5
St Marys Bay	6
Home Bay	7
Herne Bay	8
Point Chevalier	9
Blockhouse Bay	10
Waikowhai Bay	11
Granny's Bay	12
Taumanu West	13
Onehunga Lagoon	14
Taumanu Centra	15
Taumanu East	16
Point England	17